

Research Article

Application of Adaptive Genetic Algorithm in Optimal Scheduling of Aviation Materials

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The maintenance and logistics support of aircraft are critical to the flight safety. The configuration and scheduling of air materials are the basis of maintenance and logistics. This research establishes the model of air material scheduling problem and introduces NSGA-II genetic algorithm with adaptive design to optimize the air material scheduling arrangement. This adaptive design improves the local optimal solution problem of NSGA-II and makes the optimal scheduling of air materials more accurate. In some cases, the improved NSGA-II algorithm is expressed to zero deviation, which is not achieved by other traditional algorithms. The results of this research provide a solution with practical potential for aircraft material scheduling problem, which is significantly superior to traditional methods.

1. Introduction

At present, civil aviation and transportation are important driving forces to promote the economic and cultural development of countries and regions. In recent years, the development of my country's aviation industry has also shown the characteristics of high speed and high quality [1]. To ensure the operational safety of the aviation industry and further high-quality and rapid development, the advancement of aviation logistics and maintenance is an extremely important task [2]. When carrying out aircraft logistics support, unscientific air material configuration and scheduling may lead to problems such as insufficient inventory, increased maintenance costs, and reduced maintenance quality. Therefore, how to further optimize air material scheduling and reduce the occurrence of these problems has been the focus of research in this field [3]. In order to improve this problem and enhance the safety and maintenance efficiency of aviation flight, this study studies the optimization scheduling of air materials. For optimization problems including aviation material scheduling problem, genetic algorithm is a relatively mature optimization algorithm. According to the characteristics of genetic inheritance and evolution of biological genes, the algorithm encodes the problems and elements that need to be optimized into DNA

and iterates continuously in a population until the optimal solution is generated [4]. Genetic algorithms are faster and more accurate than human computing for optimization problems [5]. Based on the nature of genetic algorithm, this research uses adaptive genetic algorithm to solve the optimization problem of air material scheduling, hoping to further improve the efficiency of air material scheduling and reduce costs.

2. Literature Review

In the maintenance and scheduling of aircraft and other aircraft, a large number of researchers have explored from various aspects. Efthymiou et al. [6] introduced blockchain technology into aircraft maintenance work. This research increases data security through semistructured models and optimizes the efficiency of data sharing and use. The value of blockchain data storage is emphasized. Holkeri [7] conducted a survey on the current outsourcing of aviation logistics technology services and summarized the operation status of related service providers in the aviation service outsourcing industry. The results show that the aviation logistics technology service outsourcing industry is showing a growing trend. The operator's operating model proposes proposals to improve efficiency and increase aviation safety.

Qin et al. [8] studied the maintenance resource scheduling of aircraft hangars and aircraft overhaul problems and proposed a mixed integer linear programming model. It describes the relationship between aircraft maintenance and aircraft parking layout. The validity of the model tests has shown that it provides a viable solution for large long-running hangars. Wang et al. [9] developed a fault diagnosis method using nonlinear mode decomposition technology for the bearing fault diagnosis of aircraft engines under variable speed scenarios. The experiment indicates that the method adaptively estimate the instantaneous angular velocity according to the vibration signal of the aircraft engine, and the estimation results are more reliable.

In the research and related applications of genetic algorithm, there are many precedents for research and analysis. Aiming at the phenomenon that there are few effective methods for solving interval multiobjective optimization problems, Gong et al. [10] created a solution that combined ensemble GA. The researchers compared the solution with the current mainstream solutions through an example of car cab design and show that their solution is more efficient. Researchers such as Aziz and Krichen [11] developed a task scheduling algorithm suitable for the field of cloud computing. The algorithm is designed on the basis of GA to simulate and optimize the task scheduling problem in the cloud computing process. Their comparative experiment tells that the ability of this genetic algorithm is higher than that of the task scheduling algorithm commonly used before in this field. Elbaz et al. [12] proposed a neural network system based on genetic algorithm for the problem of life prediction and replacement of shield machine parts. They optimized the neural network structure through genetic algorithm, and the system monitored various data of shield machine through algorithm, which can predict the life of shield machine parts with high accuracy. Kansal et al. [13] proposed a cost-minimizing model for on-demand services based on genetic algorithm to solve the question of current cloud service pricing difficulties, which are difficult to fulfill the users' quests and the profitability of providers at the same time. In the model, the genetic algorithm is used for optimal evaluation of user requests and provider cases to minimize costs. Experiment indicates that the model is more efficient than existing pricing models. Among the many applications of genetic algorithm, some researchers use it for facility location optimization. In order to improve the speed and quality of prehospital medical care in the medical field, Golmakani and Eskandar [14] developed a location selection system based on nondominated sorting GA for the location of emergency centers. It helps to improve the medical quality of emergency patients. Through literature review, it is found that genetic algorithm has been applied to optimization problems in various fields. This research optimizes the main defects of genetic algorithm and improves the performance and practicability of the algorithm. At the same time, genetic algorithm is not widely used in the field of air material scheduling, so it has potential application. This research will introduce genetic algorithm into this field and expand a new direction for the research in this field.

