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Research on Integrated Production Scheduling Optimization in Aerospace Manufacturing Workshop Based on Production Processes

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Abstract. The optimization of scheduling in spacecraft manufacturing workshops is an important measure taken to reduce production costs and improve processing efficiency. In solving scheduling problems, genetic algorithms have been widely applied as efficient optimization algorithms. This study establishes a mathematical model for workshop job processing with the objective of minimizing processing time. Addressing the issues of premature convergence and low solution accuracy in standard genetic algorithms (SGA), an improved genetic algorithm is proposed. To obtain better populations, the crossover and mutation probabilities are automatically adjusted by referencing individual fitness values. Additionally, to avoid generating invalid solutions, genes are divided into different segments based on processing operations to improve crossover operations. The results of the case study demonstrate that the improved genetic algorithm exhibits better convergence and global search capabilities compared to the standard genetic algorithm, achieving significant improvements in scheduling structure optimization.

Keywords. workshop scheduling, Improved Genetic Algorithm, spacecraft manufacturing

1. Introduction

Under the context of innovation-driven development, aerospace manufacturing is constantly integrating information technology and striving towards the goals of superior quality, on-time delivery, and lower costs. However, there is a noticeable gap between its management methods and the pace of development. Aerospace product development is characterized by "multiple varieties, small batch production, and rolling development," which belongs to typical discrete manufacturing, posing significant challenges to production control in the manufacturing workshop. The collaborative relationships and coordination of aerospace products are complex, the manufacturing processes are lengthy with numerous process steps, and there are issues of imbalanced progress and

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quality in coordination and outsourcing. Additionally, the development status of product models often undergoes changes, leading to severe imbalances in the production process.

Laukotka et al. [1] proposed the application of digital twin technology in the manufacturing workshop of civil aviation products. They also discussed the potential challenges in implementing such methods and provided insights into the future development prospects of the civil aviation product manufacturing workshop. Muñoz et al. [2] emphasized the importance of software application in the entire lifecycle of aviation products. They listed management techniques that rely on software for the aviation product workshop to reduce quality issues caused by improper management. Tekin and Kapan [3], considering the potential of historical data mining, developed a data management application for an aerospace product manufacturing company, which recorded all data from raw material processing to finished product delivery. Mas et al. [4] summarized the significance of lifecycle management in the aerospace product manufacturing process, with a particular focus on historical data mining. Abollado and Shehab [5] emphasized the importance of process digitalization in the digitalization process of aerospace product manufacturing, providing an outlook for the digital management of aerospace product workshops. Liu et al. [6] analyzed the characteristics of small-batch production in the aerospace product manufacturing of multiple varieties. They proposed an intelligent scheduling method for workshop operations by combining digital twin and super network techniques. Finally, they validated their method using a case study of an aerospace engine gear production workshop.

Abdel-Basset et al. [7] proposed a novel approach that combines optimization algorithms with local search rules to solve the flow shop production scheduling problem. Lu et al. [8] considered the impact of equipment availability on shop floor scheduling and evaluated the availability of machines using a genetic algorithm. They formulated a mathematical model with the objective of minimizing machine downtime delays and verified the feasibility of the algorithm. Wu and Yang [9] investigated the integration of e-commerce and shop floor scheduling and proposed an integrated scheduling algorithm that combines deep learning neural networks with genetic algorithms. They used long short-term memory networks to optimize the genetic algorithm and achieve better shop floor scheduling results. Li et al. [10] made improvements to the initial solution and crossover operators of traditional genetic algorithms and applied them to shop floor scheduling considering equipment carbon emissions. Their approach aimed to minimize carbon emissions while ensuring early completion of processing tasks. Liu et al. [11] initialized the initial population of the genetic algorithm using greedy and random algorithms. They established a flexible shop floor scheduling model with the objectives of minimizing maximum completion time, carbon emissions, and total machine workload. The feasibility of the improved genetic algorithm was verified through case studies.

2. Analysis of Scheduling Problem

In a critical aerospace component manufacturing workshop, there are currently 62 various types of processing equipment and 39 high-precision devices, with nearly ten thousand cutting tools stored in the tool library. Due to the long processing routes of aerospace products and the relatively slow flow between workstations, the level of intelligence in the workshop's Manufacturing Execution Systems (MES) is relatively low. As a result, comprehensive scheduling relies on manual intervention, leading to inefficient scheduling and incomplete considerations. This has become an urgent problem that needs to be addressed in the aerospace production workshop.

