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A Mixed Algorithm for Integrated Scheduling Optimization in AS/RS and Hybrid Flowshop

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Abstract: The integrated scheduling problem in automated storage and retrieval systems (AS/RS) and the hybrid flowshop is critical for the realization of lean logistics and just-in-time distribution in manufacturing systems. The bi-objective model that minimizes the operation time in AS/RS and the makespan in the hybrid flowshop is established to optimize the problem. A mixed algorithm, named GA-MBO algorithm, is proposed to solve the model, which combines the advantages of the strong global optimization ability of genetic algorithm (GA) and the strong local search ability of migratory birds optimization (MBO). To avoid useless solutions, different cross operations of storage and retrieval tasks are designed. Compared with three algorithms, including improved genetic algorithm, improved particle swam optimization, and a hybrid algorithm of GA and particle swam optimization, the experimental results showed that the GA-MBO algorithm improves the operation efficiency by 9.48%, 19.54%, and 5.12% and the algorithm robustness by 35.16%, 54.42%, and 39.38%, respectively, which further verified the effectiveness of the proposed algorithm. The comparative analysis of the bi-objective experimental results fully reflects the superiority of integrated scheduling optimization.

Keywords: automated storage and retrieval system; hybrid flowshop; genetic algorithm; migratory birds optimization algorithm; GA-MBO

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1. Introduction

With the development of intelligent logistics equipment and technology, automated storage and retrieval systems (AS/RSs) are widely used in manufacturing enterprise logistics due to the advantages of high efficiency and space utilization [1,2]. The use of AS/RS in the factory warehouse is conducted with the just-in-time (JIT) contribution of various materials in the workshop. To realize the JIT distribution, the AS/RS scheduling must be closely connected with the production scheduling, which affects the efficiency of the integrated scheduling. In addition, the different scheduling optimization objectives in the AS/RS and hybrid flowshop are to maximize the efficiency of storage and retrieval and minimize the makespan. With a high warehousing efficiency, the completion time of the producing material distribution may not meet the required demand or may be unable to greatly increase the line inventory. However, the production scheduling with the minimum completion time may cause the warehouse scheduling tasks to be stacked at a certain time and cannot meet the production demand. Therefore, it is important to cooperate with the scheduling that contains the storage allocation, task sequences, and retrieval task sequences in production, which is a significant practice in manufacturing systems.

At present, the main research in AS/RS concerns storage allocation and task scheduling [3–5]. Roshan et al. [6] formulated a multi-objective model in AS/RS considering energy consumption optimization and energy sustainability. Hachemi et al. [7] determined the integration of the storage allocation and picking paths based on storage and retrieval requests with the objective of travel time. Song and Mu [8] studied the sequence sorting problem with large-scale storage/retrieval requests in AS/RS and proposed a heuristic algorithm based on assignment. Geng et al. [9] proposed a new improved Genetic Algorithm (GA)

to solve the scheduling problem in AS/RS, and indicated that it is an effective approach. Wu et al. [10] investigated the scheduling problem of retrieval jobs in double-deep type AS/RS, whose objective is to minimize the working distance.

In the hybrid flowshop, Colak et al. [11] conducted a systematic literature survey for hybrid flowshop scheduling problems, which provided a beneficial road map for the following researchers. Zhang et al. [12] proposed a muti-objective migratory birds optimization (MBO) algorithm based on the decomposition of the multi-objective flowshop rescheduling problem, which has proven to be better than other evolutionary algorithms. Zhang et al. [13] introduced lots of streaming into the hybrid flowshop scheduling problem with consistent sublots to fit the real-world scenarios, which verified the feasibility to solve the integrated scheduling problem with the hybrid flowshop. Li et al. [14] researched the distributed hybrid flowshop scheduling problem with sequenced dependent setup time, which was solved by a discrete artificial bee colony algorithm. Reddy et al. [15] solved a muti-objective problem in a flexible manufacturing system, which considered machine and vehicle scheduling. According to these studies in AS/RS and hybrid flowshop, most researchers have ignored the related effects. However, the connection between AS/RS and hybrid flowshop is important to develop smart manufacturing systems.

Problems with storage allocation, operation scheduling, and workshop scheduling are NP-hard problems that lead to low efficiency and time-consumption by using exact algorithms [16,17]. The intelligent optimization algorithm provides an effective and fast method for solving the above complex problems [18–20]. Li et al. [21] conducted a comprehensive survey of the learning-based intelligent algorithm. Katoch et al. [22] discussed the advances and introduced the pros and cons of GA. Duman et al. [23] proposed a new nature-inspired metaheuristic approach named MBO, which was proven to be an effective formation in energy saving. The algorithms of GA, MBO, and their improvement algorithms are used to solve the scheduling problems and achieve better performance. The scheduling objective in AS/RS is usually the total operation time, but it has a shortcoming by neglecting two situations. The first one is that the number of storage tasks is not equal to the number of retrieval tasks, and the other one is that retrieval arrival time needs to be considered in the connection of AS/RS and hybrid flowshop [24,25]. To obtain a better solution to the integrated scheduling problem in AS/RS and hybrid flowshop, the main contributions in this study include: (1) formulation of a bi-objective model to minimize the operation time in AS/RS and the makespan in the hybrid flowshop; (2) proposal of a two-stage mixed algorithm called GA-MBO that combines the strong global optimization ability of GA and the strong local search ability of MBO.

