Improved NSGA-II Algorithm for multi-objective flexible job shop scheduling problem

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Abstract. In order to solve the problems such as poor diversity and poor convergence ability of the offspring population of the NSGA-II Algorithm in the vehicle production scheduling problem, an improved shop scheduling algorithm based on NSGA-II is proposed. The improved NSGA-II Algorithm mainly focuses on the crossover and mutation of the traditional NSGA-II Algorithm, and proposes a new improved self-adaptive Crossover and mutation operator. By comparing the individual crowding degree with the average crowding degree of the population, and combining the iterative evolution process of the population, in order to avoid blind orientation and to improve the convergence speed of the population, the genetic probability is correlated with the individuals and the evolution iteration times of the population, and a new uniform evolution strategy is proposed to select the individuals of the population through adaptive hierarchical selection, in order to improve the quality of the solution, the problem of the poor diversity of the offspring population was solved. The improved NSGA-II Algorithm is used to carry out the experimental simulation analysis. The effectiveness of the proposed algorithm is verified by comparing the optimization results before and after the improvement.

1. Introduction
The Flexible Job Shop scheduling Problem (FJSP) can be defined as the selection of a suitable machine to accomplish a given machining goal in a set of optional machining machines. At present, the research on flexible scheduling for multi-objective problems mainly focuses on the application or improvement of intelligent algorithms, such as genetic algorithm, Ant Colony Algorithm, particle swarm optimization and NSGA-II. Mohammed [1] studied a multi-objective effective symbiosis search algorithm based on chaos optimization strategy. To solve this problem, a multi-objective discrete invasive weed optimization algorithm was proposed. Ojstersek [2] proposed an improved heuristic Emmerich Kálmán algorithm to solve the multi-objective flexible shop scheduling problem, and a flexible genetic algorithm optimization method is proposed by Karolis [3]. Lee H [4] used particle swarm optimization algorithm and improved particle swarm optimization algorithm to solve multi-objective job shop scheduling problem.

The core of multi-objective scheduling problem is also the Pareto problem. Andres[5] proposed a general local search method for multi-objective flexible job shop scheduling problem to determine the Pareto front of any conventional standard combination; Li [6] proposed an elitist non-dominated hybrid algorithm, to solve a multi objective flexible job shop scheduling problem with sequence dependent
setup time consumption. Guo [7] developed a Pareto optimization model, this paper presents a scheduling method based on NSGA-II which combines the optimization process with an effective production process simulator.

In this paper, the advantages and disadvantages of NSGA-II Algorithm are re-studied, and an improved NSGA-II Algorithm based on improved uniform evolution elite strategy and improved adaptive crossover and mutation operator is proposed, at the same time, the diversity of population is improved, the running speed is increased, the convergence is accelerated, and the local optimal solution of human is avoided.

2. Scheduling problem solving process
The flowchart of solving multi-objective intelligent job shop scheduling problem based on improved NSGA-II is shown in fig 1. According to the flow in fig 1, first, the initial parent population is generated, and the population size is set to 200. Then, the new offspring population is generated by the selection, crossover and mutation of the adaptive crossover operator, and the parent and offspring population are merged, the individuals in the population are sorted by fast non-dominated sorting and crowding degree calculation, and the excellent individuals are selected to enter the next generation population according to the individual sorting, and a new parent population is produced, and the process is repeated until the termination condition is satisfied.

When the termination condition is reached, the result is a group of Pareto optimal solutions containing multiple individuals, all of which are non-dominated optimal solutions. According to the competitive selection method based on the competitive bidding mechanism, the competition intensity based on the processing machine is calculated, the satisfactory solution is obtained, and finally the optimal scheduling scheme is obtained. The concrete steps are as follows: firstly, the competitive population is constructed according to the Pareto Optimal Solution Group; According to the OIJ information of each competitive population, the competitive strength of each processing machine is calculated, and the set of competitive strength of processing machine is generated, decoding the optimal solution to complete the scheduling. Scheduling Gantt chart output.

Figure 1. Flowchart
2.1. Coding
A feasible solution should contain all the aspects involved in the definition problem. This article uses a double-level coding strategy to take the problem of three artifacts, nine processes, and four machines as an example, as shown in fig2. The structure length of each array is converted to the total number of operations, which in this example is \((O_{21}, O_{31}, O_{11}, O_{32}, O_{12}, O_{22}, O_{33}, O_{23})\). An array on a process sequence represents an index of the work piece, and a machine allocation array represents an index of the allocation machine, derived from an optional set of machines. The code indicates that the first process of job 2 is processed on the first machine in the optional machine set of the process, the first process of job 3 is processed on the second machine in the optional machine set, and so on, the same index represents the preceding and following operations of the same artifact.