3. Construction of Adaptive Genetic Algorithm Applied to Optimal Scheduling of Aviation Materials

3.1. Construction of an Improved Nondominated Sorting Genetic Algorithm. Figure 1 is the operation flow of the genetic algorithm. The principle is to encode the variable space of the problem as chromosomes and to iteratively evolve and finally obtain the optimal solution. First of all, the genetic algorithm needs to perform a population initialization operation. In this process, an initial population will be randomly generated within the parameter range of the problem space, and then the individual fitness of the population is calculated. The fitness is expressed in the form of a function and is generated by the objective function of solving the problem. The function of the fitness function is to determine whether the individuals in the current population have high fitness [15]. Population selection refers to leaving individuals with higher fitness after the fitness function judgment, simulating the process of fittest survivor in the process of genetic evolution. After that, cross-mutation is performed, the parental genes are combined and new individuals are generated, and some gene values of the individuals are changed. In this process, the population will continue to evolve, and the search will be biased towards better areas in the space, and finally an optimal population will be calculated. When solving the optimal solution problem, the individual with the highest fitness function evaluation is the answer [16].

At present, there are many optimization algorithms under the category of genetic algorithms, among which the nondominated sorting genetic algorithm II (NSGA-II) is a mainstream algorithm, and NSGA-II is also used as the core in the aviation material optimization scheduling model. The main reason for choosing this algorithm is that it has good convergence and fast convergence speed and is more efficient in practical applications [17]. However, the NSGA-II algorithm also has defects. The genetic step of the algorithm uses fixed parameters, that is, the genetic parameters are invariable, which leads to insufficient search performance of the genetic algorithm, and it is often plagued by local optima [18]. About the problem of insufficient search of NSGA-II, an adaptive optimization scheme is proposed. This optimization scheme adds an adaptive adjustment mechanism to the crossover and mutation probability of the NSGA-II algorithm, so that the probabilities can change with the evolution process and the number of iterations, thereby enhancing the search performance. The schematic diagram of the crossover operator of NSGA-II under binary coding is shown in Figure 2. The genetic algorithm completes the exchange of genes by randomly performing a certain number of crossover operations in the coding string.

The adaptive crossover operator in the genetic algorithm generally adopts the strategy that the population evolution is smaller in the early stage and becomes larger in the later. This is because a small crossover probability can assure the diversity of the population in the early stage. A small crossover probability in the later stage will lead to the population

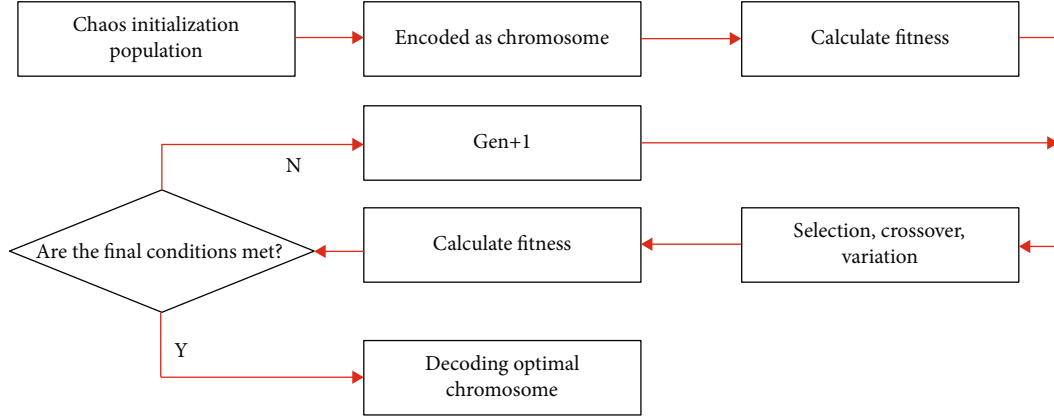


FIGURE 1: The running process of the genetic algorithm.

diversity. The individual differences are not obvious, so the crossover probability needs to be increased. The adjustment formula of crossover probability is shown in [19].

$$FC = \varepsilon - \frac{2e^{-n/N} \bullet FC}{e^{-n/N} + 1}. \quad (1)$$

In Formula (1), FC is the fixed crossover probability of the genetic algorithm, in which n is the current iteration number, and N means the possible max iteration number. FC is a parameter, and the value is set to 1.5 here. After the crossover probability is adjusted, the mutation probability is adjusted. A suitable mutation operator can avoid premature convergence of the algorithm and maintain population diversity. Traditional NSGA-II generally uses a small mutation probability. Therefore, in the early stage, increasing the mutation probability of evolution can increase the search speed of the genetic algorithm, and in the later stage, the method of reducing the mutation probability can be used to keep the population at a high quality for a long time and higher the algorithm convergence speed. The mathematical expression of the adaptive mutation operator is shown in

$$FM = \varepsilon - \frac{2e^{-n/N} \bullet FM}{e^{-n/N} + 1}. \quad (2)$$

Formula (2) is FM, the fixed mutation probability of the genetic algorithm. In traditional NSGA-II, real number encoding is performed by the analog binary crossover method, which is an imitation of the single-point crossover in binary encoding. The mathematical expression of the analog binary crossover method is shown in

$$\begin{cases} a_{1,j} = \frac{1}{2} [p_{2,j}(1 - \alpha) + p_{1,j}(1 + \alpha)], \\ a_{2,j} = \frac{[p_{1,j}(1 - \alpha) + p_{2,j}(1 + \alpha)]}{2}. \end{cases} \quad (3)$$

In Formula (3), $a_{1,j}$ sum $a_{2,j}$ is the progeny chromosome, $p_{1,j}$ and sum $p_{2,j}$ is the parent chromosome. α is a random

variable, and its value rule is shown in

$$\alpha = \begin{cases} (\text{rand} * 2)^{1/1+\eta}, & \text{rand} \leq 0.5 \\ (2 - \text{rand} * 2^{1/1+\eta})^{-1}, & \text{rand} > 0.5 \end{cases}. \quad (4)$$

