Multi-Interference and Multi-Model Dynamic Scheduling of the Small Satellite Based on Dual Population Genetic Algorithm

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Abstract

Small satellites have the outstanding advantages of flexible reconfiguration and strong system robustness through large-scale network operation, which has attracted attention at domestic and overseas in recent years. However, how to solve the scheduling problem in large-scale satellite constellation/cluster production is always the key to increasing the volume production of satellites. In this paper, the existing production line framework and the critical technologies of intelligent manufacturing are analyzed, and the intelligent production line flow is proposed. Based on the establishment of the job shop scheduling (JSP) model, the Interference of multi-model scheduling is classified, and by improving the dynamic scheduling strategy of the dual population genetic algorithm, we solve the multi-model scheduling problem. The simulation results show that the scheduling scheme can minimize the influence of interference events on the schedule, which proves the superiority and effectiveness of the scheduling strategy.

Keywords: Small satellites production line, Dynamic scheduling, Intelligent production, Dual population genetic algorithm

1 Introduction

With the development of space technology, the low-orbit constellation has the technical advantages of global coverage, rapid accessibility, flexible deployment and collaborative networking. Small satellites which have the characteristics of low-cost, convenient supplements are suitable for large-scale networking [1]. Also, they have application advantages such as manoeuvrable and flexible launch, autonomous operation of star clusters, large-scale implementation, collaborative application of star clusters, flexible reconstruction and strong system robustness [2]. Based on these reasons, small satellites have made an outstanding performance in the fields of remote sensing, information collection and transmission, communication and others [3]. However, Facing the mode of mass production for dozens or even hundreds of satellites in small satellite constellations, the traditional single-satellite production mode inevitably difficult to meet the requirements of production efficiency [4]. The market-oriented, open and integrated development of the satellite industry is the general trend [5], therefore, the rise of small satellite constellations/clusters will inevitably lead to changes in the production mode. To meet the development needs of small satellite batch production, it is necessary to research and develop an efficient, automated, high-quality and highly error-proof AIT (Assembly Integration & Test spacecraft system-level) platform, among which automation and intelligence of the production line is the core content of production mode reform.

Starlink factory in the US, which can manufacture 120 Starlink satellites per month; OneWeb Satellite Company, which is capable of producing 60 low earth orbit (LEO) satellites per month [7]; Thales Alenia Aerospace has achieved a single satellite production cycle of 60 days, with an average of 4 satellites completed per month, and innovatively proposed the AIT process in satellite batch production phase. China's Aerospace Science and Industry Corporation (CASIC) and China Aerospace Science and Technology Corporation (CASC) have both put forward plans for a network constellation of low-orbit satellites with global coverage. The "Hongyun Project" built by CASIC has an annual production capacity of 240 satellites; The "Hongyan Constellation" designed by CASC has a planned annual design capacity of about 200 satellites [8]. Although the research institutions have already carried out the construction and research of a low-orbit satellite network [6], limited by the speed of satellite manufacturing, our low-orbit satellite network is still in the design verification and experimental research stage.

The research on the job shop scheduling (JSP) problem can be traced back to the 1950s. In 1954, Johnson delved into the Flow-shop scheduling problem with two machine tools [9]. The main body of scheduling theory was established in the 1960s and 1970s when dynamic programming and integer programming were applied to the modelling of scheduling problems [10]. In the 1980s, people began to pay attention to the research on stochastic scheduling [11]. Many new job shop scheduling (JSP) methods and theories keep emerging, such as tabu search algorithms, integer programming, scheduling algorithm based on heuristic rules, deterministic optimization algorithm, simulated annealing algorithm, artificial intelligence algorithm, etc. [12-14]. From the 1990s to now, with the emergence and rapid development of the bionic algorithm, new scheduling algorithms based on intelligence theory have emerged, among which particle swarm optimization algorithm, ant colony algorithm and bee

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colony algorithm are relatively mature [15-16]. Intelligent scheduling has become a hot research direction. The basic idea of genetic algorithm (GA) came from evolutionary biology and initially introduced by Professor Holland [11] to solve complex optimization problems by designing appropriate selection, crossover and mutation operators. But the genetic algorithm has some defects, such as slow convergence or local convergence, which undermines the algorithm's solving effect. To adapt to multi-interference and multi-model dynamic scheduling of the small satellite, a dynamic scheduling strategy based on a dual-population genetic Algorithm is proposed in this paper.

The main contributions of this paper are as follows: evaluating the existing production line, constructing the overall framework of dynamic scheduling, clarifying the key technologies of an intelligent factory, and analyzing the AIT scheduling process of small satellite intelligent manufacturing. Based on the analysis of the multi-model scheduling problem with multi-interference, we establish a job shop scheduling model, and the multi-model AIT scheduling problem was solved for the multi-interference and multi-model of the small satellite manufacturing by dynamic scheduling strategy based on the improved dual population genetic algorithm.

2 Establishment of Scheduling Model and Interference Analysis of Multi-Project Scheduling

In the face of the future trend of batch production and development of small satellites [17], there is a need to shift from manual control to efficient automated control in areas such as data management, material distribution, production scheduling and other aspects. Figure 1 illustrates the overall framework of the existing technologies, technologies that require improvement, and technologies not yet available in the production line.

