ITC 4/53
Information Technology and Control
Vol. 53 / No. 4/ 2024
pp. 997-1015
DOI 10.5755/j01.itc.53.4.37410

Flexible Job Shop Scheduling Optimization with Machine and AGV Integration Based on Improved NSGA-II

Received 2024/05/23 | Accepted after revision 2024/08/01

HOW TO CITE: Liu, Y., Huang, T., Chen, Y., Liu, L., Guo. (2024). Flexible Job Shop Scheduling Optimization with Machine and AGV Integration Based on Improved NSGA-II. *Information Technology and Control*, 53(4), 997-1015. https://doi.org/10.5755/j01.itc.53.4.37410

Flexible Job Shop Scheduling Optimization with Machine and AGV Integration Based on Improved NSGA-II

Yong Liu
School of Automation and Information Engineering, Sichuan University of Science and Engineering, Zigong, China
School of Automation Engineering, University of Electronic Science and Technology of China, Chengdu, China

Tao Huang
School of Automation and Information Engineering, Sichuan University of Science and Engineering, Zigong, China

Yong Chen
School of Automation Engineering, University of Electronic Science and Technology of China, Chengdu, China

Li Liu, Tao Guo
School of Automation and Information Engineering, Sichuan University of Science and Engineering, Zigong, China

Corresponding author: Yong Liu, liuyong_cdut@sina.com

Aiming at the problem of integrated scheduling of machines and AGVs in a flexible job shop, this paper constructs a scheduling model with the optimization objectives of minimizing the maximum completion time, minimizing the machine load, and minimizing the total energy consumption. This model is based on a comprehensive consideration of the payload time and no-load time of AGVs between the loading and unloading stations and the machining machines. An improved NSGA-II algorithm is proposed to address this problem. The algorithm adopts a three-level coding structure based on processes, machines, and AGVs, and employs differentiated cross-variation strategies for different levels to enhance its global search capability. A variable domain search algorithm is introduced to boost the local search capability by combining different neighborhood search methods within the three-level coding structure. Additionally, reverse individuals are introduced to improve the elite retention strategy, thereby increasing the diversity of the population. Ultimately, the case test results demonstrate that the improved NSGA-II algorithm exhibits superior performance in solving the flexible job shop scheduling problem involving AGVs, and the effect of the number of AGVs on the scheduling objectives conforms to the law of diminishing marginal utility.

KEYWORDS: Flexible job shop, multi-targeting, integrated machine and AGV scheduling, NSGA-II, VNS.

1. Introduction

With the rapid development of the manufacturing industry and the diversification of market demands, the scheduling of workpieces and the reasonable cooperation between various equipment in the workshop is a key issue in the operation process of a flow shop, so the classical shop scheduling problem (JSP) has been widely studied and applied. In the past few decades, the flexible workshop has gradually become an important part of the modern manufacturing system, which not only includes various processing equipment such as milling machines and lathes, but also conveyor belts, distribution vehicles, AGVs, etc., for which various heuristic algorithms have been proposed to improve the effective coordination of equipment in the assembly line manufacturing workshop. Nowadays, when resources and energy become the focus topic, more and more factory companies consider reducing power consumption as an important indicator of production cost. Therefore, there is an urgent need to balance energy consumption reduction and cost reduction while maximizing production benefits in the shop floor. Therefore, effective integrated scheduling of these devices is crucial for improving production efficiency, shortening production cycle time, and reducing costs [4]. Numerous scholars have carried out in-depth studies on this issue, which not only cover the selection of processing equipment and the optimization of processing sequence, but also include the path planning and scheduling strategy of AGVs, aiming at achieving the optimal integrated scheduling of processing and distribution resources [6], but do not consider the optimization of multi-objectives.

Gu et al. [7] proposed an improved memetic algorithm (IMA) considering the transport time of workpieces between machines and the start-stop operation of machines, designing a multiple initialization rule to improve the quality of the initial population, and integrating four improved variable neighborhood search strategies and two energy-saving strategies during the optimization process in order to enhance the searching capability and reduce energy consumption. Wen et al. [15] proposed an effective hybrid algorithm for the multi-AGV flexible job shop scheduling problem, which achieves global optimization by constructing an optimization model, designing a high-quality initialization method and an improved elitist strategy, as well as integrating the key techniques of problem knowledge-driven neighborhood search. Zhang et al. [18] designed a mixed-integer linear programming model by creating an improved NSGA-II algorithm, and the improved algorithm adopts a local search operation based on critical paths and an improved congestion distance calculation method to reduce the computational complexity of the algorithm. Liu et al. [9] created a dual-resource scheduling optimization model for machine tools and AGVs, and enhanced the local search ability and quality of the algorithm by designing an improved genetic algorithm to solve the scheduling problem of flexible job shops using segmented AGVs, with the aim of minimizing the maximum completion time. Amirteimoori et al. [1] proposed a combination of mixed-integer linear programming model and Parallel Hybrid Particle Swarm Optimization-Genetic Algorithm (PPSOGA) method, which fully considers the actual situation of multiple AGVs, different processing routes and job re-entry, and utilizes parallel computing to significantly improve the operation efficiency of the algorithm.

In summary, most of the studies are aimed at completion time optimization, but in the integrated scheduling process, with the diversification of the machines and equipment involved in scheduling, such as machine energy consumption and other factors are also factors to be considered. Therefore, this paper constructs a scheduling model that minimizes the three objectives of maximum completion time, machine load and energy consumption, and proposes a hybrid algorithm of NSGA-II and VNS. A variable neighborhood search algorithm is introduced through three layers of real number coding of workpieces, machines and AGVs, and six targeted domain search strategies are designed for these three layers of coding to enhance the local search capability of the algorithm. An improved reverse elite retention strategy is used to prevent the loss of individuals with better potential and to maintain population diversity.

2. Methodology

2.1. Description of the Problem

The flexible job shop machine and AGV integration scheduling problem is an extension of the FJSP and can be defined as “A job shop with m machining machines $M=\{M_1,M_2,M_3,\dots,M_m\}$ needs to perform machining on n workpieces $J=\{J_1,J_2,J_3,\dots,J_n\}$, and the workpiece transfer process is handled by v AGVs $V=\{V_1,V_2,V_3,\dots,V_v\}$ and the transfer process of the workpieces is handled by v AGVs $V=\{V_1,V_2,V_3,\dots,V_v\}$. Each workpiece J_i is subjected to a series of operations $\{O_{i1},O_{i2},O_{i3},\dots,O_{in_i}\}$, where n_i is the number of operations for workpiece J_i. Each machining operation $O_{ij}\,(i=1,2,\dots,n;\, j=1,2,\dots,n_i)$ of the workpiece has to be processed by one of a given set of machines $M_{ij}\subseteq M$, and when the previous process is finished, it is then transferred by the AGV to the machine that is going to process the next process."

In the machining operation and AGV integrated scheduling of the machine tool in the flexible workshop, it is necessary to select the appropriate machine tool, and an AGV is also required to transfer the workpiece in an orderly manner in order to better handle each processing operation of each workpiece. The problem involves determining both the processing sequence of the workpieces, as well as the sequence of operations of the machines and the transfer sequence of the AGVs. It consists of three sub-problems: the operation sequence problem, the machining machine selection problem, and the AGV transfer order problem. In studying this problem, the following assumptions are made:

1. The components of the dispatching shop are: loading and unloading area, workpieces to be processed, processing machines and AGVs.
2. All workpieces and machining machines are available at the same time at time zero and both workpieces and AGVs are in the loading area at time zero.
3. The workpiece is independent, and each processing machine can only process one workpiece at a time.
4. Different operations on a workpiece cannot be performed simultaneously.
5. Operations must be performed in order of priority to each other, and each process must be processed after the previous process has been completed.
6. Each operation cannot be interrupted during processing.
7. Machine interruptions are ignored.

2.2. Mathematical Model

Mathematical models are constructed based on the flexible job shop machine and AGV scheduling problem description, and the definitions of each mathematical model symbol are listed in Table 1.

Table 1

Parameter definitions

parameters	define
m	Total number of machines
n	Total number of workpieces
v	Total number of AGVs
i	Serial number of workpiece
j	Work process number
k	Machine Model
a	AGV No.
n_i	Number of processes for the ith workpiece
O_{ij}	The jth process of workpiece i
C_i	Time of transportation of workpiece i to the loading area after completion of the last process
S_{ijk}	Start time of machining of process O_{ij} on machine k
C_{ijk}	End time of machining of process O_{ij} on machine k
T_{ijk}	Machining time of process O_{ij} at machine k
NST_{ija}	Start time of unloaded trip at AGV handling process $O_{i,j-1}$ of AGV No. a
NET_{ija}	End time of unloaded trip at AGV handling process $O_{i,j-1}$ No. a
LST_{ija}	Starting time of load travel for AGV No. a handling process $O_{i,j-1}$.
LET_{ija}	End time of load travel at AGV handling process $O_{i,j-1}$ of AGV No. a
$AT_{kk'}$	AGV transfer time between machines k and k'
H_{ijk}	Idle time of process O_{ij} at machine k
P_{ijk}	Processing power of process O_{ij} at machine k
P_{Hijk}	Idle power of process O_{ij} on machine k
X_{ijk}	If 1, then process O_{ij} is processed on machine k
Y_{ijghk}	If it is 1, it means that O_{ij} is processed on machine k after O_{gh} is processed on machine k.
Z_{ija}	If it is 1, then it means that process O_{ij} is completed by AGV a for transit

Construct a scheduling model with the minimization of three objectives: maximum completion time, machine load and energy consumption as the optimization index. And use Pareto method to solve the model optimization.

