An Integrated Production and Transportation Scheduling Method in Hybrid Flow Shop

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Original Article

Keywords: Hybrid flow shop, Integrated scheduling, Task pool, Hybrid algorithm

Posted Date: March 6th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-265121/v1

Version of Record: A version of this preprint was published at Chinese Journal of Mechanical Engineering on February 18th, 2022. See the published version at https://doi.org/10.1186/s10033-022-00683-7.

Title page

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ORIGINAL ARTICLE

An integrated production and transportation scheduling method in hybrid flow shop

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Received June xx, 201x; revised February xx, 201x; accepted March xx, 201x

Abstract: The connection between production scheduling and transportation scheduling is getting closer in smart manufacturing system, both of which are summarized as NP-hard problems. However, only a few studies have considered them simultaneously. This paper studies the integrated production and transportation scheduling problem (IPTSP) in hybrid flow shop, which is an extension of the hybrid flow shop scheduling problem (HFSP). In this problem, the transfer tasks of jobs are performed by a certain number of automated guided vehicles (AGV). In addition to the production scheduling on machines, we consider the transportation scheduling on AGVs as the part of the optimization process. To solve it, we make some preparation (including the establishment of task pool, the new solution representation and the new solution evaluation), which can help algorithm efficiently find satisfactory solutions while appropriately limiting the search space. Then, an effective genetic tabu search algorithm is used to minimize the makespan. Finally, two groups of instances are designed and three types of experiments are conducted to evaluate the performance of proposed method. The results show that the proposed method can achieve good results, showing the effectiveness of the presented approach.
Keywords: Hybrid flow shop • Integrated scheduling • Task pool • Hybrid algorithm

1 Introduction

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Due to the development of industry, scheduling plays a crucial role in modern manufacturing systems. As a branch of flow shop, the hybrid flow shop is widespread in modern industries, including electronics [1], textile [2], steelmaking [3] and petrochemical industries [4].

In mechanical manufacturing, production scheduling and transportation scheduling are two vital parts [5]. Optimizing both of them is a core task of advanced manufacturing and modern management, which not only allocates tasks but also affects the utilization level of resources and energy [6].

The importance of production scheduling problem and transportation scheduling problem has been emphasized by many researchers [7-11]. For the literature of production scheduling problem in hybrid flow shop (also called hybrid flow shop scheduling problem, HFSP), most of the researchers didn't consider the transport procedure between machines or put it as fixed value into the setup time. However, more and more flexible transporters like automated guided vehicle (AGV) are used to perform the transfer tasks in the modern factory, which obviously improves the productivity of manufacturing enterprises [9]. On the other hand, the use of AGVs also brings uncertainty and complexity to the current scheduling scheme. For example, unprocessed jobs can be processed on a set of alternative machines at a specific stage. All of these can cause uncertainty in transfer time during scheduling. As a result, in many manufacturing industries that are sensitive to transport time and limited transport resources, they attaches more and more importance to considering production scheduling and transportation scheduling integratedly.

So, this paper integrates the production and transportation scheduling in hybrid flow shop with identical machines, which is an extension of the hybrid flow shop scheduling problem (HFSP). Transfer tasks between machine and machine or machine and warehouse are performed by a certain number of automated guided vehicles (AGV). And the goal of the integrated scheduling problem (IPTSP) is finding optimal processing sequence of jobs on machines and optimal transport sequence of jobs on AGVs simultaneously.

Production scheduling and transportation scheduling are both well-known NP-hard problems [17-18]. There are several researches that studied the coordination between production scheduling and transportation scheduling. Bilge and Ulusoy [12] assigned the transportation task to AGVs while scheduling the processing sequence of jobs on the machine. Amir and Pedram [13] addressed a permutation flow-shop scheduling problem with a finite number of transporters carrying jobs from each machine to its subsequent machine. Nishi et al. [14] used a bilevel decomposition algorithm to solve the simultaneous scheduling and conflict-free routing problems for AGVs. Elmi et al. [15] addressed the robotic scheduling problem considering multiple part types, unrelated parallel machines, multiple robots in blocking hybrid flow shop. Zabihzadeh et al. [16] used ant colony optimization (ACO) algorithm and genetic algorithm (GA) to solve flexible flow shop scheduling problem with robotic transportation and release time.

However, in all related surveys mentioned above, they considered all stages of each job and put them as a long sequence to be optimized. When the long sequence was worked as the code in their algorithms, it might make the algorithms search too much solution space and hardly get a satisfactory solution within reasonable computation time. Therefore, this paper proposes a new method for integrated production and transportation scheduling problem in hybrid flow shop environment, including the establishment of task pool, the new solution representation, the new solution evaluation and so on. Based on it, two scheduling problems mentioned above can be treated together. Then, a genetic algorithm with tabu search is applied to solve the integrated scheduling problem.

This paper is organized as follow. Section 2 presents the notation and description of problem. Section 3 introduces some preparation for solving the IPTSP. Section 4 describes the details of the hybrid algorithm. Section 5 shows the experimental design and results. Finally, Section 6 gives the conclusion and future work.

2 Problem description and formulation

In hybrid flow shop environment, a set of n jobs needs to be processed at S stages. Each stage j has M_j identical parallel machines, while $M_j \geq 2$ for at least one stage. Once a job has completed processing at a certain stage, it needs to be transferred to the machine of its next stage by AGV. R identical AGVs are responsible for these transferring tasks. The object of scheduling is to determine the assignment of machines and AGVs at each stage for each job, the sequence of jobs on machines and the sequence of transferring tasks on AGVs, such that the makespan is minimized.

A small example is shown. There are 3 jobs to be processed without preemption on 4 machines. Each job needs to go through 3 processing stages. The number of identical machines in each stage is {1, 2, 1}. The number of AGVs is 2.The processing time of each job at each stage is shown in Table 1. The transport time between machine and machine (or warehouse) is shown in Table 2. Figure 1 shows a Gantt chart of a scheduling scheme with makespan 40.

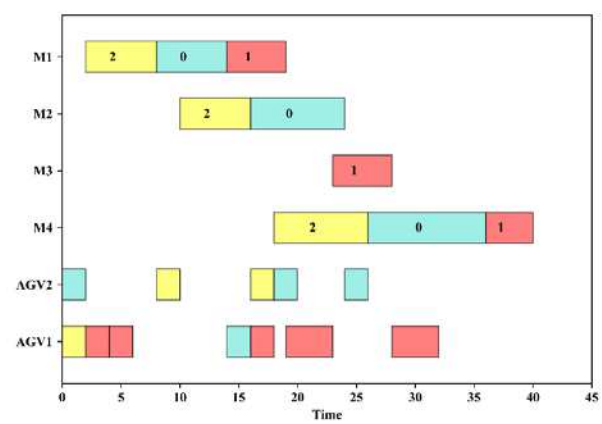


Figure 1 An example for the integrated scheduling problem

Table 1 Processing time of 3 jobs

Time(job/stage)	Stage 1	Stage 2	Stage 3
Job1	6	8	10
Job2	5	5	4
Job3	6	6	8

Table 2 Transport time between locations

Time (from/to)	Warehou-se	Machine 1	Machine 2	Machine 3	Machine 4
Warehouse	0	2	4	6	6
Machine1	2	0	2	4	4
Machine2	4	2	0	2	2
Machine3	6	4	2	0	4
Mahcine4	6	4	2	4	0

3 Some preparation for solving IPTSP

Under the same scale of jobs and machines, it's obvious that the solution space of integrated scheduling problem is much larger than that of production scheduling or transportation scheduling. For better algorithm design in next section, some preparation are considered to be completed. Firstly, the task pool is introduced to transform scheduling into task selection and assignment, which can simplify the IPTSP. Secondly, a new way of solution representation according to the proposed task pool is proposed, which provides an encoding method for the IPTSP that can be operated by subsequent algorithms. Finally, the solution evaluation can evaluate the makespan of each code. By this way, all of them can help algorithm efficiently find satisfactory solutions while appropriately limiting the search space.

3.1 Establishment of task pool

In the IPTSP, each job at each stage requires a transportation task which takes it from previous machine (or warehouse) to current machine. And the number of existing transportation tasks does not exceed the total number of jobs at the same time. According to these characteristics, this paper establishes a specific set of transportation tasks, called task pool. Then, the integrated scheduling problem can be solved through the procedure that each time the AGVs execute the tasks in the task pool in a specific order until the task pool is emptied.

