Ammunition Scheduling Method in Airborne Weapon Depot Based on Improved Genetic Algorithm

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Abstract. The scheduling of the carrier-based aircraft weapon involves many resources and is subject to many constraints. The design of the scheduling scheme belongs to a type of typical NP-Hard problem. In this paper, genetic algorithm is selected as the optimization algorithm, and a two-layer real-value coding method is designed, and the selection, cross, and mutation operations of the algorithm are improved by using the elite strategy and other methods. The improved algorithm was used to simulate the established mathematical model to verify the effectiveness and superiority of the improved algorithm.

1. Introduction

The transfer within the aircraft carrier's airborne weapons depot refers to the process in which ammunition leaves the carrier's lower ammunition depots, and is transferred to the ammunition assembly area via the lower weapon elevator, and the assembled ammunition is transferred to the flight deck via the upper weapon elevator. Airborne weapons and ammunition support tasks are guaranteed in waves. The types of ammunition that are transported for different combat tasks are different, and the demand and assembly time of each type of ammunition are also different. The distribution of different ammunition delivery order and elevator use order will make the completion time of the transfer operation very different. The efficiency of airborne weapons and ammunition support tasks directly affects the dispatch efficiency of the carrier aircraft, and affects the combat effectiveness of the aircraft carrier [1]. The purpose of this paper is to establish a mathematical model of the transfer operation in the ammunition depot, and study how to reasonably optimize the scheduling plan so that the transfer operation in the ammunition depot can be completed in the shortest time.

The ammunition scheduling of aircraft carrier recorded weapons belongs to the resource optimization scheduling problem, which has typical complexity, randomness, and multiple constraints, and is a typical NP problem. The methods to solve such problems are mainly divided into mathematical programming methods, simulation methods, intelligent optimization algorithms, etc. [2]. Traditional mathematical programming methods are often complex in calculation process, and they cannot even be solved for some large-scale problems. Simulation methods are too low in versatility and need to be re-modelled and simulated for slightly different problems. Intelligent optimization algorithms are widely used in similar optimization problems due to their simplicity and ease of implementation.

Genetic algorithm is an intelligent optimization algorithm that simulates biological genetic evolution. It has the advantages of simple algorithm, fast calculation speed, high robustness, and good global search ability. At the same time, it is a direct search algorithm that does not depend on specific problems. It has applications in many fields such as production scheduling, function optimization, and path planning.
However, traditional genetic algorithms also have shortcomings such as being easy to fall into local extremes and high dependence on the initial population. The improvement of basic genetic algorithms is generally through combining with other algorithms, parallel operations, introducing elitism, adopting adaptive strategies, and Operation operator adjustment and other methods [3,4].

2. Problem model

The dispatching operations in the carrier-based aircraft ammunition depot include the transfer of ammunition from the ammunition depot to the ammunition operation room, the assembly of ammunition, and the transportation from the ammunition operation room to the flight deck.

Assuming that there are \( m \) types of ammunition required by the carrier-based aircraft, a wave of support tasks is \( \text{Task} = [N_1, \ldots, N_i, \ldots, N_m] \), where \( N_i \) represents the number of ammunition requirements for the type of \( i \).

The transfer of an ammunition to the fight deck includes outbound and lower elevator transfer, assembly, and upper elevator transfer. It is assumed that the time of each link is as follows:

| Symbol | Description |
|--------|-------------|
| \( t_d \) | The time of ammunition out of the depot and the round-trip time of the lower elevator |
| \( t_i \) | Assembly time of the ammunition for the type of \( i \) |
| \( t_u \) | The round-trip time of the upper elevator |

Table 1. Operation time description.

The return of the upper elevator to its original position is the end time of transporting one ammunition, and the time for transporting one ammunition of type \( i \) is \( t_i = t_d + t_i + t_u \).

The ammunition transfer operation in the aircraft carrier warehouse is a parallel operation. Take the US Ford aircraft carrier as an example, and the structure of transfer system is shown in the Figure 1.