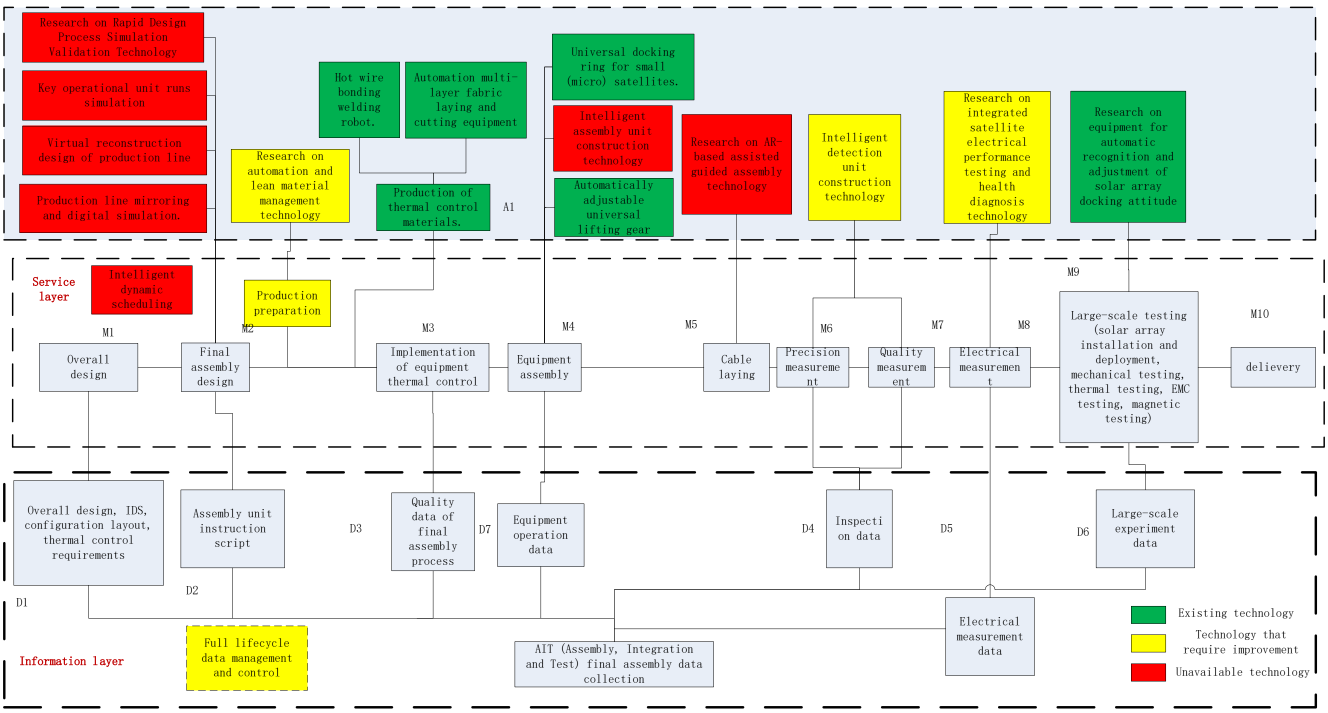

Figure 1. General framework drawing of the production line

The logical architecture of the high-efficiency and intelligent assembly production line for batch small satellites [18] includes six key elements: intelligent personnel control, intelligent equipment control, intelligent warehousing and logistics control, intelligent production control, intelligent environmental control, and intelligent information system.

Centring on the six key elements analyzed above, the organic integration of intelligent hardware equipment and intelligent software system is realized at the four levels of equipment, production line, job shop and management to support dynamic perception, real-time analysis, autonomous decision-making and accurate execution of small satellites intelligent manufacturing. The manufacturing process of the production line is shown in Figure 2.

The scheduling problem for job shops in small satellite production lines is one of the most difficult combinatorial optimization problems and is also a typical NP-hard problem. As the basis for the study of job shop scheduling, it has important theoretical significance and engineering value.

