A genetic algorithm for the distributed assembly permutation flowshop scheduling problem

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***Abstract*—This paper investigates the problem of minimizing makespan for the distributed assembly permutation flowshop scheduling problem (DAPFSP)-a new generalization of the distributed permutation flowshop scheduling problem (DPFSP). DAPFSP consists of two stages: production and assembly. The first stage is production at several identical factories. Each factory is a permutation flowshop scheduling problem with multi-machine. And the second stage is to assemble jobs produced at the first stage into final products. We proposed a genetic algorithm for this problem. An enhanced crossover strategy and three different local searches are adopted. After the exhaustive computational and statistical analysis, we can conclude that the proposed methods are robust and outperformed the existing algorithm.**

Keywords—Distributed assembly scheduling; Permutation flowshop; Genetic algorithm; Crossover; Local search

I. INTRODUCTION

Flowshop scheduling is a major issue in manufacturing system and the service industry [1]. It is significant to propose effective and efficient approaches and technologies. There is a variety of generalized version of flowshop scheduling problem. A main difference of flowshop scheduling is single or multi-factory. Recently, many researchers have studied on this field. In the single factory, the aim is to find a job sequence for machines to process. Multi-factory flowshop is an extension of single factory, which has to assign jobs to several factories. Behnamian and Fatemi Ghomi[2] describes this problem in detail.

Among the real-world applications, distributed permutation flowshop scheduling problem (DPFSP) and assembly flowshop scheduling problem (AFSP) are widely involved. In the DPFSP, a set F of f uniform factories are added on the base of the permutation flow shop. Each factory includes the same m machines and is capable of processing all jobs. Therefore, every factory is a sub-problem of PFSP. The new rule is that once a job is assigned to a factory, the job cannot be transferred to another factory. A body research has addressed on DPFSP [3-7]. Many efficient algorithms have been proposed such as scatter search, variable neighborhood descent methods, genetic algorithm, tabu search, and so on. In the AFSP, there is a hybrid producing system that contains different producing operations independently and synchronously and then transmits manufacturing parts to assembly line [8-11]. Two variants have been generated according to the assemble phase: two stage [9] and three stage model [10].

In this paper, we address a combination of DPFSP and AFSP referred to distributed assembly permutation flowshop scheduling problem (DAPFSP). Hatemi et al. [12] presented this problem for the first time. A set P of p final products is added. Each product can be assembled only when all jobs that are needed for the assembly of the product have been completed. DAPFSP contains two phase, production and assembly. At the first phase, it is to produce manufacture parts, just like in the regular DPFSP. The second phase is to assemble parts to make products in one assembly factory with only an assembly machine. This problem is more complex and practical. DAPFSP is NP-complete, since DPFSP is NP-complete [3]. To the best of our knowledge, only Hatemi et al. [12] proposed two constructive algorithms. It may lead to a bottleneck that only applies constructive approach and doesn't improve the solution. In this work, we chose genetic algorithm (GA) to solve this problem. Three local searches are applied to enhance the diversity of the algorithm. The experimental results of the GA and comparisons with other previous algorithms show that our proposed algorithm is more effective.

II. A PROPOSED GENETIC ALGORITHM

Genetic algorithms (GAs) are bio-inspired optimization methods of evolutionary algorithms (EAs) [13] and are in general use in scheduling problem [14]. The mechanism of our proposed genetic algorithm is: a set of random solutions act as the initial population of individuals, and then evolution is carried out during each generation. A crossover operator is applied to obtain better offspring. Otherwise, the mutation mechanism is not used for the complex representation of the solutions. To improve the solutions after crossover, we added some local search algorithms. The remainder subsections show a detailed description of the proposed genetic algorithm.