In Formula (4), rand means a random number. The number is uniformly distributed in the range of greater than 0 and less than 1, η is representing a constant. After integration, the simulated binary crossover method can be expressed as

$$a_{1/2} = \frac{(p_{1,j} + p_{2,j}) \pm \alpha(p_{1,j} - p_{2,j})}{2}. \quad (5)$$

The search space of the simulated binary crossover method is relatively small, so the local optimum problem is prone to occur. In order to solve this problem, an evolutionary strategy formula is added to the simulated binary crossover method, and its expression is shown in [20].

$$y = \sigma N(0, 1) + x. \quad (6)$$

In Formula (6), x is the current individual, y is the new individual generated after processing, σ is the search step, and $N(0, 1)$ indicates a random number that follows a standard normal distribution. By substituting the search step size into the expression of the simulated binary crossover method, the crossover operator combined with the evolution strategy can be obtained, and its expression is shown in

$$a_{1/2} = \frac{(p_{1,j} + p_{2,j}) \pm \beta(p_{1,j} - p_{2,j})}{2} |N(0, 1)|. \quad (7)$$

β in Formula (7) is a parameter. The relationship between β and the parameter α is shown in

$$\alpha = \beta \bullet |N(0, 1)|. \quad (8)$$

At the beginning of the improved cross-case crossover

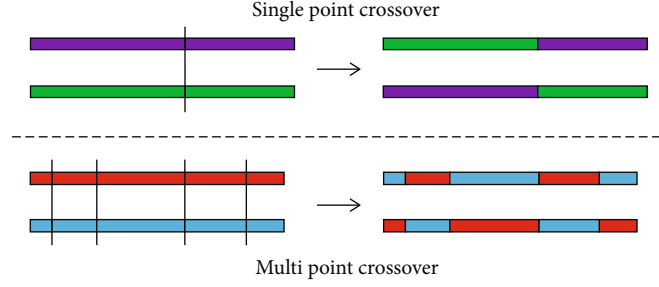


FIGURE 2: Crossover operator under binary coding.

process, a random number that is uniformly distributed between 0 and 1 needs to be generated, and the operation is carried out according to the size of the random number. The operation process is shown in

$$\begin{cases} a_{1,j} = \frac{(p_{1,j} + p_{2,j}) + \beta(p_{1,j} - p_{2,j})}{2} |N(0, 1)| \\ a_{2,j} = \frac{(p_{1,j} + p_{2,j}) - \beta(p_{1,j} - p_{2,j})}{2} |N(0, 1)| \end{cases}, \text{rand} \leq 0.5,$$

$$\begin{cases} a_{1,j} = \frac{(p_{1,j} + p_{2,j}) - \beta(p_{1,j} - p_{2,j})}{2} |N(0, 1)| \\ a_{2,j} = \frac{(p_{1,j} + p_{2,j}) + \beta(p_{1,j} - p_{2,j})}{2} |N(0, 1)| \end{cases}, \text{rand} \leq 0.5. \quad (9)$$

So far, the optimization of the NSGA-II genetic algorithm has been completed. The optimization algorithm has made improvements in search efficiency and optimization ability.

3.2. Construction of Optimal Scheduling Model for Aviation Materials. After completing the construction of the genetic algorithm, the research must construct the optimal scheduling model of aviation materials and its objective function. As an important component of aircraft maintenance resources, aviation material scheduling has a high priority in maintenance support. In fact, aviation material scheduling mainly deals with the allocation problem and the transportation assignment problem, and these two problems' nature could be considered as finding the optimal answer. Therefore, it is appropriate to use the genetic algorithm as the core algorithm of the aviation material optimal scheduling model. From the perspective of demand, the main elements of aviation material scheduling tasks include the quantity, type, and time of aviation materials. The demand analysis of aviation material scheduling is shown in Figure 3.

Tasks such as aircraft maintenance have specific requirements on the quantity, type, and time of aviation materials. The scheduling of aviation materials should prearrange the storage of aviation materials and reasonably plan transportation problems according to the needs [21]. In actual operation, it is difficult to completely avoid the conflict of

aviation material requirements from different locations, but it is still necessary to minimize the negative impact of conflicts and conflicts through scientific scheduling. In order to minimize the negative impact of aviation material conflicts, aviation material scheduling issues need to follow specific principles and requirements. The relevant principles and requirements of the aviation material scheduling problem are shown in Figure 4.

The requirement of aviation material scheduling is essentially to combine the configuration and deployment of aviation materials. This operation method allows managers to configure aviation materials from a global perspective, and the management composition of aviation materials can be more easily subdivided. At present, the airfreight industry is expanding, and the fleet size is also becoming larger and more complex. An aviation material management model that combines the configuration and deployment of aviation materials is necessary. Managers need to pay attention to the real-time update and replenishment of aviation material inventory, the limitation of transportation conditions, and the ability to respond to emergency missions [22]. When building the optimal scheduling model for aviation materials, three limiting rules are designed according to the actual situation. First, in a scheduling cycle, each aviation material warehouse can only achieve one-way transportation, and there are no restrictions on the types of aviation materials to be transported. Secondly, an aviation material transportation must be able to be completed within a scheduling cycle. Finally, different cost levels are designed in the cost calculation. The management costs, transportation costs, and downtime costs at different maintenance points of different aviation material warehouses should be calculated according to different levels. In the problem of aviation material scheduling, the most basic principle is the principle of minimum cost of aviation material configuration, that is, under the premise of not affecting the quality and speed of work, the storage and transportation costs of aviation materials should be minimized. Therefore, the objective function is first constructed according to the principle of minimum cost, and the mathematical expression of the objective function is shown in [23].