The typical production mode of aerospace products is as follows: After receiving orders, the manufacturing workshop will collect information on the required quantities and delivery times of the finished products in the orders. Based on the materials and the processing skills and capabilities of each workshop, tasks are assigned to the workshop. These tasks include information on the process routes (including processing time), earliest start time and latest delivery time for components, process priorities, and so on. To address the scheduling problem, it is necessary to enhance the intelligence level of the workshop, introduce more advanced MES systems, and utilize computer-aided technologies to support the generation of comprehensive schedules. By optimizing resource utilization and job task planning, scheduling efficiency can be improved, and the scheduling results can be optimized, thereby enhancing the production efficiency of the aerospace manufacturing workshop.

3. Problem Description

The integrated scheduling problem in an aerospace production workshop based on production processes can be described as follows: In this problem, there are n production work orders that need to be issued to work teams for processing. Each work team decomposes the work orders and assigns each process to m equipment for processing or assembly. During this process, the following constraints need to be satisfied:

(1) Each work order can only be undertaken by one work team to ensure that the processing of work orders is not duplicated or confused;

(2) Each process can only be assigned to one piece of equipment for processing or assembly, avoiding multiple equipment simultaneously processing the same process;

(3) Each piece of equipment can only process or assemble one process at a time, and the processing or assembly process of the equipment cannot be interrupted, ensuring the order and continuity of the processing process;

(4) The processing or assembly of each process must satisfy the process constraints, i.e., it can only start processing or assembly after its immediate predecessor process has been completed.

Each product has an independent processing process structure tree. As shown in **Fig. 1**, in the structure tree, each node represents a process, including the process name, the equipment required for processing or assembly, and the corresponding processing time. The direction of the arrows represents the sequence relationship between processes, with leaf node processes representing the initial processes that can be processed, and the root node representing the last process that needs to be processed. When the process of the root node is completed, it signifies the completion of the manufacturing process for that product. The goal of this problem is to achieve integrated scheduling in the aerospace production workshop through proper process allocation and equipment utilization, ensuring the order and continuity of processes, and ultimately enabling timely completion of processing or assembly for products.

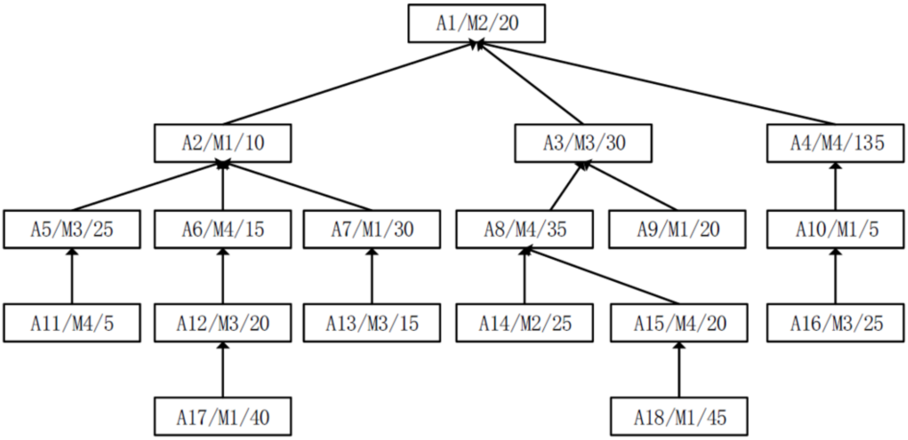

Fig.1. Process Execution Structure Tree.

Based on the production processes of different products, forming the corresponding process structure tree and considering the sequence constraints of the manufacturing processes, the integrated scheduling problem in the workshop can be formulated as a scheduling problem that requires simultaneous processing and assembly of workpieces with constraint relationships. In this problem, the following constraints need to be satisfied:

(1) At any given time, one piece of equipment can only process one process, ensuring that the equipment handles only one task at a time;

(2) At any given time, one process can only be processed by one piece of equipment, avoiding multiple equipment simultaneously processing the same process;

(3) The processing of each process needs to comply with the sequence constraints in the process requirements. It must wait for the preceding process on the corresponding equipment to be completed before it can start processing, ensuring the correctness and orderliness of the process flow;

(4) Once a process starts, it cannot be interrupted until it is completed. The corresponding equipment can only start processing other processes after the completion of the process, ensuring continuity and stability;

(5) At the initial time, all equipment is available, and any workpiece can be processed, representing the starting state of scheduling.

