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Research on Multi-Equipment Collaborative Scheduling Algorithm under Composite Constraints

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Abstract: Multi-equipment multi-process frequent scheduling under complex constraints is at the root of a large number of idle time fragments and transport waiting time in multi-equipment processes. To improve equipment utilization and reduce idle transportation time, a production process optimization scheduling algorithm with "minimum processing time and minimum transportation time" is proposed. Taking into account factors such as product priority, equipment priority, process priority, and overall task adjustment, the scheduling optimization is carried out through a hybrid algorithm combining a one-dimensional search algorithm and a dual NSGA-II algorithm. Compared with other algorithms, the scheduling algorithm proposed in this article not only shortens the minimum processing time but also strives to maximize the utilization rate of each piece of equipment, reducing the processing time of the enterprise by 8% or more, while also reducing the overall transportation time and indirectly reducing costs. The superiority of this algorithm is verified through practice, showing that that the complexity of the scheduling process is lower, and it is feasible in actual operation.

Keywords: compound constraints; multi-equipment; collaborative operation; scheduling; hybrid algorithm

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1. Introduction

Optimization of complex and variable manufacturing processes is an important basis for achieving Made in China 2025, carbon neutrality, and carbon peak targets [1–3]. Multi-equipment collaborative (MEC) operation in manufacturing processes is an important way to realize product diversification and small batch production. MEC operation is an important form of production process, which has become an effective way to improve equipment utilization ratios and reduce energy consumption [4,5].

For optimized scheduling of the production process, scholars have proposed many genetic algorithms, including particle swarm algorithms, NSGA algorithms, super-heuristic algorithms, hybrid algorithms, etc. [6–11]. Zhou et al. introduced new operators for dynamic programming based on the decomposed multi-objective evolution algorithm and verified its superiority through experiments [12]. Zhu et al. proposed a multi-objective optimal foraging algorithm based on fuzzy relative entropy to solve the scheduling problem for a workshop assembly line and compared it with various other algorithms [13]. Shao et al. proposed and verified an efficient iterative greedy algorithm that improves the heuristic algorithm to solve the distributed workshop scheduling problem [14]. Li et al. established an improved artificial immune system algorithm and validated the solution process for flexible workshop scheduling [15]. Chen et al. studied and verified a multi-objective dynamic flexible-operation workshop scheduling situation with regard to machine faults, using an NSGA-II algorithm [16]. Rakovitis et al. added flexible coefficients to the improved cell-specific temporal representation to solve flexible workshop scheduling problems and compared its advantages with other algorithms [17]. Gong et al. proposed an elite non-dominant ranking hybrid algorithm for solving the multi-objective shop tuning problem [18]. Jiang et al. proposed an improved decomposition-based multi-objective evolution algorithm for solving shop-floor green scheduling [19]. Xin et al. designed an improved discrete whale swarm optimization algorithm to solve the problem of workshop scheduling [20]. Sun et al. proposed an effective hybrid co-evolution algorithm that combines genetic algorithms with particle swarm optimization algorithms to solve the flexible scheduling problem in manufacturing systems [21]. Zhang et al. used advanced metaheuristics make dynamic job shop scheduling decisions [22]. Chen et al. proposed a hyper-heuristic genetic algorithm for network-based physical systems and validated it in steel production scheduling [23]. Gao et al. developed a hybrid genetic algorithm (hGA) with an innovative local search procedure (bottleneck shifting) for job shop scheduling problems [24]. Moin et al. proposed and verified a hybrid genetic algorithm with multi-parent crossover for job shop scheduling problems [25]. Zhao et al. proposed a piecewise cooperative genetic algorithm and solved multi-production-cell collaborative scheduling problems in parallel manufacturing [26]. Peng et al. proposed a hybrid evolutionary algorithm (HEA) for solving the multi-depot green vehicle routing problem [27,28].

A workshop schedule is carried out in a workshop, which is essentially different from the MEC process. An MEC process may use a combination of equipment types in a single workshop or the collaboration of multiple types of equipment in other workshops. A hybrid algorithm combining a one-way search algorithm and a double NAGA-II algorithm is proposed to solve the problem of large amounts of fragmentation time and transport waiting caused by multi-equipment simultaneous use under complex constraints. It is found that the proposed method can effectively improve the speed and accuracy of multi-equipment cooperative operation.

2. MEC Process

2.1. MEC Collaborative Operation Process Analysis

The MEC process mainly involves the collaborative work of multiple items of equipment that specifically undertake production tasks for different parts of the product within a specific time. Multiple types of equipment are grouped or divided into tasks, according to the production requirements [29–33].

2.2. Scheduling Requirements

The production task for each equipment item in multiple equipment processes may be different, in the process of MEC operation. Daily tasks need to be planned independently, whether they are the same or not. Multi-category products produced at the same time require a number of equipment types to complete specific production tasks within a specified time, and each equipment production process and processing method may be different. MEC operation completes the task using different combinations. Each type of equipment may undertake multiple operations in the process, and each operation may involve the operator. Therefore, the joint operation of multiple types of equipment must meet the following requirements.

Equipment.