1 Minimize the maximum completion time

$$\min C_{\max} = \min\left[\max\left(\sum_{i=1}^{n} C_i\right)\right] \quad (1)$$

2 Minimize machine load

$$\min T_{work} = \sum_{i=1}^{n}\sum_{j=1}^{n_i}\sum_{k=1}^{m} X_{ijk} T_{ijk} \quad (2)$$

3 Minimize total energy consumption

$$\min E = \min\left(\sum_{i=1}^{n}\sum_{j=1}^{n_i}\sum_{k=1}^{m} P_{ijk} \times T_{ijk} \times X_{ijk}\right) + \min\left(\sum_{i=1}^{n}\sum_{j=1}^{n_i}\sum_{k=1}^{m} P_{Hijk} \times H_{ijk} \times \left(1 - X_{ijk}\right)\right) \quad (3)$$

The constraints are as in Equation:

Equation (4) indicates that a process can be machined on only one machine

$$\sum_{k=1}^{m} X_{ijk} = 1 \quad (4)$$

Equations (5)-(6) indicate that there is at most one immediately preceding or following process for each process

$$\sum_{i=1}^{n}\sum_{j=1}^{n_i}\sum_{k=1}^{m} Y_{ijghk} \le 1 \quad (5)$$

$$\sum_{g=1}^{n}\sum_{h=1}^{n_g}\sum_{k=1}^{m} Y_{ijghk} \le 1. \quad (6)$$

Equation (7) indicates that only one workpiece can start the next process only after completing the previous process

$$S_{ij} + T_{ij} \le S_{i(j+1)}. \quad (7)$$

Equation (8) indicates that a machine can process only one process at a time

$$S_{ijk} \ge S_{ghk} + Y_{ijghk} \times T_{ghk}. \quad (8)$$

Equations (9)-(10) represent the start and end times of the AGV when it is in an unloaded state

$$NST_{ija} = \sum_{a=1}^{v}\left(LET_{ija} \times Z_{ija}\right) \quad (9)$$

$$NET_{ija} = NST_{ija} + \sum_{a=1}^{v}\sum_{k=1}^{m}\sum_{k'=1}^{m}\left(AT_{kk'} \times X_{i(j-1)k} \times Z_{ija}\right). \quad (10)$$

Equations (11)-(12) represent the start and end times during the AGV load state

$$LST_{ija} = \max\left(\sum_{a=1}^{v}\left(NET_{ija} \times Z_{ija}\right), C_{i(j-1)k}\right) \quad (11)$$

$$LET_{ija} = LST_{ija} + \sum_{a=1}^{v}\sum_{k=1}^{m}\sum_{k'=1}^{m}\left(AT_{kk'} \times X_{ijk} \times Z_{ija}\right). \quad (12)$$

3. Algorithm Design

3.1. Encoding and Decoding

In the flexible job shop scheduling problem, considering the emergence of process sequencing, equipment assignment and AGV assignment problems, this paper adopts a three-layer coding method based on process, equipment and AGV. In genetic algorithms, because FJSP contains three sub-questions, chromosomes contain three gene segments. OS segment: corresponding to the process sequencing in workshop scheduling; MS: Corresponding to machine assignment problems; AS section: AGV assignment for workpiece transfer. Each has a different way of encoding.

The OS segment represents the process order of the workpieces, and the length of the string represents the sum of all the workpieces. In this representation, each gene of the chromosome represents the ith artifact number, and by scanning the OS segment sequentially from left to right, the first occurrence of the artifact number indicates the first operation of the artifact. The initial process sequencing population is randomly generated according to the coding principle.

The MS segment then indicates the machine model selected for the corresponding operation of each workpiece. The gene segment contains n parts, the ith part denotes the set of selected machines for the operation corresponding to workpiece i, where each gene denotes the selected model of the machine for a fixed operation. The AS segment and the MS segment are represented in a similar way, where each gene denotes the selection of the AGV for each process. Thus, a solution consists of an OS segment, an MS segment, and an AS segment, and all three segments are of the same length.

Table 2 shows the data for this example, which consists of 4 jobs and 4 machines (each job contains 2 operations). The numbers in the table indicate the processing time of the process on the different processing machines, and "-" indicates that the process may not be processed on this processing machine.

Table 2

Examples of FJSP problems

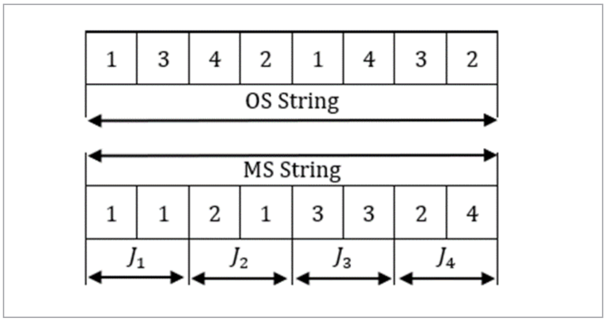
workpieces	process	Machines and processing times			
		M_1	M_2	M_3	M_4
J_1	O_{11}	—	4	1	6
	O_{12}	1	5	—	4
J_2	O_{21}	3	—	4	1
	O_{22}	4	7	6	7
J_3	O_{31}	2	—	1	6
	O_{32}	3	1	4	2
J_4	O_{41}	5	2	—	3
	O_{42}	2	1	3	4

Figure 1 shows a chromosome. It contains three gene segments. the OS segment is an unpartitioned arrangement with repeating operation numbers. Because there are four jobs, each containing two operations, the OS segment is an arrangement of two 1's, two 2's, two 3's, and two 4's, and it has a length of 8. The MS segment contains four parts because there are four processed artifacts, and it also has a length equal to 8, with each gene denoting the model of the machine selected for each process. The AS segment and the MS segment have the same coding rule, denoting the process responsible for the transfer of each AGV An example of the process sequence is provided in Figure $O_{11}\rightarrow O_{31}\rightarrow O_{41}\rightarrow O_{21}\rightarrow O_{12}\rightarrow O_{42}\rightarrow O_{32}\rightarrow O_{22}$.

The machine code is an integer value, and the integer value is equal to the index of the optional machine candidate value set by the operation. For the coding individual in Figure 1, the machine code corresponding to the machine segment is shown in Figure 2, the machine

Figure 1

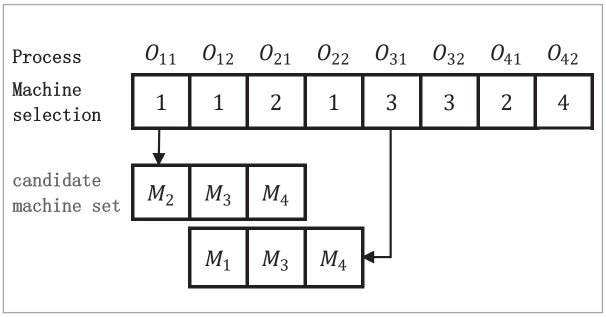
FJSP chromosome coding



selection of process O_{11} is 1, indicating that the processing machine of process O_{11} is the first set of candidate machines, and it can be seen from Figure 2 that the candidate machine set of process O_{11} is {M2,M2,M}, that is, its processing machine is M_2, and the processing machine of process O_{31} is M_4 in the same way.

Figure 2

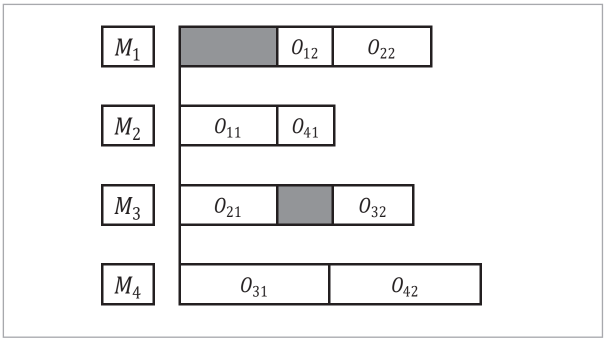
Machine code



The decoding process can transform the chromosome into a scheduling solution based on coded information and coding rules, which is generally represented as a Gantt chart [8]. In this paper, we use an insertive greedy decoding strategy that considers the machine idle time in order to generate an active scheduling solution that maximizes the use of machine resources.