Let's assume there are n processes $\{O_i\}$ for a complex product with a tree-like structure, and m pieces of equipment $\{M_k\}$ $1 \le k \le m$, where F_k represents the idle time periods of equipment M_k. S_i and C_i respectively represent the start time and completion time of process O_i. t_{jk} represents the processing time of process O_j on equipment M_k. $X_{li} = 1$ indicates that process O_l is the immediate predecessor process of process O_i. $Y_{ik} = 1$ indicates that process O_i is processed on equipment M_k. The mathematical formulation of this problem is as follows:

$$\min C_{\max} = \min\{\max(C_i)\} \tag{1}$$

s.t. $\quad {}_{\min}\{S_i\} \,\&\, \min\{F_k\}$ (2)

$$S_i \geq S_j + t_{jk}, Y_{ik} = 1, Y_{jk} = 1 \quad (3)$$

$$S_i \geq \max(C_l), X_{li} = 1 \quad (4)$$

The mathematical formulation of the problem is as follows:

Minimize:

(1) Minimize the maximum completion time of processes, representing the minimization of the overall completion time of the product.

Subject to:

(2) Start time and completion time constraints: For each process O_i, the start time S_i and completion time C_i are determined by the start time of its immediate predecessor process O_l and the processing time t_{jk} on equipment M_k. The goal is to minimize the start time and completion time of each process while satisfying these constraints.

(3) Exclusive processing constraint: Only one process can be processed on each equipment at any given time, ensuring that processes on the same equipment are processed in a serialized manner.

(4) Precedence constraint: Each process can only start after its immediate predecessor process has been completed, ensuring the correct sequence of processes.

This mathematical model aims to optimize the overall completion time of the product by minimizing the maximum completion time of processes and ensuring efficient and sequential processing of processes on the available equipment.

4. Design of Genetic Algorithm for Integrated Scheduling in Aerospace Manufacturing Workshop

4.1. Individual Encoding for Integrated Scheduling

In this study, a hybrid encoding approach is employed to address the integrated scheduling problem in the aerospace manufacturing workshop. As shown in **Fig.2**, this encoding approach divides each chromosome into two parts: the job-operation chromosome and the equipment chromosome, using the principles of integer encoding. The integers in the job-operation chromosome represent the job numbers, and the same number indicates different operations of the same job. The sequence of operations is determined by the frequency of occurrence of the corresponding integers in the job-operation chromosome. On the other hand, the integers in the equipment chromosome represent the selected equipment numbers. For the same equipment, the integers from left to right in the equipment chromosome correspond to the integers in the job-operation chromosome, indicating the processing sequence on that equipment. By employing this hybrid encoding approach, both the job-operation arrangement and the equipment processing sequence can be considered simultaneously. The integer encoding in the chromosomes allows for the representation of the sequential relationships between different operations or equipment.

job sequence chromosome	2	1	3	3	1	2	2	3	1	1
equipment chromosome	15	27	16	8	11	9	15	14	15	7

Fig.2. Chromosome Encoding.

By splitting a complete chromosome into two parts, namely the job-operation chromosome and the equipment chromosome, the meaning of the chromosome can be explained as follows:

From the perspective of jobs:

(1) This scheduling scheme involves three jobs, numbered 1, 2, and 3;

(2) Job 1 consists of four operations, which are sequentially assigned to four equipment with numbers 27, 11, 15, and 7;

(3) Job 2 consists of three operations, which are sequentially assigned to three equipment with numbers 15, 9, and 15;

(4) Job 3 consists of three operations, which are sequentially assigned to three equipment with numbers 16, 8, and 14.

From the perspective of equipment, specifically equipment number 15 processing multiple operations:

(1) This scheduling scheme assigns three operations to equipment number 15;

(2) These three operations, in order, are the first operation of Job 2, the second operation of Job 2, and the third operation of Job 1.

In summary, by using the job-operation chromosome and the equipment chromosome, obtained through the division of a complete chromosome, the chromosome represents the allocation of operations to jobs and the assignment of equipment for each operation. The chromosome's integer values indicate the job and equipment numbers, and their order or occurrence frequency signifies the sequence of operations. This encoding approach enables comprehensive consideration of job and equipment relationships in the scheduling of a manufacturing workshop, aiming to optimize production planning and scheduling in the aerospace domain.