![Figure 1. Structure of transfer system.](image)

Then the number of parallel work paths is \( n = 2 \times 2 + 2 \times 1 \), a total of six. Assuming that the scheduling sequence of the \( j \)-th path is \( A_j \), the scheduling scheme can be expressed as

\[ D = [A_1, \ldots, A_j, \ldots, A_n] \]. Each lower elevator is shared by two parallel paths. Assuming it is alternately used as two paths, the time required for the dispatch of two consecutive ammunition on the same path is

\[ \bar{t} = t + 2t_d + (t_b^i - t_f^j) \],

where \( t_b^i \) represents the assembly time of the next ammunition, \( t_f^j \) represents the assembly time of the previous ammunition, and \( t \) represents the total transport of the previous ammunition time. According to the actual assumption \( t_d > t_u \), and there are enough
ammunition assemblers to ensure that the assembled ammunition will not be blocked in the ammunition operation room. Assuming that $t_i$ represents the time of the first ammunition transported on a certain route, and the subscript $i$ represents the type of the ammunition, then the total time of the route is:

$$T_j = t_i + 2t_d \sum_{k=1}^{m} n_k + \sum_{k=1}^{m} n_k(t^i_k - t^k)$$

Where $n_k$ represents the total quantity of the k-th ammunition transported in the route, which satisfies the constraint:

$$\sum_{j=1}^{n} n_k = N_k, k = 1, ..., m$$

Then the objective function of the scheduling plan is:

$$f = \min \{ \max \{T_j\}, j = 1, ..., n \}.$$

3. Design genetic algorithm

3.1. Coding method

Coding method is the primary and core problem of genetic algorithm [5]. Coding methods usually include binary coding, floating-point number coding, sequence coding, etc. Different coding methods directly affect the optimization effect of the algorithm. Because the dispatch plan needs to determine the ammunition transfer path and the order of delivery, a single code based on the order of delivery or a code based on the transfer path cannot fully express the content of the dispatch plan, so the double-layer real-valued encoding method is used here [6], as shown in Figure 2. The method of code.

The first layer is based on the code of the outgoing order of ammunition, the number in the code represents the type of ammunition, and the length of the chromosome is the total number of ammunitions required by the mission. The second layer is based on the code of the transit route number, which corresponds to the first level of code, corresponding to the same transfer the ammunition of the route number is transferred on the same route, and the order of the ammunition dispatching on the same route is based on the order of the first layer of coding. For example, the ammunition labelled 5 in the Figure 2 and the second ammunition labelled 1 have a corresponding transfer path of 1, which means that the transfer path first transfers a type 5 ammunition, and then transfers a type 1 ammunition.

3.2. Fitness function and selection strategy

Genetic algorithm uses fitness function to measure the fitness of each chromosome to the environment. This problem is known to optimize the objective function, which is a minimization problem. The function $Fitf = \frac{1}{f}$ is used as the fitness function. According to the probability, the roulette strategy is used to implement the selection operation, and the population size is M and the individual fitness is $f_i$, then the probability of the individual chromosome being selected is
\[ p_i = k \times \frac{f_i}{\sum_{j=1}^{n} f_j} \quad k \] is the adjustment coefficient. When the population size is too large, the probability of an individual being selected will become very low, and individuals with different fitness levels will be selected the probability difference will be reduced, so by multiplying by a reasonable adjustment coefficient, the difference between individuals with different fitness levels is enlarged to ensure the effect of the selection operation.

### 3.3. Cross operation

The real-valued coding method adopted directly reflects the scheduling scheme, and the crossover operation will greatly change the chromosome and easily destroy the good individuals in the population. Therefore, the elite strategy [7] is used to improve the crossover operation. First, the selected good individuals of the previous generation are sorted according to their fitness, and the top-ranked individuals are selected to directly enter the next generation, and the remaining individuals are cross-operated.