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A. Representation and generation of solutions

In the FSP, the solution representation is a sequence of jobs representing the processing order of machines. Considering the DAPFSP, we should also consider the order of product assembly. Namely, the solutions take the order of jobs and final products into consideration. There are two methods to generate a solution according the producing order of jobs sequence and products sequence. If the jobs sequence is firstly generated, products sequence will depend on that due to the needed jobs and then may lead to long makespan. The final makespan lies on the order of making products, so we firstly produce the products sequence, and then generate the jobs sequence based on the former.

In general, the solution representation of DAPFSP contains products sequence and jobs sequence of different factories.

B. A genetic algorithm for the DAPFSP

Aimed at the distributed assembly permutation flowshop scheduling problem, we proposed a genetic algorithm which integrates an enhanced crossover operator as an intensification strategy to generate a better generation of individuals. In each generation, the parents are selected from the mating pool, and some local search algorithms are applied to advance the offspring after crossover. A detailed description about them is in the following subsection.

Pseudo-code of the proposed genetic algorithm is shown in Algorithm 1. We generated *nPop* random individuals as the initial population. After initialization, an iterate process is carried out until a stopping criterion is satisfied. This criterion could be a target solution quality, a maximum number of iterations, or a maximum number of iterations without improvement. In our algorithm, we break the loop until no obvious improvement during the evolution.

Algorithm 1. *The GA for DAPFSP*

Input :

n:	*the number of jobs*
m:	*the number of machines*
f:	*the number of factories*
t:	*the number of products*
P_t:	*a m-by-n matrix; P_t(i, j) represents the processing time of job j on machine i*
A _t:	*the assembly time vector of products*
P_s:	*the assembly program matrix; P_s(p, -) represents making product p needs to assemble which jobs*

Parameters :

nPop:	*the size of population*

Output :

x:	*the best solution*

Begin

1: *InitPopulation*();
2: *x*←the best solution of initial population;
3: **While** (stopping criterion is not met) **do**
4: *CreateMatingPool*();
5: **for** *i* = 1 : nPop/2 **do**
6: select parents from the mating Pool;
7: offspring ← *Crossover*();
8: offspring ← *LocalSearch*();
9: update the best solution *x*;
10: **end for**
11: *UpdatePop*();
12: *x*← *LocalSearch*();
13: **end while**
14: **return** *x*;

End

C. Mating selection

The mating pool is generated at each iteration and is used in the selection phase. In the classical genetic algorithms, the roulette wheel selection operator and the rank selection operator are widely used [15]. In this paper, we applied the roulette wheel selection in consideration of the feature of this problem and solutions, and we changed the conventional use. The size of mating pool is not fixed and dependent on the quality of the solutions. The following pseudo-code describes how to create the mating pool in detail. The computational formula in line 4 is:

$$\text{prior} = \text{mateP} * \frac{\text{maxFitness} - \text{curPop}_i.\text{Cmax}}{\text{maxFitness} - \text{minFitness} + 1}. \quad (1)$$

The variable prior represents the number of times the individual will appear in the mating pool, and it is equivalent to the selected probability of the individual to be a parent. In equation (1), *mateP* is a constant factor of the size of mating pool. The better the individual is, the larger the difference between makespan of the worst of the population and makespan of the current individual is, and then the larger the prior is.

In case that all individuals are the same at the end of the genetic process, the mating pool is set as the current population in line 10. In the debugging, this special situation really happened.

Algorithm 2. *CreateMatingPool*

Input :

curPop:	*the current population*
curPop_size:	*the size of the current population*

Parameters :

mateP:	*a factor of the size of mating pool*

Output :

matingPool:	*the set of mating pool*

Begin

1: matingPool = Φ;
2: find the minFitness and maxFitness of the curPop;
3: **for** i = 1 : curPop_size **do**

4: $prior = mateP * \frac{maxFitness - curPop_i.Cmax}{maxFitness - minFitness + 1}$;

5: **for** j = 1 : prior **do**

6: add $curPop_i$ into the matingPool;

7: **end for**

8: **end for**

9: **if** matingPool is empty **then**

10: add all elements of curPop into the matingPool;

11:**end if**

12:**return** matingPool;

End

D. Crossover operator

After creating the mating pool, two parents are randomly selected. Then the enhanced crossover operator is executed. So far, there are several different crossover operators in the literature. Crossover is to generate good individuals from the selected parents. Considering the complexity of the DAPFSP, common crossover is not suitable for the algorithm. We proposed a hybrid crossover operator.