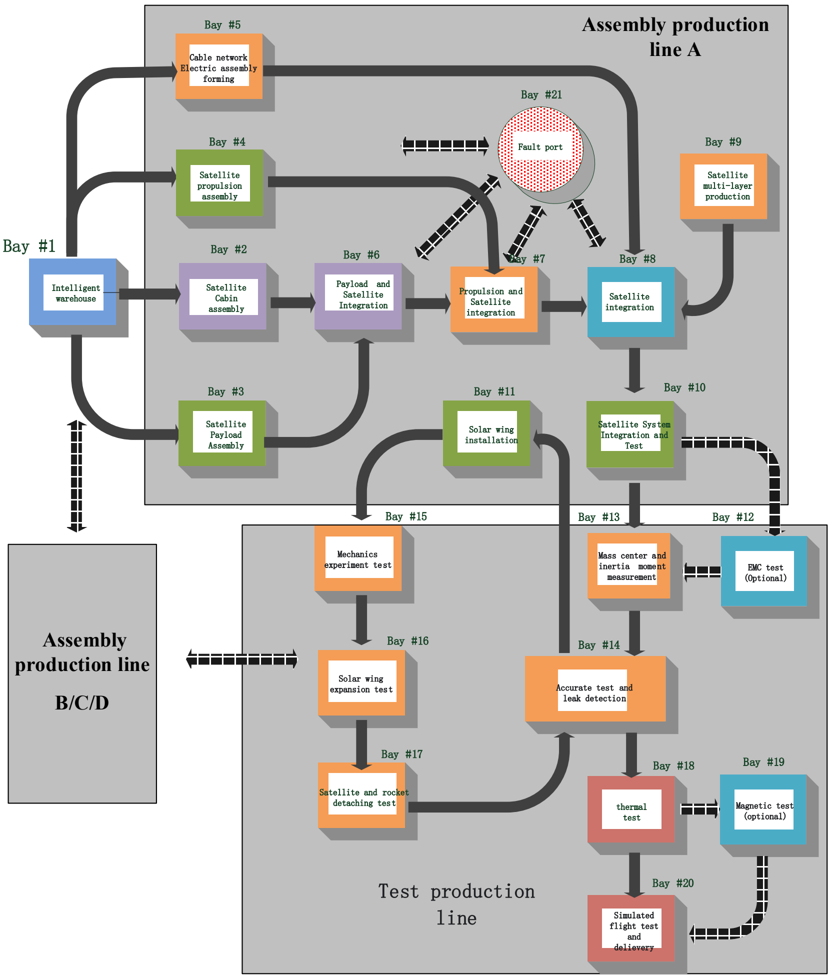

Figure 2. Manufacturing process of small satellite production line

2.1 Job Shop Scheduling Model

The AIT (Assembly, Integration and Test) job shop scheduling problem of the small satellite can be generally described as follows: n satellites are processed AIT operations on m AIT work units, where the process route for each satellite and the processing time for each operation have been determined. An AIT work unit can only perform one operation of a certain satellite at a certain time, which is known as an occupation constraint. Satellites can only perform the next AIT operation after the previous one has been completed, which is known as a sequence constraint [19]. The AIT job shop scheduling problem aims to arrange the AIT sequence for each satellite on each AIT work unit reasonably.

AIT job shop scheduling (JSP) generally meets the following constraints [20]:

(1) Each satellite has a certain processing order in the workspace;

(2) Each satellite has a certain processing time in the workspace;

(3) The next operation can only be processed after the completion of the previous one;

(4) Each workspace can only carry out AIT operation for one satellite at a time, and each satellite can only be carried out AIT operation in one workspace at a time;

(5) The start processing time of both the workspace and the satellite is 0;

(6) The process cannot be interrupted after the start of any working procedure;

The basic scheduling problem is typically represented by n/m/A/B, where n represents the number of satellites, m represents the number of AIT processing units, A represents the type of AIT processing units, and B represents the type of satellites (Cmax represents the maximum AIT job completion time, Imax represents the maximum flow time, etc.).

In AIT scheduling, the following basic mathematical symbols are defined:

n: Types of satellites;

m: Maximum number of operations in procedure;

J: Set of satellites, J={J1, J2,…, Ji,…, Jn},where Ji represents the number of i-th type of satellites;

M: Set of processing units, M={M1, M2,…, Mi,…, Mm}, where Mi represents the number of i-th type of processing units

P: Set of operations, P={P1, P2,…, Pi,…, Pn}, where Pi represents the number of operations of the i-th type of satellite;

D: Set of delivery time, D={D1, D2,…, Di,…, Dn}, where Di represents the delivery time of the i-th type of satellite;

T: Set of available processing time, T={T1, T2,…, Ti,…, TM}, Ti represents the available processing time of the i-th job unit;

C: Set of completion time of satellite AIT process, C={C1, C2,…, Ci,…, Cn}, where Ci represents the AIT processing completion time of the i-th type of satellite;

Ct: Set of the processing cost of processing units Ct={Ct1, C t2,…, Cti,…, Ctm}, where Cti represents the processing cost of the i-th type of processing unit;

Mt: Set of processing time of processing units Mt={Mt1, Mt2,…, Mti,…, Mtm}, where Mti represents the processing time of the i-th type of processing unit;

Mr: Set of working time of processing units, Mr={Mr1, Mr2,…, Mri,…, Mrm}, where Mri represents the working time of the i-th type of processing unit;

Jm: Sequence matrix of processing units, with the size of n*max{P, P2,…, Pi,…, Pn}. The term Jm(i,j) represents the sequence number of the unit which processes the j-th operation of the i-th type of satellite. The term Jm(i,*) represents the arrangement of the sequence numbers of all units that process entire operations for the i-th type of satellite. The term Jm(*,j) represents the arrangement of the sequence numbers of all satellites which are processed in the j-th unit. If the number of operations for a certain satellite is less than max{P, P2,…, Pi,…, Pn}, the remaining slots will be filled with 0.

Jt: Operation processing time matrix, also known academically as Standard Time Matrix with size n*max{P, P2,…, Pi,…, Pn}. The term Jt(i,j) represents the required time processing the j-th operation of the i-th type of satellite. The term Jt(i,*) represents the arrangement of the AIT processing time of all operations for the i-th type of satellite. The term Jt(*,j) represents the arrangement of the AIT processing time of all satellites which are processed in the j-th unit. Likewise, If the number of operations for a certain satellite is less than max{P, P2,… , Pn}, the remaining slots will be filled with 0.

2.2 Analysis of Interference Factors in Multi-model Scheduling

Single-model scheduling is relatively simple compared to multi-model scheduling, and it is easier to develop scheduling plans and recover from disruptive events that may affect it. The disruptive events in multi-model scheduling are the result of both internal and external factors. These events can be classified into three categories based on the impact of the interferences on model parameters: interference to activities, interference to resources, and interference to the network structure of the multi-model, as shown in Figure 3. The above interferences have an impact on the multi-model baseline scheduling plan, mainly reflected in four aspects: duration, customer satisfaction, cost, and resource availability.