4.2. Initial Population Generation for Integrated Production Scheduling

Please ensure that affiliations are as full and complete as possible and include the country. The optimization objective in this study is to minimize the total time required to complete all orders within a fixed time span. Based on the historical processing data in the workshop, we have observed that there are multiple available equipment options for certain critical operations. In such cases, we prefer to select the equipment with shorter processing time to improve efficiency.

The generation of the initial population follows the following rules:

(1) The job-operation chromosome is randomly generated, selecting one-fourth of the operations (rounded down if not divisible);

(2) For each operation, the equipment chromosome is determined with a 50% probability of selecting the equipment with the shortest processing time.

The job-operation chromosome is generated randomly, while the selection of the equipment chromosome takes into account the processing time, favoring shorter processing times. This approach aims to reduce the overall processing time and optimize the scheduling scheme.

4.3. Adaptive Adjustment of Crossover and Mutation Operator Probabilities

In genetic algorithms, the crossover and mutation operators play a crucial role in algorithm performance. Through these operations, favorable genes from parent individuals can be inherited by offspring, potentially leading to offspring with better gene structures than their parents and improving the search effectiveness of the algorithm. When designing a genetic algorithm, setting appropriate probabilities for crossover and mutation is crucial to balance global and local search capabilities, aiming to enhance convergence and search efficiency.

In standard genetic algorithms (SGA), a certain crossover probability and mutation probability are usually set. Based on the results of Bernoulli experiments, it is decided whether individuals undergo crossover or mutation operations. The setting of crossover and mutation probabilities significantly impacts the performance of the algorithm. If the probabilities are set too high, it may lead to excessive randomness and diffusion during the search process, preventing effective convergence to the optimal solution and resulting in the problem of random search. Conversely, if the probabilities are set too low, the algorithm may prematurely converge to local optima, getting stuck without discovering better solutions.

To address these issues, **Eqs.** (5) and (6) can be used to adopt adaptive adjustment strategies for the probabilities of crossover operators and mutation operators. This strategy dynamically adjusts the probabilities during the evolutionary process based on the algorithm's performance and convergence status. By adaptively tuning the probabilities, the algorithm can strike a balance between exploration and exploitation, promoting both global exploration and local exploitation to improve the algorithm's convergence and search efficiency.

$$p_{c1} = \begin{cases} p_{c0} & if\ w(x) \geq w_{avg} \\ \dfrac{p_{c0}(w_{\max} - w(x))}{w_{\max} - w_{avg}} & if\ w(x) < w_{avg} \end{cases}, \tag{5}$$

$$p_{m1} = \begin{cases} p_{m0} & if\ w(x) \geq w_{avg} \\ \dfrac{p_{m0}(w_{\max} - w(x))}{w_{\max} - w_{avg}} & if\ w(x) < w_{avg} \end{cases}. \tag{6}$$

In the provided context, p_{c0} and p_{m0} represent the initialized crossover probability and mutation probability, while p_{c1} and p_{m1} represent the adjusted crossover probability and mutation probability. w_{max} refers to the maximum fitness within the population, w_{avg} represents the average fitness, and $w(x)$ denotes the higher fitness between two individuals selected for crossover.

Based on the expressions in **Eqs.** (5) and (6), it can be observed that individuals with fitness lower than the average fitness have a higher probability of being eliminated, while individuals with fitness higher than the average fitness have a lower probability of being disrupted. Therefore, they are more likely to be retained in the next generation.

This mechanism can be utilized to control the evolutionary process of the genetic algorithm, where individuals with lower fitness have a higher probability of being replaced during crossover and mutation operations. Consequently, progressively eliminating individuals with lower fitness is expected, while preserving individuals with higher fitness. This approach aims to obtain a more superior population of individuals, ultimately improving the performance and search effectiveness of the algorithm.

4.4. Fitness Function Selection

For the workshop scheduling problem, the fitness function can be defined as the negative value of the total processing time of the workpieces. The fitness function can be expressed as:

$$F(x) = C - \sum_{i=1}^{n}(\sum_{j=1}^{qi}(t_{ij})), \tag{7}$$

t_{ij} represents the processing time of the *j*-th operation of the *i*-th workpiece; q_i denotes the maximum number of operations required for processing the *i*-th workpiece; n represents the maximum number of workpieces; *C* is a certain limit value to ensure that *F(x)* is non-negative, facilitating the calculation of selection and sorting probabilities.

5. Genetic Algorithm for Integrated Scheduling in Aerospace Manufacturing Workshop

The overall framework of the genetic algorithm used in this paper is shown in **Fig.3**, and each specific step is as follows:

(1) Establish the algorithm's base dataset: Collect the types of manufactured parts, the number of processing operations for each part, and the processing time for each operation. Clarify the processing capacity limitations of the machine tools and the constraints between operations.