![Figure 2. Coding schematic](image)

2.2. Pareto sort
In this paper, we use the quicksort to rank the non-dominated solutions of the population. In NSGA-II the significance of non-dominated ranking is to divide the population into different non-inferior frontiers according to dominance, which reflects the degree of the individuals, and to select the excellent individuals by non-inferior ranking. After non-inferior sorting, we get \(x\) non-inferior frontiers \((p_1, p_2, ..., p_x)\), each of which satisfies the following properties:

1) \(U \in \{p_1, p_2, ..., p_x\} \) \(p = \text{Pop}\), represents a sorted non-inferior frontier population. \(U \in \{p_1, p_2, ..., p_x\} \) \(p \) size is equal to the \(\text{Pop}\) size of the initial population.

2) \(\forall h, f \in \{1, 2, ..., X\}, h \neq f, p_h \cap p_f = \emptyset\). The non-inferior frontiers are independent of each other.

3) \(p_1 > p_2 > ... > p_x\), after non-inferior sorting, we get \(x\) non-inferior frontiers.

Individual \(h\) has two parameters, \(n_h\) and \(S_h\). The number of individuals for which \(S_h\) is dominated by individual \(h\), \(n_h\) is the number of dominant individual \(h\).

\[
n_h = |\{z | z > h, h, z \in \text{Pop}\}| \tag{1}
\]

\[
S_h = |\{f | h > f, h, f \in \text{Pop}\}| \tag{2}
\]

The individuals with \(n_h = 0\) in the population were recorded as the non-dominated Frontier \(F_1\), note that the individual rank in \(F_1\) is 1. Assign the other individual \(Z\) in \(F_1\) to the next rank noninferior frontier according to the rule \(n_z = n_{z-1} + 1\), traversing all individuals, assigning each individual its corresponding noninferior frontier.

2.3. Design of adaptive crossover operator based on NSGA-II congestion degree
NSGA-II is a multi-objective problem solving algorithm based on NSGA, which improves the non-dominated solution ranking and introduces the elite selection strategy. It has a fast convergence speed, although it is widely used, but there is also the problem of insufficient diversity. Crossover is the main operation to generate new individuals in NSGA-II, which reflects the global performance of the Algorithm. The design of crossover operator is related to the ability of global optimization. In the NSGA-II simulation process, the cross probability is usually between \([0.40, 0.99]\), and the Algorithm is easy to fall into the local optimum. The basic idea of the adaptive operator is as follows: With the
increase of the number of iterations, the similarity between individuals in the population may be increased or approached, resulting in a local optimum. In order to enhance the diversity of the population, the crossover probability is changed to avoid the algorithm falling into the local optimum. The crossover probability of different individuals in the population changes with the iteration times, and the crossover probability also changes adaptively, it can improve the adaptability of NSGA-II in the search space of feasible solution.

In this paper, by improving the crossover probability of NSGA-II, an adaptive crossover operator based on crowding degree is proposed. When the algorithm starts to converge to the local minimum, the minimum crowding degree and the maximum crowding degree become closer, and the ratio of the minimum crowding degree and the maximum crowding degree increases. By increasing the crossover probability, the diversity of the population in the search space and the uniformity of the solution set distribution are effectively ensured, and the premature of NSGA-II is improved.

Based on a certain probability of chromosome cross operation, and then to a certain extent control the convergence of the algorithm and the quality of solution. In general, the crossover probability is kept within a large search space. In this algorithm, the crossover probability is an adaptive parameter, which depends on the crowding distance of individuals in each population. With the change of congestion degree, the Cross probability based on the change of congestion degree also changes, in order to maintain the diversity of the algorithm around the local optimal region. According to the maximum and minimum of crowding degree, the adaptive crossover operator based on crowding degree is:

\[ p_c = \frac{i_{d_{\text{min}}}}{i_{d_{\text{max}}}} \]

In the formula, \( p_c \) is the adaptive crossover operator, \( i_{d_{\text{max}}} \) is the maximum and \( i_{d_{\text{min}}} \) is the minimum.