MEC operation needs multiple items of equipment to complete combined tasks in the specified or expected time.

$$F_S \geq F_1 + F_2 \tag{1}$$

In this formula, F_S is the specified time, F_1 is the total processing time, and F_2 is the total transportation time.

According to the reality of production, the urgency of production tasks can be graded such that the higher the level, the higher the priority.

$$T_1 \rangle\, T_2 \rangle\, T_3 \ldots\ldots \rangle\, T_n \tag{2}$$

Here, $T_1, T_2, \ldots\ldots T_n$ represents the production task level and $T_a, T_b, \ldots\ldots T_z$ is a specific task.

Overall utilization of equipment.

$$0 \leq U \leq 1 \tag{3}$$

We assume that during a fixed period of time, the same tasks for the same number of items of equipment for the same workpiece processing the same process requirements are consistent. The procedure's resource requirements are $MR_1, MR_2, \ldots.., MR_\mathrm{n}$. Then:

$$MR_1 = MR_2, \ldots.. = MR_\mathrm{n} \tag{4}$$

Suppose Task T_a is arranged in multi-equipment group A, with n sets of equipment $M_1, M_2, \ldots..M_\mathrm{n}$, and suppose the task T_a is completed by p_a, where p is the single-equipment estimated time for the production quantity, the earliest unused equipment is M_1, and $\mathrm{p_a} \rangle \mathrm{p}$. Then, $\mathrm{p_a} \subset M_1, M_2, \ldots\ldots M_N$, and the task output $\mathrm{p_m}$ for each item of equipment is shown in Equation (5).

$$\mathrm{p_m} = \frac{\mathrm{p}_a}{n} \tag{5}$$

When the output of a processing task is less than the capacity of a single item of equipment, the task is assigned to the earliest idle item of equipment in the production group:

$$\mathrm{p_a} \langle \mathrm{p}, \text{ then } \mathrm{p_a} \subset M_1 \tag{6}$$

2.3. Scheduling Model

The manufacturing enterprise scheduling objective mainly includes time, energy consumption, carbon emissions, cost, etc. In this study, the product total completion time and total transportation time are chosen as the objective for multiple equipment collaborative scheduling. The objective function is as follows:

$$\min f_1 = min \sum_{i=1}^{n} F_{ijm,x} \tag{7}$$

$$\min f_2 = \sum_{i=1}^{n} \sum_{j=1}^{S-1} \sum_{x=1}^{X_i} \sum_{v=1}^{V_{all}} T_{i,j(j+1),x,v} \times \left(FT_{i,j(j+1),x,v} - ST_{i,j(j+1),x,v}\right) \tag{8}$$

The objective function score f_1 is the total completion time, and $F_{ijm,x}$ is the completion time of the assumed process on machine M. The objective function f_2 is the transportation time, and $(FT_{i,j(j+1),x,v}, ST_{i,j(j+1),x,v})$ is the difference between the start transportation time and the completion transportation time [34,35].

The objective function is subject to the following constraints:

(1) The completion time of the process on the machine is not less than the transportation time from the previous process to this process, the change of tool time, and the processing time of this process on the equipment.

$$\begin{gathered} FT_{i,j(j+1),x,v} + Set_{i,(j+1),m,x} + P_{i,(j+1),m,x'} F_{i,(j+1),m,x'} \text{ when} \\ X_{i,(j+1),m,x'}\ T_{i,(j+1),x,v} = 1, \forall \mathrm{i}, \mathrm{j}, \mathrm{x} \in X_i, m \in M_{i,j+1} \end{gathered} \tag{9}$$

Among $FT_{i,j(j+1),x,v}$, for transport equipment v, the whole batch of workpieces $\mathrm{O}_{i,x}$ will be moved from stage j to stage $j+1$ by the transportation completion time. $Set_{i,(j+1),m,x}$ for $\mathrm{O}_{i,j+1,x}$ is the process time for machine m's tool change, and $P_{i,(j+1),m,x}$ for the whole batch of workpieces $\mathrm{O}_{i,x}$ in stage $j+1$ is the processing time on machine m, where $P_{i,(j+1),m,x}$ is the processing time on machine m for a single workpiece in stage $j+1$. $F_{i,(j+1),m,x}$ is the $\mathrm{O}_{i,j+1,x}$ process completion time on machine m and $X_{i,j(j+1),m,x}$ is the 0–1 decision variable: if this is 1, the whole batch of workpieces $\mathrm{O}_{i,x}$ is in stage $j+1$ processing on machine m

($T_{i,j(j+1),x,v}$ for the 0–1 decision variable) and if it is 1, $O_{i,j,x}$ is in the process of shipping from stage j to stage j + 1 by transport equipment v. X_i represents the workpiece O_i in the batch set and $M_{i,j+1}$ represents the workpiece $O_{i,x}$ in the stage j + 1 optional machining machine set.