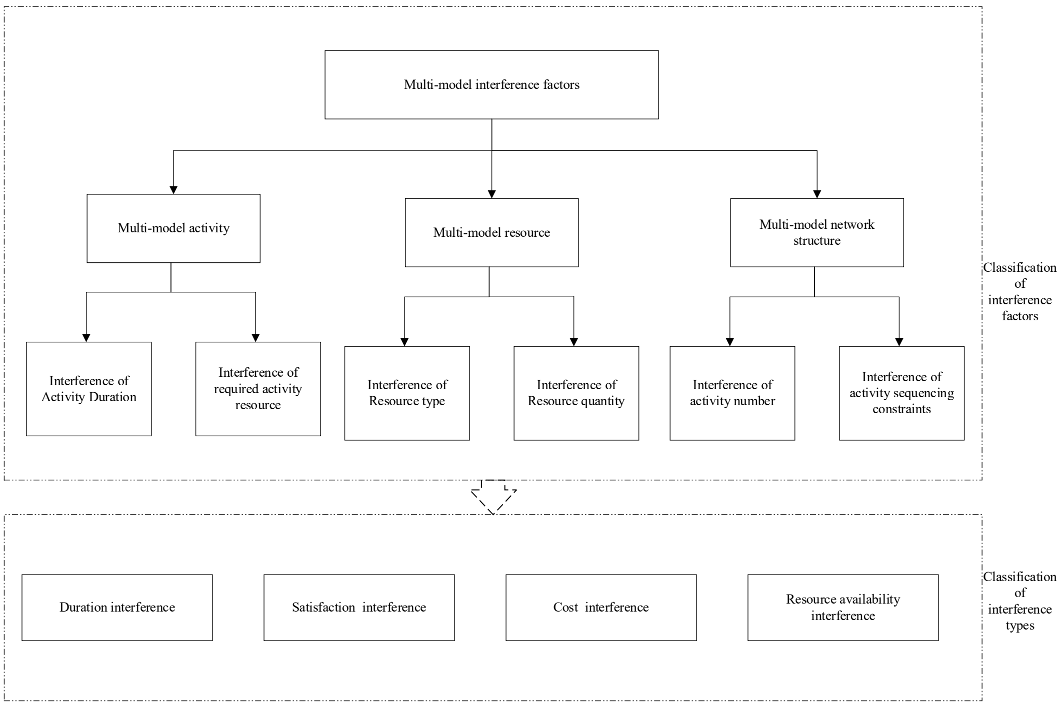

Figure 3. Analysis of interference events in multi-model scheduling

3 Dynamic Scheduling Strategy Based on Improved Dual Population Genetic Algorithm

3.1 Improved Dual Population Genetic Algorithm

To maintain the diversity of the population, assuming that two populations have the same population size, denoted as population POPL and population POPR, both populations use parallel operation mechanisms to perform operations such as reproduction, crossover, and mutation. After the operations are completed, individuals in the two populations are randomly exchanged.

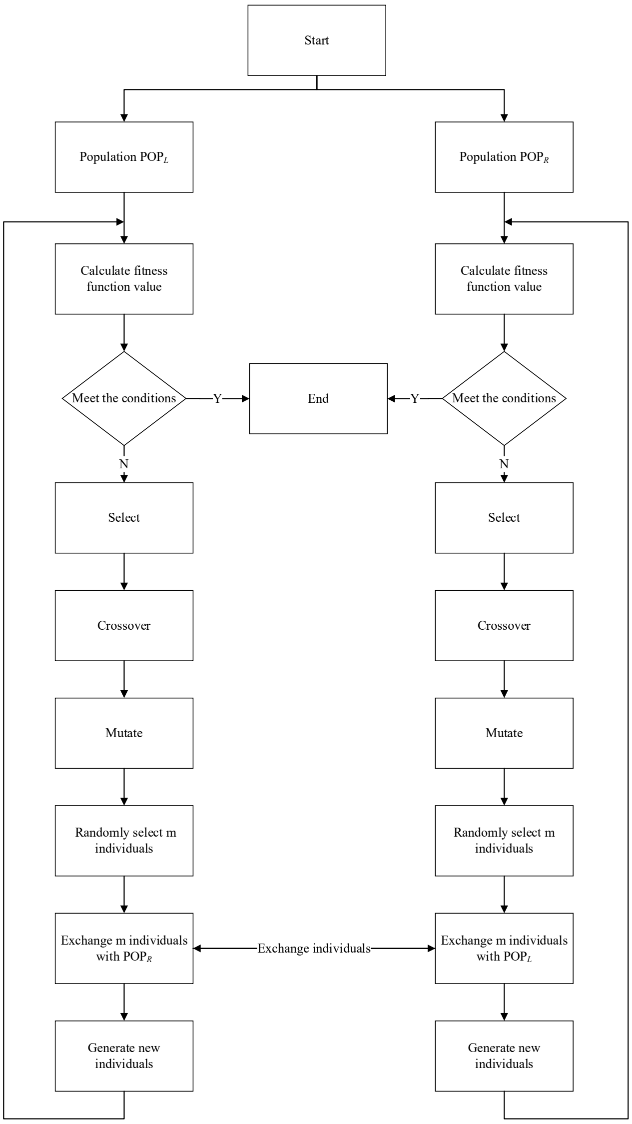

Figure 4. Flowchart of dual population genetic algorithm

To improve the searchability of the Dual Population Genetic Algorithm, POPL focuses on local search and sets a small crossover probability to prevent the destruction of excellent individuals. Population POPR focuses on global search and sets a large crossover probability to prevent premature convergence. The two populations evolve according to different evolutionary rules and strategies, and POPL and POPR evolve in parallel, which increases the speed of evolution. The random exchange of two populations improves the search performance of the algorithm. Figure 4 shows the flow of the dual population genetic algorithm.