The structure of this paper is as follows: In Section 2, we described and modeled the integrated scheduling problem in AS/RS and hybrid flowshop. In Section 3, we designed the GA-MBO and presented the operation details. In Section 4, experiments were introduced in AS/RS and hybrid flowshop, and the results were analyzed to verify the effectiveness of the GA-MBO. Finally, Section 5 presents the conclusions.

2. Materials and Methods

2.1. Problem Description

AS/RS is an information technology based on the Internet of Things, which is widely used to store and retrieve materials without any human participation. An AS/RS mainly consists of racks, cranes, input/output (I/O) points, and conveyors. The system has a crane in each aisle and a main I/O point along a conveyor. The top view of the layout schematic diagram is shown in Figure 1. The redesign of the material distribution connection in the AS/RS and hybrid flowshop saves the storage area and lowers the handling cost of the production material. The crane can be used to realize the distribution between different tiers. Under the production conditions of the workshop, intelligent logistics equipment, such as conveyors and automatic guided vehicles (AGVs), can be used to distribute materials with JIT to achieve lean logistics. The material distribution problem with the connection between

the AS/RS and the hybrid flowshop is researched. The material distribution diagram is shown in Figure 2.

Figure 1. Layout schematic diagram of AS/RS. 1. Crane. 2. Rack. 3. Aisle. 4. Input point. 5. Conveyor. 6. Output point.

Figure 2. Material distribution diagram in AS/RS and hybrid flowshop.

The integrated scheduling problem in AS/RS and hybrid flowshop is related to the storage allocation, system scheduling, and flowshop scheduling. The objective of the scheduling problem is to minimize the total operation time in AS/RS and the makespan in hybrid flowshop. The research objects are AS/RS and multi-stage hybrid flowshop.

AS/RS can be described as: in a warehouse with a determined status that racks have X rows, Y columns, and Z tiers. The corresponding material locations are the O retrieval task locations, and the number of retrieval tasks is greater than the number of the retrieval material types. The free rack locations are the I retrieval task locations. These storage and retrieval tasks are operated by S cranes, whose operation time is related to task storage allocations (multi-tasks with the same material) and the task operation sequence. Hybrid flowshop can be described as: the O retrieval tasks with the same operation sequence are processed at the K stages. Stage k has $E_k > 1$ independent parallel machines. At this stage, the task processing time is related to both the task material type and the processing machine type. The end operation time of the retrieval task in AS/RS directly affects the starting time of the production task in the hybrid flow workshop scheduling.

In the scheduling of AS/RS, operation modes for storage and retrieval goods are: single command (SC) where the crane completes for storage task or retrieval task and double command (DC) where the crane completes for storage and retrieval tasks. The DC operation should be adopted to improve the efficiency in the system. At the same time, considering the deadline requirements of retrieval tasks, the SC has a shorter retrieval time.

In addition, the mixed command of SC and DC is researched in the operation scheduling problem, which exists under the assumption that the numbers of storage and retrieval tasks are unequal. These situations form a mixed scheduling sequence.

The alternation of storage and retrieval tasks leads to the dwell-point change that affects the task operation time. The location selections of storage and retrieval tasks affect the operation sequence, the system efficiency, and the end operation time of retrieval tasks. The retrieval sequence affects the product sequence and the production efficiency in the hybrid flowshop. This paper integrates and optimizes a batch of storage and retrieval tasks in AS/RS by determining the storage location so that the total operation time in AS/RS and the makespan in workshop production are minimized. Storage selection, task sequences, and production sequences need to be studied at the same time.

2.2. Problem Modelling

2.2.1. Assumption

In the integrated scheduling optimization problem in AS/RS and hybrid flowshop, the main assumptions to simplify the problem under research and the formulated model are:

- An AS/RS has X rows, Y columns, and Z tiers, and the rack coordinates of x row, y column, and z tier can be expressed as (x, y, z). The input point is at (0, 0, 1), and the output point is at $(X + 1, Y + 1, 1)$.
- In the AS/RS storage racks which have the same size. A rack stores one bin or one pallet, and the crane can only load one bin or one pallet at a time.
- The velocity of a crane in the horizontal direction is v_y and in the vertical direction is v_z. Movements in the two directions are independent. The start-up time and braking time of crane can be ignored, while the picking time for any location is fixed.
- The crane stays in position after the task is completed.
- Considering the storage period of the material in the warehouse, it is not allowed to directly check out without checking.
- The equipment failure is not considered during the operation, and the crane is not allowed to interrupt the task.
- The equipment processing in the hybrid flowshop doesn't consider production preparation time.
- The buffer in the equipment room has infinite capacity.