$$C = \min \left[\omega_j \sum_{t=1}^T \sum_{i=1}^M \sum_{k=1}^N T_t V_i R_k + F + \sum_{i=1}^M \sum_{l=1}^N \sum_{k=1}^N \left(\sum_{t=1}^T T_t V_i R_k * \left(y_{lk} \sum_{t=1}^T T_t x_{lk} \right) \right) \right]. \quad (10)$$

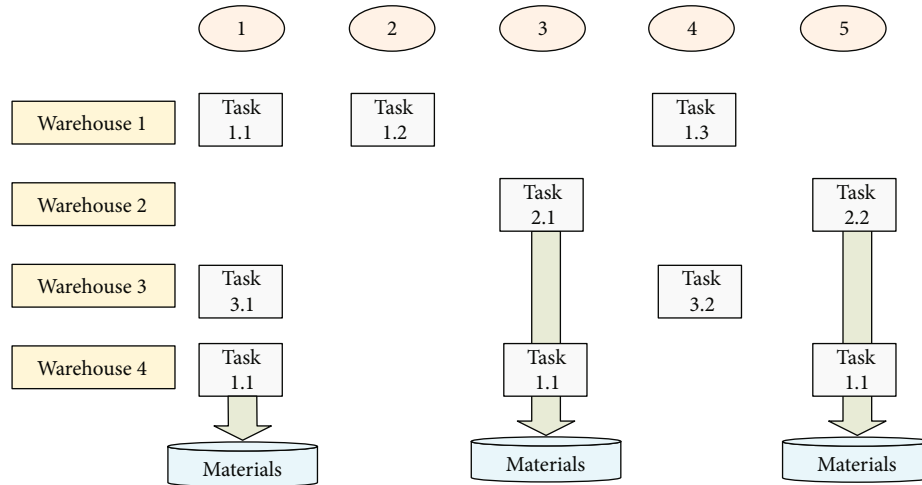


FIGURE 3: Demand analysis diagram of aviation material scheduling.

In Formula (10), N represents the total number of warehouses storing aviation materials, M is the total number of types of aviation materials, and T represents the scheduling cycle of aviation materials. In addition, ω_j is the matrix element of aviation material management cost, $T_t V_i R_k$ is the matrix element of aviation material scheduling, y_{lk} is the cost matrix element of transportation distance, $T_t x_{lk}$ is the judgment matrix element of aviation material scheduling, and F represents the aviation material penalty function. The function of the penalty function is to generate huge downtime costs and implement a preset penalty mechanism when the time window requirements of the scheduling task cannot be fulfilled. Here the penalty function is represented by linear, and its mathematical expression is shown in [24].

$$F = \begin{cases} 0 & , T_t V_{ki} \leq T_t H_{kh} \\ A(T_t V_{ki} - T_t H_{kh}) & , T_t V_{ki} > T_t H_{kh} \end{cases} \quad (11)$$

In Formula (11), $T_t V_{ki}$ represents the time T_t from the warehouse k to the task location of the aviation material in the scheduling period, $T_t H_{kh}$ represents the execution time of the scheduling task of the aviation material, and A is the penalty coefficient for the delay of the task time. After defining the objective function and penalty coefficient of the aviation material scheduling model, it is also necessary to define the aviation material warehouse supply, aviation material demand, and scheduling matrix of the model. See Formula (12) for the supply matrix of aviation materials.

$$S = \begin{pmatrix} SV_{11} & SV_{12} & \cdots & SV_{1N} \\ SV_{21} & SV_{22} & \cdots & SV_{2N} \\ \cdots & \cdots & \cdots & \cdots \\ SV_{M1} & SV_{M2} & \cdots & SV_{MN} \end{pmatrix} \quad (12)$$

In Formula (12), SV_{mn} represents the quantity of aviation material types in the n aviation material storage warehouse m . In the actual operation of the aviation material

warehouse, the maintenance tasks of different warehouses are different, so the mathematical description of the aviation material demand matrix is carried out in one warehouse as a unit, and its expression is shown in

$$H_a V = \begin{pmatrix} HV_{11} & HV_{12} & \cdots & HV_{1N} \\ HV_{21} & HV_{22} & \cdots & HV_{2N} \\ \cdots & \cdots & \cdots & \cdots \\ HV_{M1} & HV_{M2} & \cdots & HV_{MN} \end{pmatrix} \quad (13)$$

In Formula (13), HV_{mn} represents the demand for the types of aviation materials n in the maintenance tasks in the aviation m materials warehouse a . Based on the demand matrix and actual statistical data, the demand quantity of a maintenance point for a specific aviation material can be described as

$$ASV_{an} = \sum_{m=1}^M HV_{mn} \quad (14)$$

In Formula (14), ASV_{an} is the meaning in the a demand statistics of aviation material types by the aviation material warehouse n . Finally, it is necessary to complete the establishment of the scheduling matrix of the aviation material scheduling model. Scheduling refers to the act of urgently deploying and transporting aviation materials between warehouses in order to allocate aviation materials from warehouses with sufficient supplies to warehouses with shortages. When the demand of the aviation material warehouse exceeds the supply, there will be a shortage of materials. Figure 5 is the aviation material scheduling matrix in a three-dimensional matrix form.