3.2 Coding Design

The expression of individual performance in the genetic algorithm is very important. Among several representation methods, active list (AL) representation and random key (RK) representation are widely used. These two approaches embed the priority structure into the activity. In the AL method, the location of the activity determines the relative priority of the activity relative to other activities, while in the RK method, the sequence of activity scheduling is based on the priority value of each activity. This paper uses random key (RK) representation. The individual is represented by the vector λ for the priority value and μ for the pattern list. Population POP_L and population POP_R are encoded and decoded in the same way.

$$I = \begin{bmatrix} \lambda \\ \mu \end{bmatrix} = \begin{bmatrix} j_1 & j_2 & \cdots & j_J \\ m_1 & m_2 & \cdots & m_i \end{bmatrix}. \tag{1}$$

Each priority value of the vector λ is associated with an activity based on its value, and the scheduling of the activities is assigned according to the sequence. The various individuals in the populations of vector m also have a list of execution modes. This mode list assigns a mode mi to each activity i(i1, ..., iN) and determines whether the scheduling plan is feasible relative to non-renewable resources. The encoding structure is represented in Figure 5:

Activity Sequence	1	2	3	4	5	6	…	…	J
Weight	9	2	4	6	6	10	…	…	λ
Execution Mode	1	2	1	1	1	1	…	…	m_t

Figure 5. Chromosome structure

ERR defined the additional resource demand. Algorithm design uses the change of additional resource demand to represent the impact of interference events on scheduling schemes. In the ERR function, 0 indicates that the scheduling scheme is feasible. If ERR is greater than 0, the scheduling scheme is not feasible. The formula of ERR is expressed as follows:

$$ERR(u) = \sum_{j=1}^{I} \left(\max \left(0, \left(\sum_{i=1}^{N} \left(r_{ijm}^{v} - R^{\rho}(\eta) \right) \right) \right) \right). \tag{2}$$

3.3 Initial Population

The Dual Population Genetic Algorithm starts with establishing a left-aligned scheduling plan POP_L and random keys are generated. For each activity i, the execution mode is generated by random selection. To minimize the number of infeasible solutions in the initial population, a local search method is applied to transform infeasible solutions into feasible ones. If the value of ERR remains the same or similar, the mode of the activity is changed. This step is repeated until the assigned mode is feasible with ERR value is 0 or until the maximum number of tests is reached.

3.4. Fitness Function

The fitness function is the basis for evaluating the quality of chromosomes, and it directly affects the convergence speed and solution quality of the dual-population genetic algorithm. The original intention of the algorithm design is to minimize the deviation between the newly generated scheduling plan and the baseline plan, that is, to minimize the impact of perturbations on the schedule. Since the population contains infeasible solutions, these solutions must be penalized, otherwise, they will replace feasible solutions in the population. Therefore, a fitness function with a penalty function performs better.

An excellent fitness function can provide effective feedback to the genetic algorithm. If the scheduling plan is feasible with ERR of 0, the fitness function equals the objective function. If the mode is infeasible, the fitness function equals the objective function plus the value of ERR in the mode list. The higher the fitness value of the scheduling, the better the quality of the generated scheduling plan. The fitness function of the Dual Population Genetic Algorithm is represented as follows:

$$f(t)=\begin{cases} Z(t) & , ERR(\mu)=0 \\ Z(t)+ERR(\mu), & ERR(\mu)\neq 0 \end{cases}. \tag{3}$$

3.5 Selection Operator

Since POP_L of the population focuses on local search and POP_R of the population focuses on global search, the two populations adopt different selection mechanisms and carry out selection operations respectively. Population POP_L adopts the tournament selection mechanism to select individuals with high fitness from the population for the next generation and repeats this operation until the number of individuals entering the next generation reaches the specified number. Population POP_R adopts the roulette wheel selection mechanism, which is closely related to the fitness value of individuals. Individuals with high fitness have a higher probability of being selected, while individuals with low fitness have a lower probability of being selected.

3.6 Crossover Operator

The population POP_R adopts the ordered crossover operator, which randomly selects two gene points of parent 1, copies the gene string between the two points onto the offspring chromosome 1, and removes the genes with the same encoding from parent 2. Then, the remaining genes are sequentially filled into the corresponding positions of chromosome 1. The crossover operation of population POP_L is shown in Figure 6.

Population POP_L uses a position crossover operator, which randomly selects several gene positions from parent 1 and uses them as the genes for corresponding gene positions in the offspring chromosome. At the same time, the selected gene codes are removed from parent 2, and the remaining genes are sequentially filled into the corresponding gene positions in the offspring chromosome, creating a new chromosome. The crossover operation process of population POP_L is shown in detail in Figure 7.