2.2.2. Notation

In order to describe the problem and build a model by a better way, the notations are as follows:

X	Number of rows, $x = 1, 2, \ldots, X$
Y	Number of columns, $y = 1, 2, \ldots, Y$
Z	Number of tiers, $z = 1, 2, \ldots, Z$
J	Number of racks, $j = 1, 2, \ldots, J$
ZJ	Material locations
L	Rack's length
W	Rack's width
H	Rack's high
U	Aisle's width
S	Number of cranes, $s = 1, 2, \ldots, S$
v_y	Velocity of the crane in the horizontal direction
v_z	Velocity of the crane in the vertical direction
C	Load/Unload time of crane
p	Material types, $p = 1, 2, \ldots, p$
N_p	Number of in stock materials p in stock, $n = 1, 2, \ldots, N_p$
I_p	Number of retrieval materials p in stock, $i = 1, 2, \ldots, I_p$
K	Number of production stages, $k = 1, 2, \ldots, K$
E_k	Number of machines at stage k, $e = 1, 2, \ldots, E_k$
T_{pke}	Operation time of material p at stage K in machine e

R_e	Transportation time of output point to machine e
Ω	Large positive number
st_{ns}	Start time of task n in crane s
ct_{ns}	End time of task n in crane s
st_{noke}	Start time of task n at output point o and stage k in machine e
ct_{noke}	End time of task n at output point o and stage k in machine e
α_{nj}	1 if the location of task n is j, otherwise is 0
$\beta_{nn's}$	1 if the task n completes before task n' in crane s, otherwise is 0
$\chi_{nn'ke}$	1 if the task n completes before task n' at stage k in machine e, otherwise is 0

2.2.3. Objective Function

The common operational efficiency in the AS/RS scheduling problem is to measure the operation time, and in the hybrid flowshop scheduling problem, to measure the makespan. The integrated scheduling optimization of these two scheduling problems presents a conflict that needs to be evaluated in model objects.

The crane operates retrieval tasks from the dwell point to the location of the retrieval task and then moves to the output point in the aisle, which becomes a new dwell point. The retrieval operation time of the crane at SC is:

$$ct_{ns} = st_{ns} + 2C + \max\left(\frac{(y_o - y_s)\cdot W}{v_y}, \frac{(z_o - z_s)\cdot H}{v_z}\right) + \max\left(\frac{y_o \cdot W}{v_y}, \frac{(z_o - 1)\cdot H}{v_z}\right) \quad (1)$$

The crane operates storage tasks from the dwell point to the aisle output point to pick up goods and then moves to the storage task location, which becomes a new dwell point. The storage operation time of the crane at SC is:

$$ct_{ns} = st_{ns} + 2C + \max\left(\frac{y_s \cdot W}{v_y}, \frac{(z_s - 1)\cdot H}{v_z}\right) + \max\left(\frac{y_o \cdot W}{v_y}, \frac{(z_o - 1)\cdot H}{v_z}\right) \quad (2)$$

In the DC operation of the crane, the dwell point of input is the output point, which reduces the operation time. The objective function of operation time in AS/RS is:

$$f_1 = \sum_{s=1}^{S} \max(ct_{ns}) \quad (3)$$

The end operation time is the task completion time at the last production stage in hybrid flowshop. The objective function of the makespan is:

$$f_2 = \max(ct_{noke}) \quad (4)$$

To eliminate the influence of different objective dimensions, the above two evaluation objective functions need to be normalized as:

$$f(x) = \frac{f(x) - \min f(x) + 0.001}{\max f(x) - \min f(x) + 0.001} \quad (5)$$

Normalization needs to determine the extreme value of the objective function. The researched problem is NP-hard and it is difficult to obtain the exact solution for which optimization can be obtained by the single-objective function. The weight coefficient method converts the multi-objective optimization into a single-objective description as:

$$F = w_1 \cdot f_1 + w_2 \cdot f_2 \quad (6)$$

The total operating time of the warehouse and the makespan in production are the two study targets of the study. The primary goal in enterprise management is to increase production efficiency, which is also called the makespan. Increasing the operational efficiency in AS/RS cannot directly improve production efficiency but can help to reduce operating

costs. Therefore, the weights of the two evaluated objectives are taken as $w_1 = 0.3$ and $w_2 = 0.7$.