(2) Any process processing time is greater than or equal to zero.

$$P_{ijm}, P_{ijm,x} \ldots 0, x \in \{1,2,\ldots,X_i\}, m \in M_{ij}, \forall i,j \tag{10}$$

(3) All workpieces can be processed from time 0.

$$S_{ijm,x}, \ldots, 0,\ x \in \{1,2,\ldots,X_i\}, m \in M_{ij}, \forall i,j \tag{11}$$

3. Implementation Algorithm of Collaborative MEC Operation under Composite Constraint

3.1. Collaborative Operation Steps of Multiple Equipments under Compound Constraints

In the scheduling process for MEC operation under compound constraints, multiple types of equipment and each kit cycle are planned to realize production tasks as soon as possible with limited resources and processing time. The collaborative operation procedure is shown in Figure 1.

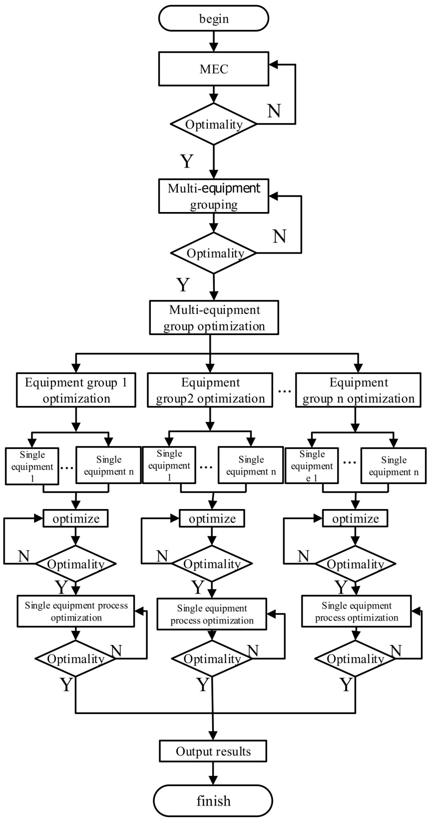


Figure 1. Flow chart for MEC operation steps.

3.2. MEC Grouping Algorithm

Multi-equipment groups are grouped according to equipment capacity differences, production capacity, progress, etc., and searched using a one-dimensional algorithm. The first step of the multi-equipment collaborative grouping algorithm is to determine whether the multi-equipment grouping is optimal, including the multi-equipment preliminary grouping, and to calculate whether the equipment is in full-time operation or not. The algorithm determines the working state of multiple equipment items in one-dimensional space and uses searching to establish the equipment working status trend. Once the equipment is about to become idle, it will be regrouped [36–41]. Flow chart for MEC packet is shown in Figure 2.

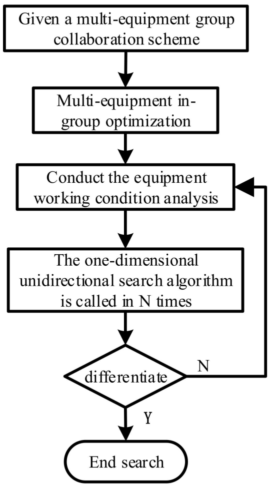


Figure 2. Flow chart for MEC packet.

3.3. *Design of the NSGA-II Algorithm in Multi-Equipment Group*

A multi-equipment group is required to complete a set of tasks in accordance with production objectives within a specified time frame. In essence, equipment scheduling within a multi-equipment group is a multi-objective optimization problem. There are many algorithms to solve multi-objective optimization problems. In this study, we chose the widely used NSGA-II algorithm to solve the problem [42,43]. Flow chart for NSGA-II algorithm is shown in Figure 3.

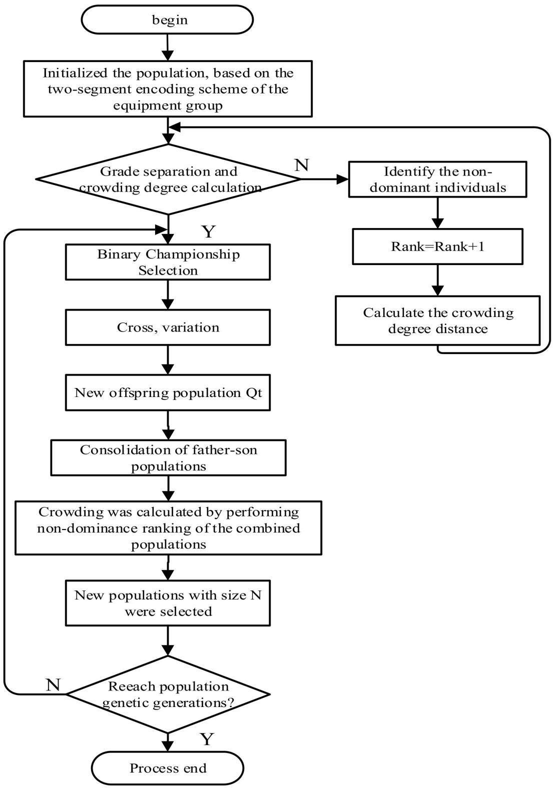


Figure 3. Flow chart for NSGA-II algorithm.

The specific steps are as follows:

1. Parameter initialization and chromosome encoding.

MEC scheduling initializes according to the equipment and product parameters within the program. The population size, cross-mutation probability and maximum iteration times of the NSGA-II algorithm are given.

Each equipment group may use different equipment sets to process different products. The processing order of products can be adjusted according to production needs. A natural number coding algorithm based on the task and the product processing order can link all the tasks using a natural number code, to form chromosome representations of individual order processing tasks.