The three-dimensional matrix $T_t V_n R_{am}$ represents the dispatch quantity of the aviation material types n transported m from the aviation material warehouse to the aviation material warehouse in the scheduling a period t . According to the three-dimensional matrix of aviation

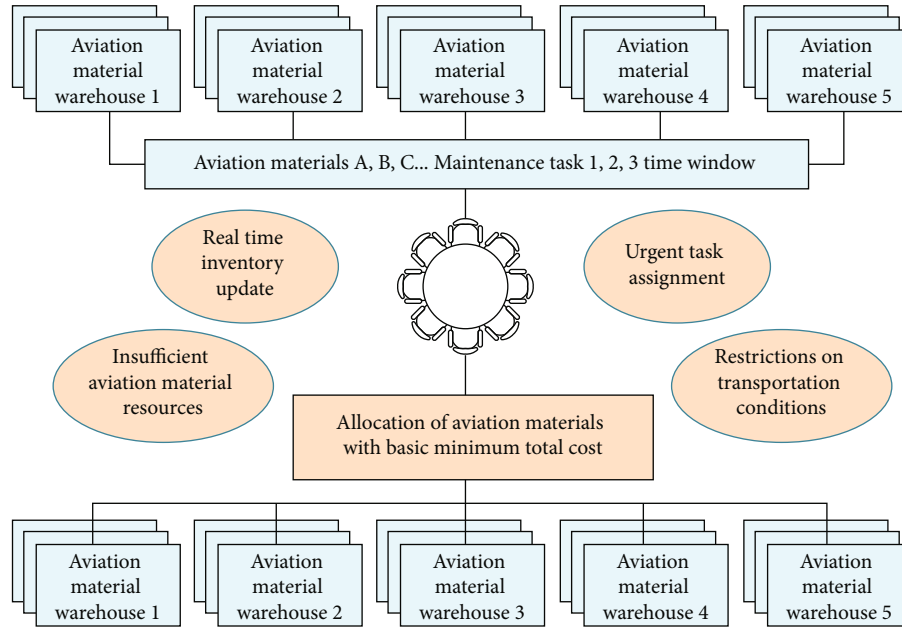


FIGURE 4: Schematic diagram of aviation material scheduling requirements.

material scheduling, the statistical expression of the number t of aviation material types after the scheduling period n is shown in

$$\sum_m^M T_t V_n R_{am} = T_t BSV_{an}. \quad (15)$$

In Formula (15), $T_t BSV_{an}$ represents the total number of aviation material types t in the aviation material warehouse a after the end of the first scheduling cycle n .

4. Performance Test and Analysis of Adaptive Genetic Algorithm for Optimal Scheduling of Aviation Materials

To comprehensively evaluate the aviation material scheduling model, it is necessary to start from the performance of the genetic algorithm and the performance of the aviation material scheduling model in practical applications. The improved NSGA-II genetic algorithm is the core of the aviation material scheduling model, and its performance directly affects the results of the aviation material scheduling operation. First, the algorithm is evaluated from the adaptive situation of the improved crossover and mutation operators of NSGA-II. The results are shown in Figure 6.

Figure 6(a) is the crossover probability adaptive function curve of the improved NSGA-II algorithm, and Figure 6(b) is the mutation probability adaptive function curve. Observing the change of the crossover probability with the number of iterations, the crossover probability takes a small value at the initial stage of the algorithm, which is 0.401, and shows a gradually increasing trend with the increase of the number of iteration steps. This change shows the adaptive ability of the crossover operator. The crossover probability is small

to maintain the diversity at first, and in the later stage, the crossover probability is increased to increase the individual differences. Observing the similarity coefficient, it is found that the observation coefficient takes a value below 0.4 in the first five iterations, and then fluctuates in the interval of 0.4 to 0.8. This situation occurs because the population at the early stage of the iteration has not been crossed and changed, and the similarity is low. With the increasing iteration number, the similarity also increases rapidly and shows a certain decrease with the increase of the crossover probability. Observing the variation of mutation probability and stagnation coefficient with the number of iteration steps, the results show that the stagnation phenomenon will evolve within five times in the first 32 iterations, indicating that the adaptive design of the mutation operator has a good effect, and the population is in the mutation calculation. Under the influence of subinfluence, it can break through the bottleneck stage of the algorithm at a faster speed. After evaluating the performance of adaptive crossover and genetic operators, the next step is to test the fitness changes of the algorithm in iterations. The test results are shown in Figure 7.

Figure 7 shows the fitness change of the improved NSGA-II algorithm with the increase of iteration steps. The figure includes the fitness curve and average fitness curve of the optimal individual in the population. In addition, the adaptation of the traditional NSGA-II algorithm is also added in degree curve for comparison. Since the improved NSGA-II is used for aircraft material scheduling, the ordinate is based on the cost of scheduling, and the lower the index, the better the algorithm fitness. The optimal individual fitness of the improved NSGA-II algorithm is significantly better than the fitness of traditional NSGA-II algorithm, and the optimal individual fitness of the improved algorithm reaches the global optimal solution in

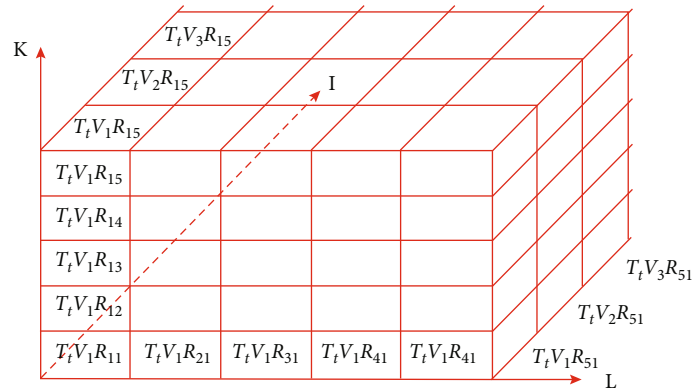


FIGURE 5: Schematic diagram of the three-dimensional matrix of aviation material scheduling.