Specifically, a task can be described as:

$$Task = (job\_no, stage\_no, st, from\_location), \qquad (1)$$

Where *job_no* is the index number of the job involved, *stage_no* is the current stage number of the job involved, *st* is the earliest start time of the task, *from_location* is the starting location of the task (if *stage_no* =1, it represents the warehouse; else, it represents the processing machine of job at stage *stage_no* -1).

Here, task pool is a collection of all tasks to be scheduled. Initially, in task pool, the number of tasks is equal to the number of jobs, the *job_no* of all tasks represent all jobs to be scheduled, the *stage_no* of all tasks represent stage one, the *st* of all tasks are zero, the *from_location* of all tasks represent warehouse. Once a task in task pool is completed by AGV, if the *stage_no* of the task is not equal to the last stage of the job, the completed task ($Task_{old}$) will be removed from the task pool. At the same time, a new task ($Task_{new}$) representing the next stage of the same job is added to the task pool. The old and new tasks satisfy the following relationship:

- The job_no_{new} is equal to job_no_{old}.
- The $stage\_no_{new}$ represents the next stage of $stage\_no_{old}$.
- The st_{new} is equal to the completion time of the job i at stage j involved in the $Task_{old}$.
- The $from\_location_{new}$ is the processing machine of the job i at stage j involved in the $Task_{old}$.

Where, job_no_{new} and $stage\_no_{new}$ is the *job_no* and *stage_no* of $Task_{new}$, job_no_{old} and $stage\_no_{old}$ is the *job_no* and *stage_no* of $Task_{old}$, st_{new} and $from\_location_{new}$ is the *st* and *from_location* of $Task_{new}$. A simple example is shown in Figure 2. Once the old task $Task_2$ is completed and stage one is not the last stage of job_2, a new $Task_2$ which represent the next stage of the job is added in task pool. In the new task, "6" represents the completion time of job_2 on $machine_2$ at stage one (also the earliest start time of the new task). And "$machine_2$" represents the processing machine selected for job_2 at stage one (also the starting location of the new task).

After this, the object of scheduling is to assign the tasks in the task pool to each AGV in a certain order and then to schedule the trip and processing, making the makespan smaller. While the task pool is emptied, the scheduling is complete.

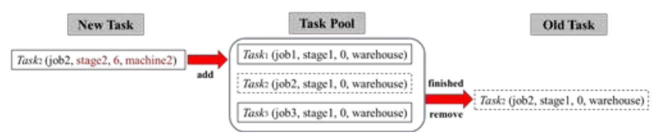


Figure 2 Simple description of the task pool

3.2 Solution representation

A new way of solution representation according to the proposed task pool is proposed, which provides an encoding method for the IPTSP that can be searched efficiently by subsequent algorithms.

Under some task selection rules based on time target (like: FCFS, EDT, GWTQ and so on [19]), we find that the assignment of AGVs and the order of tasks transporting at the first stage have a great impact on the makespan. This is because of the fact that the earliest start time of tasks in task pool are all zero and starting locations are all warehouses (at the first stage). Therefore, we consider transforming the assignment of AGVs and the order of tasks transporting at the first stage into a coding sequence to be optimized. For that a new solution representation is introduced, based on tasks in task pool at the first stage. The new solution representation is composed of two parts:

- Transport sequence vector (also called v_1)

● Transporter assignment vector (also called v_2)

Transport sequence vector v_1 represents the order of transport for each task at the first stage. Figure 3 illustrates a transport sequence vector. For example, the transport sequence shown in Figure 3 can be translated into a list of ordered tasks below: Task3 ≻ Task2 ≻ Task1 ≻ Task4 ≻ Task5.

Position: Priority u	1	2	3	4	5
Task Indicated	$Task_3$	$Task_2$	$Task_1$	$Task_4$	$Task_5$
Transport sequence $v_1(u)$	3	2	1	4	5

Figure 3 Illustration of the transport sequence vector

In each transporter assignment vector v_2, $v_2(u)$ represents the AGV selected for the $Task_u$ indicated at position u. Figure 4 illustrates a transporter assignment vector. For example, position 3 indicates $Task_3$, and $v_2(3)$ represents the AGV assigned for $Task_3$.

Position: v	1	2	3	4	5
Task Indicated	$Task_1$	$Task_2$	$Task_3$	$Task_4$	$Task_5$
Transporter Assignment $v_1(v)$	2	2	1	2	1

Figure 4 Illustration of the transporter assignment vector

With the new solution representation, the assignment of AGVs and the sequence of tasks at the first stage have been confirmed. Furthermore, such algorithm applying requires a makespan evaluation with a computationally fast sub procedure. It will be presented in the next section.

3.3 Solution evaluation

Using the proposed solution representation method, the makespan evaluation is described as follows:

● At stage one, the transport sequence and the assignment of AGVs are determined according to the two-vector representation;

● At stage j (j > 1), a task is assigned to the earliest idle AGV with a specific task selection rule. Repeat the above process until the task pool is emptied.

Among them, after the task is selected and assigned to an AGV, the processing machine (also the destination of the task) at this stage is selected according to the improved First Available Machine (FAM [20]) rule. When the task is completed, if the stage involved in this task doesn't represent the last stage, the task is removed from the task pool and a new task is added (refer to section 3.1 for the details).

The steps are shown below:

Step 1.Schedule the tasks in task pool at stage one:

1a).Read the position information in v_1 from left to right, and get the corresponding task $Task_m$ to be scheduled;

1b).Get other information about $Task_m$. For example, we can know the assigned AGV R_v for the task in v_2, the involved job J_i, the processing time p_{ij}, the earliest start time of the task st, the starting location M_k;

1c). Plan the empty trip (from the destination $M_{k'}$ of the previous task to machine M_k) for R_v. The start time of the empty trip is earliest idle time of R_v. The arrival time of the empty trip is calculated as follow:

$$CT_{i1}^{'} = AIT_v + pt_{k'k}, \tag{2}$$

Where, $pt_{k'k}$ represents the transport time from location $M_{k'}$ to location M_k, AIT_v is the earliest idle time of R_v;

1d). Select the processing machine for J_i at stage one according the improved FAM rule. The estimated completion time $C_{i1}^{p}{'}$ of J_i at stage one on each available machine M_p is calculated as follow:

$$C_{i1}^{p}{'} = \max(\max(CT_{i1}^{'}, st) + pt_{kp}, MIT_p) + p_{i1}, \tag{3}$$

Where, MIT_p represents the earliest idle time of machine M_p, pt_{kp} represents the transport time from location M_k to location M_p, p_{i1} represents the processing time of J_i at stage one.

Then, select the machine M_q with the smallest estimated completion time as the processing machine for J_i at stage one.

1e). Plan the loaded trip (from location M_k to location M_q) for R_v. The start time ST_{i1} of the loaded trip is the maximum between the earliest start time of the task and the arrival time of the empty trip:

$$ST_{i1} = \max(CT_{i1}^{'}, st), \tag{4}$$

And the arrival time of the loaded trip is calculated as follow:

$$CT_{i1} = ST_{i1} + pt_{kq}, \tag{5}$$

Where, pt_{kq} represents the transport time from location M_k to location M_q;

1f). Plan J_i to be processed on M_q. The start time S_{i1} of processing on machine M_q is the maximum between the earliest idle time of machine M_q and the arrival time of the loaded trip:

$$S_{i1} = \max(CT_{i1}, MIT_q), \tag{6}$$

Where, MIT_q represents the earliest idle time of machine M_q;

1g). Update the earliest idle time of machine M_q and AGV R_v as follow:

$$MIT_q = S_{i1} + p_{i1}, \tag{7}$$

$$AIT_v = CT_{i1}, \tag{8}$$

1h). Update the task pool referred to section 3.1;

1i). Repeat steps (1a)~(1h) until the last position of two-vector representation is read.

Step 2. Schedule the tasks in task pool at stage j (j > 1):

2a). Select the AGV R_u with the earliest idle time (AIT);

2b). Select a task from task pool as the next task for R_u. According to first come first served (FCFS) rule, the way that selecting the task $Task_m$ with the smallest st is applied;

2c). Plan the empty trip and loaded trip for R_u, select processing machine, plan the job processing and update information. All of these procedures are similar with steps from (1b) to (1h);

2d). Repeat steps (2a)~(2c) until the task pool is emptied.

Step 3. Get the makespan of current two-vector solution representation.

