Research on NSGA-II Flexible Job Shop Scheduling Based on Variable Length Chromosomes

Yuanfeng Hao¹, Chunlei Ji*¹ and Wei Xiao¹

¹School of Electronic Information, Shanghai Dianji University, Shanghai, 201306, China

*Corresponding author’s e-mail: jicl@sdju.edu.cn

Abstract. As the core of enterprise production management, production scheduling plays a pivotal role in the optimal allocation of resources and scientific operation. A more optimized workpiece scheduling method can greatly reduce the staying time of workpieces in the workshop and improve production efficiency. Most of the existing scheduling algorithms are coded according to the length of the number of workpieces and machines, and the number of workpieces in each batch of the factory is often different. This scheduling method has certain limitations. How to perform different batches and varying numbers of workpieces? Production scheduling has become an urgent problem for modern enterprises. Based on this, this paper proposes a variable-length chromosome encoding method, which can perform production scheduling on different batches and different numbers of workpieces, greatly improving the scope of application of scheduling scenarios. At the same time, because of the shortcomings of low population diversity and slow operation speed in the non-dominated sorting genetic algorithm, an adaptive layering strategy is proposed. Simulation experiments show that the improved algorithm can better complete scheduling tasks and improve production efficiency.

1. Introduction

As the core of enterprise production management, production scheduling plays a pivotal role in the optimal allocation of resources and scientific operation. Statistics show that 95% of the time in the manufacturing process is spent in non-processing processes [1]. Therefore, scientific and effective planning and scheduling have become the key to the smooth and efficient operation of the manufacturing system. Flexible job shop scheduling (Flexible Job-shop Scheduling Problem, FJSP) is the job path scheduling problem of workpiece processing on multiple machines, which is an extension of the job-shop scheduling problem (Job-shop Scheduling Problem, JSP). How to plan the operation path scientifically and effectively is a key method for an enterprise to reduce production costs, improve production efficiency and product quality, and maximize enterprise benefits.

At present, the commonly used methods to solve FJSP include Taboo Search (TS), Simulated Annealing (SA), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), etc. [2][3][4][5]. Among them, genetic algorithm is widely used because of its good robustness, versatility and computer advantages. Wu Shaomin et al. [6] developed a method based on matrix coding to improve the genetic algorithm, and described the method of generating the initial population in detail. Cui Qi et al. [7] improved the genetic algorithm by using a hybrid variable neighborhood method in search. Yao Lili et al. [8] proposed a heuristic positive-sequence scheduling algorithm, which uses two improved processing of scheduling rules and logical constraints as the overall scheduling method. Kai [9] et al. established a multi-objective FJSP model based on the four goals of maximum completion time, minimum advance
and delay average, and minimum total machine workload, and proposed four sets of heuristic algorithms for FJSP for new job insertion. Zou Pan [10] and others proposed a hierarchical ant colony genetic algorithm based on resource-driven multi-objective FJSP, which uses a mixture of genetic algorithm and hierarchical ant colony algorithm to solve the multi-objective FJSP, and finally obtains an optimized solution through stepwise selection.

To sum up, the existing literature mostly studies the scheduling of FJSP problems in the same batch and the same number of artifacts and ignores the scheduling problem of different batches and different numbers of artifacts. In response to this problem, this paper proposes a coding method for variable-length chromosomes with different numbers of machines and workpieces. In the non-dominated set sorting process, an adaptive layering method is introduced to increase population diversity and speed up convergence.

2. Problem description

2.1. Problem description of flexible job shop

Under the limitation of the maximum load capacity of the production unit of the flexible workshop, there are n (i=1,2,\cdots, n) substitute machining workpieces, and the set of workpieces is denoted as J={J1, J2, J3, J4,\cdots, Jn}, represents the set of n workpieces, where Oij is the j-th process of the i-th workpiece, which can be expressed as Oi={Oi1, Oi2, Oi3,\cdots, Oij}, production There are m (k=1,2,\cdots, m) processing machines in the workshop, and each process can choose one machine from the optional processing machine set M={M1, M2,\cdots, Mn} For processing, each processing machine has a different processing time, that is, the processing time of the same process varies with the choice of the machine.