2. Initialize the population.

The chromosome size of the parent population is set to compare the randomly produced chromosomes with all existing individuals. The results of the comparison are used to decide whether or not they should join the initial population.

3. Grade separation and crowding degree calculation.

According to the equipment task urgency, the scheduling task priority is set and the population is classified and sorted. The more urgent the task, the more adaptive the individual. Individual fitness is measured by crowding, which is generally expressed as a crowding distance and is obtained by calculating the difference in the objective functions of the corresponding points.

4. Binary league choice.

The approach of the population to the PARETO optimal solution is the basis for ensuring the program runs effectively. A non-dominant rank comparison between the randomly selected individuals is made continuously; the smaller individuals are selected with unequal rank and the larger ones with uniform rank. By comparing the non-dominant ranking of individuals, two parent individuals are selected.

5. Genetic operator.

The operation of the genetic operator on the parent population produces the offspring population.

6. Elite retention strategy.

Parent and child populations exist simultaneously. The excellent individuals in the parent population and the excellent individuals in the child populations are combined to select the new generation population. Individuals from the new generation population are selected by comparing their non-dominant ranking and crowding degree.

7. Number of iterations test.

The algorithm terminates at the maximum number of iterations, and the result is the output.

3.4. Process Optimization of NSGA-II Algorithm Design

In this paper, we use the NSGA-II algorithm to optimize the working procedure of the same equipment. The algorithm flow is basically the same as for the NSGA-II algorithm in the equipment group.

3.5. Flow Chart for the Hybrid Algorithm

The hybrid algorithm gives full play to the advantages of both NSGA-II and the one-way search algorithm. After encoding the actual problem, the single-item search algorithm is responsible for multi-device cooperative grouping. If the multi-equipment cooperative grouping carried out by NSGA-II is optimal, multi-equipment cooperative grouping is not the optimal restart search. The NSGA-II algorithm is used to optimize the allocation of equipment and the selection of the working procedure in the group, and whether the state is optimal or not is decided by continuing the execution. The NSGA-II algorithm and the one-way search algorithm are used to ensure that the multi-equipment coordinated grouping and single-equipment allocation are in the optimal state. Flow chart for the hybrid algorithm is shown in Figure 4.