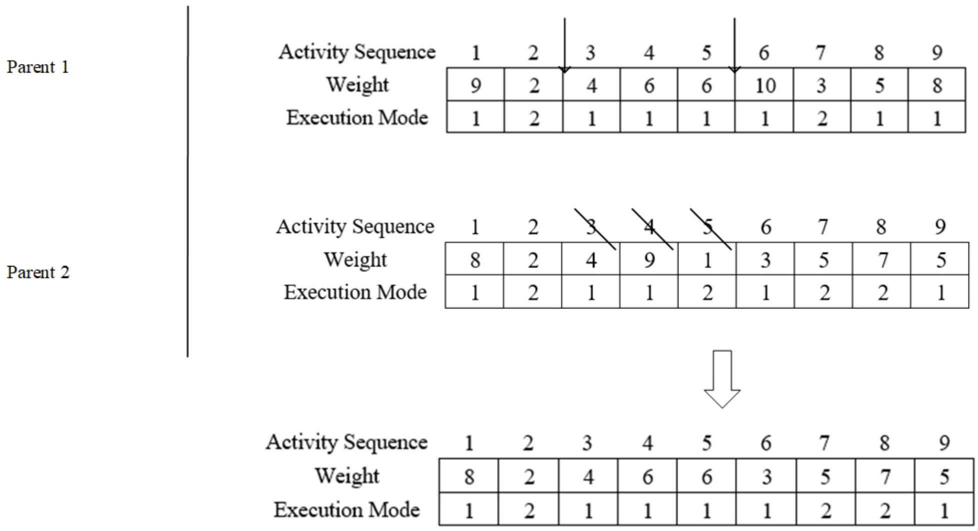

Figure 6. Crossover operation for population POP_R

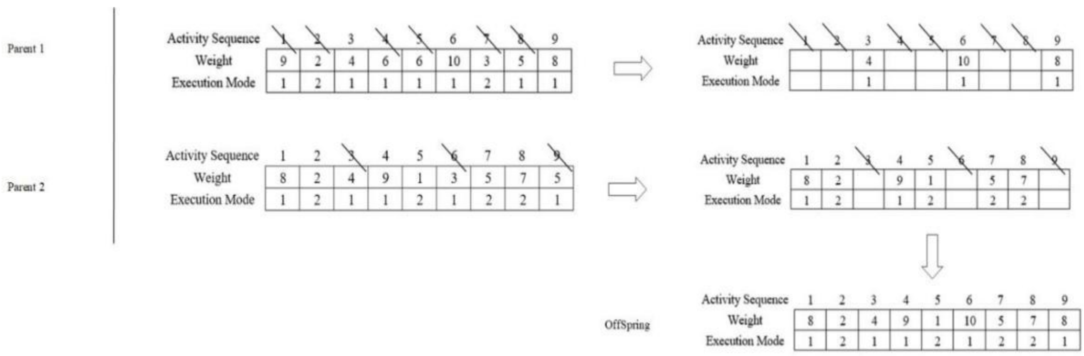

Figure 7. Crossover operation for population POPL

3.7 Mutation Operator

The two populations of POP_L and POP_R adopt different mutation modes and carry out mutation operations respectively. As shown in the Figure 8, The population POP_R uses the method of inversion variation, randomly selects a segment of a gene on a chromosome, and reverses the gene string.

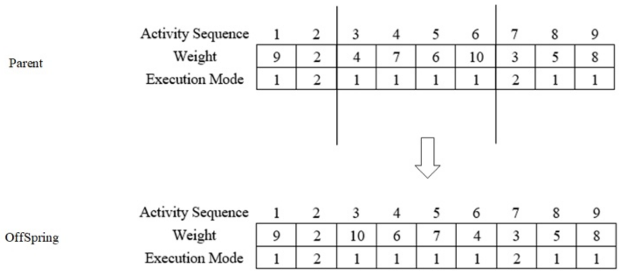

Figure 8. Mutation operation for population POP_R

The population POP_L of the genetic algorithm uses the exchange mutation method to randomly select two gene loci, exchange the values of the gene codes, and generate a new chromosome. The mutation operation of population POP_L is shown in detail in Figure 9.

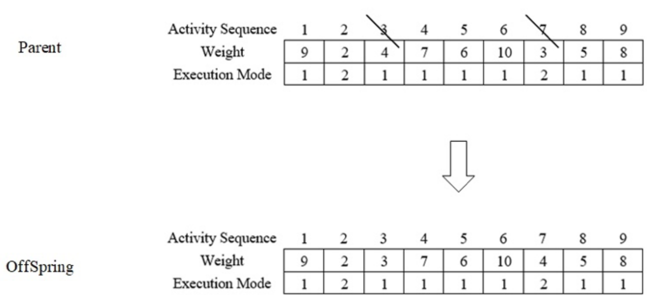

Figure 9. Mutation operation for population POP_L

3.8 Stopping Criterion

In the Dual Population Genetic Algorithm, the offspring population replaces the parent population, which means that the population size remains unchanged. The survival of the fittest principle is followed during replacement. For each individual i that is replaced, the parent has been selected and a new individual has been generated. Even if a deteriorating result occurs, the offspring with the highest fitness value is selected to replace individual i in the population. However, to select high-quality scheduling solutions, if an individual corresponds to a schedule that achieves the best completion time, no replacement operation is performed. The Dual Population Genetic Algorithm stops running and outputs the corresponding results when it reaches the specified number of evolution generations.

