Int j simul model 23 (2024) 3, 531-542
Original scientific paper

EVOLUTIONARY ALGORITHM FOR DYNAMIC RESOURCE ALLOCATION AND ITS APPLICATIONS

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Abstract
In modern manufacturing, dynamic allocation of resources is key to enhancing production efficiency and competitiveness. With the advancement of intelligent manufacturing and Industry 4.0, the manufacturing environment has become increasingly complex and variable, making traditional static resource allocation methods insufficient for practical needs. This paper aims to explore multi-objective optimization methods for dynamic manufacturing resource allocation by constructing a multi-objective optimization model and proposing an improved NSGA-II algorithm to address this issue. The study demonstrates that the improved algorithm significantly enhances population diversity and global search capability, effectively coping with dynamic manufacturing environments to provide efficient and reliable resource allocation solutions. This research not only offers new insights into dynamic resource allocation but also serves as a valuable reference for related fields.
(Received in May 2024, accepted in July 2024. This paper was with the authors 1 month for 2 revisions.)

Key Words: Dynamic Manufacturing Resource Allocation, Multi-Objective Optimization, NSGA-II, Intelligent Manufacturing, Industry 4.0

1. INTRODUCTION

In modern manufacturing, efficient allocation and dynamic scheduling of manufacturing resources are crucial for enhancing production efficiency, reducing production costs, and increasing market competitiveness [1-4]. With the continuous advancement of intelligent manufacturing and Industry 4.0, the manufacturing environment has become increasingly complex and variable, and traditional static resource allocation methods can no longer meet actual production needs [5-7]. The multi-objective optimization problem of dynamic manufacturing resource allocation involves comprehensive optimization of multiple indicators, such as equipment utilization, production efficiency, and resource consumption, making it a hot and challenging topic in the field of manufacturing.

Researching multi-objective optimization methods for dynamic manufacturing resource allocation has significant theoretical and practical importance. Firstly, it can effectively improve the overall performance of the manufacturing system, reduce resource waste, and achieve green manufacturing [8, 9]. Secondly, it helps to enhance the flexibility and adaptability of the manufacturing system, enabling it to quickly respond to changes in market demand and the production environment [10, 11]. Moreover, resource allocation methods based on multi-objective optimization can provide multiple feasible optimization schemes, offering more choices for decision-makers and assisting in the realization of intelligent decision-making.

Despite numerous studies dedicated to the optimization of manufacturing resource allocation and scheduling, most methods still have some shortcomings. For example, traditional optimization methods often struggle to handle multi-objective optimization problems, easily fall into local optima, and lack global search capability [12-15]. Meanwhile, there is relatively little research on dynamic manufacturing environments, and existing methods often exhibit low efficiency and adaptability when dealing with real-time changes and complex, variable manufacturing environments [16, 17]. Additionally, existing evolutionary algorithms still have room for improvement in terms of population diversity and convergence, and they fail to balance multiple optimization objectives [18-22].

This paper aims to construct a multi-objective optimization model for dynamic manufacturing resource allocation and proposes an improved NSGA-II algorithm for this model. Firstly, by analysing the characteristics and requirements of dynamic manufacturing resource allocation, a multi-objective optimization model is established, clarifying the optimization objectives and constraints. Secondly, considering the complexity and dynamics of the model, the traditional NSGA-II algorithm is improved by proposing an adaptive hierarchical retention strategy and an interval population expansion strategy to enhance the algorithm's population diversity and global search capability. The research results show that the improved algorithm can achieve higher efficiency and reliability in solving the dynamic manufacturing resource allocation problem in terms of multi-objective optimization and dynamic environment response. This not only provides an effective solution for dynamic manufacturing resource allocation but also offers valuable insights for related research fields.