In the crossover operator, three sequences are needed to determine, including making products sequence, jobs sequence of the needed products and processing jobs sequence of each factory. The crossover operator of the first two kinds of sequences is in the same way, based on the change of the single-point crossover. Taking the making products sequence for example and assuming the number of products is five, we have an example in Fig. 1. Two parents are shown in Fig. 1(a) and one point *p* is randomly selected from parent1. Products from the first position to the *p* position are copied to the offspring1 and products from *p*+1 position to the end are copied to the offspring2. Especially, point *p* is set to 2. Consequently, offspring1 will contain the products of parent1 from position 1 to 2. Offspring2 is formed with products of parent1 from position 3 to the last one (Fig. 1(b)). Then, the products of parent2 which don't appear in the offspring are inserting into the back (Fig. 1(c)). The making products sequence and the corresponding needed job sequence of products are generated with this method.

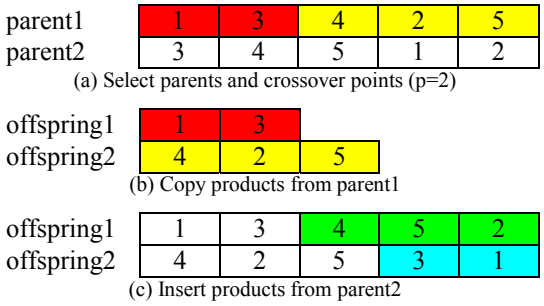

Fig. 1. Example of crossover for products sequence

The processing jobs sequence of each factory is the most complicated to produce, on account of the restrictive correlation of the making products sequence. We applied alocal search algorithm to enhance the crossover in this section. In the algorithm, we made two rules to simplify the crossover:

- Rule 1: The jobs needed for a product are processed successively in each factory.
- Rule 2: The order of processing jobs of factories corresponds to the order of making products. That is the jobs needed for the first product to be made are processed firstly.

In this way, we ensure the whole production process of DAPFSP is unified, and they are available for reducing the search space. Some solutions that meet and not meet the two rules are shown in Fig. 2. Fig. 2(a) shows the assembly programs to make each product. For example, only when the job 2 and job 4 are all completed, the product 1 can be made. Fig. 2(b) tells the order of making products. Fig. 2(c) gives an example breaking the rule 1, because job 3 and job 5 which are all needed for the product 3 should be processed successively. Meanwhile, the principle of illegal reasons of instance in Fig. 2(d) is that job 2 and 4 needed for product 1 should be processed after job 7 and 1 needed for product 2, since the product 1 is made after product 2. However, the example in Fig. 2(e) obeys both of the two rules.

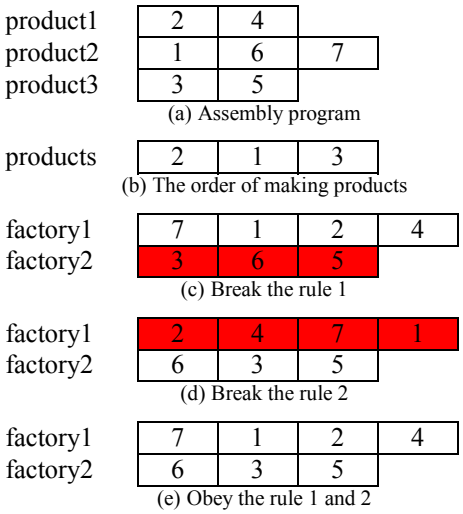

Fig. 2. Example of solutions about the rules. The sizes of products, factories, jobs are 3, 2, 7 correspondingly.