2.2.4. Modelling

Based on the above descriptions, the integrated scheduling model of AS/RS and hybrid flowshop can be given as follows:

$$\min(F) = \min(w_1 \cdot f_1 + w_2 \cdot f_2) \tag{7}$$

which is subject to:

$$\sum_{j=1}^{X \cdot Y \cdot Z} \alpha_{nj} = 1 \tag{8}$$

$$ct_{noke} = st_{noke} + T_{pke}; (p = p_{no}) \tag{9}$$

$$st_{n's} \geq ct_{ns} - (1 - \beta_{nn's}) \cdot \Omega \tag{10}$$

$$st_{n'o'ke} \geq ct_{n'o'ke} - (1 - \chi_{nn'ke}) \cdot \Omega \tag{11}$$

$$st_{no'e} \geq ct_{ns} + R_s + \frac{(2S - 1) \cdot \left(L + \frac{U}{2}\right)}{v_x} \tag{12}$$

$$st_{no(k+1)e'} \geq ct_{noke}; (k \neq K) \tag{13}$$

Equation (7) indicates the bi-objective that contains the total operation time in AS/RS and the maximum makespan in production. Equation (8) represents that each task can only correspond to one position in racks. Equation (9) indicates the relationship between the start operation time and the end operation time of the retrieval tasks. Equations (10) and (11) each represent the constraints in the crane and production equipment at the start of the operation time of the next task and at the end of the operation time of the previous task. Equation (12) represents that the start operation time of the production task is larger than the arrival time of the production material. Equation (13) indicates that the production phase in which the start time of the next stage of the task is greater than or equal to the end time of the previous stage of the operation.

3. GA-MBO Design

Intelligent optimization algorithms are more suitable than accurate algorithms to solve NP-hard problems and are conducted to deliver fast solutions. GA is a classic intelligent optimization algorithm which has been widely used in production scheduling, combinatorial optimization, etc. To fix the poor local search ability of GA, this paper adopts the MBO algorithm which has high local search efficiency and outstanding convergence performance. GA-MBO algorithm is proposed to solve the integrated scheduling optimization problem in AS/RS and workshop.

The GA-MBO algorithm consists of three modules, including coding rules, GA rules, and MBO rules. The flow chart of the GA-MBO is shown in Figure 3. The following parameters are defined as: *NG* represents the number of populations in the GA phase; *Mgen* represents the number of iterations in the GA phase; *Pc* represents the probability of crossover; *Pm* represents the probability of mutation; *NM* is the number of flocks in the MBO phase; *a* represents the number of neighborhood solutions generated by an individual; *b* indicates the number of neighborhood solutions that each individual passes to the next individual; and *G* represents the number of tours.

Figure 3. Flow chart of GA-MBO.

3.1. Coding Rules

The real coding method is used to solve the problems, such as multiple storage locations in the AS/RS, various material types of storage and retrieval tasks, mixed operation of storage and retrieval tasks, and complex operation sequences of production tasks. The coding and the decoding mechanism are illustrated with the warehousing information in the AS/RS with 6 rows, 6 columns, and 5 tiers, which are shown in Table 1. The storage and retrieval tasks are numbered as shown in Figure 4. The storage racks are successively numbered with rows, columns, and tiers, starting from 1. The total number of racks is:

$$J = X \cdot Y \cdot Z \tag{14}$$

Table 1. The warehousing information.

Number of Retrieval Types	Number of Bins	Number of Storage Types	Number of Kins
1	2	3	4
2	3	4	2
3	2	5	3

	Retrieval tasks							Storage tasks								
Task number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Material number	1	1	2	2	2	3	3	3	3	3	3	4	4	5	5	5

Figure 4. Mixed storage and retrieval tasks and material numbers.

3.1.1. Coding

Considering that coding of rack locations, which is much longer than storage and retrieval tasks, increases the complexity of the algorithm and reduces the search efficiency, coding is performed mainly for the storage and retrieval tasks, as shown in Figure 5. The number of storage and retrieval tasks is used as the coding length, and the tasks are arranged in the order of execution. In the retrieval tasks, it is randomly selected from the corresponding material locations in AS/RS. In the storage tasks, it is randomly selected from the free locations in AS/RS.

Task number	8	4	6	11	10	3	15	5	2	14	1	16	13	12	9	7
Location number	78	67	18	86	133	5	46	8	61	24	2	104	113	25	138	134

Figure 5. Coding diagram.

3.1.2. Decoding

Each code represents the storage locations of the storage and retrieval tasks and the operation sequence in AS/RS. The code needs to be decoded to find the operation sequence of the crane and the production stage of the machines. The crane number is determined by the location number in multi-crane operations. The racks of a crane can store two rows, which are numbered as:

$$S = \left[\frac{j}{2Y \cdot Z}\right] + 1 \tag{15}$$

The decoding progress is:

Step 1: Determine the crane number by the location number in AS/RS and determine the task sequence by the task number to obtain the operation sequence in cranes.

Step 2: The total operation time of cranes is obtained by the end operation time of the task on each crane.

Step 3: The travel times of shelves in different rows to the production equipment are calculated based on the end operation time of the crane retrieval tasks in step 1 and obtain the arrival time from retrieval tasks to the production stage.

Step 4: According to the arrival time of the retrieval task to the production stage, the operation time sequence of tasks can be obtained by the rules of "First-Come-First-Service" of tasks, "First Idle", and "Capacity Priority" (workpiece processing time) of machines.

Step 5: The makespan is obtained by the end operation time of each task at the final production stage.