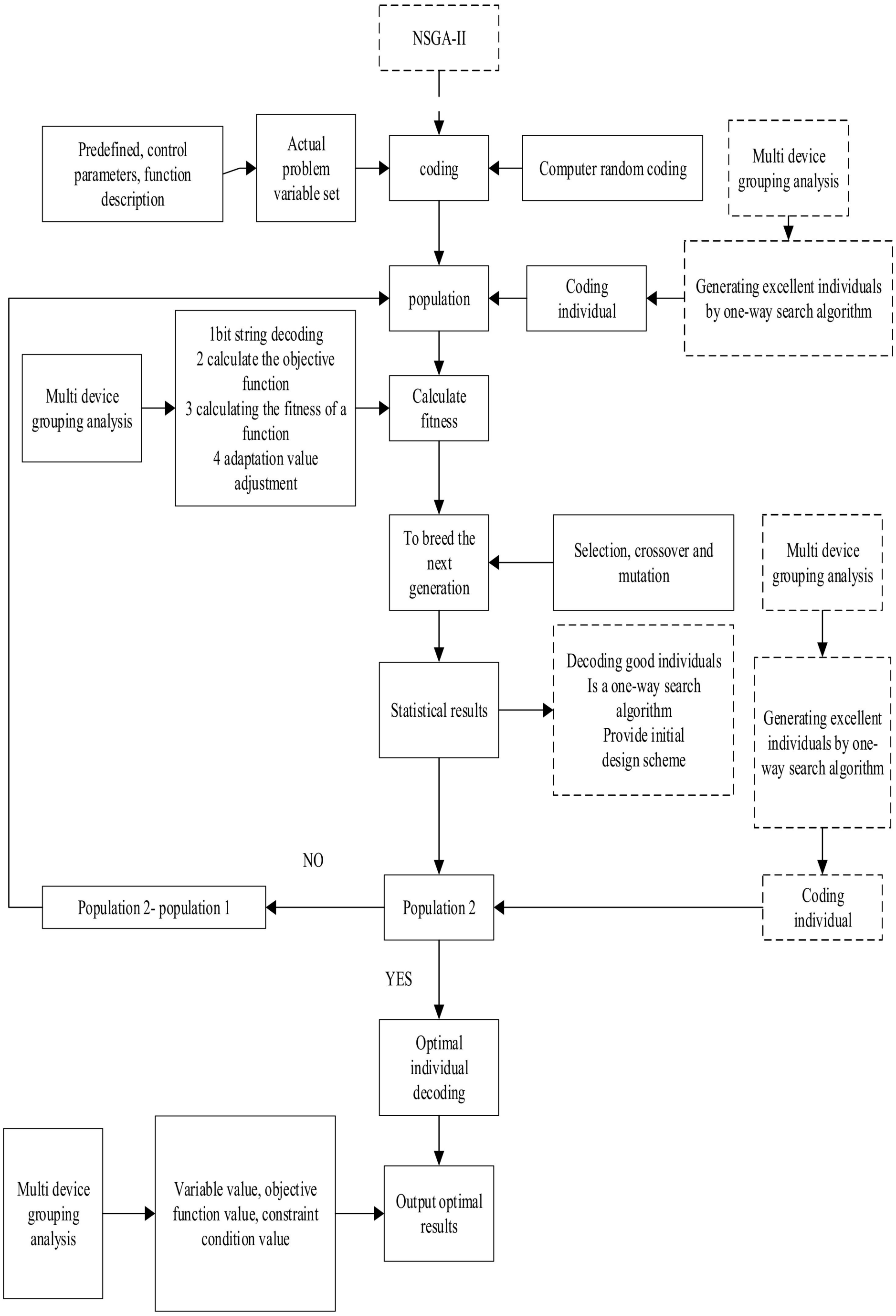


Figure 4. Flow chart for the hybrid algorithm.

4. Application of MEC Collaborative Operation Scheduling Algorithm under Compound Constraints

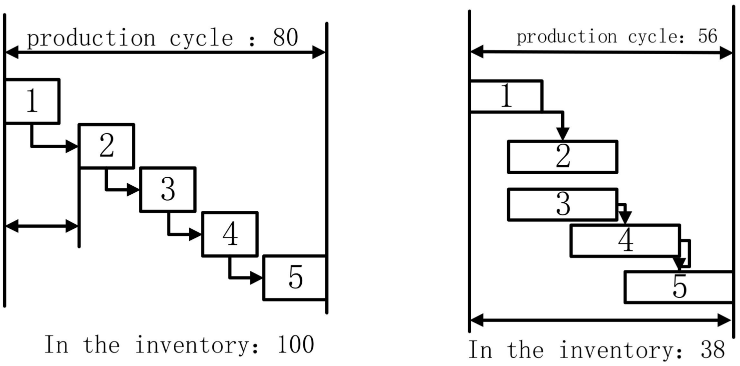
4.1. Advantages of MEC Operation

Multi-equipment simultaneous processing with multi-process multi-products is a common enterprise situation. The characteristics of traditional multi-equipment serial processing and multi-equipment collaborative processing are compared as follows:

(1) The traditional multi-equipment processing production cycle is longer, as the general product is processed in sequence. Multi-equipment collaborative operation can effectively distribute products over several equipment groups at the same time, and can dynamically adjust equipment groups, product groups, and product processing procedures while processing.

(2) Traditional multi-equipment processing cannot adjust the equipment combination and processing procedure in a timely way, according to the task urgency. In order to guarantee the whole equipment task process, multi-equipment cooperation can adjust the equipment combination in real time, according to the processing requirements.

(3) MEC operation is based on product type, product production planning, and equipment production capacity. Enterprises with multi-equipment cooperation can adjust the supply chain according to the production needs and effectively reduce the inventory cost and transportation cost. In the example in Figure 5, the serial processing time of the production products is 80, and the collaborative operation can be adjusted between multiple products according to the overall needs. As a result, the production time is reduced by $80 - 56/80 \times 100\% = 40\%$.



Independent processing Coordinated operation

Figure 5. Multi-product processing time chart.

4.2. Advantages of Hybrid Algorithm

The hybrid algorithm presented in this paper has the following advantages: The hybrid algorithm combines static production planning with dynamic adjustment to find the optimal solution quickly. The hybrid algorithm can effectively establish the product grade and equipment grade by setting the production in layers such as the product, equipment, process-level coding into the algorithm, and whether there is a high-level task, to sort the re-scheduling and ensure the shortest overall time.

(1) Compared with other algorithms, the hybrid algorithm is more targeted, faster, and less crowded, and it converges to the optimal solution quickly.

(2) The algorithm is specially designed for the multi-equipment collaborative optimization process. The hierarchical algorithm can identify production problems quickly and solve them quickly within the hierarchy.

4.3. Case Study

To verify the differences between algorithms, MATLAB 2014 was used for programming, to set the parameters of five algorithms. Figures 6–9 shows a comparison of the algorithms. Figures 6 and 8 show the results for the APSO algorithm, the NSGA-II algorithm and the hybrid algorithm for the objective functions F1 and F2. Figures 7 and 9 are the results for the previously mentioned hybrid algorithms and the hybrid algorithm proposed in this paper for the objective functions F1 and F2. The advantages of the hybrid algorithm in solving speed and stability can be seen by comparison.