To determine the order of processing jobs of each factory, there are two implements to assign jobs to factories [3]:

- NEH1: Assign job *j* to each position of the factory with the lowest current makespan, not including job *j*.
- NEH2: Assign job *j* to each position of the factory with the lowest makespan, after including job *j*.

There will be less assigning positions because of the rule 1. For example, if we assign job 6 to the factory 1 in Fig. 2(e), the logical positions can be three positions between the beginning and the position of job 2. In addition, it saves the running time.

E. Three local searches for the proposed algorithm

We applied three local searches for the sake of obtaining better offspring, which only changed the order of processing

jobs: Swap, Insert and Reverse. And the results also obey the two rules, especially the first one.

- Swap: Exchange two jobs that are needed for the same product. In Fig. 2(e), we can exchange job 6 and job 7 or job 1.
- Insert: Insert job j into each factory at the logical positions, just like in the crossover phase.
- Reverse: Reverse the subsequence of jobs needed for the same product of each factory. We can reverse two subsequence 7, 1 and 2,4 of factory 1 and one subsequence 3,5 of factory 2 in Fig. 2(e).

These local searches can promote the diversity of the population and help to explore better offspring.

F. Generation replacement

The last important step is to update the population that is known as generational scheme. In general, there are some common methods. One is that the parents are replaced with offspring directly, or they conserve the best individuals from the last generation first. Some accept the offspring only better than the worst individuals of the old population and different from the population. The common goal is to produce a new generation which preserves the best individuals acquired so far and maintain a good diversity of population.

In this work, the next generation consists of all the offspring and the best *nKeep* individuals in the current population. *nKeep* is a factor parameter and depend on the size of the population. And the same individual of new population is deleted. With this method, offspring are accepted, and the best individuals from the last iteration are kept at the same time. There are no identical individuals in the new population. That keeps diversity and avoids premature convergence to a locally optimal solution.

III. Computational Experiment and Results

A. Benchmark of instances and test environment

We tested all variants of the proposed genetic algorithm. Hatemi et al. [12] generated random instances, including 900 small instances and 810 large instances. We use the same datasets to evaluate our algorithm. The small instances are with the following combinations: the number of jobs n = {8, 12, 16, 20, 24}, the number of machines m = {2, 3, 4, 5}, the number of factories f = {2, 3, 4} and the number of products t = {2, 3 , 4}. In large instances, the following values are tested: n = {100, 200, 300}, m = {5, 10, 20}, f = {4, 6, 8} and t = {30, 40, 50}. And there are five replications of each combination for small instances and ten replications for large instances. Therefore, the total instances for the small are 5×4×3×3×5 = 900 and the large are 3×3×3×3×10 = 810. The datasets are available from http://soa.iti.es.

All experiments with the proposed genetic algorithm were tested on a PC with Intel Core i7-2600 3.40 GHz Processor and 3.24 GB memory, running Windows 7. The code was implemented in C++ compiled by GNU GCC Compiler with Code::Blocks 12.11. For each of the small and large instances, 5 independent runs of each variants combination were conducted and the best target solution was recorded.

B. Experimental parameter settings of the proposed GA

Four different versions of the proposed genetic algorithms were tested. They all share the features of local search enhanced crossover.

- GA_nLS: In this case, only the crossover operator with local search is applied and there is no local search procedure.
- GA_swp: The swap local search is applied in this version.
- GA_ins: The third version includes the insertion local search.
- GA_rev: The reverse local search is applied, based on the first version.

We first start from a simple genetic algorithm and add new strategy to increase the efficiency. Regarding the parameters of the algorithms, the four versions have different parameter values, in order to keep at the roughly same total time. The time limit of all small instances is set to 900s.

