Joint Optimization of Level of Repair Analysis and Civil Aircraft Inventory System Based on PSO Algorithm

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Abstract. The traditional optimization approach for the level of repair analysis (LORA) of civil aircraft and inventory system allocation is to optimize repair level and spare parts allocation separately. But the joint cost of maintenance and inventory allocation policy will not be the necessarily optimal, due to the fact that the direct effect on the inventory system is neglected in the LORA process. Thus, in this paper, a joint optimization model for LORA and civil aircraft inventory system is constructed with the system total cost as the objective function and the fleet availability as the constraint. Next, the particle swarm optimization (PSO) algorithm is applied to solve the proposed multivariable nonlinear optimization model. Finally, some components of the landing gear system are selected as the examples, and through the comparison with the results from traditional sequence method and iterative algorithm, the proposed method is validated to be feasible and effective.

1. Introduction
Level of repair analysis (LORA) has a significant impact on civil aircraft supportability and maintainability, it generally starts from the aircraft design and development stage to determine which failed components to repair or discard and which echelon to conduct the repair or discard decision. Especially for the expensive products like the engine, landing gear and cabin door systems, LORA can formulate more economical maintenance strategies to allocate the logistics support resources by identifying the best maintenance options and the best repair locations.

Although an estimated cost for spare parts stocking can be considered in the LORA process, this cost is too rough to mimic the accurate stocking policy. Therefore, in the traditional optimization method for LORA and inventory system allocation, the repair level and spare parts stocking are optimized separately. So, the first step in the traditional sequence method is to find the best maintenance strategy, and then according to the repair level decided from the previous step to get the most economical inventory configuration policy. But the joint cost will not be the necessarily optimal, due to the fact that repair or discard option is only decided by the repair or discard cost. The backorder levels, transportation time between echelons as well as the difference of repair time at different locations are neglected in the LORA process. For example, if there is a component decided to be repaired at the central depot in LORA, but actually, it will take more time for transportation and repair when comparing the base repair option, which means it will result in higher number of backorders and inventory quantity. So, in order to acquire the same fleet availability and the minimum system total cost, repair at the base level may be the best choice. Therefore, it is necessary to establish the joint optimization model for LORA and inventory system.
To the best of our knowledge, the first model for solving LORA problem is proposed by Barros, and the problem is considered as an integer linear programming model [1]. Saranga and Kumar develop a different model with Barros, and the genetic algorithm is applied to solve this new nonlinear problem [2]. Wu et al. use an improved particle swarm optimization (PSO) algorithm to solve a three-echelon three-indenture LORA model for civil aircraft [3]. Basten et al. establish a minimum cost flow model with side constraints, and remarkably decrease the computation time [4]. Xue et al. propose a concept of LORA decision flow, and take into consideration the maintenance characteristics of the aircraft in the economic analysis model [5]. Jia et al. combine the analytical hierarchy process (AHP) and set pair analysis (SPA) to present a comprehensive analysis model of AHP-SPA for the LORA problem [6]. Besides, a large number of scholars have conducted researches on spare parts stocking problem. Sherbrooke develops the METRIC model (Multi-Echelon Technique for Recoverable Item Control), which is considered as the seminal work in this field [7]. Sun et al. establish a multi-echelon inventory optimization model based on VARI-METRIC model, and use the marginal analysis to optimize the inventory of civil aircraft components [8]. Francesco et al. combine the Italian Air Force data to research the multi-echelon multi-indenture inventory configuration of spare parts based on VARI-METRIC model and marginal analysis method [9]. Basten et al. study the existing single-echelon and multi-echelon inventory configuration models and further explore the scope of application of these classic models [10]. Feng et al. integrate the maintenance rate into the METRIC model, and accomplish the multi-echelon inventory allocation of civil aircraft spare parts [11]. What’s more, in order to deal with the defect of the sequence method, Basten et al. develop a joint optimization model and an integrated algorithm, but this method is restricted to two-echelon single-indenture problems [12]. Both Basten and Xue propose to use the iterative algorithm to solve the generalized multi-echelon multi-indenture problem [13, 14]. However, the iterative algorithm is only used for solving symmetrical network problems, it assumes each component owns the same configuration quantity in every base, which is insufficient in practice. Although it can be extended to the asymmetric problems, the extended iterative algorithm is quite complex and difficult to program due to the frequent iterative process for inventory cost. Therefore, in order to solve the problems above, a joint optimization model of LORA and inventory system is established in this paper with the system total cost as the objective function and the fleet availability as the constraint. Then, the PSO algorithm is applied to solve the proposed asymmetric model due to its characteristic of easy programming and the superior ability for direct search and global optimization. Finally, some spare parts from the civil aircraft landing gear system are chosen as an example, and the model proposed in this paper is validated to be feasible and effective through comparing with the traditional sequence method and iterative algorithm.