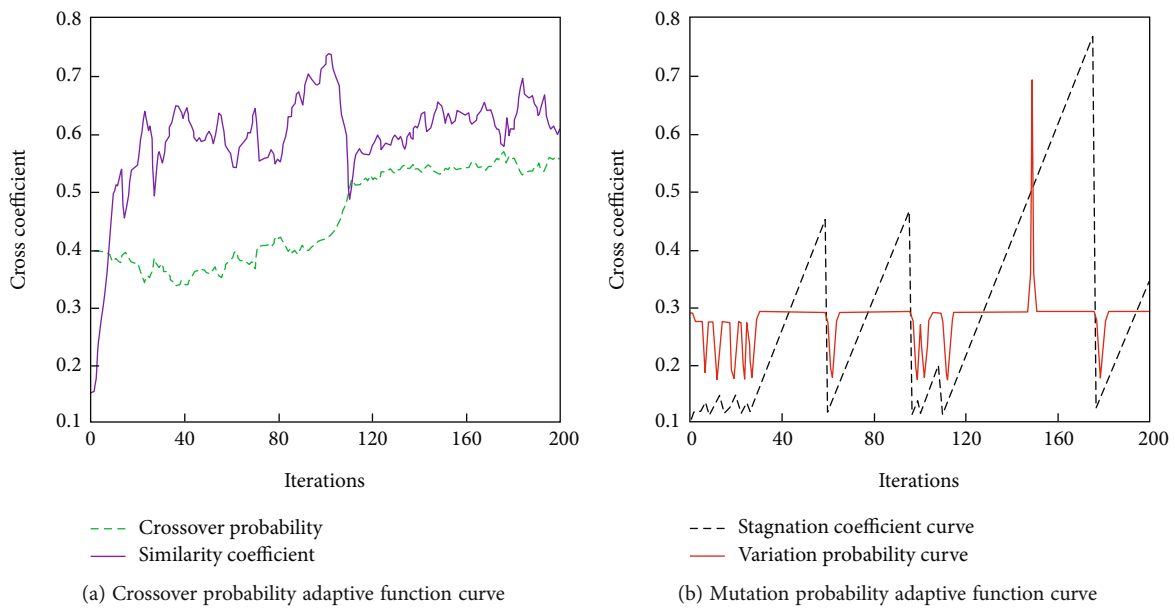


FIGURE 6: Crossover and genetic operators of the improved NSGA-II genetic algorithm.

the eleventh iteration. The optimal solution of the improved algorithm is 27.3, and the optimal solution obtained by the traditional algorithm is 33.9. From the average fitness curve, the average fitness curve of the improved NSGA-II shows an obvious convergence trend, and the average fitness of the improved NSGA-II algorithm is better than the optimal individual fitness of the traditional NSGA-II algorithm. Approximation, combined with the optimal fitness of the improved algorithm, is not difficult to see that the overall fitness of the improved algorithm is significantly higher than that of the traditional algorithm. Among the factors affecting the performance of the genetic algorithm, the population size of the algorithm is more important. The time-consuming and optimization accuracy of the algorithm will change greatly with the change of the population size. Therefore, the performance of the algorithm under different population sizes is tested and determined. An optimum population size is necessary. The performance changes of the algorithm under different population sizes are shown in Figure 8.

Figure 8(a) is the variation of the error accuracy with the population size of the algorithm, and Figure 8(b) is the variation of the algorithm simulation time with the population size. In this test, the traditional NSGA-II algorithm is also used as a comparison. From the perspective of error accuracy, the optimization accuracy of the improved NSGA-II shows a certain fluctuation, but overall it increases when the population size increases. When the population size is 40, the optimization accuracy reaches 0.0236. The minimum error accuracy of the improved algorithm is 0.0135, and the population size is 25. In comparison, the error accuracy of the improved algorithm is always lower than traditional algorithm error accuracy under the same scale, which shows that the improved algorithm has smaller error than traditional algorithm. From the perspective of simulation time, the time required for simulation also increases with the increase of the scale. When the population size is 5, the simulation time of the improved is 27.8 seconds, which is the shortest. Considering the error accuracy and simulation time, the performance of the improved algorithm is more