3.2. GA Rules

GA includes the operations of the population initialization, selection, crossover, and mutation. The population initialization method is randomly generated according to the encoding method. The selection mechanism is based on the elite reservation and the binary tournament selection mechanism. The crossover and mutation operations are needed because the coding method is two-layer coding. The operation tasks are allocated. The retrieval tasks are constrained by the corresponding material storage locations in AS/RS, and the storage tasks are constrained by the free locations in AS/RS.

3.2.1. Crossover

The main purpose of the GA phase is to obtain a better solution, which is to make full use of the global optimization performance of GA and to avoid the generation of useless solutions. Crossover is designed as follows: In retrieval tasks, an improved crossover operation that extracts the corresponding code in process coding is designed based on the type of material. In storage tasks, a uniform crossover operation that extracts partial code of different storage locations is adopted, which considers the same retrieval location under different solutions. After that, the extraction code is put back to the original solution's extraction position accordingly, and the specific process is shown in Figure 6.

Figure 6. Schematic diagram of the intersection of storage and retrieval tasks.

Useless solutions can be avoided by the above operations under the constraints of task locations. It is beneficial for the global search ability of the algorithm by fully adjusting the old solutions according to different cross operations of storage and retrieval tasks.

3.2.2. Mutation

The sequence of storage and retrieval tasks is generated by four mutation operations, namely random exchange, pre-insertion, post-insertion, and sequential pair exchange. The allocation of storage and retrieval tasks is designed by the single-point mutation and the exchange mutation. The single-point mutation randomly makes a location in a feasible location set of a task to mutate a new location that is not in the solution. The exchange mutation randomly exchanges the locations of two tasks in the set of retrieval tasks or the set of storage tasks of the same material in the solution.

3.3. MBO Rules

The MBO is a neighborhood search-based algorithm that performs a sufficient local search on the neighborhood of each solution, and it compensates for the deficiency of the GA's local search ability. In addition, the MBO algorithm can deeply explore the optimal solution at the late population convergence stage of the algorithm.

3.3.1. Neighborhood Structure Design

The neighborhood structure directly affects the MBO solution quality and the convergence speed of the algorithm. An efficient neighborhood structure needs to be identified. For the sequence of tasks, the formation of the sequence neighborhood structure considers random exchange, pre-insertion, post-insertion, sequence pair exchange, optimal insertion, and optimal exchange.

For the product allocation, the scale of the feasible storage location is larger than the scale of the feasible retrieval locations. Therefore, different operations are designed to construct different neighborhood structures for the storage and retrieval tasks.

- Neighborhood structure for retrieval tasks. A neighborhood structure based on an improved optimal exchange operation is designed. The process is to randomly select a retrieval task for its feasible location set, then delete the original location of the task from that set, and the number of operations is the number that feasible storage locations minus 1. If a storage location of other tasks in the code overlaps with the new feasible storage location of the indicated task, this storage location of other tasks needs to be replaced by the original location of the indicated task. The values of objective function values for these new individuals are calculated respectively and the most optimal one is chosen.
- Neighborhood structure for storage tasks. A neighborhood structure based on an improved optimal exchange operation is designed. In a retrieval task, a new location that is not in individual code is randomly selected from the free locations to replace the original location and the number of operations is the number of retrieval tasks. The values of objective function values for these new individuals are calculated respectively and the most optimal one is chosen.

3.3.2. Adaptive Adjustment of Neighborhood Structure

The total of eight neighborhood structures above present different search effects in the solution at different stages of the algorithm. At the early stage of the algorithm, the effect of the eight neighborhood structures to get better solutions is not much different, but the search efficiencies of random exchange, pre-insertion, post-insertion, and sequence pair exchange are higher, which improve the application frequencies. At the late stage of the algorithm, the two neighborhood structures based on optimal insertion, optimal exchange, and storage assignment are better than the other four structures. The application frequencies of these four structures should be increased. Therefore, an adaptive adjustment strategy is introduced to control the usage frequency of each structure during the search period to optimize the algorithm's efficiency.

Weight ω_0 is assigned to each neighborhood structure. The roulette method is used to randomly select the neighborhood structure according to the neighborhood structure weight ω_i to generate the neighborhood solution, and the weight is updated after each iteration. The adjust weight is contributed by:

$$\omega_{i,seg+1} = (1 - \eta_i) \cdot \omega_{i,seg} + \frac{\eta_i \cdot \beta_{i,seg}}{\alpha_{i,seg}} \tag{16}$$

where α_i is the number of times of structure i; β_i is the cumulative score of structure i. If the solution is better than the original solution generated by structure i, $\beta_i = \beta_i + 1$, $\eta_i \in [0, 1]$ is the speed of the response to the effect of structure i of weight ω_i.