(2) Initialize parameters: Set the initial parameters of the genetic algorithm, including the population size (number of individuals in the population), the number of iterations, the crossover probability, and the mutation probability. Generate an initial population by randomly creating a set of individuals as initial solutions.

(3) Calculate the fitness value: Based on the optimization objective of the problem, calculate the fitness value for each individual. The fitness function can be defined based on the minimization of the total processing time for all parts, which represents the total time spent on processing the workpieces.

(4) Update the best solution: Keep track of the individual with the highest fitness value in the current generation as the current best solution.

(5) Check convergence criteria: Determine if the convergence criteria of the algorithm are met. This can be based on predefined convergence conditions, such as reaching the maximum number of iterations or achieving a certain threshold fitness value, to decide whether to terminate the algorithm.

(6) Adaptive adjustment of crossover and mutation probabilities: Dynamically adjust the crossover and mutation probabilities based on the fitness values of the individuals in the population. Increase or decrease the probabilities of crossover and mutation based on the fitness value to guide the direction of the algorithm's search.

(7) Crossover operation and mutation operation: Perform crossover operation using the adjusted crossover probability to generate new individuals. Perform mutation operation using the adjusted mutation probability to introduce genetic variations in certain individuals. Crossover and mutation operations help increase the diversity of the population and facilitate exploration of the search space.

(8) Selection operation: Select excellent individuals as parents for the next generation based on their fitness values using a roulette wheel selection method.

(9) Update the population: Use the individuals obtained through genetic operations (crossover and mutation) and selection operation as the population for the next iteration.

(10) Iteration: Repeat steps 3 to 9 until the convergence criteria are met.

(14) Output the results: Obtain the best individual, which has the highest fitness value, as the optimal solution. Output the optimized result.

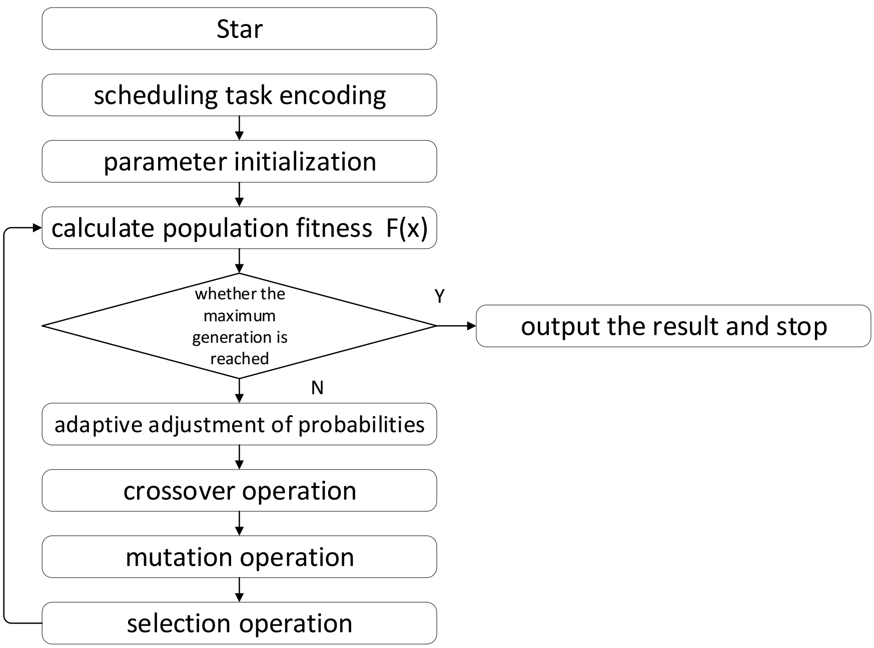

Fig.3. Algorithm Execution Flowchart

6. Example Analysis

Taking the X Bracket series, a commonly used component in aerospace manufacturing, as an example, there are a total of 10 component types with 18 production operations for each type. Excluding heat treatment and surface treatment, the operations include rough turning, fine turning, polishing, rough milling, semi-fine milling, fine milling, and polishing. Each type of machine tool is responsible for completing the corresponding operations of a single component. Due to differences in machine tool precision and performance, the processing time for each operation varies across different machine tools. The current workshop has 3 lathes, 3 milling machines, and 2 grinders available, meeting the required precision. The specific production situation is shown in the **Table 1** (operation time unit: hours).