The decoding strategy records the processing time period of each machine first, when the workpiece needs to be processed, the machining machine also has an idle time period, judges whether the idle time period meets the processing time requirements of the workpiece, and then judges whether the greedy plug-in decoding strategy is effective by judging whether inequality 7 is true. The decoded Gantt chart in Fig-

Figure 3
Machine code



ure 1 is shown in Figure 3. This approach helps to optimize the maximum completion time, increase machine utilization and reduce energy losses.

3.2. Hereditary Operator

It is important to use good genetic operators to deal with this problem efficiently and to produce good individuals in the population efficiently [12]. Genetic operators can be generally categorized into three types: selection, crossover and mutation [3]. In this paper, chromosomes contain three gene segments: the OS segment, the MS segment and the AS segment, each with its own genetic operator.

In the algorithm of this paper, the selection operation is mainly based on fast non-dominated sorting and congestion distance sorting. In fast non-dominated sorting, all individuals in the population are first sorted according to their fitness values, and then starting from the non-dominated frontier, the individuals are selected sequentially into the next generation of the population. In this process, the probability of each individual being selected is proportional to its fitness value. Individuals who are well adapted and away from crowded distances are more likely to be selected for the next generation of the population. The selection operation is a combination of multiple strategies, which ensures the optimization of the algorithm and the efficiency of the search.

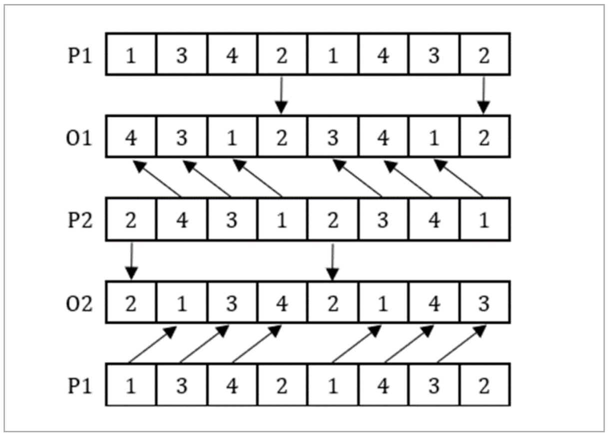
Precedence operation crossover (POX) is used for the OS part. The basic workflow of POX is described as follows (the two parents are denoted as P1 and P2; the two children are denoted as O1 and O2).

Step 1: Several artifacts are randomly selected as job1 in the parent generation;

Step 2: All elements in P1 belonging to Job1 are added to the same position in O1 and deleted in P1; all elements in P2 belonging to Job1 are added to the same position in O2 and deleted in P2;

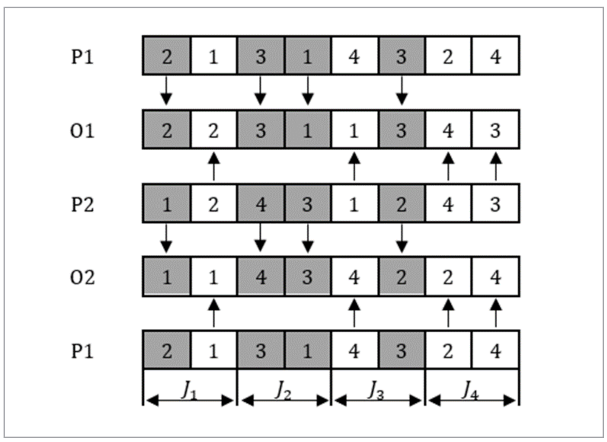
Step 3: The remaining elements in P2 are sequentially added to the remaining empty positions in the O1 sequence; the remaining elements in P1 are sequentially added to the remaining empty positions in the O2 sequence.

Figure 4
Priority operation crossover



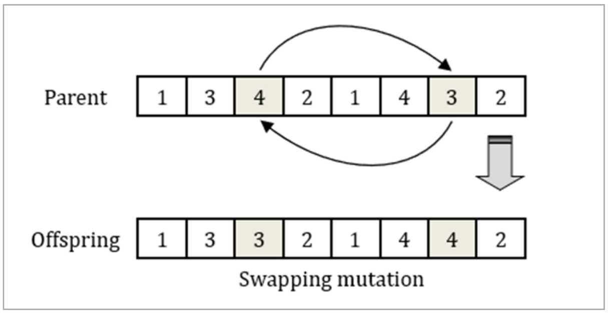
Since MS and AS segments are encoded in a similar way, the same crossover, mutation operator is used. Since each gene in this string represents the machine or AGV selected to perform the fixation operation, if the selected parent is viable throughout the crossover and mutation process, then the offspring produced by the crossover and mutation operations are also viable.

Figure 5
Two-point crossover



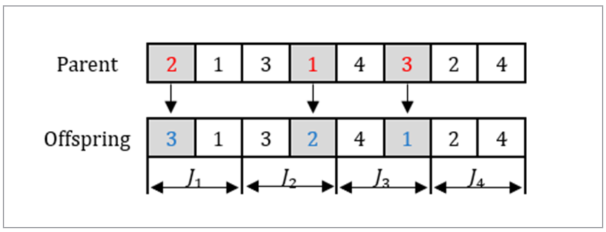
The basic working process of exchange mutation is shown in Figure 6, whereby a new zygote is produced by exchanging any two genes on the paternal chromosome.

Figure 6
Exchange mutations



The mutation operation in the MS and AS parts is to randomly generate several process positions that require mutation operations, the number of which is not more than half of the length of the string, and mutate them into other machines or AGVs that can be selected. The 1st, 4th and 6th positions are selected as shown in Figure 7, which represent the machines or AGVs selected for O11, O22, and O32, and a new offspring is generated by changing the value of these positions into the machine in the corresponding operation another machine or AGV in the set.

Figure 7
Machine code variation



3.3. Introduction of Variable Neighborhood Search Algorithm

In order to improve the local search ability and solve the comprehensive scheduling problem of multi-objective optimization in the later stage of the algorithm, a variable neighborhood search [14] (VNS) is introduced which designs six kinds of targeted neighborhood search strategies for the workpieces, machines, and AGVs, respectively, and combines them into eight actions.

1: Target the neighborhood structure of the workpiece:

O1: Randomly select two neighboring positional work processes and insert them into any position in reverse order; O2: randomly delete several processes, and then insert them into the process code segment in the order of deletion.

2: for the machine's neighborhood structure:

M1: randomly select a process for a machine with the smallest processing time; M2: randomly select a process, change the machine of the process to the one with the smallest energy consumption.

3: For the neighborhood structure of AGV:

A1: Randomly select two neighboring processes and exchange the serial numbers of the AGVs they are responsible for transferring. A2: Randomly select a process and replace the AGV with another AGV.

The pseudocode is as follows:

```
#Algorithm initialization
1. Select an initial solution
   X_best
2. Specify a list of neighborhood structures
   Y=[Y_1,Y_2,...,Y_k]
3. Establish a stop rule
4. Set neighborhood index
   i=1
   #Main loop
5. While(the stop guidelines):
      Local search
         X_local_best= part(X_best,Y_1)
      Check to see if you find a better solution
         If(f(X_local_best)<f(X_best)):
            X_best=X_local_best
6. Updates the current neighborhood index I=
(I mod |Y|)+1
#Pull the plug
7. Output the optimal solution X_best
```

Table 3
Domain structure combination actions

a1	a2	a3	a4	a5	a6	a7	a8
O1 M1 A1	O1 M1 A2	O1 M2 A1	O1 M2 A2	O2 M1 A1	O2 M1 A2	O2 M2 A1	O2 M2 A2

3.4. Improved Elite Retention Strategies

NSGA-II's cross-variance operator has a certain effect on preventing the algorithm from falling into local optimum [13], and an improved elite retention strategy is now adopted. For each generation of the elite population, the individuals with better performance are retained, but for the several individuals at the end of the dominance ranking, their reverse individuals are generated, and the original individuals are replaced if the new individuals dominate.

In order to ensure the convergence of the algorithm, the number of generated individuals decreases with the number of iterations, and the direction of the generated number of individuals is shown in Equation (13).

$$Rn = N \times \left[\min \Pr + \left(\max \Pr - \min \Pr \right) \times \frac{G-g}{G} \right], \quad (13)$$

where N denotes the population size; minPr denotes the lower limit of the reverse generation ratio; maxPr denotes the upper limit of the reverse generation ratio; G denotes the maximum number of iterations; and g denotes the current number of iterations.