4. Simulation Experiments

4.1. Test Examples

The algorithms for the integrated scheduling problem are coded in MATLAB2016a and run on the Intel i7-7700 k CPU with 16 GB memory. The operation process in an AS/RS of a manufacturing enterprise is used as an example to research the scheduling problem and is modified to obtain the experimental data. The production process consisted of an AS/RS and a hybrid flowshop. The AS/RS has 6 rows, 60 columns, and 15 layers, and the number of racks is 5400. The coordinates of the input point and the output point is (0, 0, 1) and (7, 61, 1). The parameters of each index are shown in Table 2. There are 30 kinds of materials in the system, and the quantity of each material is $N \in \mathrm{U}(30, 50)$; the types of storage and retrieval materials are $P \in \{5, 10, 15, 20\}$; the quantity of each material is $O_P \in \mathrm{U}(1, 5)$; the number of scheduling stages is $K \in \{3, 5, 7\}$; the number of machines was $E_k \in \mathrm{U}(2, 6)$; the material processing time is $T \in \mathrm{U}(10, 70)$; material weight is $M \in \mathrm{U}(10, 30)$, and the frequency of storage and retrieval is $f \in \mathrm{U}(1, 10)$. There are 12 groups of experiments set by the types of storage and retrieval materials and the number of scheduling stages. The data format $\mathrm{U}[x, y]$ represents a discrete uniform distribution between x and y.

Table 2. Each index parameter of the AS/RS.

Describe	Value
Rack length/width/high (m/m/m)	1/0.8/0.6
Velocity of the crane in the horizontal direction (m/s)	3
Velocity of the crane in the vertical direction (m/s)	1
Pick-up and set-down times of the crane (s)	5
Velocity of the conveyor (m/s)	0.5
Output point to production machine time (s)	60

4.2. Parameter Settings

The relevant parameters of the GA-MBO are *NG*, *Mgen*, *Pc*, *Pm*, *NM*, *a*, *b*, *G*. Some parameters of reference were set: $Pc = 0.8$, $Pm = 0.05$, $a = 3$, $b = 1$ [25,26]. It was found that this setting has a good effect on the solution of this paper by experiments. *NG*, *Mgen*, *NM*, and *G* are related to the problem scale. The corresponding Taguchi experiment was designed for the factor levels [27]. The parameter level table is shown in Table 3. Experiments are carried out with an example of $p = 10$, $K = 3$, and the algorithm is run 10 times independently under each combination of parameters. The maximum running time is $10(K+1) \cdot \sum_{p=1}^{P} \left(O_p + I_p\right) \cdot s$ [28]. The average values of 10 experimental results are taken as the response values, as shown in Table 4.

Table 3. Parameter level of GA-MBO.

Parameters	Level Value			
	1	2	3	4
NG	150	200	250	300
Mgen	100	150	200	250
NM	25	51	81	101
G	5	8	10	15

Table 4. Orthogonal matrix and response value.

Test Numbers	Parameters				Response Value
	NG	Mgen	NM	G	
1	150	100	25	5	0.09346
2	150	150	51	8	0.09180
3	150	200	81	10	0.08936
4	150	250	101	15	0.09304
5	200	100	51	10	0.09175
6	200	150	25	15	0.09232
7	200	200	101	5	0.09175
8	200	250	81	8	0.08790
9	250	100	81	15	0.09397
10	250	150	101	10	0.08947
11	250	200	25	8	0.08876
12	250	250	51	5	0.08636
13	300	100	101	8	0.09258
14	300	150	81	5	0.09072
15	300	200	51	15	0.08941
16	300	250	25	10	0.08974

The results under the combinations of parameters are analyzed by Minitab 17 in Figure 7, the parameter change trend diagram, and Table 5, the average response value. It can be seen the performance of the algorithm is the best when *NG* = 250, *Mgen* = 250, *NM* = 51, and *G* = 10. This parameter scheme is adopted in subsequent experiments.

Figure 7. The graph of parameter change trend.

Table 5. Response value of different parameters.

Level	NG	Mgen	NM	G
1	0.09191	0.09294	0.09107	0.09057
2	0.09093	0.09108	0.08983	0.09026
3	0.08964	0.08982	0.09049	0.09008
4	0.09061	0.08926	0.09171	0.09218
Delta	0.00227	0.00368	0.00188	0.0021
Rank	2	1	4	3

4.3. Algorithms Comparison

In the integrated scheduling optimization problem of AS/RS and hybrid flowshop, a comparison with the improved GA, improved particle swarm optimization (PSO) algorithm, and hybrid algorithm of GA and PSO (GA-PSO), the algorithm performance of GA-MBO is verified. With the NP-hard characteristics of the problem, the evaluation indexes, including average (Avg.) and the standard deviation (Std.), are solved by the repeated experiments of 10 times of the four algorithms. The Avg. is used to measure the efficiency and the Std. is used to measure the robustness of the algorithm. The 12 groups for the comparative analysis are shown in Table 6, which set the types of storage and retrieval materials $P \in \{5, 10, 15, 20\}$ and the number of scheduling stages in AS/RS $K \in \{3, 5, 7\}$. From Table 6, compared with three algorithms, including IGA, IPSO, and GA-PSO, it is obvious that GA-MBO has the most optimal solutions of Avg. and Std.

Table 6. Comparison results of four algorithms.