4 Simulation Experiment

This chapter takes small satellite AIT job shop scheduling as an example to analyze the impact of dynamic changes in customer requirements (such as the addition of urgent tasks) on multi-model AIT scheduling in satellite manufacturing enterprises. An optimization model is established and a dual-population genetic algorithm is used for experimental simulation. Each activity in the case represents a corresponding operation in the AIT manufacturing production procedure, which includes 28 activities and virtual start and end activities, requiring a total of 5 types of resources, including 3 updatable resources and 2 non-updatable resources. The sequential relationships between various activities of multiple models are detailed in Figure 10. The indirect cost of a unit task is c=4, and the unit prices of the five resources are 1, 3, 2, 7, and 2, respectively. Table 1 shows the relevant information for each activity in the baseline scheduling scheme, including the execution pattern, task duration, and the type and quantity of resources used for 28 AIT tasks (each activity has two execution patterns). The model network diagram can be determined based on the activity relationship table in Table 2. In multi-model baseline scheduling scheme, updatable resources L1= 63, L2 = 58, L3 = 52 and non-updatable resources K1 = 48, K2 = 44. The AIT duration for sub-model 1, sub-model 2 and sub-model 3 is 11, 14, and 10 respectively.

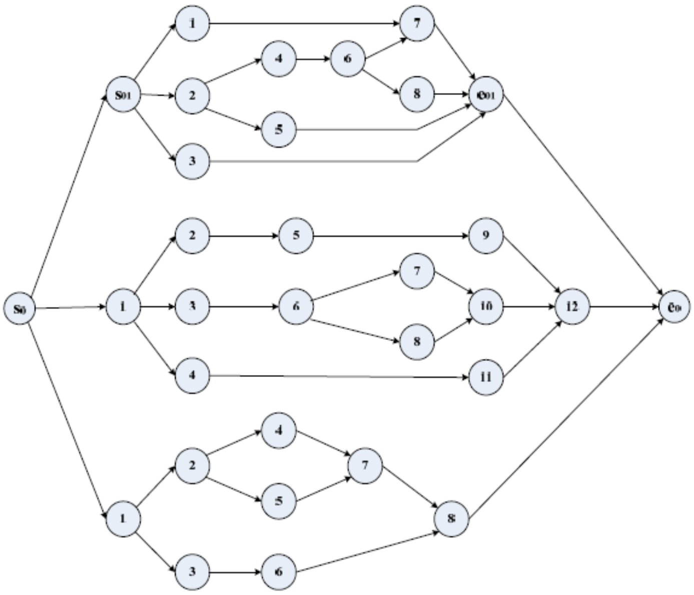

Figure 10. Network structure diagram of the benchmark scheduling scheme

Table 1. Related information of the benchmark scheduling scheme

$Submodel_1$	$Pattern_{m_i}$	$Duration$	L_1	L_2	L_3	K_1	K_2	$Submodel_2$	$Pattern_{m_i}$	$Duration$	L_1	L_2	L_3	K_1	K_2	$Submodel_3$	$Pattern_{m_i}$	$Duration$	L_1	L_2	L_3	K_1	K_2
1	1	3	2	3	3	2	1	1	1	1	2	2	1	2	2	1	1	2	2	3	2	2	2
2	2	3	2	1	2	1	1	2	1	2	2	1	3	1	1	2	2	2	2	2	1	1	2
3	2	2	2	2	3	2	2	3	2	3	2	2	1	2	1	3	2	2	3	1	1	2	2
4	2	3	3	2	2	3	2	4	1	2	2	3	1	1	1	4	1	3	3	3	2	2	1
5	1	2	3	3	2	4	2	5	2	3	1	2	2	1	2	5	1	3	3	1	2	3	3
6	1	2	3	2	2	1	0	6	2	2	2	3	2	2	1	6	1	2	2	2	2	2	3
7	1	3	2	2	2	1	1	7	1	2	3	3	2	2	1	7	1	1	2	2	1	1	2
8	2	3	2	1	2	1	1	8	1	3	3	3	1	2	1	8	2	2	2	1	3	3	2
								9	1	1	2	2	2	1	2								
								10	2	2	2	2	3	1	2								
								11	2	2	3	2	1	1	2								
								12	2	3	1	2	1	3	2								

Table 2. Model activity relationship table

$Submodel_1$			$Submodel_2$			$Submodel_3$		
$ActivitySequenceNo.$	$PrecedingNo.$	$SubsequentNo.$	$ActivitySequenceNo.$	$PrecedingNo.$	$SubsequentNo.$	$ActivitySequenceNo.$	$PrecedingNo.$	$SubsequentNo.$
1	—	7	1	—	2, 3, 4	1	—	2, 3
2	—	4, 5	2	1	5	2	1	4, 5
3	—	—	3	1	6	3	1	6
4	2	6	4	1	11	4	2	7
5	2	—	5	2	9	5	2	7
6	4	7, 8	6	3	7, 8	6	3	8
7	1	—	7	6	10	7	4, 5	9
8	6	—	8	6	10	8	6, 7	—
				5	12			
				7, 8	12			
				4	12			
				9, 10, 11	—			