By introducing the adaptive crossover operator based on crowding degree, the diversity of the searching space and the uniformity of the distribution of the solution set can be guaranteed, which is beneficial to the inheritance of excellent genes.

2.4. crossover procedure
The flexible job shop scheduling problem is mainly divided into two aspects, that is, selecting the right machine for the process and sequencing the multi-process on the same machine. Based on the characteristics of flexible workshop, this paper uses IPOX crossover for process-coded gene strings and multi-point crossover for machine-coded gene strings. Here’s how it works.

Step 1: Calculate the adaptive crossover probability of Gen generation according to the adaptive crossover operator.

Step 2: determine the cross location of genes based on process coding and machine coding.

Step 3: Perform the crossover operation according to the design of the adaptive crossover operator.

Suppose \( P_1, P_2 \) is two parent chromosomes, and the offspring chromosomes produced by the crossover operation are \( C_1 \) and \( C_2 \). The Intersectional Strategy of Working Procedure in chromosome is: randomly divide the set of work pieces into two subsets \( S_1 \) and \( S_2 \), copy the work pieces containing \( S_1 \) in \( P_1 \) into \( C_1 \) and \( C_2 \), and keep the gene position unchanged. In the same way, the \( P_2 \) containing \( S_2 \) is copied to \( C_1 \) and \( C_2 \), leaving the gene location unchanged, and the process based crossover is shown in figure 3.

\[ \]

**Figure 3.** Process-based crossover procedure
The partial crossover strategy of machining machine is as follows: first, to generate offspring from the parent, to sort the sub-problem, to arrange the path of the workpiece based on the sort order obtained from the sequence, and then, use the balanced crossover, single crossover, and two-point crossover mechanisms shown in figure 4.

![Figure 4. Machine based crossover procedure](image)

3. Simulation experiment
In this paper, a flexible job shop scheduling problem as an example, Matlab software simulation analysis, and the algorithm of the population size set to 200, the maximum number of iterations set to 200. Finally, a series of Pareto feasible solutions are obtained. By pruning the redundant solutions, the Pareto optimal solution set as shown in Table 1 is obtained. The data in Table 1 are the objective values corresponding to the PARETO optimal solution set on the optimal machine

| Numble | Cmax | Delay Time | Machine load | Energy consumption |
|--------|------|------------|--------------|--------------------|
| 1      | 66   | 0          | 259          | 125.364            |
| 2      | 66   | 0          | 259          | 125.363            |
| 3      | 66   | 0          | 260          | 121.790            |
| 4      | 64   | 0          | 262          | 124.538            |
| 5      | 64   | 0          | 263          | 120.964            |
| 6      | 64   | 0          | 263          | 120.963            |
| 7      | 64   | 0          | 262          | 120.963            |
| 8      | 64   | 0          | 262          | 124.567            |
| 9      | 64   | 0          | 262          | 124.324            |
| 10     | 64   | 0          | 262          | 124.535            |
| 11     | 66   | 0          | 260          | 121.790            |
| 12     | 65   | 0          | 260          | 124.007            |
| 13     | 66   | 0          | 259          | 121.589            |
| 14     | 64   | 0          | 263          | 121.528            |
| 15     | 63   | 0          | 262          | 124.898            |
| 16     | 64   | 0          | 262          | 120.374            |
| 17     | 64   | 0          | 263          | 124.784            |
| 18     | 64   | 0          | 263          | 124.624            |
| 19     | 65   | 0          | 260          | 121.790            |
| 20     | 66   | 0          | 259          | 124.986            |

According to the strategy proposed in this paper, the pareto optimal solution set is competitively selected, and the final optimal scheduling is obtained. The Gantt Chart is shown in Fig. 5. The maximum completion time is 64, the delay time is 0, and the machine load is 263, energy consumption is 120.96.
4. Conclusions
In order to realize multi-objective intelligent scheduling in flexible workshop, this paper proposes an adaptive crossover operator based on crowding degree, aiming at the shortcomings of NSGA-II, such as low population diversity and slow operation speed, it can ensure the diversity of the searching space and the uniformity of the distribution of the solution set, which is beneficial to the inheritance of excellent genes. Based on the idea of competitive bidding mechanism, competitive selection method is introduced into non-dominated sorting algorithm to improve the solution quality. The effectiveness and feasibility of the proposed algorithm are verified by experimental simulation.

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