2. Assumptions and mathematical model

2.1. Assumptions

In the field of civil aviation, the airlines prefer to use the two-echelon maintenance support system with a number of bases and one central depot as the Fig.1 shows below.
When spare parts demands occur at the bases, the central depot will provide direct replenishment to the base stocks. And most capital goods in the civil aircraft consist of several line replaceable units (LRUs), which can be replaced by functioning spare parts at the base echelon. Besides, the LRUs are made up of a number of subcomponents, shop replaceable units (SRUs), which are generally repaired at the central depot as shown in the Fig. 2.

\[ \text{Product} \]

\[ \begin{array}{c}
\text{Ind. 1} \\
\text{LRU 1} & \text{LRU 2} & \ldots & \text{LRU n} \\
\text{Ind. 2} \\
\text{SRU 1,1} & \text{SRU 1,2} & \ldots & \text{SRU n,1}
\end{array} \]

**Figure 2.** Two-indenture component system.

In this paper, combined the stocking theory of the METRIC model, this paper develops a joint optimization model with two-echelon and two-indenture. In order to simplify the modeling process and improve the engineering applicability, some basic assumptions are proposed here:

- The LRUs can be repaired at the base echelon, or transferred to the central depot for repair.
- The SRUs only can be repaired or discarded in the depot.
- If an LRU is chosen to be discarded, it means all the subcomponents will be discarded together.
- All the discard options will be performed at the central depot only, since the newly purchased components in practice will be sent to the depot generally.
- The (S-1, S) stocking control policy (one for one replenishment) is applied to each location.
- Component faults yield to the Poisson distribution.
- Replacement of a defective component takes zero time, but the repair time, transportation time, as well as the reorder time will be taken into consideration.
- The repairs are considered always successful.
- Spare parts are generally allocated in both levels unless the failed components are discarded or repaired in the central depot.
- There are no lateral transshipments allowed among the bases.

### 2.2. Joint optimization model

Let the maintenance support system consist of two levels with \( m \) bases (\( J_1, \ldots, J_m \)) and one central depot (\( J_0 \)). The product is made up of some LRUs and several SRU subcomponents, the LRU total number \( I \) is set to \( n \). And the maintenance option \( P \) includes \{r, d, t\}, represent repair at base, discard and transfer respectively. Then define the nonlinear joint optimization model for two-echelon two-indenture LORA and spare part stocks as follows:

\[
\min \sum_{j=0}^{m} \sum_{p \in P} \sum_{i \in I} v_c \cdot x_{j,p,i} \cdot \beta_i \cdot x_{j,p,i} + \sum_{j=0}^{m} \sum_{i \in I} f_c \cdot x_{j,r,i} + \sum_{j=0}^{m} \sum_{i \in I} h_c \cdot s_{j,i}
\]

Subject to:

\[
\sum_{p \in P} x_{j,p,i} = 1, \quad \forall j \in \{ J_1, \ldots, J_m \}, \forall i \in I
\]
\[ x_{j,t,i} \leq \sum_{p \in P} x_{j_0,p,i} \cdot \forall e \in \{J_1, L, J_m\}, \forall i \in I \]  
\[ x_{j,d,i} \leq x_{j,d,0} \cdot L \cdot x_{j_0,0} \cdot \forall j \in \{J_0, L, J_m\}, \forall i \in I \]  
\[ x_{j,p,i} \in \{0, 1\}, \forall j \in \{J_0, L, J_m\}, \forall i \in I, \forall p \in P \]  
\[ A \geq A_{\text{min}} \]  

in which, \( v_{c,j,p,i} \) is defined as the variable cost for component \( i \) \((i=1, \ldots, n)\) at location \( j \in \{J_1, \ldots, J_m\}\) to perform the maintenance option \( p \in P \). Besides, \( f_{c,j,p,i} \) is the fixed cost for component \( i \) when the repair option is chosen at location \( j \). Generally, the variable costs consist of labor costs, transportation costs and storage costs. And the fixed costs may include the maintenance tools, equipments as well as technical documents. Additionally, \( \beta_i \) represents the annual average number of failures for each component. \( s_{j,i} \) is defined as the spare parts quantity of every component at each location, and \( h_{c,i} \) is the unit price for each component.