3.4 Advantages of the proposed solution representation

The proposed solution representation has major differences with that of the literatures. Literatures [15-16] represent a solution by three long vectors which considered the sequence of operations, machine assignment and transporter assignment for each operation at the all stages from a global view. They had proved the effectiveness of it and succeed in many cases. However, when the size of problem becomes larger, it may cause the algorithm to perform a lot of invalid searches and hardly to find an optimal solution.

The proposed solution representation uses two vectors representing the order sequence and assignment of AGVs at the first stage which has a big impact on result. The heuristic rules select tasks for corresponding AGV and select machine for jobs at the other stage. The advantage of it is that each two-vector representation can be transformed into feasible scheduling scheme. And when applied to algorithms, it can limit the search space within a considerably range. For large-scale problems, a satisfactory solution can be obtained easily within a limited time. Detailed comparative experiments will be presented in Section 5.

4 Proposed Genetic algorithm with tabu search for IPTSP

Genetic algorithm (GA) is a well-known meta-heuristic algorithm proposed by Holland inspired by the laws of biological evolution in nature. Tabu search (TS) is a local search algorithm proposed by Glover [21] to simulate human memory function. In this paper, the tabu search algorithm is nested into GA for improving offspring individuals in each generation. The framework of the method is shown in Figure 5.

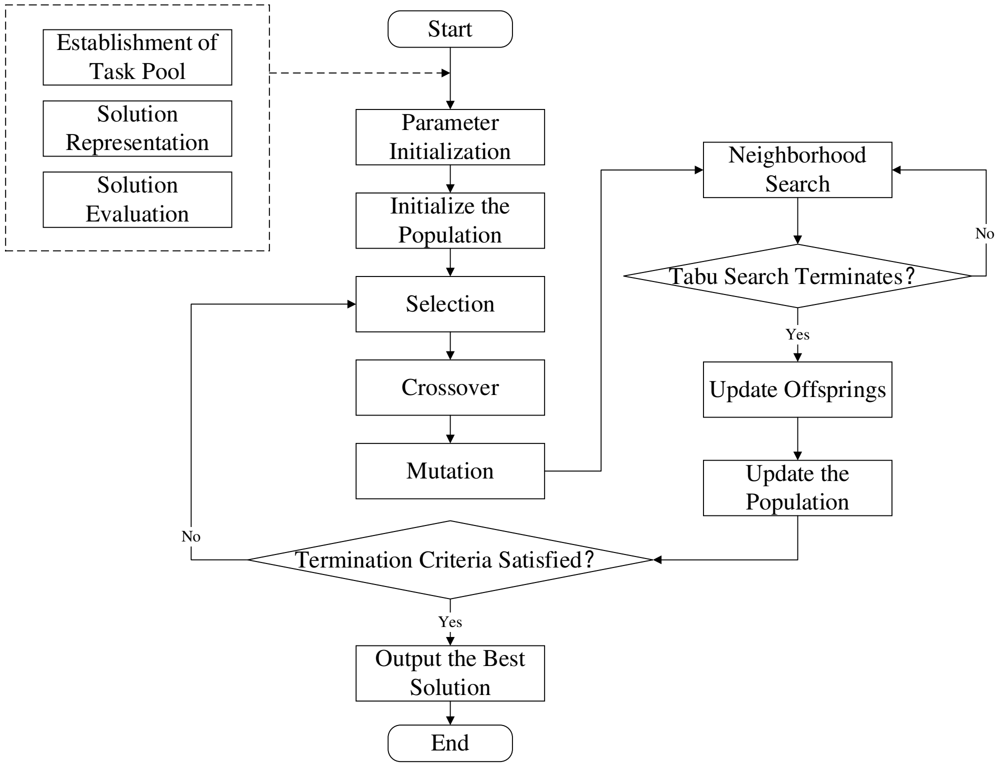


Figure 5 Framework of the method

4.1 Population initialization

The chromosomes in GA are corresponding to the solutions or gantt charts of the integrated scheduling problem. The method of chromosome representation and decoding is as same as that described in section 3. In order to ensure the diversity of the population, the algorithm initialize the individuals in the initial population randomly.

4.2 Crossover operator

In GA, the crossover operator determines the way that parents produce new individual, and promotes the algorithm's global search capabilities. In this paper, two crossover operators have been adopted for the two vectors.

The first one is the position-based crossover (PBX) for transport sequence vector (v_1). The basic procedure of PBX is described as follow (two parents are noted as P1 and P2; two offspring are noted as C1 and C2):

Step1. Randomly generate several gene positions, and C1 and C2 respectively inherit the genes of the corresponding gene positions from P1 and P2;

Step2. C1 and C2 inherit the remaining genes from another parent (P2 and P1) on the unselected gene position.

The second one is the multi-point crossover (MPX) for transporter assignment vector (v_2). The basic procedure of MPX is described as follow (two parents are noted as P1 and P2; two offspring are noted as C1 and C2):

Step1. Randomly generate a sequence composed of 0 and 1, and the length of the sequence is equal to the length of v_2;

Step2. Select the same genes in P2 and P1 corresponding to position 1 in the sequence, and copy them to C1 and C2, that is, exchange the assigned transporter;

Step3. Keep the remaining genes in P1 and P2 to C1 and C2, thus generating offspring C1 and C2.

4.3 Mutation operator

In GA, the mutation operator is used to make perturbations on chromosomes in order to maintain the algorithm's local search capabilities. In this paper, two mutation operators have been adopted for the two vectors.

The first mutation operator is used for transport sequence vector (v_1), which selects two genes randomly and inserts the back one before the front one or the front one after the back one.

The second mutation operator is used for transporter assignment vector (v_2), which selects one gene randomly and change the value of this selected gene to the other AGV.

4.4 Neighborhood structure

In TS, neighborhood structure is a mechanism for generating new solutions by making small disturbances to the current solution. In this paper, four ways of neighborhood structure are adopted.

1. Binary exchange: select two points randomly in chromosome and reverse the order of all genes between these two points.

2. Two points exchange: select two points randomly in chromosome and exchange the gene value of these two points.

3. One point insert: select two point randomly and insert the back one before the front one.

4. Transporter change: select one point randomly and change the AGV assignment of this gene to the other AGV.

4.5 Tabu list

The purpose of the tabu list is to avoid roundabout searches and guide the algorithm to better explore other areas of the solution space. The length of the tabu list is the tenure of the subject staying in the tabu list. If the length is *L*, the tabu list can be expressed as a ring table composed of *L* subjects. Whenever a new subject is added to the tabu list, it is possible to overwrite one of the oldest elements with this new subject.

4.6 Termination criterion

The termination criterion determines whether the algorithm should stop. In this paper, the GA with TS terminates when the number of iterations reaches to the maximum iterations (*MaxIter*); TS terminates when the number of iterations reaches to the maximum iterations (*MaxTSIter*).

5 Experiments and computational results

Since there is no corresponding benchmark for the integrated scheduling problem in hybrid flow shop environment, we design two groups of instances for the problem in this section. Then we adapt three types of experiments to verify the proposed method. Finally, we make some analysis based on the results. All of the experiments have been coded in C++ and run on Intel Core i5 2.3 GHz PC with 8 GB memory.

5.1 Instances design

This paper has designed two groups of instances. And all of them can be found at the website [29].

5.1.1 Group 1

Literature [22] specializes in the benchmark of HFSP. We take some instances in the literature [22] as a part of input information of the instances of the integrated scheduling problem, and the corresponding transportation time between machines is generated according to number of machines. The instances of proposed benchmark is divided into small-size and large-size according to the number of jobs, as follows:

●Small-size: number of jobs: {10, 20, 30}; number of stages: {5, 10}; number of AGVs: {2, 4, 6};

●Large-size: number of jobs: {80, 160}; number of stages: {5}; number of AGVs: {4, 6, 8}.

When generating the problems, an important characteristic considered is the relative magnitude of the travel times and the processing times [23]. We consider using a variable α to distinguish different types of instances, and further generate large-α type and small-α type in large/small-size instances. The α represents the ratio between the average machine-to-machine transportation time and the average processing time of the instance. The value of α in each instance is calculated as follows:

$$\alpha = \frac{(\sum\sum p_{ij})/(\mathrm{n}*\mathrm{s})}{(\sum\sum pt_{pq})/(\mathrm{m}+1)^2}, \tag{9}$$

Where, p_{ij} is the processing time of job *i* at stage *j*; pt_{pq} is the transportation time of location *p* to location *q*; *n* is the number of jobs; *s* is the number of stages; *m* is the number of machines.