Table 1. Part Process Time Schedule

	1# lathe		2# lathe	3# lathe	1# milling machine	2# milling machine	3# milling machine	1# grinding machine	2# grinding machine
1#bracket	4.0		4.5	5.5	8.7	7.0	9.1	2.5	2.2

	1# lathe		2# lathe	3# lathe	1# milling machine	2# milling machine	3# milling machine	1# grinding machine	2# grinding machine
2#bracket	5.2		6.3	4.1	9.2	7.0	7.5	2.5	2.5
3#bracket	5.8		5.6	6.5	7.3	8.5	8.9	2.2	2.6
4#bracket	6.2		5.7	6.1	7.6	8.0	7.1	2.3	2.1
5#bracket	6.2		6.0	6.3	8.4	8.0	9.5	2.6	2.3
6#bracket	5.2		4.5	6.4	9.3	9.2	8.5	2.6	2.3
7#bracket	5.1		5.9	5.8	9.8	8.2	7.8	2.4	2.7
8#bracket	4.5		4.6	5.7	9.0	8.2	7.1	2.0	2.0
9#bracket	4.9		5.0	4.2	9.2	7.7	8.7	2.4	2.6
10#bracket	5.4		5.0	4.6	7.7	9.1	9.9	2.2	2.6

We set the initial crossover probability as p_{c0} = 0.6 and the initial mutation probability as p_{m0} = 0.05. The population size is M = 200, and the number of generations is T = 100. We conduct independent runs 20 times and take the average value of the results.

Table 2. Algorithm Results Comparison Table

algorithm	optimal solution(h)	average(h)	volatility(%)	runtime(s)
standard genetic algorithm	171.8	186	3.32	2.7
improved genetic algorithm	152.4	162	2.61	3.1

It can be seen from **Table 2** that the optimal maximum completion time obtained by the standard genetic algorithm for this dataset is 171.8 hours. However, our proposed algorithm achieved a better result with a maximum completion time of 152.4 hours, representing an improvement of 11.3% compared to the standard genetic algorithm. Moreover, our algorithm demonstrates lower volatility and higher stability, indicating superior scheduling performance compared to the standard genetic algorithm. The specific scheduling chart is depicted in **Fig.4**.

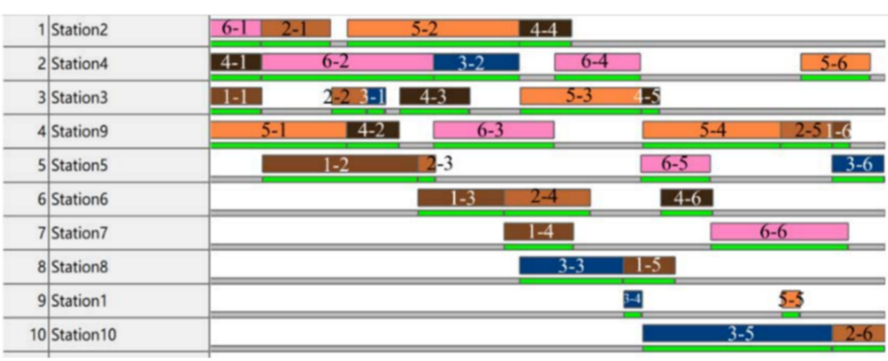

Fig.4. Scheduling Gantt Chart

7. Conclusion

By studying the aerospace manufacturing workshop integrated scheduling problem and establishing a mathematical model, combined with the genetic algorithm for solving, significant improvements can be achieved in the convergence speed and search capability of the algorithm, thereby optimizing the workshop scheduling problem.

Adaptive adjustment of crossover and mutation probabilities: By dynamically adjusting the crossover and mutation probabilities based on individual fitness values, individuals with higher fitness values have a higher probability of being selected in crossover and mutation operations, thus increasing the likelihood of retaining their excellent gene structures.

Improvement of crossover operation: Considering the characteristics of the aerospace manufacturing workshop scheduling problem and the information of the processing operations, the crossover operation can be improved. Specific crossover operators can be designed to take into account constraints such as the order of operations and equipment selection, making the crossover operation more aligned with the requirements of actual production.

Through the above improvements, the genetic algorithm can converge to the optimal solution more quickly in the aerospace manufacturing workshop integrated scheduling problem and effectively reduce the total production time. Compared to existing algorithms, the improved algorithm exhibits more significant optimization effects and provides valuable insights for the optimization of workshop scheduling problems.

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