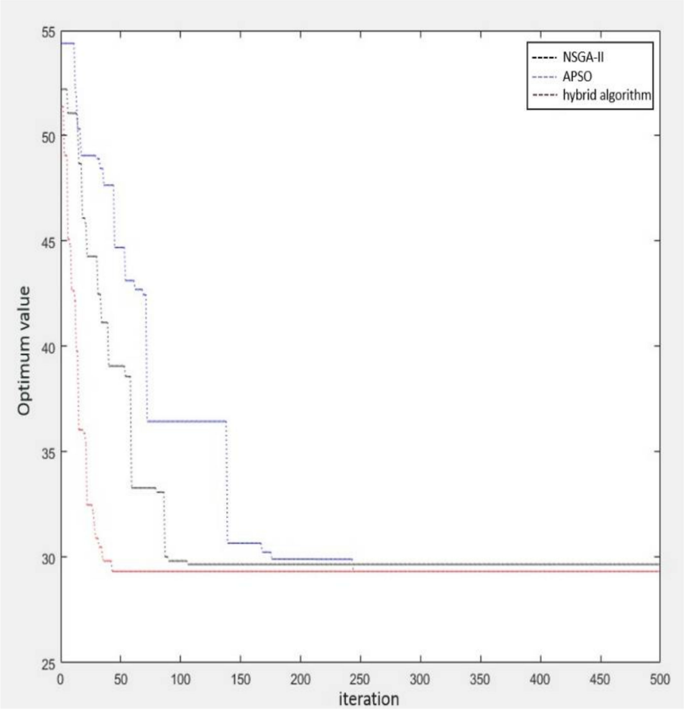


Figure 6. Comparison with classical traditional algorithms for optimizing F1.

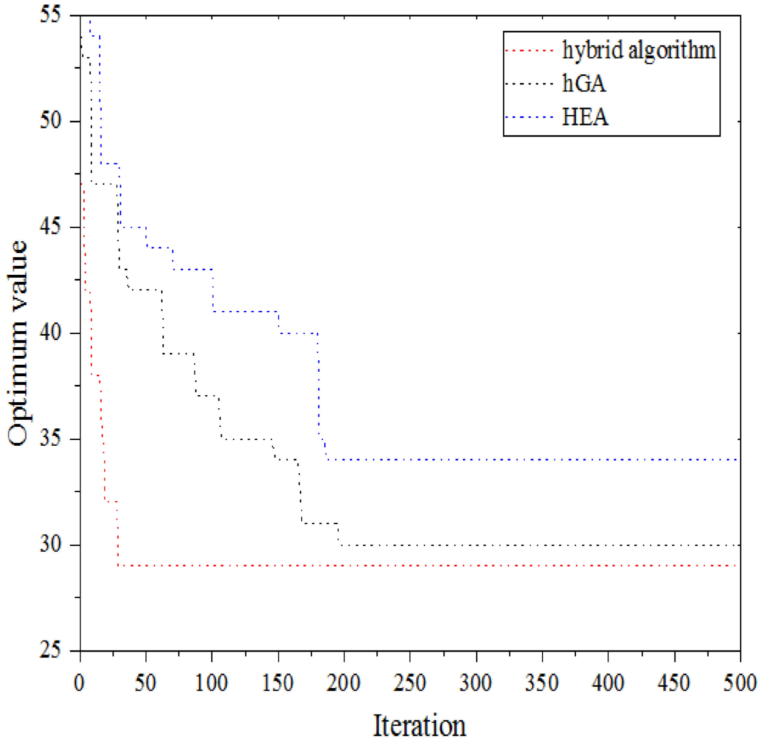


Figure 7. Comparison with mentioned hybrid algorithms for optimizing F1.

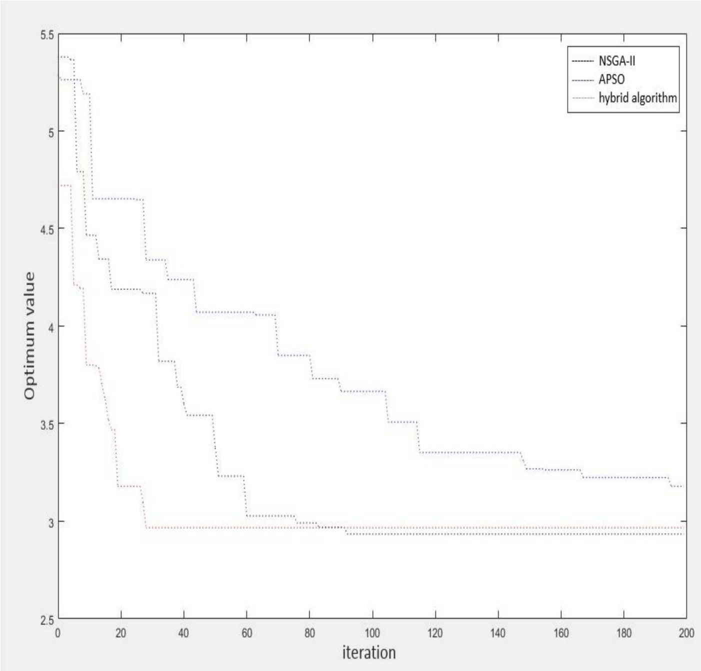


Figure 8. Comparison with classical traditional algorithms for optimizing F2.