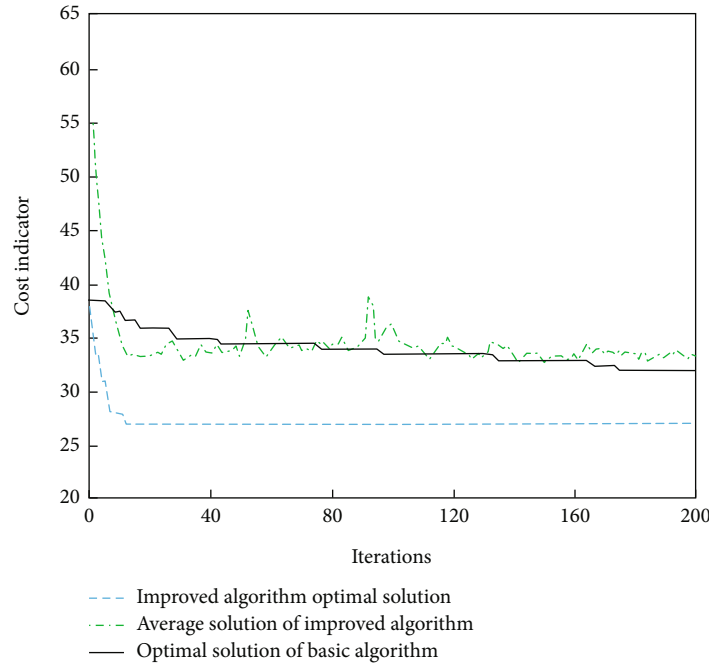
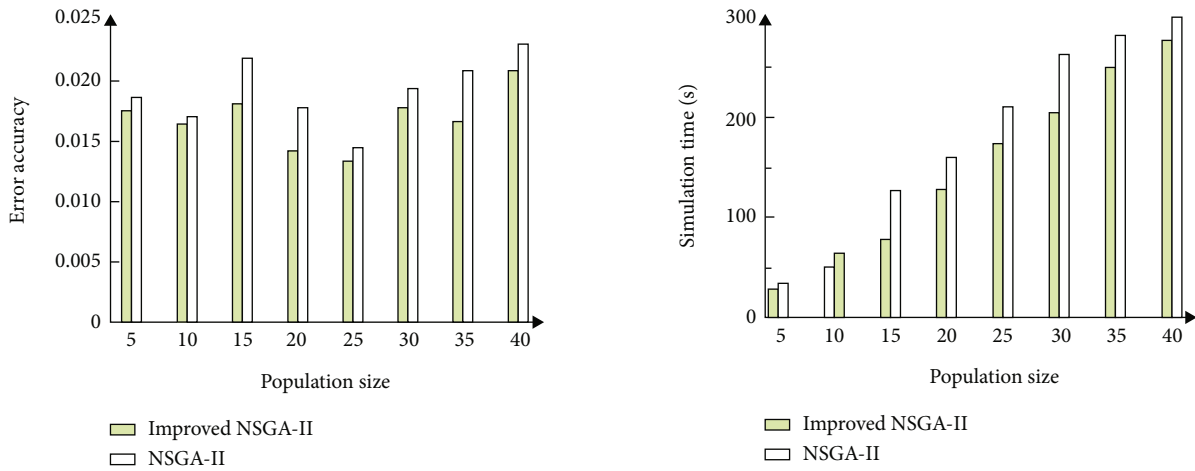


FIGURE 7: The fitness change of the improved NSGA-II genetic algorithm in iterations.



(a) Variation of the error accuracy with the population size of the algorithm (b) Variation of the algorithm simulation time with the population size

FIGURE 8: Changes in the performance of the improved NSGA-II algorithm with the population size.

suitable when the population size is 20. Finally, the performance of the improved NSGA-II genetic algorithm is comprehensively tested through the performance of the algorithm in the actual optimization case. The test results are shown in Figure 9.

Figure 9(a) is the comparison of the running time of different algorithms, Figure 9(b) is the evolution iterations of the two algorithms, and Figure 9(c) is the deviation of the two algorithms. It can be figured that the completion time and deviation of the improved NSGA-II have obvious advantages against the traditional NSGA-II. In case 1 and case 2, the deviation degree of the improved NSGA-II is 0. In other cases, the deviation degree of the improved NSGA-II is also significantly smaller than the degree of tra-

ditional NSGA-II, which again shows the improvement against the traditional algorithm, and the optimization performance of the NSGA-II algorithm has been greatly improved. The completion time of the improved algorithm in each case is less than that of the traditional algorithm, and the difference between the two is the largest in case 4. The completion time of the improved algorithm is 66 seconds, which is 13 seconds less than the traditional algorithm. This shows that while the optimization ability is improved, the calculation speed of the improved algorithm also has certain advantages. After testing the performance of the improved NSGA-II genetic model, the practical application of the aircraft material optimization scheduling model is tested. The research selects 11 aviation material scheduling