2. CONSTRUCTION OF MULTI-OBJECTIVE OPTIMIZATION MODEL FOR DYNAMIC MANUFACTURING RESOURCE ALLOCATION

2.1 Basic assumptions and variable definitions

Fig. 1 shows the flowchart of dynamic manufacturing resource allocation. In dynamic manufacturing resource allocation, various manufacturing resources such as machines, workstations, and warehouses in a factory can be considered as points in a two-dimensional coordinate system. This modelling approach helps to intuitively represent the distribution of resources in the manufacturing workshop while minimizing the distance between resources, thereby reducing the time for resource scheduling and material transportation and improving production efficiency. Faced with dynamic changes in the demands and conditions of the manufacturing process, the two-dimensional coordinate system model can quickly calculate and adjust the positions of resources in w rows and o columns, with columns represented by the a-axis and rows by the b-axis. The position at the a^{th} column and b^{th} row is represented by (a, b).

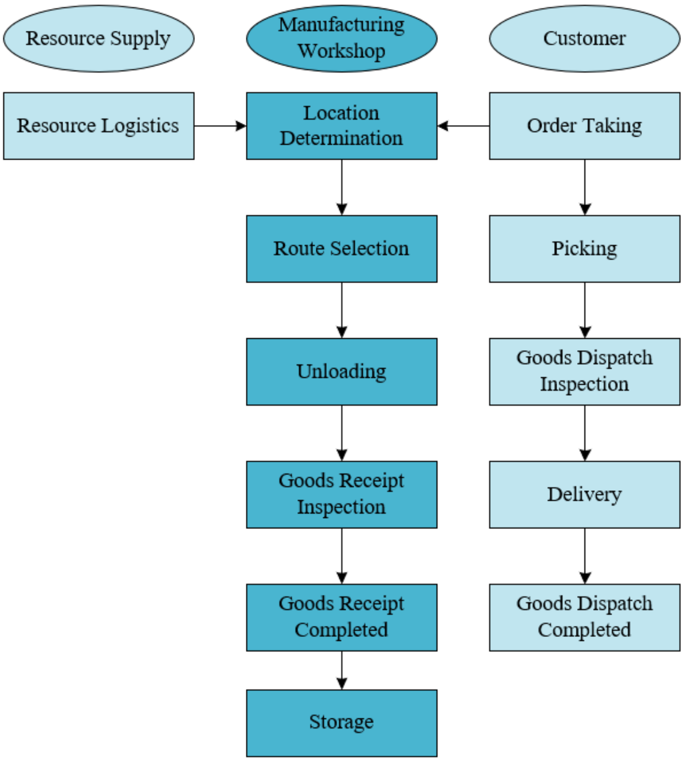


Figure 1: Flowchart of dynamic manufacturing resource allocation.

In the process of constructing a multi-objective optimization model for dynamic manufacturing resource allocation, a series of parameters and variables need to be defined to accurately describe various resources in the system and their allocation methods. The following are the parameter and variable definitions for the multi-objective optimization model of dynamic manufacturing resource allocation: 1) u: Row number of the resource location, it indicates the row position of the manufacturing resource in the factory layout. 2) k: Column number of the resource location, it indicates the column position of the manufacturing resource in the factory layout. 3) j: Resource type number, it is used to distinguish different types of manufacturing resources, such as different models of machines or workstations with different functions. 4) t: Resource allocation type, $t = 1$ indicates that resources are allocated in a fixed manner, $t = 2$ indicates that resources are allocated dynamically. 5) h: Product specifications, it indicates different specifications of products, requiring different manufacturing resources for processing. 6) O: Total number of manufacturing areas in the factory, the total number of different manufacturing areas into which the entire factory is divided. 7) W: Total number of resources in each manufacturing area, the number of manufacturing resources contained in each manufacturing area. 8) o_j: Usage frequency of the j^{th} resource, it indicates the frequency of use of a certain resource over a period of time. 9) W_j: Demand for the j^{th} resource, it indicates the total quantity of a certain resource that needs to be allocated. 10) s_{uk}: Time required from the entry point to the position of the resource at row i, column j, it indicates the transportation time required from the factory entry point to a certain resource location. 11) G_{MAX}: Maximum carrying capacity of each position, it indicates the maximum weight or quantity that each position can carry. 12) n: Operating speed of transportation tools within the factory, it is the average operating speed of transportation tools such as AGVs and forklifts within the factory.