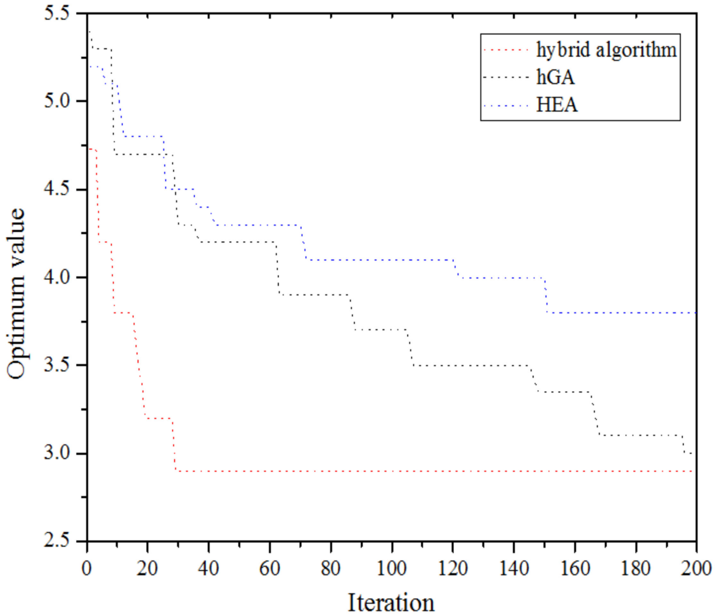
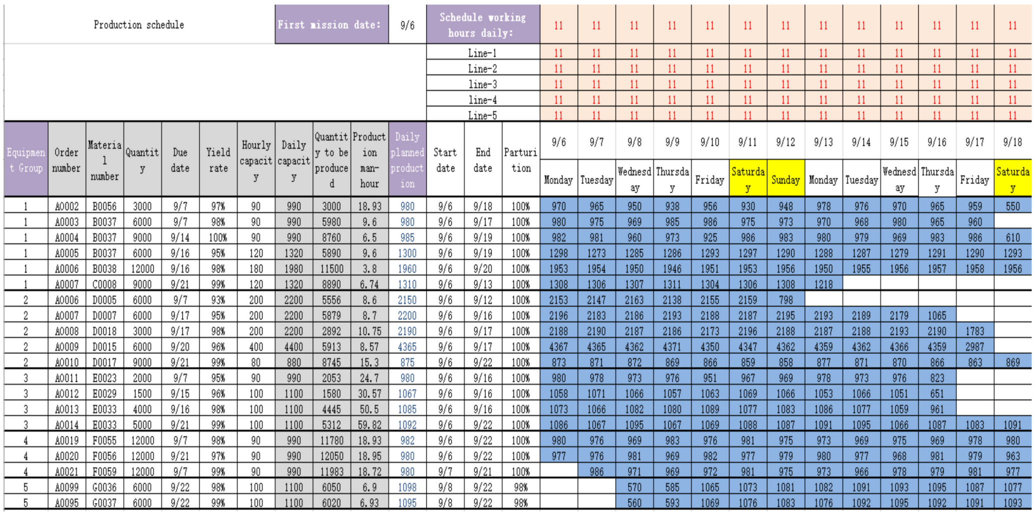


Figure 9. Comparison with mentioned hybrid algorithms for optimizing F2.

Taking the actual production of a workshop as an example, there are 20 machine tools altogether in the workshop, producing four kinds of products, a, b, c, and d, which need to be combined into product e. Product a consists of 9 processes, product b consists of 12 processes, product c consists of 7 processes, and product d consists of 15 processes. Product e consists of products a, b, c, and d assembled via 5 processes. Figure 10 shows a multi-equipment collaborative scheduling plan.