What’s more, \( x \) is the decision variable defined in this paper:

\[ x_{j,p,i} = \begin{cases} 1 & \text{if the component } i \text{ chooses the maintenance option } p \text{ at the location } j \\ 0 & \text{else} \end{cases} \]  

There are three parts in the objective function, the maintenance variable costs, repair fixed costs and the spare parts costs. The constraint (2) assures that for each component a decision will be made at the base level. Constraint (3) makes sure that there will be an option made at the central depot, if a component decides to transfer. Constraint (4) guarantees that when an LRU is discarded, all the subcomponents will be discarded together. Constraint (5) is value range for the decision variable, and Constraint (6) is the minimum requirement for the fleet availability \( A \).

2.3. Inventory allocation model

In the joint optimization model, the spare parts cost is a significant part, so it is necessary to elaborate the inventory allocation model and theory.

2.3.1. Annual average demand. Component faults may occur at any time during the operation of the aircraft, and the average annual demand for each component is equal to the average replacement in one year.

\[ \lambda_i = \frac{FH \cdot QPA_i \cdot N}{MTBUR_i} \]  

where \( \lambda_i \) is the annual average demand for each component, the aircraft annual flight time is \( FH \), and \( QPA_i \) is the installation number for each plane. \( N \) is the number of fleet size and \( MTBUR_i \) is the mean time between unscheduled removals for every component.

The plane may pass through multiple bases in one route, so the demand of each base can be calculated based on the flight distance.

\[ \lambda_{j,i} = \frac{D_j}{\sum D} \lambda_i \]  

where \( \lambda_{j,i} \) is considered as the annual demand of base \( j \) for each component, and \( D_j \) is the distance between base \( j \) and the former base.
And the average annual demand of central depot is:

$$\lambda_{0,i} = \sum_{j=1}^{m} \lambda_{j,i} \cdot x_{j,i} \quad (10)$$

in which $\lambda_{0,i}$ is the average annual demand of depot for each component.

2.3.2. Annual average number of supply channel. $\mu_{0,i}$ is defined as the number of supply channel for the central depot, $RT_{0,i}$ is the expected repair time in depot maintenance spot, and $Ts_{0,i}$ is the expected reorder time for every component. According to the assumption, component faults obey Poisson distribution. So, the equation below can be derived by Palm theorem.

$$\mu_{0,i} = \begin{cases} \lambda_{0,i} \cdot RT_{0,i}, & x_{0,r,i} = 1 \\ \lambda_{0,i} \cdot Ts_{0,i}, & x_{0,d,i} = 1 \end{cases} \quad (11)$$

And according to Palm theorem, the number of supply channel for each base is:

$$\mu_{j,i} = \begin{cases} \lambda_{j,i} \cdot RT_{j,i}, & x_{j,r,i} = 1 \\ \lambda_{j,i} \cdot (TRT_{j,i} + MWT_{0,i,j}), & x_{0,r,i} = 1 \\ \lambda_{j,i} \cdot (TRT_{j,i} + MWT_{0,d,i}), & x_{0,d,i} = 1 \end{cases} \quad (12)$$

where $RT_{j,i}$ is the expected repair time in each base, and $TRT_{j,i}$ is the expected transportation time between the base and depot. Besides, according to the Little formula, the delay time due to depot backorder $MWT_{0,i}$ can be calculated by:

$$MWT_{0,i} = \frac{EBO(s)_{0,i}}{\lambda_{0,i}} \quad (13)$$

2.3.3. Expected number of backorders and fleet availability. The expected number of backorders in the central depot and bases are:

$$EBO(s)_{0,i} = \sum_{k=s+1}^{+\infty} (k-s) \frac{(\mu_{0,i})^{k} e^{-\mu_{0,i}}}{k!} \quad (14)$$

$$EBO(s)_{j,i} = \sum_{k=s+1}^{+\infty} (k-s) \frac{(\mu_{j,i})^{k} e^{-\mu_{j,i}}}{k!}$$

And the fleet availability is calculated as below:

$$A_j = \prod_{i=1}^{a} \left( 1 - \frac{EBO(s)_{j,i}}{N \cdot QPA_i} \right)^{QPA_i} \quad (15)$$

3. Algorithm

It is clear that the joint optimization model established here is a multivariable nonlinear problem, which is quite hard to solve. Although Basten develops an iterative algorithm, the method for adding spare parts costs into the variable costs in every iteration is complex and hard to program. So, it is important to find a new algorithm for the proposed model. It is noticed that the PSO algorithm has a great potential to solve such problems, since it is simple to program and has a strong generality.
Additionally, it also owns a superior ability for direct search and global optimization. Thus, in this paper, the PSO algorithm is applied for the joint optimization of LORA and inventory system. The PSO algorithm steps are summarized as the following:

Step 1: Set the particle quantity $Q$, and initialize the velocity and position for each particle.