5.1.1 Group 2

Zabihzadeh and Rezaeian [16] have researched similar problems to this paper. They gave the parameters which were used to generate the instances, but did not give specific instances they used. In this group, parameters are generated randomly based on Zabihzadeh and Rezaeian's research [16]. For each job, standard processing time, unloading, transferring and loading time at each stage are generated from the uniform distribution U [10, 100], U [5, 20], U [5, 20], U [5, 20], respectively. The match between the number of jobs, the number of stages, and the number of AGVs still refer to their research.

5.2 Experimental Setup

5.2.1 Experiment 1: Comparison of solution representations

Using the same genetic algorithm in literature [16], under the same number of iterations and other parameters, this paper solves proposed two groups of instances in three different solution representations (coding and decoding methods) in order to verify the effectiveness of the proposed one:

- Mode1: Use the coding and decoding method of the HFSP problem in literature [27], and whenever the job is scheduled to be processed on the machine, use the AGV assignment rule in literature [28] to allocate the appropriate AGV to complete the corresponding transportation task.
- Mode2: Use the same coding and decoding method of the integrated scheduling problem with literature [16]. Blocking and release time have been considered in literature [16], both of which are ignored here.
- Mode3: Use the coding and decoding method proposed in Section 3.

5.2.2 Experiment 2: Comparison of selection rules

According to Section 3.3, the task selection rule has an important impact on solution evaluation. Here, four common and classic rules are used for experiment and comparison, each of which is worked as a part of solution evaluation in the proposed GATS independently [19].

- Rule1: First Come First Served (FCFS). Each time, select the task with the minimum earliest start time (*st*);
- Rule2: Longest Time Between Arrival (LTBA). Each time, select the task with the minimum difference between the AGV's estimated arrival time and the earliest start time;
- Rule3: Shortest Travel Distance Rule (STD). Each time, select the task closest to the current location of the AGV;
- Rule4: Greatest Waiting Time in Queue (GWTQ). Each time, select the task with the longest waiting time in the buffer.

5.2.3 Experiment 3: Comparison of algorithms

In order to verify the effectiveness of the hybrid algorithm, the following five algorithms have been selected and programmed to solve the two groups of instances and compared with the hybrid GATS algorithm.

- Genetic algorithm (GA);
- Simulated annealing algorithm (SA);
- Artificial bee colony algorithm (ABC) [24];
- Grey wolf optimizer algorithm (GWO) [25];
- Migrating birds optimization algorithm (MBO) [26].

5.3 The experimental results

5.3.1 Results of Experiment 1

For each instance in benchmark, run it five times and record its best makespan and average makespan. The parameters of GA used here are set as follows: the population size = 20; the crossover probability = 0.9; the mutation probability = 0.5; the maximum number of iterations = 500. The computational results are presented in Tables 3~7. Among them, “Mode3” represents the solution representation proposed in Section 3.

Table 3 Comparison on Group 1 with small-size and small-α

Job	Stage	AGV	α	Mode1		Mode2		Mode3	
				Best	Average	Best	Average	Best	Average
10	5	2	0.10	612	622	534	591	**424**	**435**
		4		508	512	526	577	**423**	**434**
		6		449	458	514	563	**423**	**431**
	10	2	0.14	1092	1111	1159	1227	**832**	**854**
		4		951	967	1107	1157	**830**	**845**
		6		888	905	1085	1145	**835**	**843**
20	5	2	0.10	1176	1183	1000	1038	**688**	**707**
		4		1058	1068	938	988	**686**	**698**
		6		925	949	894	959	**688**	**698**
	10	2	0.17	1812	1841	1703	1767	**974**	**1007**
		4		1574	1596	1482	1552	**871**	**892**
		6		1422	1443	1472	1495	**867**	**885**
30	5	2	0.11	1481	1488	1228	1273	**742**	**758**
		4		1377	1391	1126	1184	**719**	**729**
		6		1276	1291	1156	1178	**707**	**724**
	10	2	0.16	2959	2966	2443	2508	**1485**	**1510**
		4		2720	2729	2217	2382	**1149**	**1197**
		6		2531	2537	2213	2301	**1151**	**1176**

Table 4 Comparison on Group 1 with small-size and large-α

Job	Stage	AGV	α	Mode1		Mode2		Mode3	
				Best	Average	Best	Average	Best	Average
10	5	2	0.41	736	757	763	813	**611**	**635**
		4		578	589	655	698	**471**	**484**
		6		509	520	560	643	**469**	**478**
	10	2	0.60	1412	1430	1674	1775	**1255**	**1291**

		4		1099	1111	1425	1486	**940**	**961**
		6		999	1016	1270	1339	**914**	**930**
20		2		1417	1435	1435	1508	**1269**	**1312**
	5	4	0.38	1144	1159	1068	1164	**797**	**808**
		6		1034	1042	1057	1129	**742**	**759**
		2		2610	2646	2974	3061	**2505**	**2540**
	10	4	0.72	1849	1867	2105	2222	**1461**	**1492**
		6		1614	1634	1921	1989	**1136**	**1174**
30		2		2081	2094	2156	2202	**1965**	**2005**
	5	4	0.45	1473	1478	1420	1517	**1067**	**1098**
		6		1364	1371	1244	1366	**811**	**848**
		2		4160	4193	4734	4837	**3908**	**3977**
	10	4	0.67	3005	3020	3175	3339	**2279**	**2298**
		6		2737	2754	2742	2879	**1732**	**1757**

Table 5 Comparison on Group 1 with large-size and small-α

Job	Stage	AGV	α	Mode1		Mode2		Mode3	
				Best	Average	Best	Average	Best	Average
		4		4449	4474	3246	3321	**2066**	**2085**
80	5	6	0.10	4337	4347	3122	3255	**2014**	**2053**
		8		4214	4240	3110	3254	**2054**	**2068**
		4		9783	9794	7106	7410	**4300**	**4366**
160	5	6	0.10	9661	9684	7305	7514	**4265**	**4291**
		8		9537	9544	7097	7302	**4234**	**4268**

Table 6 Comparison on Group 1 with large-size and large-α

Job	Stage	AGV	α	Mode1		Mode2		Mode3	
				Best	Average	Best	Average	Best	Average
		4		4544	4552	4086	4212	**3078**	**3093**
80	5	6	0.43	4440	4441	3793	3800	**2288**	**2308**
		8		4315	4333	3442	3610	**2133**	**2152**
		4		9859	9876	8435	8545	**6441**	**6463**
160	5	6	0.40	9753	9773	7687	7737	**4871**	**4926**
		8		9648	9653	7540	7700	**4534**	**4567**

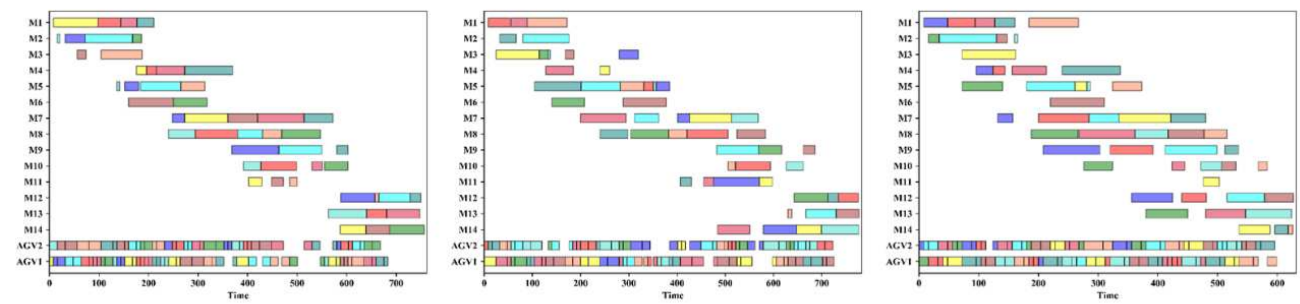
Table 7 Comparison on Group 2

Job	Stage	AGV	α	Mode1		Mode2		Mode3	
				Best	Average	Best	Average	Best	Average
	2	4	0.80	393	400	448	475	**387**	**397**
	4	6	0.73	499	504	656	677	**485**	**493**
10	6	6	0.71	756	771	1013	1043	**728**	**735**
	8	10	0.69	901	911	1273	1288	**835**	**846**
	10	10	0.69	1092	1108	1535	1639	**1058**	**1062**
	2	6	0.77	578	584	590	633	**496**	**502**
	4	8	0.65	923	930	1081	1129	**746**	**766**
20	6	12	0.67	1112	1121	1415	1530	**895**	**910**
	8	12	0.70	1494	1504	1965	2046	**1241**	**1245**
	10	14	0.67	1733	1748	2309	2388	**1336**	**1364**

In the two groups of instances shown in Tables 3~7, the solution representation (Mode3) proposed in this paper get all optimal solutions in best makespan and average makespan, which is much better than others.