Production schedule							First mission date:			9/6	Schedule working hours daily:			11	11	11	11	11	11	11	11	11	11	11	11	11
											Line-1			11	11	11	11	11	11	11	11	11	11	11	11	11
											Line-2			11	11	11	11	11	11	11	11	11	11	11	11	11
											line-3			11	11	11	11	11	11	11	11	11	11	11	11	11
											line-4			11	11	11	11	11	11	11	11	11	11	11	11	11
											Line-5			11	11	11	11	11	11	11	11	11	11	11	11	11
Equipment Group	Order number	Material number	Quantity	Due date	Yield rate	Hourly capacity	Daily capacity	Quantity to be produced	Production man-hour	Daily planned production	Start date	End date	Parturition	9/6	9/7	9/8	9/9	9/10	9/11	9/12	9/13	9/14	9/15	9/16	9/17	9/18
														Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
1	A0002	B0056	3000	9/7	97%	90	990	3000	18.93	980	9/6	9/18	100%	970	965	950	938	956	930	948	978	976	970	965	959	550
1	A0003	B0037	6000	9/7	98%	90	990	5980	9.6	980	9/6	9/17	100%	980	975	969	985	986	975	973	970	968	980	965	960	
1	A0004	B0037	9000	9/14	100%	90	990	8760	6.5	985	9/6	9/19	100%	982	981	960	973	925	986	983	980	979	969	983	986	610
1	A0005	B0037	6000	9/16	95%	120	1320	5890	9.6	1300	9/6	9/19	100%	1298	1273	1285	1286	1293	1297	1290	1288	1287	1279	1291	1290	1293
1	A0006	B0038	12000	9/16	98%	180	1980	11500	3.8	1960	9/6	9/20	100%	1953	1954	1950	1946	1951	1953	1956	1950	1955	1956	1957	1958	1956
1	A0007	C0008	9000	9/21	99%	120	1320	8890	6.74	1310	9/6	9/13	100%	1308	1306	1307	1311	1304	1306	1308	1218					
2	A0006	D0005	6000	9/7	93%	200	2200	5556	8.6	2150	9/6	9/12	100%	2153	2147	2163	2138	2155	2159	798						
2	A0007	D0007	6000	9/17	95%	200	2200	5879	8.7	2200	9/6	9/16	100%	2196	2183	2186	2193	2188	2187	2195	2193	2189	2179	1065		
2	A0008	D0018	3000	9/17	98%	200	2200	2892	10.75	2190	9/6	9/17	100%	2188	2190	2187	2186	2173	2196	2188	2187	2188	2193	2190	1783	
2	A0009	D0015	6000	9/20	96%	400	4400	5913	8.57	4365	9/6	9/17	100%	4367	4365	4362	4371	4350	4347	4362	4359	4362	4366	4359	2987	
2	A0010	D0017	9000	9/21	99%	80	880	8745	15.3	875	9/6	9/22	100%	873	871	872	869	866	859	858	877	871	870	866	863	869
3	A0011	E0023	2000	9/7	95%	90	990	2053	24.7	980	9/6	9/16	100%	980	978	973	976	951	967	969	978	973	976	823		
3	A0012	E0029	1500	9/15	96%	100	1100	1580	30.57	1067	9/6	9/16	100%	1058	1071	1066	1057	1063	1069	1066	1053	1066	1051	651		
3	A0013	E0033	4000	9/16	98%	100	1100	4445	50.5	1085	9/6	9/16	100%	1073	1066	1082	1080	1089	1077	1083	1086	1077	1059	961		
3	A0014	E0033	5000	9/21	99%	100	1100	5312	59.82	1092	9/6	9/22	100%	1086	1067	1095	1067	1069	1088	1087	1091	1095	1066	1087	1083	1091
4	A0019	F0055	12000	9/7	98%	90	990	11780	18.93	982	9/6	9/22	100%	980	976	969	983	976	981	975	973	969	975	969	978	980
4	A0020	F0056	12000	9/21	97%	90	990	12050	18.95	980	9/6	9/22	100%	977	976	981	969	982	977	979	980	977	968	981	979	963
4	A0021	F0059	12000	9/7	99%	90	990	11983	18.72	980	9/7	9/21	100%		986	971	969	972	981	975	973	966	978	979	981	977
5	A0099	G0036	6000	9/22	98%	100	1100	6050	6.9	1098	9/8	9/22	98%			570	585	1065	1073	1081	1082	1091	1093	1095	1087	1077
5	A0095	G0037	6000	9/22	99%	100	1100	6020	6.93	1095	9/8	9/22	98%			560	593	1069	1076	1083	1076	1092	1095	1092	1091	1093

Figure 10. MEC scheduling plan.

4.4. Results Compared with Related Research

In this paper, the collaborative operation scheduling of multiple production equipment items under compound constraints was carried out. Factors such as product priority, equipment priority, process priority, and overall task adjustment were comprehensively considered, and a hybrid algorithm was proposed to solve the problem. Use of the hybrid algorithm improved the utilization ratio of resources remarkably. Compared with the traditional algorithm for multi-equipment production scheduling, the minimum processing time and the minimum transportation time of production were ensured, the equipment utilization ratio of the enterprise was increased by more than 10%, and the time of product transportation was reduced by more than 15%. Some hybrid algorithms have previously been applied in the production scheduling process [24–27]. These algorithms were practical for the corresponding scheduling. However, these studies did not consider the particularity of multi-equipment joint operation under compound constraints in production scheduling. Compared with the hybrid algorithm mentioned above, the equipment utilization ratio of the enterprise was increased by more than 8% and the time for product transportation was reduced by more than 10%.

5. Conclusions

MEC operation scheduling under compound constraints is a complex problem that affects the production schedule and resource utilization of enterprises. Based on the characteristics of multi-equipment collaborative operation under compound constraints, a hybrid scheduling algorithm was established. This method can comprehensively consider the influence of product priority, equipment priority, operation priority, and overall task adjustment on production scheduling, which is conducive to achieving scheduling quickly, according to production changes and needs.

The main contributions are as follows:

1. The joint operation of multiple types of equipment under compound constraints was proposed, and the collaborative processing process for multiple types of equipment under compound constraints was analyzed. Considering that compound constrains restricted the production process, the collaborative processing operation scheduling model for multiple types of equipment under compound constraints was constructed.
2. A hybrid algorithm combining a one-dimensional search algorithm and an NSGA-II algorithm was proposed for the collaborative grouping of multiple equipment items and the collaborative operation optimized scheduling of equipment within multiple equipment groups.
3. The hybrid algorithm was applied to a production scheduling process for electromechanical products in multi-equipment joint production, and the proposed method

effectively improved the utilization rate of equipment and resources and reduced the transportation time.

Due to the different internal conditions of different industries, the research results of this paper are limited to the application of the algorithm in the process of machining multi-equipment cooperation. In addition, this study did not consider the characteristics of the coordinated operation of multiple devices in different industries. Future research could establish various hybrid algorithms with various advantages combined with the characteristics of different industries and apply them in the process of coordinated operation and scheduling of multiple equipment items.

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