The reverse operation is performed only for the OS segment, and its operation steps are as follows:

Step 1: Randomly select several genes in the OS section of the chromosome;

Step 2: Determine the reverse operation, i.e., O`i(S)=n+1-Oi(S). Where Oi(S) the value of the gene without reverse operation, O`i(S) is the new value obtained after reverse operation and n is the number of artifacts;

Step 3: Perform the reverse operation on the gene selected in step 1 and store the values before and after the reverse operation in the sets M and N, respectively;

Step 4: Finding the location of the gene in the OS segment that agrees with the value of the set N;

Step 5: replacing the genes found in step 4 sequentially after randomly ordering the values of set M.

3.5. Algorithmic Flow

INSGA-II introduces the VNS algorithm into the local search process of NSGA-II and proposes a new elite retention strategy. The algorithm flow of INSGA-II is shown in Figure 8. Its specific steps are as follows:

Step 1, Generate an initial population containing 100 individuals, each of which represents a potential solution.

Step 2, Calculate the fitness. For each individual, calculate its fitness in the objective function space, including maximum completion time, machine load and energy consumption.

Step 3, Fast non-dominated ranking. Determine the non-dominated rank of each individual.

Step 4, Crowding degree calculation. Measure the density of individuals in the objective space.

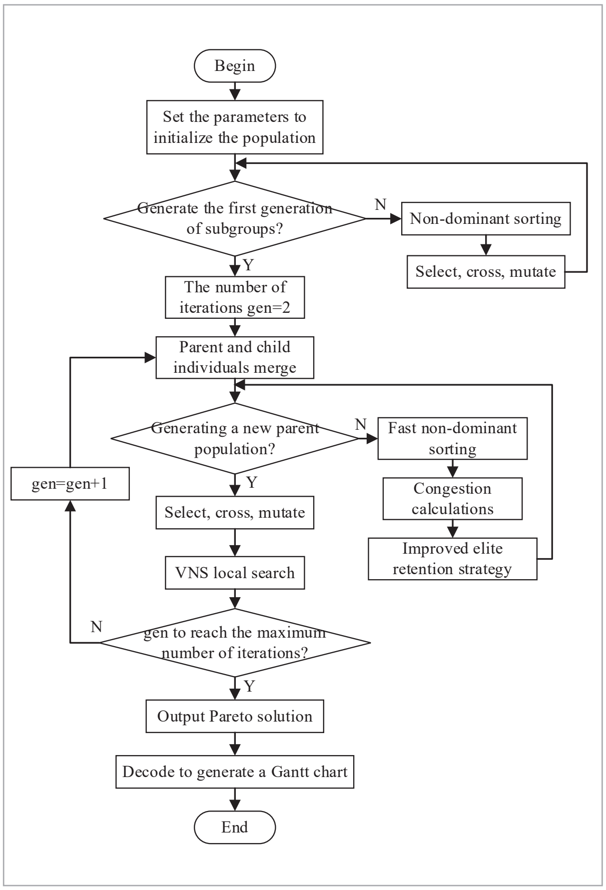
Step 5, Perform selection, crossover, and mutation operations on individuals to increase the diversity of the population.

Step 6, Variable neighborhood search. In the local search range, eight neighborhood structures were systematically constructed.

Step 7, merge the child and parent populations and judge whether the termination condition is satisfied, if it is satisfied, it ends, otherwise it jumps to Step 2.

Figure 8

Algorithm flowchart



4. Simulation Test and Analysis

4.1. Parameter Settings

In the optimization process of NSGA-II, the convergence speed of the algorithm and the coverage ability of the search space can be effectively balanced by reasonable adjustment of parameters, so as to improve the performance and convergence accuracy of the algorithm. Therefore, this paper cites the moderately sized MK01 dataset from the Brandimarte benchmark algorithm and designs orthogonal experiments to determine the algorithm parameters. In this paper, the main parameters to improve the NSGA-II algorithm are: population size popsize, iteration number gen, crossover probability Pc, mutation probability Pm, lower limit of reverse generation ratio Pr_min, upper limit of reverse generation ratio Pr_max, determining that the population size is 100, the number of iterations is 100, and setting three levels for the latter four parameters, and the values of each level are shown in Table 4.

Table 4
Table of parameter levels

parameters	standards		
	1	2	3
Pc	0.6	0.7	0.8
Pm	0.1	0.15	0.2
Pr_min	0.1	0.15	0.2
Pr_max	0.7	0.75	0.8

Since there are 4 parameters and 3 levels, L9 (34) orthogonal table is chosen to design the experiment. The algorithm is run 10 times under 9 parameter combinations, and IGD (inverted genera-tional distance) is used as the evaluation index, and the smaller value of IGD indicates that the corresponding combination of parameter levels is solved more efficiently. The table of orthogonal experiments is shown in Table 5, each number in the table indicates the parameter level selection, such as parameter combination 2, the values of Pc, Pm, Pr_min and Pr_max are 1, 2, 3 and 2, respectively, and the actual values of Pc, Pm, Pr_min and Pr_max are 0.6, 0.15, 0.2 and 0.75, respectively, according to Table 4.

Table 5
Table of orthogonal experiments

Parameter combinations	standards				IGD
	popsize	gen	Pc	Pm	
1	1	1	1	1	50.03
2	1	2	3	2	35.22
3	1	3	2	3	52.36
4	2	1	3	3	55.02
5	2	2	2	1	48.78
6	2	3	1	2	31.09
7	3	1	2	2	55.75
8	3	2	1	3	38.68
9	3	3	3	1	23.02

Table 5 shows the experimental results of the improved algorithm running 10 times under each parameter combination, from the table it can be seen that the ninth parameter combination has the smallest IGD value, which indicates that the Pareto optimal solution set obtained under this parameter combination has better convergence and diversity, so the initial population size of the algorithm is set to 100, the maximum number of iterations is set to 100, the crossover probability is set to 0.8, the variance probability is set to 0.2, the reverse generation ratio lower limit is 0.2 and direction generation ratio upper limit is 0.7.

4.2. Algorithm Performance Validation

For the flexible job shop machine and AGV integration scheduling optimization, a total of 18 datasets were used in this paper, 9 datasets from the Brandimarte benchmark algorithm MK01-MK09 and 9 datasets from the Dauzère-Pérès benchmark algorithm 01a-18a are used as examples [2, 5], and sets the objectives to minimize the maximum completion time, minimize the machine load, and minimize the total energy consumption.The transfer time of AGVs in the loading and unloading area and between each machine is shown in Table 6, and the idle energy consumption of each machine and the machining energy consumption are shown in Table 7.

Table 6
AGV transit times

Time	LU	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
LU	0	2	1	1.5	1.2	1.6	2	0.4	0.8	0.4	1.2
M1	2	0	1.8	0.6	1.2	2.4	1.8	0.6	1.2	1.8	1.2
M2	1	1.8	0	1.2	1.8	0.6	2.4	1.8	1.8	1.2	1.2
M3	1.5	0.6	1.2	0	0.6	1.2	1.2	1.8	1.8	2.4	0.6
M4	1.2	1.2	1.8	0.6	0	2.4	0.6	2.4	1.2	1.8	1.2
M5	1.6	2.4	0.6	1.2	2.4	0	1.2	1.8	1.2	1.8	0.6
M6	2	1.8	2.4	1.2	0.6	1.2	0	0.6	1.8	1.2	0.6
M7	0.4	0.6	1.8	1.8	2.4	1.8	0.6	0	2.4	0.6	1.2
M8	0.8	1.2	1.8	1.8	1.2	1.2	1.8	2.4	0	1.2	2.4
M9	0.4	1.8	1.2	2.4	1.8	1.8	1.2	0.6	1.2	0	1.8
M10	1.2	1.2	1.2	0.6	1.2	0.6	0.6	1.2	2.4	1.8	0

Table 7
Machine energy consumption

Energy consumption	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Operate	1.65	1.50	2.25	1.66	0.80	1.45	1.88	0.62	1.76	1.54
Leisure time	0.12	0.25	0.10	0.15	0.25	0.11	0.20	0.13	0.22	0.30

Based on the traditional NSGA-II., the improved algorithm in this paper puts forward the idea of improving the elite retention strategy and introducing variable neighborhood search, and compares the performance of the traditional NSGA-II., only improving the elite retention strategy, introducing only the variable neighborhood search algorithm and the improved algorithm in this paper. As shown in Tables 8 and 9, the 9 datasets of MK01-MK09 and the 9 datasets of 01a-18a were run independently for 20 times, and the average value of the 3 optimization targets obtained by each dataset was 3 and the number of AGVs was 3. As can be seen from the table, the improved NSGA-II algorithm is significantly better than the traditional NSGA-II algorithm and the (IGA-PSO) [17] hybrid optimization algorithm in the optimization of the two objective functions of machine load and completion time, which is mainly due to the local search ability of variable neighborhood search. However, due to the mutual constraints of the optimization objectives, the improved NSGA-II algorithm is unable to take the minimum value of the objective function of maximum completion time, but the degree of backwardness is not large, and this differentiation is gradually reduced as the solution scale of the algorithms increases. Overall, the improved algorithm in this paper is a suitable algorithm for solving multi-objective FJSP compared to other algorithms.