Step 2: Calculate the fitness value for each particle, and the fitness value $y$ is as the same as the objective function (1):

$$
y = \sum_{j=0}^{m} \sum_{p \in P} \sum_{r \in I} v_{c,j,p,r} \cdot x_{j,p,r,i} + \sum_{j=0}^{m} \sum_{r \in I} f_{c,j,r,i} \cdot x_{j,r,i} + \sum_{j=0}^{m} h_{c,i} \cdot s_{j,i}$$

(16)

Step 3: For each particle, compare the fitness value with the best fitness value ($P_{best}$) in history, and update the fitness value and position of $P_{best}$.

Step 4: Choose the particle with the best fitness value in history from all the particles, and assign the best as the global best ($G_{best}$).

Step 5: Update the speed and position values according to equation (17) and (18).

$$V_{i}^{k+1} = w \cdot V_{i}^{k} + c_{1} \cdot r_{1} \cdot (Pb_{i}^{k} - X_{i}^{k}) + c_{2} \cdot r_{2} \cdot (Gb_{i}^{k} - X_{i}^{k})$$

(17)

$$X_{i}^{k+1} = X_{i}^{k} + V_{i}^{k+1}$$

(18)

where $V$ represents the particle vector, $X$ represents the particle position, and $k$ is the number of iterations. $w$ is the inertia weight factor, $c_{1}$ and $c_{2}$ are the acceleration constants. Besides, $r_{1}$ and $r_{2}$ are random numbers over the range [0,1]. $Pb$ and $Gb$ are defined as the particle best position and global best position separately.

Step 6: Once the search criteria are attained, the global best fitness value is the searched solution. Otherwise, return to Step 2.

What’s more, the marginal analysis method is used in this algorithm for calculating the spare parts quantity $s_{j,i}$. The process of marginal analysis method is elaborated a lot in the papers introduced above, so it won’t be repeated here.

4. Computational experiment

In this section, a computational experiment is used here to compare solving the joint optimisation problem using PSO algorithm with using the traditional sequence method and iterative algorithm. 10 components of the civil aircraft landing gear system are selected as the research objects. The fleet is made up of 10 Boeing 787 airplanes with an average flight time of 2950 hours per year as well as the minimum fleet availability at 0.97. And the inventory system consists of 1 central depot and 3 bases as shown in Fig. 3.

![Figure 3. Inventory allocation system for landing gear system.](image)

And the parameters for inventory allocation are given in Table 1. And the input parameters relating to LORA, such as variable costs and fixed costs, are shown in Table 2. Then, the PSO algorithm is
applied to solve the example, the computational experiment is carried out with 50 particles with the iteration criterion of 50 steps. Besides, the inertia value \( w \) and the acceleration factors \( c_1 \) and \( c_2 \) are set as 0.7, 0.8 and 0.8 respectively. It is noticed that the PSO algorithm stops at the 4th step, and acquires the new maintenance options as well as the minimum joint cost at 5.011 million dollars.

Table 1. Parameters for inventory allocation of each component.

| No. | \( QPA_i \) | MTBUR/h | \( TRT_i/\text{year} \) | \( RT_j/\text{year} \) | \( RT_{0,j}/\text{year} \) | \( TS_{0,i}/\text{year} \) | \( hc_i/\$ \) |
|-----|-------------|---------|-----------------|-----------------|-----------------|----------------|------------|
| LRU1 | 32.0        | 3975    | 0.0029          | 0.012           | 0.012           | 0.014         | 9510       |
| LRU2 | 3.0         | 48133   | 0.0055          | 0.052           | 0.028           | 0.038         | 149905     |
| LRU3 | 8.0         | 1383    | 0.0035          | 0.02            | 0.0195          | 0.017         | 35984      |
| LRU4 | 8.0         | 4564    | 0.006           | 0.081           | 0.039           | 0.041         | 176815     |
| LRU5 | 2.0         | 1191    | 0.003           | 0.017           | 0.0165          | 0.016         | 15359      |
| LRU6 | 1.0         | 4020    | 0.0042          | 0.018           | 0.0175          | 0.02          | 65868      |
| SRU6,1| 2.0        | 53606   | 0.00275         | 0.021           | 0.012           | 0.013         | 7599.7     |
| SRU6,2| 2.0        | 4057    | 0.0027          | 0.017           | 0.01           | 0.013         | 3374       |
| LRU7 | 4.0         | 4639    | 0.0033          | 0.013           | 0.012           | 0.017         | 25752      |
| LRU8 | 1.0         | 13392   | 0.006           | 0.082           | 0.04            | 0.042         | 179161     |