To study the mechanism of the three different solution representations deeply, we analyzed lots of the final Gantt charts for instances of these three solution representations (one group of which is shown in Figure 6). Meanwhile, combined with the characteristics of the HFSP, we got some findings: (1) For Mode1, affected by HFSP, processing and transportation of jobs are carried out depending on the stage (the order sequence at the latter stages is determined by the end time of jobs at the previous stage). This will make each AGV only transport jobs with the same stage in a period of time. As a result, the scheduling schemes obtained with this mode are too limited; (2) For Mode2, under the same scale of problem, the coding length is much larger than that of others. On the one hand, it can almost represent all the solutions in the solution space, providing the possibility for the algorithm to find global optimal solutions. On the other hand, due to the large search range, it is difficult for the algorithm to find a satisfactory solution in a limited time; (3) For Mode3, by optimizing the order sequence at the first stage that has a greater impact on the makespan, and combining with effective heuristic rule, the solution representation performs better.

The above results show that the proposed solution representation can help algorithm obtaining more and better results than others, under the same number of iterations and other parameters of the algorithm used.



(a) Gantt chart of Mode1 (b) Gantt chart of Mode2 (c) Gantt chart of Mode3

Figure 6 Gantt charts of three different solution representations

5.3.2 Results of Experiment 2

For each instance in benchmark, run it five times and record its best makespan and average makespan. The parameters of GATS used here are set as follows: the population size = 20; the crossover probability = 0.9; the mutation probability = 0.5; the length of tabu list = 10; the maximum iterations of the hybrid GA and TS = 50; the maximum iterations of the TS is 20. The computational results are presented in Tables 8~12. Among them, "GATS_FCFS" represents the hybrid GA and TS with FCFS rule.

Table 8 Comparison on Group 1 with small-size and small-α

Job	Stage	AGV	α	GATS_FCFS		GATS_LTBA		GATS_STD		GATS_GWTQ	
				Best	Average	Best	Average	Best	Average	Best	Average
		2		424	426	**423**	427	456	467	**423**	**424**
	5	4	0.10	423	423	**422**	**422**	441	455	423	423
10		6		**423**	**423**	**423**	**423**	433	442	**423**	**423**
		2		**830**	**833**	842	844	948	996	**830**	845
	10	4	0.14	**830**	835	**830**	**833**	926	967	**830**	840
		6		**830**	839	**830**	**830**	859	888	**830**	834
		2		687	**694**	689	698	820	837	**686**	696
	5	4	0.10	681	685	677	682	779	799	**675**	**681**
20		6		679	685	**678**	**682**	780	795	679	**682**
		2		**974**	**991**	1024	1038	1166	1190	975	992
	10	4	0.17	860	861	861	869	1074	1093	**851**	**859**
		6		**842**	855	**842**	**854**	1046	1102	848	855
		2		**720**	**731**	729	741	900	918	721	740
	5	4	0.11	**696**	**700**	708	709	831	856	697	705
30		6		**686**	**699**	694	702	838	849	692	702
		2		**1485**	**1531**	1590	1603	1500	1602	1510	1532
	10	4	0.16	1161	1167	1155	1187	1448	1486	**1135**	**1154**
		6		1115	**1123**	1132	1144	1385	1395	**1111**	1127
Number of optimal solutions				10	9	7	6	0	0	10	6

Table 9 Comparison on Group 1 with small-size and large-α

Job	Stage	AGV	α	GATS_FCFS		GATS_LTBA		GATS_STD		GATS_GWTQ	
				Best	Average	Best	Average	Best	Average	Best	Average
		2		604	615	615	640	644	664	**596**	**613**
	5	4	0.41	469	**471**	471	475	504	519	**467**	**471**
10		6		464	465	**461**	**463**	492	497	466	467
		2		**1250**	**1278**	1330	1345	1416	1451	1276	1302
	10	4	0.60	938	944	950	967	1043	1108	**929**	**938**
		6		905	913	911	920	983	1030	**900**	**909**

20	5	2	0.38	1269	**1293**	1333	1350	**1245**	1307	1277	1303
		4		789	796	810	816	897	922	**773**	**785**
		6		728	**732**	**724**	736	820	861	728	734
	10	2	0.72	**2545**	**2573**	2646	2706	2572	2642	2551	2590
		4		1465	**1490**	1588	1603	1508	1561	**1451**	**1490**
		6		**1145**	**1167**	1266	1278	1309	1334	1171	1181
30	5	2	0.45	1929	1969	2038	2057	**1813**	**1877**	1919	1952
		4		**1084**	1118	1159	1177	1088	**1108**	1094	**1108**
		6		**816**	828	864	873	938	974	**816**	**826**
	10	2	0.67	3983	4022	4204	4222	**3794**	**3853**	3990	4032
		4		2322	2329	2451	2489	**2214**	**2234**	2301	2331
		6		1784	**1794**	1936	1958	**1776**	1830	1786	1799
Number of optimal solutions				5	8	2	1	5	4	7	8

Table 10　Comparison on Group 1 with large-size and small-α

Job	Stage	AGV	α	GATS_FCFS		GATS_ LTBA		GATS_STD		GATS_GWTQ	
				Best	Average	Best	Average	Best	Average	Best	Average
80	5	4	0.10	2024	2037	1995	**2005**	2282	2310	**1994**	2013
		6		1996	2008	**1995**	2011	2300	2306	2000	**2007**
		8		**1989**	**1998**	1992	2003	2151	2204	**1989**	2001
160	5	4	0.10	**4212**	**4241**	4238	4272	4803	4817	4261	4276
		6		**4195**	**4213**	4205	4226	4680	4720	4210	4234
		8		4199	4213	4233	4237	4671	4694	**4192**	**4212**
Number of optimal solutions				3	3	1	1	0	0	3	2

Table 11　Comparison on Group 1 with large-size and large-α

Job	Stage	AGV	α	GATS_FCFS		GATS_ LTBA		GATS_STD		GATS_GWTQ	
				Best	Average	Best	Average	Best	Average	Best	Average
80	5	4	0.43	3022	3039	3212	3231	**2732**	**2747**	3004	3026
		6		**2183**	2207	2333	2345	2423	2470	2187	**2198**
		8		2076	2085	**2068**	2099	2324	2381	2069	**2075**
160	5	4	0.40	**6380**	**6414**	6771	6774	6450	6453	6444	6446
		6		**4681**	**4701**	5071	5072	5002	5027	4736	4763
		8		**4373**	**4416**	4385	4453	4902	4924	4433	4451
Number of optimal solutions				4	3	1	0	1	1	0	2

Table 12　Comparison on Group 2

Job	Stage	AGV	α	GATS_FCFS		GATS_LTBA		GATS_STD		GATS_GWTQ	
				Best	Average	Best	Average	Best	Average	Best	Average
10	2	4	0.80	**377**	**380**	381	387	379	381	378	381
	4	6	0.73	474	479	491	498	475	486	**471**	**477**
	6	6	0.71	**712**	731	738	755	734	752	717	**719**
	8	10	0.69	**832**	**838**	842	846	846	860	838	843
	10	10	0.69	**1038**	**1050**	1045	1056	1084	1106	1050	1052
20	2	6	0.77	**465**	**481**	484	489	504	513	473	483
	4	8	0.65	740	755	788	799	767	795	**732**	**754**
	6	12	0.67	**885**	899	915	924	977	994	888	**897**
	8	12	0.70	**1216**	**1229**	1277	1285	1267	1290	1221	1234
	10	14	0.67	**1348**	**1369**	1404	1424	1428	1439	1374	1377
Number of optimal solutions				8	6	0	0	0	0	2	4

In each type of instances, the statistics of the total number that each rule can achieve optimal result about best makespan and average makespan among the four are shown in the Tables 13~14. In the 58 instances, the GATS with FCFS rule achieves 30 optimal results about best makespan and 29 optimal results about average makespan, which is better than other three. It is evident that the FCFS rule used in solution evaluation is effective and reliable when solving integrated scheduling problem.