During the multi-model AIT processing, an interference event occurred at time t = 5. Sub-model 2’s process 3, 23 A, needs to be reworked due to quality issues, while activity 26 A has already started for one unit of time. Subsequently, internal resource conflicts within the multi-model scheduling caused by rework led to activity 16A not being completed on time at time t = 8. From previous research, it is known that the delay of AIT duration of activity 23A will have an impact on subsequent activities and is likely to create resource conflicts between sub-models. The impact of the interference event on the scheduling plan is mainly manifested in the interference of the duration and cost, which also affects the delivery date of the model project. The research focus of this chapter is to develop a recovery strategy within an acceptable range of duration interference for customers. Based on the experience of project decision-makers and the actual situation of the model project, it is known that a deviation of the project duration within 10% can be accepted by the customer. Therefore, according to the baseline scheduling plan, it is known that the critical activities of the multi-model scheduling are in sub-model 2, and the recovery time windows of each activity in the multi-model scheduling can be determined. Using Mpple 12.0 to implement a dual-population genetic algorithm programming to solve the established model. The population size is set to 50, and the value of the evolution generation is set to 50 to meet the requirements of population diversity. Firstly, a multi-interference multi-models scheduling model is established based on the status of each activity when the interference event occurs. Then the interference event is recognized, and the set of subsequent activities is confirmed. After that, the initial time window of the local schedule is established, and the scheduling strategy is optimized according to the interference event. The dual-population genetic algorithm is used to solve the problem. If the optimal solution or approximate optimal solution cannot be found, the time window range is extended, which is based on the initial time window extended by 10%, until the optimal solution is found or the number of iterations is reached. According to the objective function, the recovery plan results are shown in Table 3.

According to Table 3, it can be seen that after the disturbance event, the rework of Activity 23A poses the risk of delaying the AIT duration and causing resource conflicts between operations of multi-models. Therefore, a local optimization was carried out to develop the interference recovery plan, as shown in Table 3. After the interference in activity 23A, subsequent activities 26 A and 27 A were affected, and optimization strategies were adopted including changing the execution mode of activities and using resource substitution.

Based on the above analysis results and the data in Table 3 to Table 5, we can know that the scheduling problem for small satellite manufacturing facing multiple interferences is very complex. By establishing a problem model and optimizing it, the efficiency of scheduling can be significantly improved, while minimizing costs and AIT operation time, and increasing customer satisfaction. The designed dual-population genetic algorithm can efficiently solve the scheduling problem for multi-models in a multi-interference environment. Based on the frequency of interference events, further research will be conducted on the multi-level interference problem of multi-model scheduling. This paper studies the AIT scheduling problem faced by small satellite manufacturing companies in a multi-interference environment due to the dynamic customer demands, focusing on the effects of three types of interference on multi-model scheduling., namely customer dissatisfaction, project schedule and project cost. The goal is to develop a reasonable multi-model scheduling plan interference recovery strategy under resource constraints and project deadline restrictions, minimizing the impact of interference events on multi-model scheduling.

Table 3. Recovery plan

$Acticity$	$StartTime$	$EndTime$	L_1	L_2	L_3	K_1	K_2	$IncreasedCost$	$Dissatisfaction$	$RemedialWork$
A_{23}	5.5	7	4	5	3	3	2	33	0.75	rush work
A_{26}	7	8	3	3	2	1	2	10	0.4	change activity mode
A_{28}	8	9	6	6	4	4	2	38	0	rush work
A_{16}	8	9	3	3	3	1	1	12	0	substitute resource

Table 4. Scheduling scheme according to the original scheduling plan

$Acticity$	$StartTime$	$EndTime$	L_1	L_2	L_3	K_1	K_2	$IncreasedCost$	$Dissatisfaction$
A_{23}	5	8	2	2	1	2	1	33	0.75
A_{26}	8	10	2	3	2	2	1	10	0.4
A_{27}	10	12	3	3	2	2	1	38	0.5
A_{28}	10	13	3	3	1	2	1	32	0.26
A_{210}	13	15	2	2	3	1	2	39	0.33
A_{212}	15	18	6	6	4	4	2	38	0
A_{16}	8	10	1	2	1	3	2	12	0

Table 5. Comparison of interference management optimization schemes

	Cost Deviation	Schedule Deviation	Dissatisfaction Deviation
Original Plan	6.32%	18.32%	9.91%
Optimized Plan(Management Interference)	2.47%	6.75%	4.16%

Through case simulations, the proposed scheduling plan can achieve the goal of minimizing the impact of interference events on the schedule, while also verifying the superiority of the dual-population genetic algorithm. we can conclude that:

(1) The local rescheduling approach is more in line with the actual needs of the multi-interference and multi-model scheduling problem and can quickly formulate a plan to restore the interference events' impact on the scheduling system.

(2) The POP_L population of the dual-population genetic algorithm focuses on local search and sets a small crossover probability to prevent excellent individuals from being destroyed. The POP_R population focuses on global search and sets a large crossover probability to prevent premature convergence. The dual-population genetic algorithm improves both the speed of evolution and the search performance of the algorithm.

5 Conclusion

This paper analyzed the current situation and application prospects of scheduling for small satellite production lines and systematically analyzed the factors influencing the scheduling problem in small satellite job shops and production lines. Through analysis and summary of the logical structure of the efficient and intelligent assembly production line for small satellites with variable batch sizes, six key elements were proposed to achieve the organic integration of intelligent hardware equipment and intelligent software systems.

This paper modelled and analyzed the dynamic scheduling problem, and proposed an improved dual-population genetic algorithm with different designs for different populations. The effectiveness of the proposed dual-population genetic algorithm in solving the multi-model scheduling problem under multi-interferences was verified through experiments. This study focused on the production scheduling problem of subcontracting enterprises in a multi-interference environment, analyzed the interference factors, and established a multi-model scheduling model oriented towards multi-interferences to minimize the impact of interferences on multi-model scheduling from the perspectives of customer dissatisfaction, project duration and project cost. A dual-population genetic algorithm was designed to solve this problem. Through examples, it was concluded that local rescheduling is a better approach for multi-model scheduling problems with multiple interferences.

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