A more detailed introduction to INSGA-II is given by taking the MK02 dataset in Table 8 as an example of a 10×6 FJSP problem instance, i.e., the problem represents 10 workpieces to be processed that need to be processed in an orderly manner on 6 machines. Taking 3 transfer AGVs as an example, the scheduling Gantt chart of INSGA-II for this 10×6 FJSP problem is shown in Figure 9, in which the machine processing time period is labeled with a combination of workpiece number and process number, and the AGV

Table 8

Algorithm performance comparison 1

data set		MK01	MK02	MK03	MK04	MK05	MK06	MK07	MK08	MK09
		10*6	10*6	15*8	15*8	15*4	10*15	20*5	20*10	20*10
NSGA-II	F_1	56.4	54.9	250	103	196.4	158.6	180.9	572	456.3
	F_2	155	159	919	333	677	413	694	2519	2339
	F_3	141.9	127.6	741.2	285.3	609.1	369.1	536.4	2131	1867.5
NSGA-II+i-elitism	F_1	57.7	54.9	257	104	191.8	135.6	188.5	582.4	447.3
	F_2	153	152	930	337	678	370	680	2515	2353
	F_3	141.7	113.7	751.3	277.7	608.9	359.3	514.2	2150.7	1872.1
NSGA-II+VNS	F_1	56	56	244	107.2	194.1	126.2	209.6	570.4	447.1
	F_2	163	146	865	338	678	334	658	2531	2265
	F_3	150	112.3	728.5	278	608.2	308.5	482.7	2143.4	1787.1
IGA-PSO	F_1	56	53	250	103.6	194.6	132.2	185.5	570.2	433.6
	F_2	153	143	865	342	677	345	667	2523	2272
	F_3	141.7	112.3	733	278.3	608.6	309.8	482.3	2115.7	1787.6
INSGA-II	F_1	59.9	52.2	253	103.4	195.4	131.8	184.7	563.9	423.8
	F_2	153	142	865	348	675	342	677	2529	2279
	F_3	141.6	111	730	277.3	608.6	308.2	480.6	2105.8	1787.8

Table 9

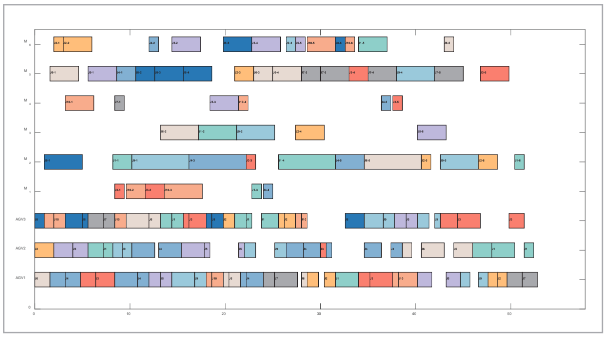
Algorithm performance comparison 2

data set		01a	02a	06a	07a	08a	12a	13a	14a	18a
		10*5	10*5	10*5	15*8	15*8	15*8	15*8	20*10	20*10
NSGA-II	F_1	3095	2989	2856	3308	3298	3300	3756	3785	3587
	F_2	11137	11137	10892	16485	16485	15966	21610	21610	20963
	F_3	8877	8175	7880	12581	11285	11250	17365	17252	15623
NSGA-II+i-elitism	F_1	2910	2909	3030	3388	3288	3265	3658	3642	3486
	F_2	11137	11137	10874	16485	16485	15966	21610	21610	20963
	F_3	8791	8199	7760	12600	11290	11158	17256	17158	15598
NSGA-II+VNS	F_1	2894	2926	2857	3221	3220	3258	3592	3652	3472
	F_2	11137	11137	10855	16485	16485	15966	21610	21610	20963
	F_3	8808	8050	7669	12522	11198	11160	17158	16252	15536
IGA-PSO	F_1	2898	2971	2792	3210	2998	3168	3526	3560	3452
	F_2	11137	11137	10852	16485	16485	15966	21610	21610	20963
	F_3	8821	8109	7650	12596	11185	11123	17123	16195	15506
INSGA-II	F_1	2878	2902	2793	3197	2999	2970	3504	3525	3473
	F_2	11137	11137	10845	16485	16485	15966	21610	21610	20963
	F_3	8805	8058	7761	12520	11185	11125	17103	16187	15519

transfer time period is only labeled with the workpieces it transfers, and a blank labeling implies that the AGVs are unloaded at that time. The three target optimal values of this scheduling result are maximum completion time 52.8, machine load 149, and total energy consumption 111.765.

Figure 9

MK02 Example Scheduling Gantt Chart



The convergence curves of the maximum completion time, machine load and total energy consumption of the NSGA-II algorithm with different improvement strategies for solving this scheduling problem are shown in Figures 10-12. As can be seen from the figures, under the same parameter settings, the improvement strategy combined with VNS effectively balances the global search and local search in the optimization process. On this basis, the integration

Figure 10

Maximum completion time convergence curve

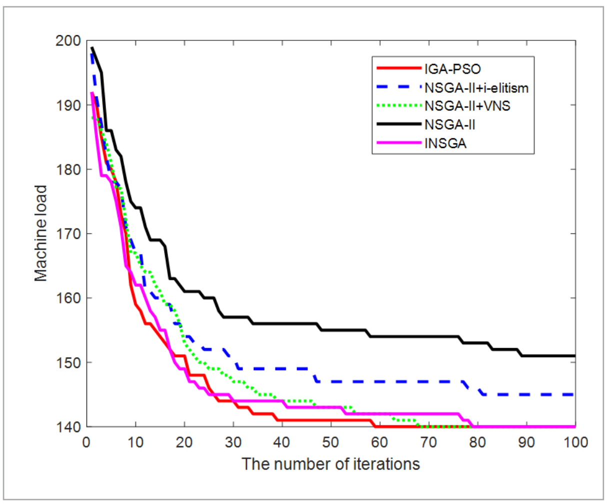


Figure 11

Machine load convergence curve

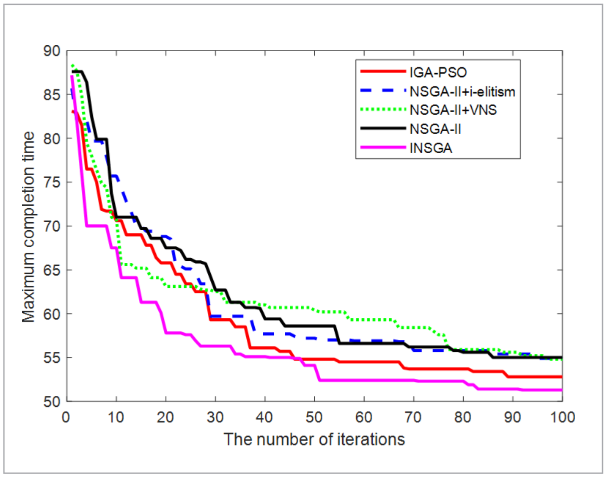
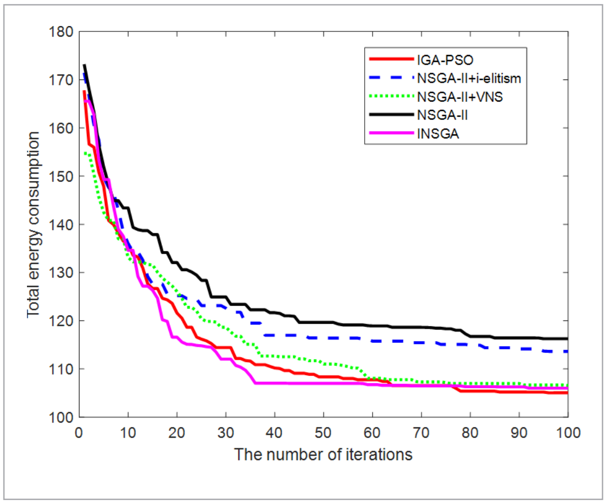


Figure 12

Convergence curve of total energy consumption

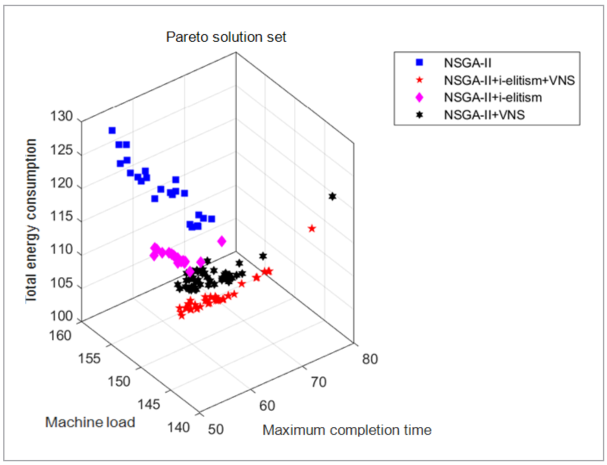


of the improved elite retention strategy enables the algorithm to find a better solution in a shorter iteration period, which further improves the convergence speed and convergence accuracy of the algorithm, and verifies the effectiveness of the improved strategy in this paper. Compared with the optimization ability of other algorithms to solve the three objectives, the average completion time of the improved NSGA-II algorithm is 20 times smaller than that of other algorithms, 5.13% less than that of IGA-PSO algorithm, and 8.21% less than that of traditional NSGA-II, so INSGA-II is more suitable for solving the optimal solution in complex systems. Comparing the machine load of the five algorithms, according to Figure 9, the machine load of the improved NSGA-II algorithm is 10.71% higher than that of the traditional NSGA-II algorithm and 12.85% higher than that of the IGA-PSO algorithm when the same number of iterations is 70 times. The improved NSGA-II. algorithm has a large improvement in completion time and machine load, but it is higher than other algorithms in terms of energy consumption, which is mainly due to the constraints of the three-objective optimization.