Group	p	K	GA-MBO		IGA		IPSO		GA-PSO	
			Avg.	Std.	Avg.	Std.	Avg.	Std.	Avg.	Std.
1		3	0.10159	0.00192	0.11131	0.00253	0.12152	0.00454	0.10707	0.00254
2	5	5	0.10440	0.00133	0.11919	0.00328	0.12981	0.00446	0.11451	0.00283
3		7	0.10805	0.00136	0.12076	0.00209	0.13058	0.00271	0.11423	0.00269
4		3	0.08701	0.00167	0.09689	0.00209	0.10896	0.00255	0.08997	0.00190
5	10	5	0.08678	0.00148	0.09920	0.00359	0.11416	0.00337	0.09318	0.00353
6		7	0.09021	0.00134	0.10475	0.00321	0.11856	0.00510	0.09533	0.00212
7		3	0.09872	0.00142	0.10968	0.00232	0.12371	0.00688	0.10662	0.00196
8	15	5	0.10328	0.00140	0.11177	0.00211	0.12789	0.00466	0.10536	0.00263
9		7	0.10548	0.00141	0.11464	0.00202	0.12960	0.00244	0.11135	0.00312
10		3	0.09766	0.00148	0.10865	0.00243	0.12666	0.00330	0.10449	0.00205
11	20	5	0.10741	0.00136	0.11451	0.00212	0.12855	0.00512	0.11194	0.00341
12		7	0.11153	0.00286	0.11568	0.00257	0.13227	0.00262	0.11306	0.00365

To display the promotion of the GA-MBO more clearly, the optimization results by comparing with other algorithms are shown in Table 7. In Table 7, the experimental results of IGA, IPSO, and GA-PSO show that: (1) compared with IGA, IPSO, and GA-PSO, GA-MBO, the optimization efficiencies are achieved at 13.88% in Group 6, 23.98% in Group 5, and 8.83% in Group 2, and the average promotions are 9.48%, 19.53%, and 5.12%, respectively; (2) in Group 12, the GA-MBO is not as stable as IGA and IPSO; (3) compared with IGA, IPSO, and GA-PSO, GA-MBO, the optimization robustness are achieved at 59.45% in Group 2, 79.36% in Group 7, and 60.12% in Group 11, and the average promotions are 35.16%, 54.42%, and 39.38%, correspondingly. Although the robustness of GA-MBO is poor in Group 12, it is much better in other groups, and the average value is much higher. Therefore, it is still considered that the GA-MBO has the best robustness.

The T-test uses t-distribution theory to infer the probability of difference and compare whether the difference between two averages is significant. In the test examples, the normally distributed data are assumed, and the operation time is 10 in each group. The t-test is studied to test the statistical difference of the GA-MBO with other three algorithms, and the confidence is 0.95. The results are shown in Table 8. In Table 8, the values of upper confidence and lower confidence between GA-MBO and other algorithms are negative and within the confidence interval, which verifies the effectiveness of the GA-MBO. The advantage of GA-MBO is further proved by indicating that the Avg. of the optimal solution of GA-MBO is stably better than other algorithms again.

Table 7. The optimization efficiency and robustness of algorithms.

Group	OE_1 [1]	OE_2 [2]	OE_3 [3]	OR_1 [4]	OR_2 [5]	OR_3 [6]
1	8.73%	16.40%	5.12%	24.11%	57.71%	24.41%
2	12.41%	19.57%	8.83%	59.45%	70.18%	53.00%
3	10.53%	17.25%	5.41%	34.93%	49.82%	49.44%
4	10.20%	20.15%	3.29%	20.10%	34.51%	12.11%
5	12.52%	23.98%	6.87%	58.77%	56.08%	58.07%
6	13.88%	23.91%	5.37%	58.26%	73.73%	36.79%
7	9.99%	20.20%	7.41%	38.79%	79.36%	27.55%
8	7.60%	19.24%	1.97%	33.65%	69.96%	46.77%
9	7.99%	18.61%	5.27%	30.20%	42.21%	54.81%
10	10.12%	22.90%	6.54%	39.09%	55.15%	27.80%
11	6.20%	16.44%	4.05%	35.85%	73.44%	60.12%
12	3.59%	15.68%	1.35%	−11.28%	−9.16%	21.64%
Average promotion	9.48%	19.53%	5.12%	35.16%	54.42%	39.38%

[1] OE_1 is the optimization efficiency promotion of the GA-MBO relative to IGA. It is calculated as OE_1 = (IGA Avg. − GA-MBO Avg.)/IGA Avg. [2] OE_2 is the optimization efficiency promotion of the GA-MBO relative to IPSO. [3] OE_3 is the optimization efficiency promotion of the GA-MBO relative to GA-PSO. [4] OR_1 is the optimization robustness promotion of the GA-MBO relative to IGA. It is calculated as OR_1 = (IGA Std. − GA-MBO Std.)/IGA Std. [5] OR_2 is the optimization robustness promotion of the GA-MBO relative to IPSO. [6] OR_3 is the optimization robustness promotion of the GA-MBO relative to GA-PSO.

