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Distributed Flexible Job Shop Scheduling Based on an Improved Genetic Algorithm

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Abstract: Aiming at the multi-dimensional and highly complex decision-making characteristics of distributed flexible job shop scheduling, and the local convergence and slow convergence speed of the traditional genetic algorithm, an improved genetic algorithm- the dynamic hierarchical genetic algorithm is proposed. The algorithm enhances the global search ability and local optimization ability of the traditional genetic algorithm through a dynamic hierarchical structure, a multi-neighborhood local search strategy, and adaptive adjustment of the crossover and mutation rates. The simulation results show that after 10 independent runs on several improved Kacem (MK) series test cases, the algorithm has a lower minimum average maximum completion time than the traditional genetic algorithm. Especially in the complex cases of MK03 and MK09, not only is the completion time reduced by 24%, but also the number of iterations is reduced. This fully verifies the ability of the algorithm to improve scheduling efficiency and stability in distributed flexible manufacturing workshops. The completion time of MK09 is reduced by about 24%, and the number of iterations is also reduced. This fully verifies the ability of the algorithm to improve the scheduling efficiency and stability in the distributed flexible manufacturing workshop scheduling problem.

Keywords: Distributed flexible job shop scheduling; Dynamic population classification; Multi-neighborhood local search

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1. Introduction

At present, most mechanical manufacturing industries adopt a flexible job shop scheduling mode, which can flexibly adjust processing procedures and allocate multiple machines according to resource load [1]. With the popularization of the distributed production mode, the distributed flexible job shop scheduling problem has become the core optimization problem in the field of intelligent manufacturing [2]. DFJSP is an NP-hard problem, which needs to complete three key decisions at the same time: the selection of workpiece processing plants, the allocation of processing machines, and the determination of processing sequence.

The scheduling plan directly affects equipment utilization, production cycle, and energy consumption level [3]. Reasonable scheduling can significantly improve production efficiency, while unreasonable scheduling will lead to idle equipment and production delay [4].

For the solution of DFJSP, numerous studies have been conducted by scholars both at home and abroad. SANG Y W constructed a multi-objective DFJSP model to solve the production scheduling problem in distributed intelligent factories and designed a memetic algorithm for its solution [5]. XU W X considered the scenario of outsourcing of workpiece operations and combined the tabu search algorithm with the genetic algorithm to solve the multi-objective DFJSP model [6]. WANG S Y, for the DFJSP model with assembly machines, completed the model solution in a vector manner [7]. LI J proposed an improved artificial bee colony algorithm for DFJSP and improved the performance by optimizing the initial population and local search [8]. Li Y W employed an improved heuristic algorithm to solve the DAFJSP model for multi-objective optimization [9]. Although the existing algorithms have made certain progress, the traditional genetic algorithm (GA) still has the defects of slow convergence speed and an easy tendency to fall into a local optimum when solving DFJSP, and is difficult to handle large-scale and complex scheduling scenarios efficiently [10].

To address the aforementioned issues, this paper proposes the Dynamic Hierarchical Genetic Algorithm (DH-GA). By implementing a dynamic population hierarchical strategy to balance the retention of high-quality solutions and the global search capability, it designs multi-neighborhood local search operators to deeply explore the improved space of the solutions. Combined with adaptive genetic operations to enhance the algorithm's stability, it ultimately provides a more efficient and feasible solution for the engineering application of DFJSP.

2. Problem description

The mathematical problem of DFJSP can be specifically described as:

(1) The set of workpieces $J=\{J_1,J_2,...J_i,...J_n\}$, where n represents the total number of workpieces, and Ji indicates the i-th workpiece.

(2) The factory set $U=\{U^1,U^2,...U^l,...U^q\}$, where q represents the total number of factories, and each factory U^l is a flexible production workshop.

(3) Each factory U^l has a set of processing units (machines) forming $M=\{M^{l1},M^{l2},...M^{lk},...M^{lm}\}$, where m represents the number of processing units in this factory, and M^{lk} indicates the kth processing unit of factory U^l.