Figure 13 shows the Pareto front of each algorithm, from which it can be seen that the Pareto front of NSGA-II has a wider distribution of the solution set, showing its diversity in the three objectives, but does not have a better convergence in the later stages of the iteration. The algorithm incorporating VNS, on the other hand, has a clear distribution concentrated closer to the origin of the three axes, indicating the effectiveness of VNS in exploring the solution space. The improved elite retention strategy makes the algorithm in combination with VNS closer to the region of the best optimization direction, further proving the effectiveness of the improved strategy in this paper.

Figure 13

Pareto Frontier Distribution



4.3. Evaluation Indicators

In multi-objective optimization, it is often necessary to compare and evaluate the performance of different algorithms [10]. Commonly used evaluation metrics include Hypervolume (HV), Spacing and C-metric.

1 The HV metric measures the volume of the region consisting of the non-dominated solution set generated by the algorithm with a reference point (usually an ideal point) [11]. A larger value of hypervolume means that the solution set not only covers a larger region, but is better distributed in the target space.

2 The Spacing metric is used to measure the uniformity of the distribution of distances between individuals in the solution set. Ideally, a good solution set should be evenly distributed across the target space. The expressions are shown in Equations (14)-(15).

$$Spacing(U) = \sqrt{\sum_{c=1}^{|U|} \frac{\left(d_{2c} - \bar{d}\right)^2}{|U|-1}} \quad (14)$$

$$d_{2c} = \min_{U^g \in U, U^c \neq U^g} \left(\sum_{g=1}^{|U|} \left| U^c - U^g \right| \right), \quad (15)$$

where there is the minimum Manhattan distance between the first solution in the solution set; is the mean of all; is the first solution in the solution set.

3 The C-metric, also known as the coverage metric, is used to measure the degree to which a solution in one solution set dominates a solution in another solution. It is usually expressed as a value from 0 to 1, with 1 indicating that one solution set completely dominates the other. The expression is shown in Equation (16).

$$C(A,B) = \frac{\left|\{b \in B \mid \exists a \in A : a \succ b\}\right|}{|B|}, \quad (16)$$

where:there is the value of solution set A covering solution set B; a and b are any one of the solutions in solution sets A and B, respectively; |B| is the number of solutions in solution set B.

Table 10 is the table of three performance evaluation indexes of traditional NSGA-II and different improved strategy algorithms after normalization, in which C-metric only evaluates the mutual domination between traditional NSGA-II and other three improved algorithms. From the table, it can be seen that the HV metric of the improved algorithm in this paper is much higher than that of the traditional NSGA-II, indicating that the explored solution space is more comprehensive. INSGA-II spacing indicators. Higher

Table 10
Table of performance evaluation indicators

	INSGA-II	IGA-PSO	NSGAII+i-elitism	NSGAII+VNS	NSGA-II
HVmark	0.98	0.92	0.47	0.80	0.20
Spacingmark	0.042	0.049	0.058	0.057	0.033
Improvements - traditional	1.00	1.00	0.79	0.92	—
Traditional-improved	0	0	0	0	—

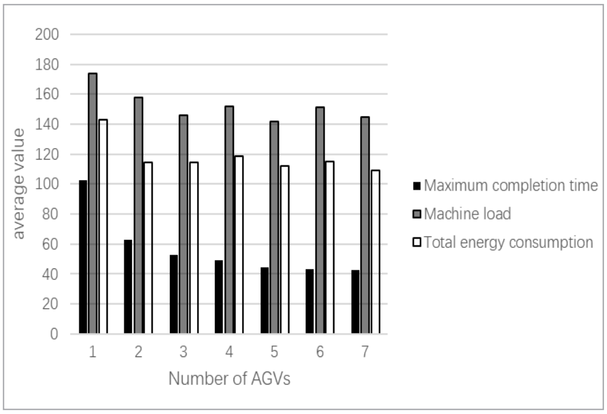
than conventional NSGA-II. The spacing index of INSGA-II is higher than that of the traditional NSGA-II, but lower than that of the algorithm of the single improved strategy, which indicates that the solutions in the Pareto solution set are more evenly distributed in the target space.

4.4. Analysis of the Relationship Between the Number of AGVs and Scheduling Objectives

In order to study the effect of the change of AGV number on the scheduling target, this paper is based on the MK02 arithmetic example, take different AGV numbers for independent testing, take the average of 20 times results to study the change of three scheduling targets, and the obtained results are shown in Figure 14.

During AGV deployment in a flexible job shop, as the number of AGVs increases, a significant reduction in the maximum completion time in the job shop can initially be observed, reflecting the direct impact of adding AGVs on improving productivity. However, the additional benefit on maximum completion time reduction gradually decreases as the number of AGVs continues to increase. This phenomenon can be attributed to the law of diminishing marginal utility, which states that as resource inputs increase, the contribution of each additional unit of resource to total utility gradually decreases. In this scenario, while more AGVs can still improve efficiency, the efficiency gains from each additional AGV become smaller. Considering the high cost of AGVs, it becomes especially critical to accurately determine the number of AGVs in order to maximize cost-effectiveness. This requires finding an optimal balance between resource input and output efficiency to ensure that the input-output ratio is optimized.

Figure 14
Effect of the number of AGVs on the value of the objective function



5. Results and Discussion

5.1. A Piston Ring Manufacturing Workshop Production Information

The Piston Ring Fabrication Shop is a crucial part of the manufacturing process for automotive or other internal combustion engine equipment, where the quality of the piston rings directly affects the performance and reliability of the internal combustion engine. In this shop, a range of highly sophisticated machinery and equipment are used to create and mold metal materials into piston rings that can withstand extremely high pressures and temperatures. CNC lathes, CNC grinders, CNC milling machines and other equipment are utilized to provide the necessary precision and efficiency to the machining process. Every aspect of the piston ring manufacturing process requires meticulous planning and operation. For example, the heat treatment process enhances the hardness and wear resistance of piston rings, while the surface treatment process improves the surface finish and corrosion resistance of piston rings. Quality control is carried out throughout the production process, with rigorous inspection and testing to ensure that each piston ring meets specifications.

In order to further verify the applicability of the improved algorithm, the optimization of the scheduling scheme is carried out with the production information of a piston ring manufacturing workshop. The workshop has a total of 8 machining machines and 2 AGVs, and has received a task order for the machining of 14 types of piston rings with different specifications, each of which has several machining processes. Combined with the task requirements and the optimization objectives of completion time, machine load and total energy consumption, the integrated scheduling of the machines and AGVs makes a scheduling plan that meets the requirements. Table 10 shows the transportation time of AGVs between 8 machining machines in the workshop, LU is the workpiece loading and unloading area, which is also the starting position of AGV transportation. Table 11 shows the rated and unloaded power of the 8 machining machines. Table 12 shows the machining processes of the batch of workpieces and the optional machining machines for each process and their machining times.