Table 13　Statistical result of the best makespan

Size	α	Total number	Number of optimal solutions			
			GATS_FCFS	GATS_LTBA	GATS_STD	GATS_GWTQ
small	small	18	10	7	0	10
small	large	18	5	2	5	7
large	small	6	3	1	0	3
large	large	6	4	1	1	0
Group2		10	8	0	0	2
Total		58	30	11	6	22

Table 14 Statistical result of the average makespan

Size	α	Total number	Number of optimal solutions			
			GATS_FCFS	GATS_LTBA	GATS_STD	GATS_GWTQ
small	small	18	9	6	0	6
small	large	18	8	1	4	8
large	small	6	3	1	0	2
large	large	6	3	0	1	2
Group2		10	6	0	0	4
Total		58	29	8	5	22

5.3.3 *Results of Experiment 3*

For each instance, run each algorithms five times and record its best makespan and average makespan. The computational results are presented in Tables 15~24.

Table 15 Comparison about best makespan on Group 1 with small-size and small-α

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
10	5	2	0.10	424	425	**421**	423	**421**	**421**
		4		**423**	424	**423**	**423**	**423**	**423**
		6		**423**	424	**423**	**423**	**423**	**423**
	10	2	0.14	832	844	835	842	**830**	**830**
		4		**830**	837	836	834	**830**	**830**
		6		835	**830**	**830**	834	**830**	**830**
20	5	2	0.10	688	707	709	724	**681**	687
		4		686	699	690	700	682	**681**
		6		688	685	693	698	**677**	**677**
	10	2	0.17	974	996	997	992	**948**	974
		4		871	876	861	896	862	**860**
		6		867	877	880	880	850	**842**
30	5	2	0.11	742	724	766	763	**714**	720
		4		719	725	734	734	703	**696**
		6		707	718	718	733	700	**686**
	10	2	0.16	1485	1497	1522	1531	**1459**	1485
		4		1149	1194	1201	1200	**1152**	1161
		6		1151	1159	1186	1178	1137	**1115**
Number of optimal solutions				3	1	4	2	12	13

Table 16 Comparison about average makespan on Group 1 with small-size and small-α

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
10	5	2	0.10	435	433	425	428	**422**	426
		4		434	428	425	424	425	**423**
		6		431	427	424	424	424	**423**
	10	2	0.14	854	848	844	851	837	**833**
		4		845	844	841	843	838	**835**
		6		843	840	835	844	**833**	839
20	5	2	0.10	707	711	714	736	**688**	694
		4		698	705	700	711	686	**685**
		6		698	698	702	712	686	**685**
	10	2	0.17	1007	1009	1011	1017	**961**	991
		4		892	893	885	906	876	**861**
		6		**885**	881	889	897	**855**	**855**
30	5	2	0.11	758	752	775	772	733	**731**
		4		729	730	743	738	711	**700**
		6		724	728	737	736	707	**699**
	10	2	0.16	1510	1519	1529	1536	**1464**	1531
		4		1197	1201	1212	1211	1173	**1167**
		6		1176	1171	1188	1185	1144	**1123**
Number of optimal solutions				1	0	0	0	6	13

Table 17 Comparison about best makespan on Group 1 with small-size and large-α

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
10	5	2	0.41	611	610	593	613	**577**	593
		4		471	**468**	478	480	470	**468**
		6		469	467	466	466	465	**464**
	10	2	0.60	1255	1264	1242	1259	**1226**	1250
		4		940	939	**934**	945	948	**934**
		6		914	911	911	923	909	**905**
20	5	2	0.38	1269	1287	1280	1325	**1268**	**1268**
		4		797	792	796	802	796	**776**

		6		742	742	753	763	738	**728**
		2		2505	2524	2490	2542	**2481**	2487
	10	4	0.72	1461	**1451**	1486	1484	1455	1465
		6		**1136**	1151	1158	1167	1150	1145
		2		1965	1986	1964	1973	1941	**1929**
	5	4	0.45	**1067**	1113	1100	1123	1091	1084
30		6		**811**	850	838	856	845	816
		2		**3908**	3948	3912	3950	3928	3975
	10	4	0.67	2279	2291	2287	2294	**2236**	**2236**
		6		**1732**	1790	1782	1768	1763	1784
Number of optimal solutions				5	2	1	0	5	9

Table 18 Comparison about average makespan on Group 1 with small-size and large-α

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
		2		635	620	608	633	**596**	615
	5	4	0.41	484	474	480	485	474	**472**
10		6		478	472	467	469	466	**465**
		2		1291	1273	1258	1283	**1243**	1278
	10	4	0.60	961	950	946	961	954	**944**
		6		930	918	918	930	917	**913**
		2		1312	1313	1297	1334	**1287**	1293
	5	4	0.38	808	802	807	825	801	**796**
20		6		759	753	758	772	746	**732**
		2		2540	2548	2512	2555	**2498**	2506
	10	4	0.72	1492	1495	1495	1495	**1467**	1490
		6		1174	1164	1176	1180	1167	**1155**
		2		2005	1992	1972	1986	1964	**1963**
	5	4	0.45	**1098**	1124	1114	1125	1104	1118
30		6		848	856	852	859	849	**828**
		2		3977	4000	**3960**	3980	3979	4022
	10	4	0.67	2298	2309	2297	2308	2267	**2255**
		6		**1757**	1795	1788	1783	1773	1794
Number of optimal solutions				2	0	1	0	5	10

Table 19 Comparison about best makespan on Group 1 with large-size and small-α

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
		4		2066	**2000**	2056	2057	2041	2024
80	5	6	0.10	2014	2019	2046	2048	2027	**1996**
		8		2054	2014	2051	2034	2036	**1989**
		4		4300	4265	4390	4279	4254	**4212**
160	5	6	0.10	4265	4219	4315	4248	4233	**4195**
		8		4234	4205	4305	4239	4278	**4199**
Number of optimal solutions				0	1	0	0	0	5

Table 20 Comparison about average makespan on Group 1 with large-size and small-α

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
		4		2085	2037	2070	2068	2061	**2035**
80	5	6	0.10	2053	2022	2057	2066	2039	**2008**
		8		2068	2018	2059	2057	2050	**1998**
		4		4366	4266	4398	4311	4340	**4241**
160	5	6	0.10	4291	4231	4320	4257	4248	**4213**
		8		4268	**4212**	4350	4258	4281	4213
Number of optimal solutions				0	1	0	0	0	5

Table 21 Comparison about best makespan on Group 1 with large-size and large-α

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
		4		3078	3091	3067	3063	3067	**3022**
80	5	6	0.43	2288	2254	2334	2281	2235	**2183**
		8		2133	2126	2186	2139	2093	**2076**
		4		6441	6498	6485	6465	6501	**6380**
160	5	6	0.40	4871	4799	5008	4772	4792	**4681**
		8		4534	4416	4659	**4367**	4518	4373
Number of optimal solutions				0	0	0	1	0	5

Table 22 Comparison about average makespan on Group 1 with large-size and large-α

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
		4		3093	3093	3077	3079	3074	**3039**
80	5	6	0.43	2308	2287	2342	2301	2283	**2207**
		8		2152	2131	2198	2167	2121	**2085**
		4		6463	6504	6501	6471	6515	**6414**
160	5	6	0.40	4926	4812	5029	4799	4813	**4701**
		8		4567	4430	4663	**4394**	4594	4416
Number of optimal solutions				0	0	0	1	0	5

Table 23 Comparison about best makespan on Group 2

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
	2	4	0.80	387	384	378	393	381	**377**
	4	6	0.73	485	479	**472**	490	479	474
10	6	6	0.71	728	728	717	724	718	**712**
	8	10	0.69	835	**832**	845	848	834	**832**
	10	10	0.69	1058	1047	1053	1058	1051	**1038**
	2	6	0.77	496	494	497	519	476	**465**
	4	8	0.65	746	751	751	750	**740**	**740**
20	6	12	0.67	895	911	906	914	894	**885**
	8	12	0.70	1241	1230	1222	1240	**1203**	1216
	10	14	0.67	**1336**	1365	1362	1363	**1336**	**1336**
Number of optimal solutions				1	1	1	0	3	8

Table 24 Comparison about average makespan on Group 2

Job	Stage	AGV	α	GA	SA	ABC	GWO	MBO	GATS
	2	4	0.80	397	389	384	396	383	**380**
	4	6	0.73	493	482	480	492	481	**479**
10	6	6	0.71	735	733	725	739	**722**	731
	8	10	0.69	846	843	847	852	**837**	838
	10	10	0.69	1062	1060	1057	1060	1053	**1050**
	2	6	0.77	502	500	502	526	484	**481**
	4	8	0.65	766	763	762	775	**746**	755
20	6	12	0.67	910	920	920	925	900	**899**
	8	12	0.70	1245	1238	1233	1247	**1214**	1229
	10	14	0.67	1364	1371	1364	1372	**1344**	1369
Number of optimal solutions				0	0	0	0	5	5

In each type of instances, the statistics of the total number that each algorithms can achieve optimal results about best makespan and average makespan among the six are shown in the Tables 25~26. In the 58 instances, the GATS achieves 40 optimal results about best makespan and 38 optimal results about average makespan, which is better than other five. This means that the hybrid GA and TS has both effectiveness and efficiency for solving integrated scheduling problem.