In order to improve the randomness of the generated chromosomes, expand the search space of the solution, and cross over the double-layer codes of the chromosomes respectively. For coding based on the outbound order, the feasibility of the solution must be ensured, that is, the crossover operation does not change the number of various types of ammunition out of the library, and the crossover operation needs to be improved. First, randomly select a gene segment of the parent chromosome, remove the same number of genes from the mother chromosome from front to back, then insert the gene segment into the tail of the mother chromosome, and then do the same operation on the parent chromosome to complete the crossover. For the encoding based on the serial number of the transit route, changing the number of the serial number of each route will not generate illegal solutions, but can increase the diversity of the population. The multi-point crossover method is used to randomly select the same length gene fragments on the parent chromosomes to exchange and place them at the tail of the chromosome to complete the crossover. This method will change the number of ammunitions dispatched by each path, ensure the diversity of chromosomes, and expand understanding Search space.

### 3.4. Mutation operation

The main purpose of mutation operation is to maintain the richness of the population, avoid premature convergence of the algorithm, and help jump out of local extremes. For the same reason as the crossover operation, mutation also adopts an elite strategy, and only performs mutation operations on individuals with lower fitness rankings. For coding based on the order of delivery, the mutation operation cannot change the quantity of various ammunition. This article adopts the method of randomly selecting \( k = \frac{\sum_{i=1}^{N} N_i}{20} \) pairs of gene pairs according to the length of the chromosome. The mutation operation based on the encoding of the transport path randomly selects the number of k mutation positions according to the length of the chromosome and mutates them into random numbers within the allowable range. Selecting the number of mutant genes adaptively according to the length of the chromosome is to ensure the effect of the mutation operation, improve the efficiency of the mutation, and avoid weakening the effect of the mutation due to the length of the chromosome.

### 4. Simulation and results

Assuming that a wave of support tasks is to support 10 aircraft, there are 5 types of ammunition, and the assembly time and demand for each ammunition are as follows. The assembly time of each ammunition is as follows

| Type of ammunition | A  | B  | C  | D  | E  |
|--------------------|----|----|----|----|----|
| Assembly time      | 300| 360| 420| 480| 540|
| Required quantity  | 20 | 20 | 10 | 10 | 20 |
Table 3. Experimental result.

| Algorithm               | Best solution | Worst solution | Average | Average number of iterations to reach the best solution |
|-------------------------|---------------|----------------|---------|-------------------------------------------------------|
| Improved genetic algorithm | 4310          | 9870           | 5259    | 50                                                    |
| Genetic algorithm        | 4430          | 10890          | 5564    | 107                                                   |

Figure 3. Improved genetic algorithm.       Figure 4. Genetic algorithm.

The example is realized by Python programming simulation, and the improved genetic algorithm is compared with the traditional genetic algorithm, and the average value is taken from 20 experiments. The experiment set the population size to 500, the number of iterations is 200, and the top 30% of the population are elite individuals. The experimental comparison results are shown in Table 3.

It can be seen from the experimental results that the improved genetic algorithm converges faster and has higher efficiency, while the unimproved genetic algorithm is not only slower, but it can also be seen from the Figure 4 that its results are very unstable, and at the same time it is the best the solution and population average are also slightly worse than the improved genetic algorithm.

5. Conclusion

After mathematically modelling the transportation problem in the ammunition depot, compared with traditional mathematical methods, the steps of using genetic algorithm to solve the problem are simple and easy to understand. Especially when the large number of dispatching ammunitions makes the scale of the problem very large, the advantages of genetic algorithm are more prominent. Aiming at the characteristics of the problem, a double-layer real-value coding method is designed to encode the problem, and the elite strategy is used to improve the selection, crossover, and mutation operations of the genetic algorithm. According to the analysis of the experimental results, the convergence speed and stability of the improved genetic algorithm have been improved. The mathematical model established in this paper and the improved genetic algorithm have a certain practicability for solving the scheduling problem in the airborne weapon depot.

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