Table 2. Variable and fixed costs of each component.

| No. | \( \beta_i \) | \( fc/\$ \) | \( VC_{j,r,i}/\$ \) | \( VC_{j,t,i}/\$ \) | \( VC_{0,r,i}/\$ \) | \( VC_{0,d,i}/\$ \) |
|-----|--------------|---------|-----------------|-----------------|----------------|----------------|
| LRU1 | 4            | 800    | 3600            | 360             | 3500           | 9510           |
| LRU2 | 2            | 5000   | 35000           | 480             | 25000          | 149905         |
| LRU3 | 9            | 1300   | 9670            | 420             | 6100           | 35984          |
| LRU4 | 7            | 5000   | 40000           | 500             | 26000          | 176815         |
| LRU5 | 3            | 900    | 4995            | 400             | 4900           | 15359          |
| LRU6 | 1            | 1500   | 16200           | 430             | 13200          | 65868          |
| SRU6,1| 1           | 500    | /               | 360             | 2500           | 7599.7         |
| SRU6,2| 4           | 500    | /               | 360             | 970            | 3374           |
| LRU7 | 2            | 1000   | 6150            | 410             | 6090           | 25752          |
| LRU8 | 2            | 5000   | 42000           | 500             | 25000          | 179161         |

In order to verify the feasibility and effectiveness of the proposed algorithm, this example is also solved by the iterative algorithm and sequence method separately. By using the iterative algorithm, the obtained optimal cost is as the same as the result of PSO algorithm, which is 5.011 million dollars, but it is found that the solving process iterates 6 times before stopping. However, the result of the traditional sequence method reaches 5.375 million dollars, which is 6.76% higher than the PSO algorithm and the iteration algorithm. What’s more, it can be found that all the three methods have achieved the minimum fleet availability requirement, and the fleet availabilities of PSO and iterative algorithm are slightly higher than the sequence method. Through comparing with the results of iterative algorithm and sequence method, it is cleared that the PSO algorithm can solve the joint optimization problem accurately and effectively. The comparison for results of three methods is shown in Table 3.
Table 3. Results comparison for three methods.

| Method               | Iteration times | Fleet availability | Joint cost/$ | Cost reduction |
|----------------------|-----------------|--------------------|--------------|---------------|
| Sequence method      | /               | 0.9714             | 5.375x10^6   | /             |
| PSO algorithm        | 4               | 0.9719             | 5.011x10^6   | 6.76%         |
| Iteration algorithm  | 6               | 0.9719             | 5.011x10^6   | 6.76%         |

Table 4. Maintenance option and inventory quantity by PSO algorithm.

| No.   | Base repair cost/$ | Depot repair cost/$ | Discard cost/$ | Inventory quantity |
|-------|--------------------|---------------------|----------------|-------------------|
| LRU1  | 45600              | /                   | /              | 14                |
| LRU2  | /                  | 157880              | /              | 1                 |
| LRU3  | /                  | 177340              | /              | 23                |
| LRU4  | /                  | 561500              | /              | 12                |
| LRU5  | 47655              | /                   | /              | 7                 |
| LRU6  | /                  | 42390               | /              | 4                 |
| SRU6,1| /                  | 9080                | /              | 4                 |
| SRU6,2| /                  | 16460               | /              | 7                 |
| LRU7  | 39900              | /                   | /              | 4                 |
| LRU8  | /                  | 158000              | /              | 2                 |
| LORA cost/$ | 1255805         |                     |                |                   |
| Inventory cost/$  | 4118788          |                     |                |                   |
| Joint cost/$      | 5374593          |                     |                |                   |

Table 5. Maintenance option and inventory quantity by sequence method.