(4) Process set $O_i=\{O_{i1},O_{i2},...O_{ij}...O_{in_i}\}$, where n_i represents the total number of processes for workpiece i, and O_{ij} indicates the jth process of workpiece i.

The core optimization objective of DFJSP is to minimize the maximum completion time for all workpieces (see **Figure 1**).

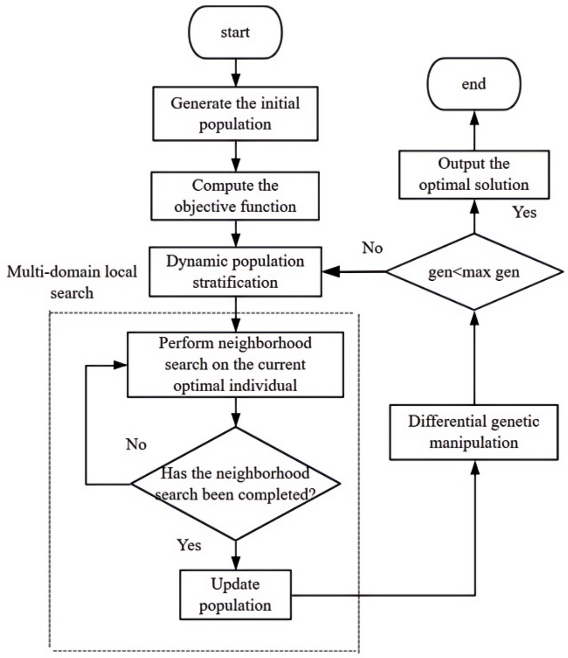

Figure 1. DH-GA Algorithm flowchart.

$$C_{max}=\max_{i,j,l,k}\left\{C_{i,j,l,k}\right\} \tag{1}$$

3. DH-GA algorithm

The flow of the DH-GA algorithm is shown in Figure 1, starting with parameter initialization, and finally completing population update and iteration termination through coding population initialization, decoding and fitness calculation, dynamic population stratification, differential genetic operation, and three-layer multi-neighborhood local search. Through the synergy of dynamic population stratification and multi-neighborhood search, this framework realizes the dynamic balance between global exploration and local development, and provides a feasible technical way to solve the DFJSP problem efficiently.

Dynamic population classification adjusts the retention rate of excellent individuals in the iterative process. For example, in the early iteration stage, the retention rate of high-quality individuals is set to 0.5. Quickly screen elite features at the beginning of iteration to prevent the loss of high-quality genes at the beginning of iteration. In the middle of the iteration, the retention rate dropped linearly to 0.3, which expanded the population of ordinary individuals and enhanced the global search ability. In the later stage, the retention rate increased to 0.4, and the population diversity was increased to avoid the algorithm falling into a local optimum.

Multi-neighborhood local search adopts a three-layer multi-neighborhood search based on DFJSP decision-making feature design, and carries out local optimization search for high-quality individuals produced in the population iteration process. Firstly, the adjacent process of the optimal individual is exchanged; Secondly, some processes are randomly selected. Finally, the processes in the selected factory are redistributed to other idle processing units.

Differential genetic operation fully combines the linear decreasing crossover rate with the adaptive mutation rate. The crossover rate decreased linearly from 0.9 to 0.7, which promoted population diversity in the early iterations and remained stable in the later period to protect elite individuals. In order to ensure the diversity of the population, when the population coincidence rate exceeds the threshold, the mutation rate increases to 0.02; otherwise, it is kept at 0.01 to prevent the algorithm from falling into a local optimum.

4. Analysis of experimental results

In this paper, MATLAB R2023b is used for programming, and the DH-GA algorithm and the traditional GA algorithm are compared and analyzed, and the minimum and maximum completion times of the target are optimized according to the experimental results.

In order to verify the effectiveness of the algorithm, this paper selects a subset of MK test cases, and the corresponding test data set is shown in **Table 1**.