The values of parameters with each version are shown in TABLE I. Detailedly, *nPop* (Algorithm 1. in section II. B.) is the size of the population during the genetic process; notImprove (Algorithm 1. in section II. B.) is the maximum times of not improving to break the iteration loops; *nkeep* is a factor of the number to conserve the best individuals of the last population and *nKeep* (section II. F.) is equal to *nkeep* multiplied by *nPop*; *mateP* (Algorithm 2. in section II. C.) is a factor of the times the individual will appear in the mating pool. The size of the mating pool depends on the total appearing times of each individual and is around 1.5 times of *nPop*. The values of *nkeep* and *mateP* are set to fixed values, and the values of *nPop* and *notImprove* are not fixed because they mainly affect the running time. The parameter settings for small and large instances are the same.

TABLE I. PARAMETER SETTINGS OF FOUR VERSIONS OF THE PROPOSED GENETIC ALGORITHMS

Algorithms	Parameters			
	nPop	***notImprove***	***nkeep***	***mateP***
GA_nLS	110	15	0.2	10
GA_swp	110	15		
GA_ins	60	10		
GA_rev	110	15		

C. Comparison Result

A computational study was conducted to evaluate the efficiency and the effectiveness of the proposed algorithms. We used the results from MILP (Mixed Integer Linear Programming), H11, H12, H21, H22 [12] to compare with our proposed genetic algorithms in TABLE II and TABLE III. The time-consuming MILP model was only used for comparison of small instances. We run five replicates of each algorithm for each instance.

Regarding comparison of these algorithms, the average Relative Percentage Deviation (RPD) is measured for each instance in the following expression:

$$RPD = \frac{Method_{sol} - Best_{sol}}{Best_{sol}} \times 100, \quad (2)$$

Where $Best_{sol}$ is the best known solution from H22, and $Method_{sol}$ reports the solution obtained by a given version of genetic algorithms. The smaller the value is, the better the solution is. The last line of TABLE II and TABLE III is the average RPD of instances, and bold data is the best result among all algorithms.

First, we carry out a comparative evaluation of all the aforementioned algorithms using the set of 900 small instances. The result is shown in TABLE II. It can be seen that the values of GA, GA_swp, GA_ins and GA_rev are all smaller than H11, H12, H21, H22. There is some negative value with the instances of 2×20, 2×24 and 3×24, which means that we find better solutions than the best known. When the number of jobs is large (n=16, 20, 24), the results of our proposed algorithms are equal to or even better than MILP. And as to the final average RPD of small instances, the result of GA_ins is the smallest among all comparative algorithms.

The difference between the four versions of proposed genetic algorithms is also obvious. The results of genetic algorithms with local search are better than the one without local search, except for GA_rev. Consequently, local search is a good reinforcement strategy to improve algorithms.

TABLE II. THE AVERAGE RPD OF MILP, H22 AND PROPOSED ALGORITHMS FOR THE SMALL INSTANCES

f×n	*MILP*	*H11*	*H12*	*H21*	*H22*	*GA*	*GA_swp*	*GA_ins*	*GA_rev*
2×8	**0.00**	14.62	13.61	6.91	5.99	0.39	0.32	0.27	0.38
2×12	**0.01**	13.70	12.78	5.74	5.17	0.41	0.39	0.36	0.40
2×16	0.42	12.52	11.40	5.77	5.10	0.18	**0.12**	0.14	0.15
2×20	1.26	9.92	9.28	4.25	3.48	-0.12	**-0.21**	-0.13	-0.15
2×24	2.70	7.75	7.38	4.07	3.81	-0.28	**-0.33**	-0.31	-0.31
3×8	**0.00**	11.35	9.96	4.57	3.15	0.39	0.18	0.10	0.39
3×12	**0.00**	9.96	9.13	3.03	2.55	0.12	0.12	0.10	0.13
3×16	**0.06**	10.10	9.16	3.77	3.14	0.09	0.07	**0.06**	0.08
3×20	0.35	9.86	8.93	2.72	2.19	0.11	**0.09**	0.11	0.11
3×24	1.18	7.65	6.37	3.00	2.40	-0.06	**-0.12**	-0.09	-0.07
4×8	**0.00**	9.03	8.01	2.16	1.25	0.19	0.05	0.04	0.18
4×12	**0.00**	5.63	4.53	1.82	1.38	0.29	0.22	0.15	0.30
4×16	**0.04**	7.21	6.34	2.86	2.27	0.18	0.15	0.12	0.19
4×20	0.23	6.80	6.00	2.96	2.61	0.10	**0.08**	0.11	0.11
4×24	0.44	5.13	4.42	2.00	1.59	0.02	**0.00**	0.04	0.01
Average	0.45	9.41	8.49	3.71	3.07	0.13	0.08	**0.07**	0.13