This article makes the following assumptions:
1) The processing path of the workpiece is variable, that is, the number and sequence of the workpiece are randomly changed
2) Each machine can only process one workpiece at a time
3) There is no sequential constraint relationship between the processes of different workpieces
4) The processing of the working procedure is not interrupted
5) All resources are available at t=0

2.2. The mathematical model is as follows:

1) Minimize the maximum completion time:

\[
\min f_1 = \min C_m = \min \left( \max_{k \in M} C_k \right)
\]  

In formula (1): \(f_1\) is the first objective function; \(C_m\) is the completion time of all equipment; \(C_k\) is the completion time on the k-th equipment; \(k\) is the equipment index, \(k = 1,2,\cdots, m\); \(m\) is the total number of devices.

2) Minimize the delay time

\[
\min f_2 = \min \left( \max |C_i - d_i| \right)
\]  

In formula (2), \(f_2\) is the second objective function, \(C_i\) is the completion time of the workpiece \(J_i\), and \(d_i\) is the predetermined completion time.

3. Scheduling problem solving process

The flow chart of the multi-objective optimization algorithm of NSGA2 flexible job shop based on variable length chromosomes is shown in Figure 1. According to the process in Figure 1, the parent population is first initialized and evaluated. By performing operations such as selection, crossover, and mutation on the parent, a new offspring population is generated, and then the newly arrived offspring population is merged with the original parent population to obtain a new population Rt. Perform non-dominated sorting on Rt to obtain different non-dominated layers Fi. In the non-dominated sorting set, an adaptive layering strategy is used to select individuals with less crowdedness in the same layer from
different non-dominated sets to enter the next generation, and iteratively loop until the algorithm terminates.

Figure 1. Algorithm flowchart

3.1. The coding method of unequal length chromosomes
Coding is a crucial step in the algorithm process. The quality of coding directly affects the speed and quality of the optimization problem. The coding of traditional workshop scheduling mainly includes two types: process-based coding and processing machine-based coding. Process-based coding means that the same serial number in the chromosome means belonging to the same workpiece, different workpieces are represented by different serial numbers, and the process of a workpiece is represented by the number of times the same workpiece serial number appears; the coding based on processing machines uses one in the coding Consider the matrix encoding method of processing machine information. At present, most flexible workshops use the same length method for the number of workpieces and machines for coding. At this stage, the number of workpieces and the number of each batch of the factory is often different. This coding method has certain limitations, so the unequal length chromosome coding method is proposed, such as shown in Figure 2.
3.2. Adaptive hierarchical genetic algorithm design

NSGA2 is a multi-objective solution algorithm formed by improving non-dominated solution sorting and introducing elite selection strategies based on NSGA. It has a faster convergence rate. Although it is widely used, it also has the problem of insufficient population diversity. Among them, the selection of individuals after non-dominant sorting is a key step in determining the population quality of the next generation of parents. Therefore, how to select the next generation of parents has become particularly important. In the NSGA2 simulation process, the selection of the next-generation parent individuals is usually through the non-dominant sorted branch distribution layer, which is selected in turn. But in this selection process, there will be a problem, that is, each time the non-dominated individuals are selected, it is easy to cause the algorithm to converge in advance, and it may fall into a local optimum.

The basic idea of the adaptive hierarchical design is: after sorting through non-dominated layers, for each different non-dominated layer, some individuals are selected to enter the next generation of parents. Compared with NSGA2 only select the first few layers to enter the next generation of parents, adaptive layering design selects some poor individuals to enter the next generation, increasing the diversity of the population, and adaptive layering can also ensure that most of the better ones enter the next layer. The formula is:

\[ n_i = \frac{2(K + 1 - i)n}{(K + 2)(K - 1) + 2(K + 1 - i)} \]

Among them, \( n_i \) is the number of individuals selected at the \( i \)-th level, \( K \) is the maximum non-dominated level of the population, and \( i \) is the number of the level of individuals to be selected.