Table 11

AGV transportation time

Time/min	LU	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
LU	0.0	2.1	3.2	2.2	2.5	2.4	2.5	1.7	2.4
M_1	2.1	0.0	2.4	2.3	2.3	2.2	2.1	2.2	2.3
M_2	3.2	2.4	0.0	2.2	2.5	2.4	2.3	2.5	2.5
M_3	2.2	2.3	2.2	0.0	1.8	2.2	2.4	2.2	2.2
M_4	2.5	2.3	2.5	1.8	0.0	2.3	2.4	2.2	2.3
M_5	2.4	2.2	2.4	2.2	2.3	0.0	2.5	2.5	2.5
M_6	2.5	2.1	2.4	2.2	2.3	2.5	0.0	2.3	2.3
M_7	1.7	2.2	2.5	2.2	2.2	2.5	2.3	0.0	2.4
M_8	2.4	2.3	2.5	2.2	2.3	2.5	2.3	2.4	0.0

Table 12

Machine processing power

Unit /kW	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
Machine type	Automatic grinding machine	Automatic grinding machine	Automatic grinding machine	Semi-automatic grinding machine	Semi-automatic grinding machine	Semi-automatic grinding machine	Profiling lathe	Profiling lathe
Rated power	20	20	20	12	12	12	15	15
unloaded power	3.45	3.45	3.45	1.58	1.58	1.58	2.82	2.82

Table 13
Workpiece processing time

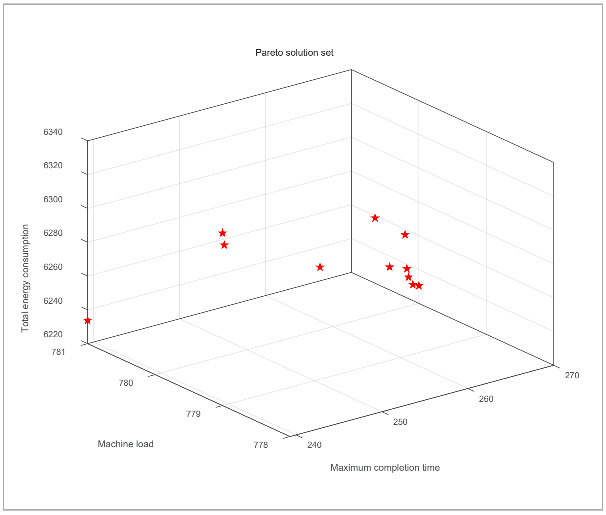
workpieces	process	Processing time for each processing machine /min							
		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
J_1	O_{11}	20	25	24	—	—	—	—	—
	O_{12}	—	—	—	18	24	23	—	—
	O_{13}	—	—	—	—	—	—	22	23
J_2	O_{21}	—	—	—	31	25	22	—	—
	O_{22}	—	—	—	—	—	—	24	23
J_3	O_{31}	24	—	26	—	—	—	—	—
	O_{32}	—	—	—	22	23	34	—	—
	O_{33}	—	—	—	—	—	—	23	17
J_4	O_{41}	22	24	22	—	—	—	—	—
	O_{42}	—	—	—	21	24	23	—	—
	O_{43}	—	—	—	—	—	—	25	23
J_5	O_{51}	23	25	22	24	—	—	—	—
	O_{52}	—	—	—	—	—	—	24	31
J_6	O_{61}	24	26	31	—	—	—	—	—
	O_{62}	—	—	—	22	32	24	—	—
	O_{63}	—	—	—	—	—	—	23	27
J_7	O_{71}	22	24	22	—	—	—	—	—
	O_{72}	—	—	—	18	24	23	—	—
	O_{73}	—	—	—	—	—	—	24	23
J_8	O_{81}	23	15	22	—	—	—	—	—
	O_{82}	—	—	—	18	24	23	—	—
J_9	O_{91}	24	16	32	—	—	—	—	—
	O_{92}	—	—	—	22	23	24	—	—
	O_{93}	—	—	—	—	—	—	23	27
J_{10}	O_{101}	20	24	22	—	—	—	—	—
	O_{102}	—	—	—	21	24	23	—	—
	O_{103}	—	—	—	—	—	—	24	23
J_{11}	O_{111}	24	16	34	—	—	—	—	—
	O_{112}	—	—	—	24	23	24	—	—
	O_{113}	—	—	—	—	—	—	25	28
J_{12}	O_{121}	20	24	24	—	—	—	—	—
	O_{122}	—	—	—	21	24	17	—	—
	O_{123}	—	—	—	—	—	—	28	29
J_{13}	O_{131}	—	—	—	24	16	35	—	—
	O_{132}	—	—	—	—	—	—	22	23
J_{14}	O_{141}	—	—	—	20	25	22	—	—
	O_{142}	—	—	—	—	—	—	21	24

5.2. Optimal Scheduling Program

Based on the production information of this piston ring manufacturing plant, 100 iterations of the INSGA-II algorithm were utilized to obtain Pareto non-dominated solution sets in terms of the three scheduling objectives: completion time, machine load and total energy consumption. These solution sets exhibit the spatial distribution of the scheduling solutions, as shown in Figure 15.

Figure 15

Pareto non-dominated solution set



Each Pareto nondominated solution represents a scheduling solution, but in actual shop floor scheduling, only a set of optimal solutions will be selected. Therefore, this section uses gray correlation analysis [6] to select from multiple nondominated solutions in the set of Pareto nondominated solutions to provide scheduling solution support to decision makers.

Grey correlation analysis can help to analyze the degree of association between multiple factors through the dimensionless quantification of data, correlation coefficient calculation, and correlation calculation, so as to provide a scientific basis for decision-making. The specific steps are as follows:

1 Data discretization

Data dimensionless is to transform the data of each indicator into a dimensionless form, so as to facilitate the comparison and analysis between different indicators. as shown in the specific formula (17).

$$\xi_{i,j} = \frac{\left| f_{i,j} - f_j^* \right|}{f_j^*}. \quad (17)$$

2 Calculation of gray correlation coefficient

The correlation coefficient between the indicators is calculated, and the correlation coefficient reflects the degree of correlation between the two serials, which is calculated according to the similarity and fluctuation degree between the serials, as shown in Equation (18).

$$\eta_{i,j} = \frac{\xi_j^{\min} + \rho \xi_j^{\max}}{\xi_{i,j} + \rho \xi_j^{\max}}. \quad (18)$$

3 Gray correlation calculation

The grey correlation calculation is used to measure the degree of correlation between each indicator and the research object, and through comparison, it can reflect the degree of influence of each indicator on the research object, determine which factors have a greater impact, and provide a reference basis for further analysis and decision-making, the specific formula is as follows.

$$\overline{\lambda_j} = \frac{1}{n} \sum_{i=1}^{n} \eta_{i,j} \quad (19)$$

$$\lambda_j = \frac{\overline{\lambda_j}}{\sum_{j=1}^{m} \overline{\lambda_j}} \quad (20)$$

$$\omega_i = \sum_{j=1}^{m} \left(\eta_{i,j} \cdot \lambda_j \right). \quad (21)$$

Gray correlation analysis was performed on the Pareto non-dominated solution set, where m=3 and n=11, as follows.

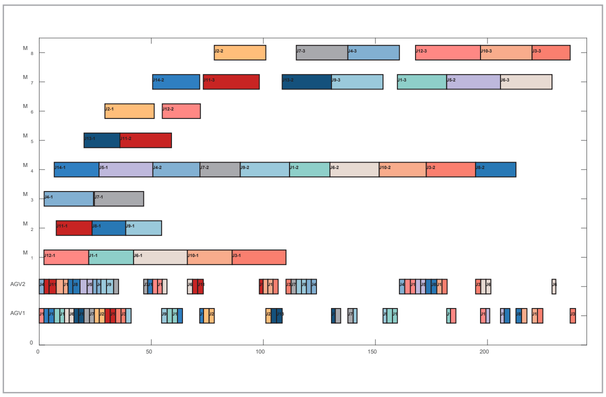
$$f = \begin{bmatrix} 239.3 & 779 & 6322.1 \\ 239.3 & 781 & 6233.8 \\ 239.5 & 779 & 6314.7 \\ 249.2 & 778 & 6335.7 \\ 252.7 & 778 & 6321.0 \\ 252.9 & 778 & 6300.6 \\ 253.1 & 778 & 6295.4 \\ 253.6 & 778 & 6290.3 \\ 254.3 & 778 & 6288.6 \\ 258.5 & 780 & 6257.2 \\ 266.6 & 780 & 6246.2 \end{bmatrix} \quad \xi = \begin{bmatrix} 0.000 & 0.001 & 0.014 \\ 0.000 & 0.004 & 0.000 \\ 0.001 & 0.001 & 0.013 \\ 0.041 & 0.000 & 0.016 \\ 0.056 & 0.000 & 0.014 \\ 0.057 & 0.000 & 0.011 \\ 0.058 & 0.000 & 0.010 \\ 0.060 & 0.000 & 0.009 \\ 0.063 & 0.000 & 0.009 \\ 0.080 & 0.003 & 0.004 \\ 0.114 & 0.003 & 0.002 \end{bmatrix} \quad \eta = \begin{bmatrix} 1.000 & 0.600 & 0.366 \\ 1.000 & 0.333 & 1.000 \\ 0.986 & 0.600 & 0.386 \\ 0.580 & 1.000 & 0.333 \\ 0.505 & 1.000 & 0.369 \\ 0.501 & 1.000 & 0.433 \\ 0.497 & 1.000 & 0.453 \\ 0.488 & 1.000 & 0.474 \\ 0.476 & 1.000 & 0.482 \\ 0.416 & 0.429 & 0.685 \\ 0.333 & 0.429 & 0.804 \end{bmatrix} \quad (21)$$

$$\lambda = [0.323 \quad 0.401 \quad 0.276]^T \tag{23}$$

$$\omega = [0.665 \; 0.733 \; 0.666 \; 0.680 \; 0.665 \; 0.682 \; 0.686 \; 0.689 \; 0.688 \; 0.495 \; 0.501]^T, \tag{24}$$

where f is the data matrix of the optimal solution set of the 11 groups of Pareto three objectives, is the dimensionless data matrix, is the gray scale correlation coefficient matrix, is the weight coefficient matrix, is the gray correlation matrix, and is the gray correlation matrix, and the larger the gray correlation value is, the better the scheduling scheme is. From the gray correlation matrix, it can be seen that group 2 has the largest correlation value, which corresponds to the completion time of the scheduling scheme is 239.3, the total energy consumption is 781, and the machine load is 6,233.8, and the Gantt chart of this scheduling scheme is shown in Figure 16. From the figure, it can be seen that the scheduling scheme can make balanced decisions in terms of completion time, machine load and energy consumption, and it can also allocate the carrying time of each AGV in a more reasonable way, so that the loading time of each AGV is relatively close to each other, and improve the efficiency of the use of AGVs.