2.2 Configuration model based on the principle of proximity

For the design of dynamic manufacturing resource allocation, special attention should be given to the first three principles. Additionally, a reasonable allocation plan must consider the characteristics of manufacturing resources. Manufacturing resources typically include various equipment, tools, raw materials, and fixtures, which have significant differences in form, function, and usage frequency. For example, CNC machines, welding robots, raw materials like metal sheets and plastic pellets, and assembly tools and fixtures. These resources not only have different physical characteristics and operational requirements but may also require frequent replacement and adjustment during production. Therefore, resource allocation must consider their diversity and complexity to ensure flexible response to changes in production needs. Meanwhile, manufacturing resources often need to meet the demands of multi-variety, small-batch production. The manufacturing industry has a wide variety of products, with small production batches and frequent changes, requiring resource allocation to be highly refined and precise. For example, during a production cycle, the positions of equipment and tools may need to be adjusted multiple times to adapt to the production processes and flows of different products. Hence, resource allocation must not only consider the rationality of space and layout but also ensure that resources can be scheduled and used quickly and precisely. Moreover, manufacturing resource allocation requires strong dynamic adjustment capabilities to cope with changes in production plans and market demands. Unlike the relatively static storage allocation in a steel logistics park, the allocation of manufacturing resources must be able to respond in real-time to changes in the production line. For instance, when a bottleneck or failure occurs in a production process, the resource allocation system needs to quickly adjust resources and re-optimize the production process to ensure continuity and efficiency in production. Therefore, dynamic manufacturing resource allocation needs to have high flexibility and rapid response capabilities. Lastly, the allocation of manufacturing resources needs to consider the collaborative working capabilities between resources. For example, certain equipment and tools may need to be used simultaneously or sequentially to complete a complete production process. This requires resource allocation to consider not only the positioning of individual resources but also the optimization of their collaborative cooperation to enhance overall production efficiency and effectiveness. The resource allocation plan should support the integrated use of different resources, ensuring seamless connections in each process.

Thus, in the construction of the multi-objective optimization model for dynamic manufacturing resource allocation, a flexible, efficient, and safe allocation plan should be formulated by combining the characteristics of diversity, refinement requirements, dynamic adjustment capability, integration, and safety maintenance of resources. The core goal of the constructed model is to optimize resource allocation, ensuring that frequently used resources are close to the main working areas to reduce handling time and distance, thereby improving production efficiency. This is similar to storing high-demand and frequently accessed goods near the entrance in a warehouse. To achieve this goal, the model needs to perform statistical analysis on the usage frequency of various resources and prioritize allocating resources close to the usage points based on usage frequency and demand. The model expression is:

$$MIN\ d_1 = \sum_{j=1}^{J}\sum_{u=1}^{o}\sum_{k=1}^{q} O_j \cdot W_j \cdot s_{uk} \cdot a_{ukj} \tag{1}$$

where, $s_{uk} = (x + u \cdot m + k \cdot q)/n$.

Decision variable: $a_{ukj} = \begin{cases} 1, & \text{The location is equipped with resources} \\ 0, & \text{The location is not equipped with resources} \end{cases}$