Table 8. T-test of optimal solution between GA-MBO and other algorithms with confidence of 0.95.

Group	GA-MBO~IGA		GA-MBO~IPSO		GA-MBO~GA-PSO	
	Upper Confidence	Lower Confidence	Upper Confidence	Lower Confidence	Upper Confidence	Lower Confidence
1	−0.01212	−0.00765	−0.02377	−0.02014	−0.00496	−0.00097
2	−0.01305	−0.00893	−0.03178	−0.02622	−0.00868	−0.00498
3	−0.01298	−0.00894	−0.03000	−0.01999	−0.00968	−0.00614
4	−0.01186	−0.00758	−0.02290	−0.01697	−0.00799	−0.00299
5	−0.01522	−0.00962	−0.02981	−0.02494	−0.00933	−0.00347
6	−0.00903	−0.00517	−0.02496	−0.01732	−0.00748	−0.00159
7	−0.01038	−0.00662	−0.02766	−0.02157	−0.00425	0.00008
8	−0.01740	−0.01218	−0.02887	−0.02195	−0.01250	−0.00772
9	−0.01724	−0.01184	−0.03249	−0.02421	−0.00703	−0.00321
10	−0.00752	−0.00077	−0.02246	−0.01902	−0.00511	0.00204
11	−0.01102	−0.00730	−0.02622	−0.02202	−0.00814	−0.00361
12	−0.01476	−0.01067	−0.02468	−0.02039	−0.00819	−0.00417

To find the iteration situation of these algorithms, the convergence comparisons between the GA-MBO and other three algorithms are carried out with the calculation example of p = 10 and K = 3 as shown in Figure 8. In Figure 8, the abscissa is the iteration times of the four algorithms, and the ordinate is the value of objective function which calculated by the algorithms. The optimal solution of the GA-MBO is the best among the other three algorithms when the iteration is greater than 276, and the iteration tends to be flat when the iteration is greater than 350, which means the GA-MBO can find a best value of objective function. Based on the above analysis, the GA-MBO is superior to IGA, IPSO, and GA-PSO in terms of the efficiency and robustness of the solution.

Figure 8. Iteration diagrams of four algorithms.

4.4. Bi-Objective Comparison

To verify the superiority of the integrated scheduling optimization of AS/RS and hybrid flowshop, three experiments with p = 10 and K = 3 are tested and compared. Objectives of these experiments are operation time in AS/RS, makespan in hybrid flowshop, and the bi-objective. The results are shown in Table 9, which shows that while f_2 only changes 4.43%, f_1 has a 26.34% improvement. This condition is more suitable for the actual production which concerns the total profit and reflects the superiority of the integrated scheduling optimization.

Table 9. Comparison of results between bi-objective optimization and single objective optimization.

Objective	Value	Variation	Value	Variation
f_1	609.8	22.77%	595.4	−38.72%
f_2	997.6	−26.34%	410.2	4.43%
f_1 and f_2	789.6	None	429.2	None

5. Conclusions

In this paper, considering the combination of distribution and production, the study of the integrated scheduling problem of AS/RS and hybrid flowshop is conducted to establish an integrated scheduling optimization model with the bi-objective of minimizing the total operation time and makespan. A mixed optimization algorithm of GA-MBO combining the global optimization performance and search capability of GA with a strong local search ability of the MBO algorithm is proposed to improve the efficiency and robustness of the algorithm solution.

In a simulation case of an AS/RS with 5400 storage locations, the model and algorithm of repeat experiments were verified by a comparison of commonly intelligent algorithms with GA-MBO. The experimental results of IGA, IPSO, and GA-PSO show that the average promotions of efficiencies are 9.48%, 19.53%, and 5.12% and the average promotions of robustness are 35.16%, 54.42%, and 39.38%, correspondingly. Comparative analysis of the bi-objective verified the superiority of integrated scheduling optimization. This verification helps to coordinate the scheduling in warehouse distribution and workshop production to reduce distribution costs. The gap in the integrated scheduling optimization of AS/RS and the hybrid flowshop is filled.

At present, the rapid development of intelligent warehousing systems makes the AS/RS and hybrid flowshop closely connected. The integrated scheduling optimization problem of the AS/RS and hybrid flowshop is one of the problems in the integrated AR/RS and hybrid flowshop, which should be solved to build a complete intelligent factory, and it is a critical problem facing the intelligent factory. The collaboration between machines

and between the AS/RS and hybrid flowshop are hard to realize, and the system cannot be actually used in the research [29].

The devices have the effect factors of energy consumption, delivery waste, machine handling time, and maintenance when operated in the AS/RS and hybrid flowshop. In the future, a corresponding optimization model in the scheduling problem should be established by introducing factors that further conform to the real production situation. In addition, different structures of AS/RS and hybrid flowshop as well as different types and numbers of AGVs and cranes may also be researched to adapt the development of the flexible manufacturing workshop and enhance the efficiency.

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