Table 25 Statistical result of best makespan

Size	α	Total number	Number of optimal solutions					
			GA	SA	ABC	GWO	MBO	GATS
small	small	18	3	1	4	2	12	13
small	large	18	5	2	1	0	5	9
large	small	6	0	1	0	0	0	5
large	large	6	0	0	0	1	0	5
Group2		10	1	1	1	0	3	8
Total		58	9	5	6	3	20	40

Table 26 Statistical result of average makespan

Size	α	Total number	Number of optimal solutions					
			GA	SA	ABC	GWO	MBO	GATS

small	small	18	1	0	0	0	6	13
small	large	18	2	0	1	0	5	10
large	small	6	0	1	0	0	0	5
large	large	6	0	0	0	1	0	5
Group2		10	0	0	0	0	5	5
Total		58	3	1	1	1	16	38

6 Conclusions and future work

This paper proposes an integrated scheduling method for production and transportation in hybrid flow shop environment. Firstly, some preparation for the problem has been made. Then, a hybrid genetic algorithm with tabu search has been adapted. Finally, two groups of instances have been designed and three types of experiments have been carried out for verifying the effectiveness of the proposed method.

The contributions of this research include:

- A new solving method for IPTSP, including the establishment of task pool, the new solution representation and the new solution evaluation has been proposed for the problem. Taking it as coding and decoding method, the algorithm can search for a satisfactory solution within appropriate time;
- A hybrid algorithm which hybridizes the genetic algorithm and tabu search has been proposed to solve the integrated scheduling problem. The hybrid algorithm combines the advantages of the two algorithms. The experimental results show that this algorithm has both effectiveness and efficiency for solving integrated scheduling problem.

Although the method proposed in this paper has achieved good results, there are still some works can be made in the future. Firstly, we can use multiple rules instead of single rule in solution evaluation, which may make the results more stable. Secondly, we can design some efficient methods of population initialization instead of the random one, and design efficient neighborhood structure to improve the hybrid algorithm

7 Declaration

Acknowledgements

Not applicable

Funding

Supported by the National Key R&D Program of China (Grant no. 2019YFB1704603) and the National Natural Science Foundation of China (Grant no.51775216).

Availability of data and materials

The datasets supporting the conclusions of this article can be found at the website [29].

Authors' contributions

The author' contributions are as follows: Wangming Li was in charge of the whole trial; Wangming Li wrote the manuscript; Xinyu Li assisted with problem analyses. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing financial interests.