Second, to analyze algorithms for the large instances, experiments are also carried out using the set of 810 instances. The MILP model is not used in this section. In TABLE III, we can find that the average RPDs of the four versions of proposed genetic algorithms are equal to or better than that of H11, H12, H21, H22. The exception is that the result for n=100 of H22 is smaller than the proposed algorithms. And there also appears negative values in our proposed genetic algorithms when f=4, t=30 and n=500. It is obvious that the GA_swp is best in general.

TABLE III. THE AVERAGE RPD OF MILP, H22 AND PROPOSED ALGORITHMS FOR THE LARGE INSTANCES

	f(Number of factories)			*t(Number of sets)*			*n(Number of jobs)*			*Average*
Algorithms	4	6	8	30	40	50	100	200	500	
H11	5.39	3.72	3.07	3.66	4.20	4.31	6.21	3.69	2.27	4.06
H12	4.91	3.24	2.65	3.23	3.76	3.80	5.53	3.21	2.06	3.60
H21	0.14	0.06	0.02	0.10	0.06	0.07	0.09	0.04	0.07	0.07
H22	0.01	0.01	**0.00**	0.00	**0.00**	**0.01**	**0.00**	**0.00**	0.00	**0.00**
GA	0.00	**0.00**	**0.00**	**-0.01**	**0.00**	**0.01**	0.01	0.01	-0.01	**0.00**
GA_swp	**-0.01**	**0.00**	**0.00**	**-0.01**	**0.00**	**0.01**	0.01	**0.00**	**-0.02**	**0.00**
GA_ins	0.00	**0.00**	**0.00**	**-0.01**	**0.00**	0.02	0.02	0.01	**-0.02**	**0.00**
GA_rev	0.00	**0.00**	**0.00**	**-0.01**	**0.00**	**0.01**	0.02	**0.00**	**-0.02**	**0.00**

To summarize, the four versions proposed genetic algorithms can produce more optimal solutions compare with the algorithms already proposed for the DAPFSP. And after applying local search in the genetic algorithm, the result is improved, especially for small instances. The local search enhanced crossover and the local search process are an intensification strategy. Besides, the two rules applied helps to reduce the search space. Therefore, our proposed genetic algorithms are capable of shrinking the searching solution space significantly and acquiring better solutions than other algorithms.

IV. CONCLUSIONS AND FUTURE RESEARCH

The distributed assembly permutation flowshop scheduling problem is significant in industry fields, and it is *NP*-complete. In our work, four versions of genetic algorithms with local search enhanced crossover for solving the DAPFSP have been presented, which is a heuristic. This methodology combines the classical genetic algorithm with enhanced crossover and several local searches, and two rules are applied to reduce the search solutions space; the enhanced crossover as an intensification strategy explores better individuals during the genetic process; three local searches are effectively integrated into GA. Results show that our algorithms are able to provide fine-quality solutions and can compete with other existing algorithms.

However, there are also some strategies to improve. The three local searches we applied only change the order of a part of jobs, while we can also change the order of making products in the future work. Besides, we can compare efficiency between the enhanced crossover and the local search process, and then intensify application of the better one. In brief, the DAPFSP is a new problem, and there is much development space to explore.

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