By introducing an adaptive layering algorithm, the diversity of the population search space and the uniformity of the distribution of the solution set can be guaranteed, which is conducive to the inheritance of excellent genes and promotes the generation of optimal solutions.

4. Experimental simulation and analysis:

In the comparative experiment, each algorithm was run 100 times, and the average value of a set of data was compared every 20 times in sequence, and finally, 10 sets of comparative data were obtained. The experimental results are shown in Table 1.
Table 1. Experimental results and average values in each comparison group

| Experiment group number | Objective function value | Average value |
|-------------------------|--------------------------|---------------|
| 1                       | Not improved algorithm   | 50.23665      |
|                         | Improved algorithm       | 49.98658      |
| 2                       | Not improved algorithm   | 49.81476      |
|                         | Improved algorithm       | 47.79094      |
| 3                       | Not improved algorithm   | 52.11345      |
|                         | Improved algorithm       | 48.30556      |
| 4                       | Not improved algorithm   | 49.607221     |
|                         | Improved algorithm       | 49.266825     |
| 5                       | Not improved algorithm   | 49.651948     |
|                         | Improved algorithm       | 49.266825     |

The comparison chart of the experimental results is shown in Figure 3. The scheduling Gantt chart is shown in Figure 4

![Comparison group](image-url)

Figure 3. Comparison group
5. Conclusion
In the workshop scheduling problem, although the genetic algorithm plays an important role, the existing encoding methods of the number of workpieces and the number of machines are often difficult to adapt to the production scheduling problem of different batches and varying numbers of workpieces. This problem is proposed. The chromosome encoding method of unequal length and the introduction of adaptive selection strategy expand the diversity of the population and speed up the convergence speed of the population. Finally, an example is used to verify the feasibility and superiority of the algorithm.

References
[1] Lin L, Li Y, Sun L and Gen M. (2019) Cooperative hybrid EA for large-scale flexible job shop scheduling. In: IEEE International Conference on Smart Manufacturing, Industrial & Logistics Engineering (SMILE), Hangzhou, China, 235-239.
[2] Zhang Guohui, Zhu Baoying, Yang yangyang, Sun Jinghe. (2019). Research on Flexible Job Shop Scheduling Considering Adjustment Time. Combined machine tool and automatic machining technology, 152-156.
[3] Liu Yi. (2017) The Research on Job Shop Dynamic Scheduling Based on Simulated Annealing Genetic Algorithm. Jinan: Shandong University
[4] Zhang Chaoyong, Rao Yunqing, Li Peigen, et al. (2007) Two-level genetic algorithm for flexible job shop scheduling problem. Journal of Mechanical Engineering, 43: 119-124.
[5] Liu Min, Zhang Chaoyong, Zhang Guojun, et al. (2011) Research on displacement flow shop scheduling problem based on hybrid particle swarm optimization algorithm. China Mechanical Engineering, 22: 2048-2053.
[6] Wu Shaomin, Hu Xiaobing, Wang Jiangwu, et al. (2018) Improved genetic algorithm for solving order-oriented multi-target scheduling problem. Mechanical Design and Manufacturing, 108:102-104.
[7] Cui Qi, Wu Xiuli, Yu Jianjun. (2017) Improved genetic algorithm variable neighborhood search for solving hybrid flow shop scheduling problem. Computer integrated manufacturing system, 23 (9): 1917-1927.
[8] Yao Lili, Shi Haibo, Liu Chang. (2014) Research on Scheduling in Semiconductor Assembly and
Test Manufacturing. Acta Automatica Sinica, 40: 892-900

[9] Kai. Z. G, Suganthan. P.N, Tasgetiren. M.F. (2015) Effective ensembles of heuristics for scheduling flexible job shop problem with new job insertion. Computers & Industrial Engineering, 90: 107-117.

[10] Zou Pan, Li Beizhi, Yang Jiangguo. (2015) Hierarchical Ant-Genetic Algorithm-based Multi-objective Intelligent Approach for Flexible Job Shop Scheduling. China Mechanical Engineering, 26:27-32.