Consent for publication

Not applicable

Ethics approval and consent to participate

Not applicable

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Figures

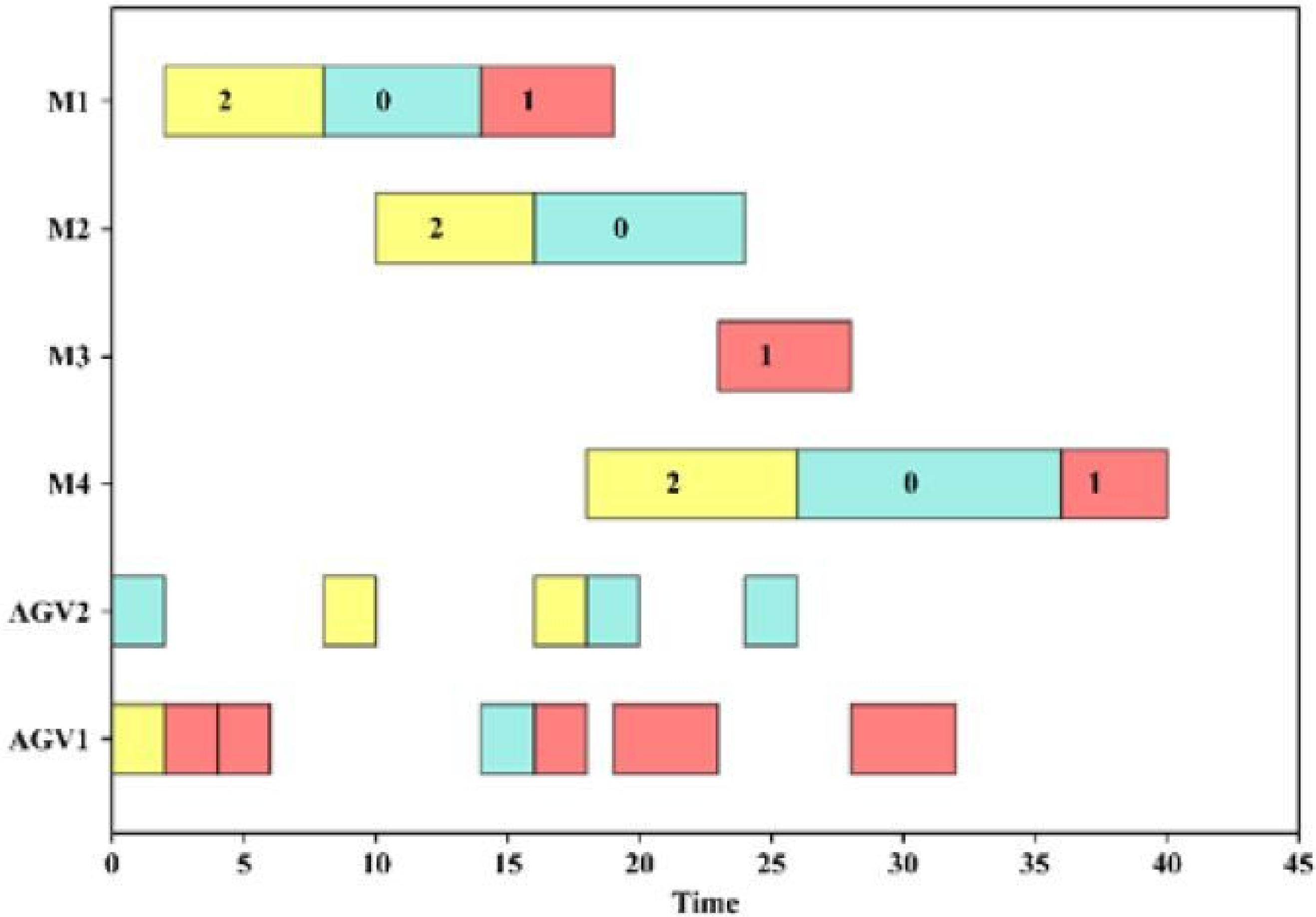

Figure 1

An example for the integrated scheduling problem

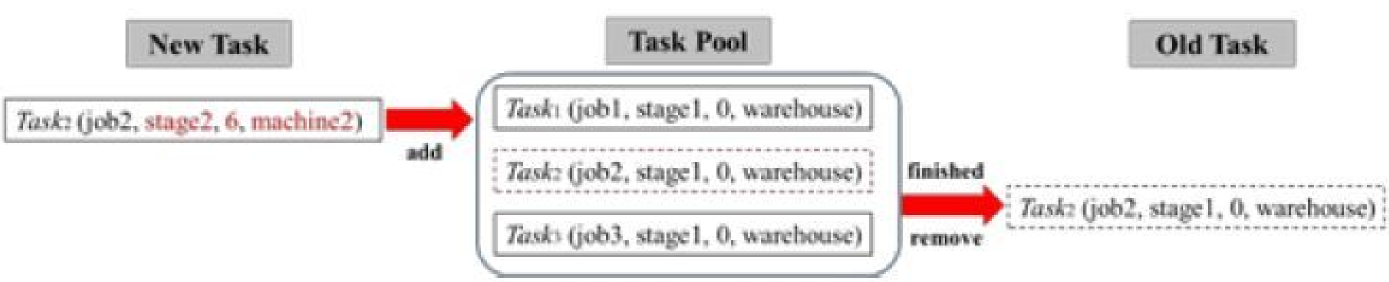

Figure 2

Simple description of the task pool

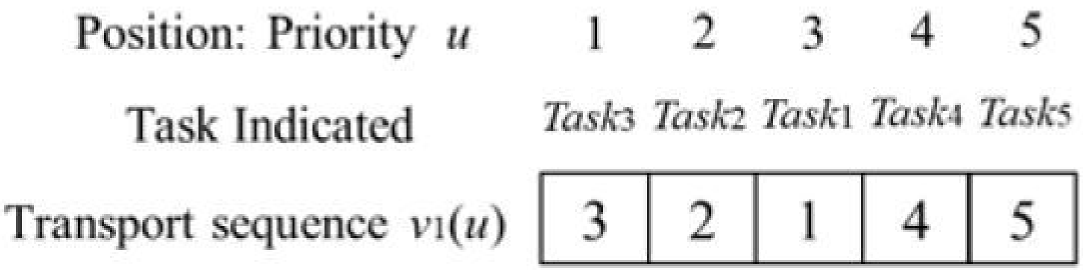

Figure 3

Illustration of the transport sequence vector

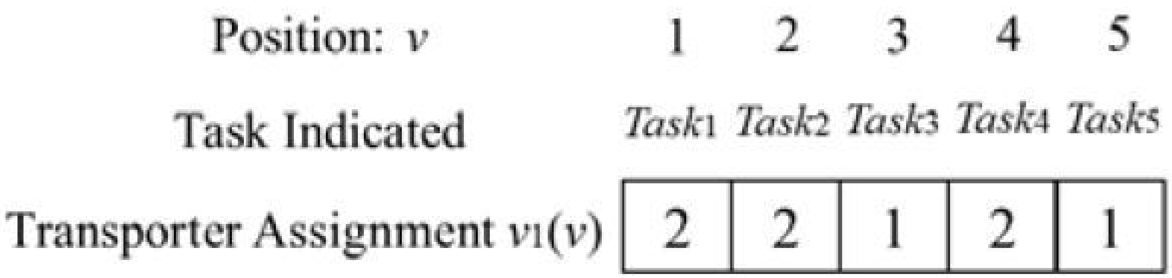

Figure 4

Illustration of the transporter assignment vector

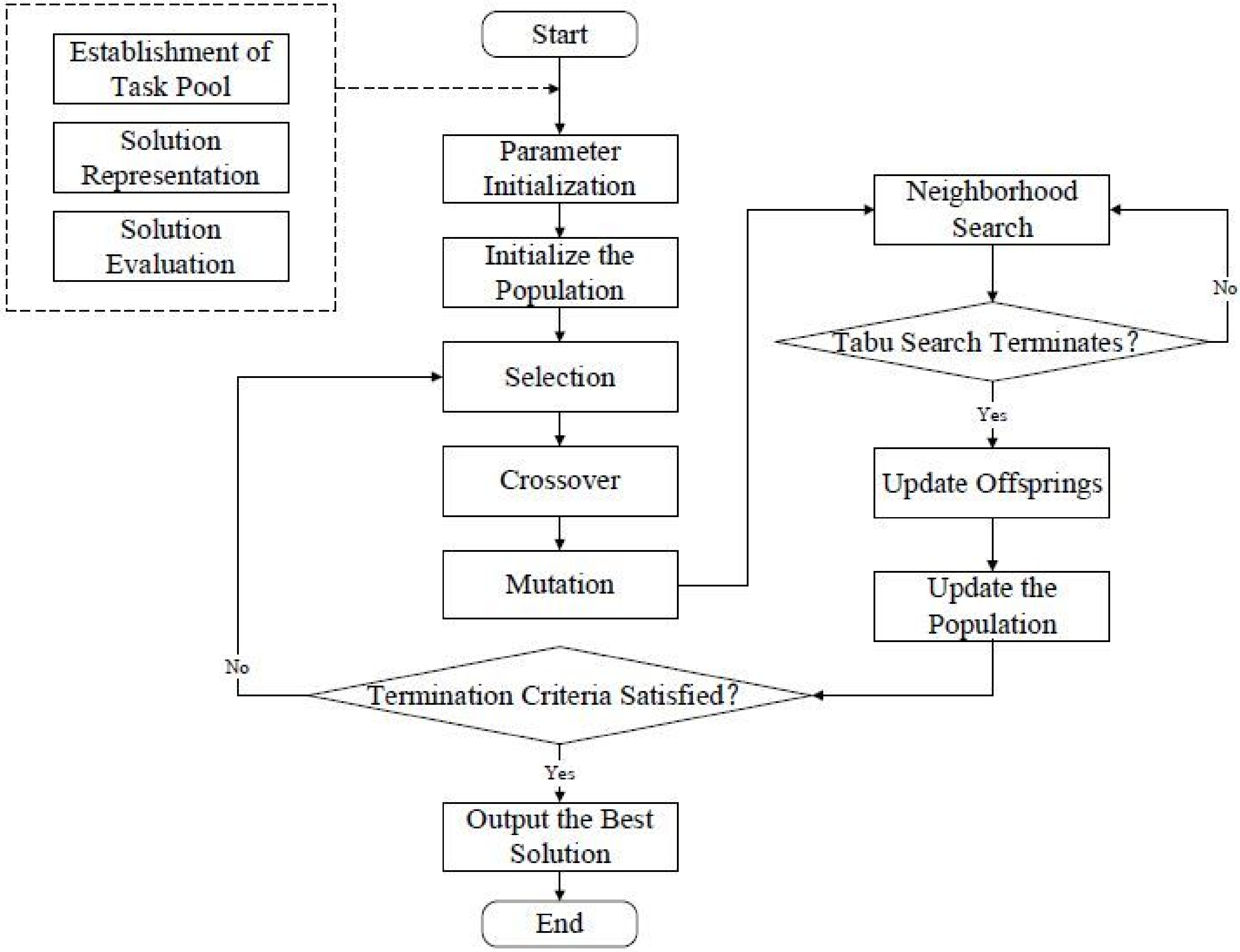

Figure 5

Framework of the method

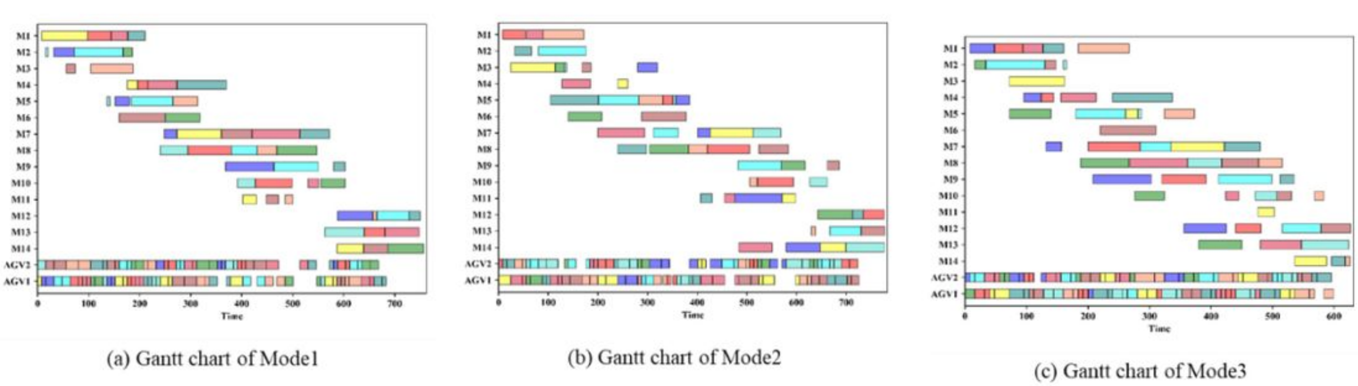

Figure 6

Gantt charts of three different solution representations