Algorithm parameters: iteration number 150, population size 200, initial crossover probability 0.9, initial mutation probability 0.01. In order to ensure the fairness of the experiment, the parameters of the genetic algorithm are consistent.

Table 1. Example parameters

Example	Workpiece count	Machine count	Factory count	Process count
MK01	10	6	2	55
MK02	10	6	2	58
MK03	15	8	3	150
MK04	15	8	3	90
MK05	15	4	2	106
MK06	10	10	3	150
MK07	20	5	2	100
MK09	20	10	3	240

The case of MK03 is tested by the DH-GA and GA algorithms, respectively. In **Figure 2**, at the beginning of the iteration, the DH-GA algorithm converges faster than the GA algorithm. In the middle of the iteration, the search ability of the GA algorithm drops and falls into a local optimum, while the DH-GA algorithm continues to optimize and finally converges in 155 minutes. This shortens the completion time by about 24% compared with the GA algorithm. This shows that the DH-GA algorithm provides superior optimization performance and greater stability.

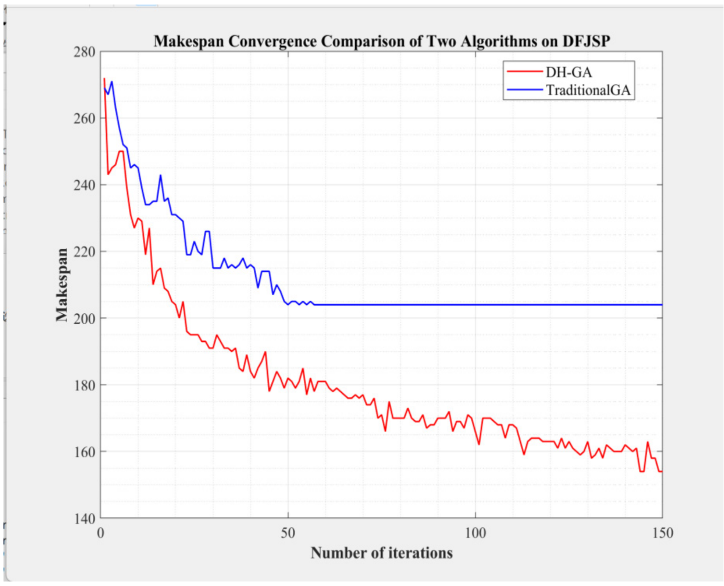

Figure 2. Iteration comparison of DH-GA and GA algorithms under case study MK03.

Based on the MK case, DH-GA and GA have been tested 10 times respectively, and the average results of 10 runs are shown in Table 2. The results show that compared with the traditional GA algorithm, the proposed DH-GA algorithm achieves better completion time in the MK case. It is worth noting that in the complex MK09 case, its ability to search the global optimum is significantly improved, which fully verifies that the DH-GA algorithm improves the scheduling efficiency (see **Table 2**).

Table 2. Average value of the calculation example

Example	DH-GA/min	GA/min
MK01	42	42
MK02	29	30
MK03	199	204
MK04	64	66
MK05	176	179
MK06	73	75
MK07	147	149
MK09	308	321

5. Conclusion

This study solves the limitations of local convergence and slow convergence of the traditional genetic algorithm in solving NP-hard DFJSP. In order to overcome these challenges, the DH-GA algorithm is proposed. Through dynamic population stratification, multi-neighborhood local search, and adaptive genetic operation, the algorithm effectively solves the multi-dimensional optimization problem of DFJSP. Compared with the traditional genetic algorithm, it has a significant improvement in convergence speed, solution accuracy, and load balance, and the maximum completion time is reduced by 24% for complex MK test cases. This research provides a feasible technical solution for distributed flexible workshop scheduling in intelligent manufacturing. At present, the research is limited to single-objective optimization. Future work will extend to multi-objective optimization, adaptive parameter adjustment based on machine learning, and practical application in dynamic scheduling scenarios.

Disclosure statement

The authors declare no conflict of interest.

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