| No.   | Base repair cost/$ | Depot repair cost/$ | Discard cost/$ | Inventory quantity |
|-------|--------------------|---------------------|----------------|-------------------|
| LRU1  | 45600              | /                   | /              | 14                |
| LRU2  | /                  | 157880              | /              | 1                 |
| LRU3  | /                  | 264990              | /              | 12                |
| LRU4  | /                  | 561500              | /              | 12                |
| LRU5  | 47655              | /                   | /              | 7                 |
| LRU6  | 53100              | /                   | /              | 3                 |
| SRU6,1| /                  | 9080                | /              | 4                 |
| SRU6,2| /                  | 16460               | /              | 7                 |
| LRU7  | 39900              | /                   | /              | 4                 |
| LRU8  | /                  | 158000              | /              | 2                 |
| LORA cost/$ | 1354165         |                     |                |                   |
| Inventory cost/$  | 3657096          |                     |                |                   |
| Joint cost/$      | 5011261          |                     |                |                   |

What’s more, Table 4 and Table 5 show the new maintenance options after the joint optimization by PSO algorithm and the original options decided according to the sequence method. It can be seen that LRU3 and LRU6 change the maintenance option from depot repair to base repair due to the reduction of spare parts allocation quantity by 11 and 1 respectively. Although the LORA cost increase slightly, the inventory cost shows a remarkable decrease because of the reduction of inventory quantity. The reason can be explained by the theory from METRIC model, because the repairs are considered always successful, so the base repair option will lead to zero spare parts demand in the central depot, but all the other options will cause a high demand instead. Thus, once the base repair option is decided,
the expected number of backorders in the depot is 0, which will lead the depot inventory allocation quantity to 0, too.

Take LRU3 as an example, the average backorder numbers for all bases by base repair, depot repair and discard option are shown in Fig. 4, and the average backorder numbers of the whole inventory system with the different options are presented in Fig. 5. It can be seen that the bases average backorder numbers share the similar level, although the backorder numbers for base repair and discard are slightly less than the depot repair. But it is clear that when considering the depot backorder numbers, the system average backorder numbers for depot repair option and discard option increase dramatically. Therefore, for LRU3, the base repair option will lead less spare parts quantity than the depot repair or discard, which is the reason for its maintenance option changing.

![Figure 4](image1.png)

**Figure 4.** Average expected number of backorders in all bases by different maintenance option.

![Figure 5](image2.png)

**Figure 5.** Average expected number of backorders for whole system by different maintenance option.
Figure 6. Influence for the inventory system backorder number by the change of base repair time when repair at the base.

Figure 7. Influence for the inventory system backorder number by the change of transportation time when repair at the depot.

Figure 8. Influence for the inventory system backorder number by the change of depot repair time when repair at the depot.
Figure 9. Influence for the inventory system backorder number by the change of reorder time when discard at the depot.

However, the great difference among central depot backorder numbers caused by the METRIC model is only one reason for the repair location change. The maintenance time for repair, reorder and transportation also has an important impact on the backorder numbers. Still take LRU3 as an example, the influences for the inventory system backorder numbers by the changes of maintenance time are shown in the following figures. In Fig. 6 and Fig. 7, it is noticed that the base repair time and transportation time show a slight effect on the backorder numbers. However, the depot repair time and reorder time present a large impact on the backorder numbers in Fig. 8 and Fig. 9. Especially, if the depot repair time drops to 0.0095 and the base repair time rises to 0.025, the system backorder number of base repair will exceed that of the depot repair, which means repair at bases will cause more spare parts stocks and the depot repair option will be the better choice.

5. Conclusion
In this paper, the following conclusions can be obtained:
(1) Based on the existing research on LORA and inventory allocation, a joint optimization model for LORA and inventory system is established with the system total cost as the objective function and the fleet availability as the constraint.
(2) The PSO algorithm is applied to solve the joint optimization problem, and the solution steps are elaborated in detail.
(3) 10 components of the aircraft landing gear system are selected as the research objects, and the PSO algorithm is validated to be feasible and effective for solving this joint optimization model through comparing with the traditional sequence method and iterative algorithm.
(4) The joint optimization method leads to a joint cost reduction of 6.76%, and in this paper, the reasons for causing maintenance option change and cost decrease are discussed in detail.

Acknowledgments
The authors wish to thank the anonymous referee for the helpful comments. The authors gratefully acknowledge the support of the National Natural Science Foundation of China (Grant No. 5187051969). Besides, the research work has also been supported by the Civil Aircraft Special Scientific Research Technology Research Project (Grant No. MJZ-2016-Y-84).
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