Figure 16
Gantt chart of optimal decision-making



6. Conclusion

Aiming at the problem of integrated scheduling of machines and AGVs in flexible job shop, this paper establishes a scheduling model with the optimization objectives of minimizing the maximum completion time, minimizing the machine load, and minimizing the total energy consumption, and proposes an improved NSGA-II algorithm. In order to better solve the problem of simultaneous scheduling of machine and AGV, a three-layer coding structure based on process, processing machine and AGV was designed. In order to solve the problem of poor diversity of NSGA-II. solution set and easy to fall into local optimum, an improved elite retention strategy was designed, in which the inferior individual generated its inverse individual, and a variable domain search algorithm was introduced to enhance the local search ability of the algorithm by combining different neighborhood search methods at each layer of the coding structure. The effectiveness of the algorithm's improved strategy is verified through several benchmarking examples, and it is found that the efficiency improvement of the maximum completion time shows a decreasing trend with the increase of the number of AGVs. Finally, taking a piston ring manufacturing workshop as the research object, the gray correlation analysis is applied to evaluate the Pareto non-dominated solution set, and a most satisfactory scheduling scheme is identified from the non-dominated solution set.

Meanwhile, there are some limitations in this study, such as high computational complexity, long computation time, and the design of the domain structure still has more invalid process moves. This will affect the production efficiency of the workshop, resulting in a waste of resources In the next study, more influencing factors and constraints will be considered, such as AGV charging problem, rescheduling problem due to equipment failure, etc., in order to more realistically simulate the actual production, find a scheduling strategy that conforms to the actual environment, and consider the introduction of reinforcement learning to enhance the search efficiency of the algorithm, which is more suitable for the current complex and dynamic discrete manufacturing environment.

Acknowledgements

2022 Provincial Transfer Payment Key R&D Project: R&D of Automated Cellar Stepping System for Baijiu Brewing Based on Three-Dimensional Force Feedback (22ZFSHFZ0001).

References

1. Amirteimoori, A., Kia, R. Concurrent Scheduling of Jobs and AGVs in a Flexible Job Shop System: A Parallel Hybrid PSO-GA Meta-Heuristic. Flexible Services and Manufacturing Journal, 2023, 35(3), 727-753. https://doi.org/10.1007/s10696-022-09453-y
2. Brandimarte, P. Routing and Scheduling in a Flexible Job Shop by Tabu Search. Annals of Operations Research, 1993, 41(3), 157-183. https://doi.org/10.1007/BF02023073
3. Chang, J., Yu, D., Zheng, Z., He, W., Zhang, L. Hierarchical Reinforcement Learning for Multi-Objective Real-Time Flexible Scheduling in a Smart Shop Floor. Machines, 2022, 10(12), 1195-1195. https://doi.org/10.3390/machines10121195
4. Cheng, W., Meng, W. Collaborative Algorithm of Workpiece Scheduling and AGV Operation in Flexible Workshop. Robotic Intelligence and Automation, 2024, 44(1), 34-47. https://doi.org/10.1108/RIA-11-2022-0266
5. Dauzère-Pérès, S., Paulli, J. An Integrated Approach for Modeling and Solving the General Multiprocessor Job-Shop Scheduling Problem using Tabu Search. Annals of Operations Research, 1997, 70. https://doi.org/10.1023/A:1018930406487
6. Fazlollahtabar, H., Amiri, N. M. An Optimal Path in a Bi-Criteria AGV-based Flexible Jobshop Manufacturing System having Uncertain Parameters. International Journal of Industrial and Systems Engineering, 2013, 13(1), 27. https://doi.org/10.1504/IJISE.2013.050544
7. Gu, Y., Xu, H., Yang, J., Li, R. An Improved Memetic Algorithm to Solve the Energy-Efficient Distributed Flexible Job Shop Scheduling Problem with Transportation and Start-Stop Constraints. Mathematical Biosciences and Engineering, 2023, 20(12), 21467-21498. https://doi.org/10.3934/mbe.2023950
8. Liu, H., Li, R., He, Y. Adaptive Genetic Algorithm for Scheduling Problem in Flexible Workshop with Low Carbon Constraints. International Journal of Wireless and Mobile Computing, 2021, 20(1), 84-92. https://doi.org/10.1504/IJWMC.2021.113227
9. Liu, Q. H., Wang, N. J., Li, J., Ma, T., Li, F., Gao, Z. Research on Flexible Job Shop Scheduling Optimization Based on Segmented AGV. Computer Modeling in Engineering & Sciences, 2023, 134(3), 2073-2091. https://doi.org/10.32604/cmes.2022.021433
10. Pang, Z., Yang, B., Chen, R., Zhang, Z., Mo, F. A Multi-Phase Scheduling Method for Reconfigurable Flexible Job-Shops with Multi-Machine Cooperation Based on a Scout and Mutation-based Aquila Optimizer. CIRP Journal of Manufacturing Science and Technology, 2023, 46, 116-134. https://doi.org/10.1016/j.cirpj.2023.08.003
11. Schworm, P., Wu, X., Klar, M., Glatt, M., Aurich, J. C. Multi-objective Quantum Annealing Approach for Solving Flexible Job Shop Scheduling in Manufacturing. Journal of Manufacturing Systems, 2024, 72, 142-153. https://doi.org/10.1016/j.jmsy.2023.11.015
12. Shao, X., Kshitij, F. S., Kim, C. S., Kshitij, F. S., Kim, C. S. GAILS: An Effective Multi-Object Job Shop Scheduler Based on Genetic Algorithm and Iterative Local Search. Scientific Reports, 2024, 14(1). https://doi.org/10.1038/s41598-024-51778-1
13. Yahui, W., Ling, S., Cai, Z., Liuqiang, F., Xiangjie, J. NSGA-II Algorithm and Application for Multi-Objective Flexible Workshop Scheduling. Journal of Algorithms & Computational Technology, 2020, 14, 174830262094246-174830262094246. https://doi.org/10.1177/1748302620942467
14. Wang, X., Zou, W., Meng, L., Zhang, B., Li, J., Sang, H. Effective Metaheuristic and Rescheduling Strategies for the Multi-AGV Scheduling Problem with Sudden Failure. Expert Systems with Applications, 2024, 123473-123473. https://doi.org/10.1016/j.eswa.2024.123473
15. Wen, X., Fu, Y., Yang, W., Wang, H., Zhang, Y., Sun, C. An Effective Hybrid Algorithm for Joint Scheduling of Machines and AGVs in Flexible Job Shop. Measurement and Control, 2023, 56(9-10), 1582-1598. https://doi.org/10.1177/00202940231173750
16. Xiang, J., Zhang, Y., Cao, X., Zhou, Z. An Improved Multi-Objective Hybrid Genetic- Simulated Annealing Algorithm for AGV Scheduling under Composite Operation Mode. Computers, Materials & Continua/ Computers, Materials & Continua (Print), 2023, 77(3), 3443-3466. https://doi.org/10.32604/cmc.2023.045120
17. Yan J., Liu Z. F., Zhang C. X., Zhang T., Zhang Y. Z., Yang C. B. Research on Flexible Job Shop Scheduling Under Finite Transportation Conditions for Digital Twin Workshop. Robotics and Computer-Integrated Manufacturing, 2021, 72. https://doi.org/10.1016/j.rcim.2021.102198
18. Zhang, H., Qin, C., Zhang, W., Xu, Z., Xu, G., Gao, Z. Energy-Saving Scheduling for Flexible Job Shop Problem with AGV Transportation Considering Emergencies. Systems, 2023, 11(2), 103-103. https://doi.org/10.3390/systems11020103