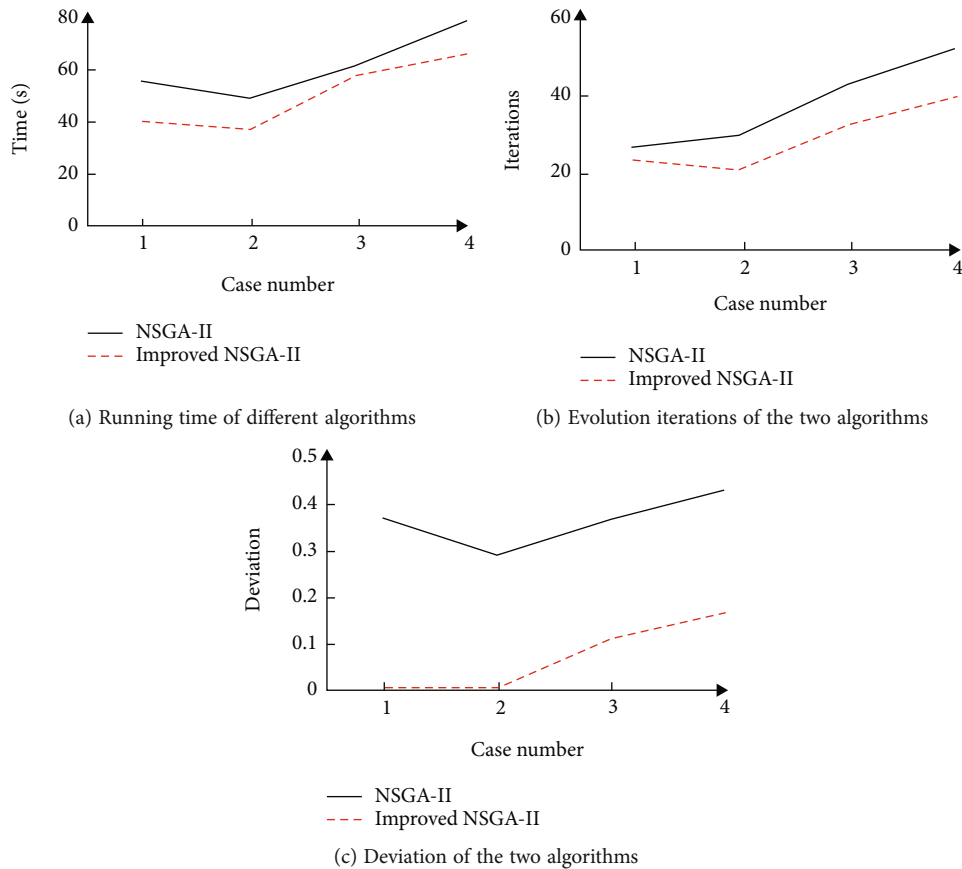


FIGURE 9: The performance of the algorithm in the actual optimization cases.

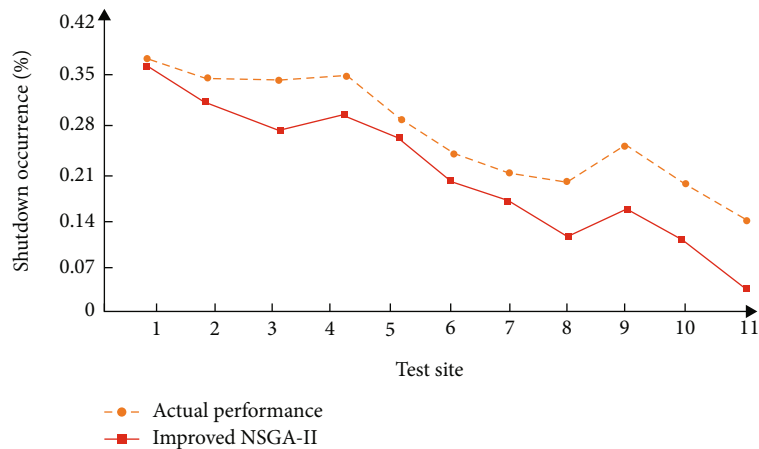


FIGURE 10: The performance of the aviation material optimization scheduling model in practical applications.

tasks and conducts simulation tests through the improved MSGA-II algorithm. The results are shown in Figure 10.

Figure 10 tests the optimal scheduling model of aviation materials based on the adaptive genetic algorithm with the probability of occurrence of downtime of aircraft maintenance work as the measurement index. In addition, the analysis is carried out using the occurrence of actual downtime incidents in the corresponding event as a comparison. The simulation results of the aviation material optimization

scheduling model are better than the actual processing results of the events in all events, which shows that the model has better scheduling ability than the current aviation material scheduling model, and this advantage is relatively stable. The aircraft material optimization scheduling model based on adaptive genetic algorithm has a minimum occurrence rate of downtime accidents of 0.06%, while the actual occurrence probability in the same event is 0.14%.

5. Conclusion

In the process of aviation material scheduling, when the inventory of aviation materials is insufficient or cannot be transported in time, it may lead to serious losses. Aiming at this problem, this study proposes an optimized scheduling model for aviation materials based on improved NSGA-II genetic model and analyzes NSGA-II which is adaptively designed. The performance test results of the aviation material scheduling model indicates that the improved NSGA-II as the core obtains an optimal solution of 27.3 in the test, while the traditional algorithm is 33.9, and the improved algorithm has advantages. In the actual optimization case, the deviation degree of the improved NSGA-II genetic is at least 0. Besides, the algorithm's deviation degree in all cases is smaller than that of conventional algorithm. In the practical application experiment of the aviation material optimization scheduling model, the aviation material optimization scheduling model based on the adaptive genetic algorithm has the lowest occurrence rate of downtime accidents of 0.06%, while the actual occurrence probability in the current aviation material scheduling model is 0.14%. From the results, this research improved the local optimal solution problem of the traditional NSGA-II genetic algorithm by introducing an adaptive mechanism and improved its performance. The improved algorithm is applied to the air material scheduling problem. The algorithm shows relatively reliable performance and effectively optimizes the correctness and efficiency of air material scheduling. There is still room for improvement in this study. The single task of the aviation material optimization scheduling model based on the adaptive genetic algorithm is only in one scheduling cycle. If the possibility of a single task spanning multiple cycles is taken into account in the scheduling model, the scheduling results of the model can be further optimized, which is the direction of further research.

Data Availability

The data used to support the findings of this study are within the article.

Conflicts of Interest

The author declares that there is no conflict of interest.

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