The constraints of the model need to reflect the actual conditions of the manufacturing environment. The spatial layout of the workshop has a significant impact on resource allocation. The model needs to consider the available space in each area of the workshop and ensure that the resource allocation does not exceed the available space range. The following equations represent the lateral and longitudinal quantities of the allocation positions:

$$1 \le u \le o \tag{2}$$

$$1 \le k \le w \tag{3}$$

Certain equipment and tools have weight restrictions, especially the placement of large equipment which requires consideration of the floor load-bearing capacity. The model needs to define the load-bearing limits of different areas, similar to the load-bearing limits of linear and grid-type storage positions in steel logistics parks, ensuring that the allocated equipment and tools do not exceed the load-bearing capacity of the area. The related constraints are:

$$0 \prec W \prec G_{MAX} \tag{4}$$

2.3 Configuration model considering balanced yard operations

The core goal of dynamic manufacturing resource allocation is to achieve efficient utilization and balanced operations of resources, avoiding reduced work efficiency and production bottlenecks due to unreasonable resource allocation. In this case, the optimization objectives should include: (1) Reducing resource handling distance: Frequently used resources should be as close to the main work areas as possible, reducing handling time and distance, and improving production efficiency. (2) Balancing operational load: Avoid excessive concentration of resource usage in certain areas, which could lead to overburdening the equipment and personnel in these areas, resulting in queuing and waiting phenomena. The model expression is:

$$MIN\ d_2 \sum_{j=1}^{J} T_j \cdot \sum_{u=1}^{o}\sum_{k=1}^{w} \sqrt{\left[\left(u \cdot a_{ukj} - \sum_{v=1}^{o}\sum_{l=1}^{w} v \cdot a_{vlE_j}\right)\cdot m\right]^2 + \left[\left(k \cdot a_{ukj} - \sum_{v=1}^{o}\sum_{l=1}^{w} l \cdot a_{vlE_j}\right)\cdot q\right]^2} \tag{5}$$

where,

$$T_j = MAX\left(O_j - O_{E_j}\right) \tag{6}$$

This paper calculates the turnover rate difference of manufacturing resources to balance the frequency of inbound and outbound operations. The manufacturing resource allocation model at this time needs to calculate the usage frequency difference of various resources and adjust the storage positions of resources based on the difference. Resources with larger frequency differences should be stored as close to each other as possible to balance the operational load in each area. The related constraints are as follows:

$$E_j = 1, 2, \cdots, j \tag{7}$$

The spatial layout of the manufacturing workshop has a significant impact on resource allocation. The model needs to reasonably allocate resources based on the available space in each area of the workshop, ensuring that the resource allocation does not exceed the available space range. The space constraint conditions are as follows:

$$1 \leq u, v \leq o \tag{8}$$

$$1 \leq k, l \leq w \tag{9}$$

The positive difference constraint of the allocation resource frequency with other allocation resources is as follows:

$$T_j > 0 \tag{10}$$

3. IMPROVED NSGA-II ALGORITHM FOR SOLVING MULTI-OBJECTIVE OPTIMIZATION MODEL OF DYNAMIC MANUFACTURING RESOURCE ALLOCATION

Unlike multi-objective optimization models in other application scenarios, the optimization of dynamic manufacturing resource allocation involves more complex production factors and a dynamically changing environment. That is, dynamic manufacturing resource allocation not only considers the spatial distribution of equipment and tools but also focuses on resource usage frequency, the collaborative relationship between equipment, and the overall efficiency of the production line. Therefore, the application of the improved NSGA-II algorithm in dynamic manufacturing resource allocation requires special attention to maintaining population diversity and dynamically adapting to the complex production environment.

3.1 Adaptive stratified retention strategy

In this algorithm, the core idea of the adaptive stratified retention strategy is to reasonably select the number of individuals based on the non-dominated rank and its sorting, selecting new generation population individuals from the population as a whole. Specifically, this strategy uses a stratified sampling method to limit the size of elite retention, particularly improving the diversity of the solution set in the early stages of evolution. First, the algorithm performs non-dominated sorting on the population, assigning individuals to different levels. Then, according to the size and ranking of each non-dominated level, the retention scale of individuals at each level is adaptively determined. The purpose is to retain elite solutions while also ensuring that the diversity of worse solutions is preserved, preventing the population from prematurely converging to local optima. Assuming the u^{th} individual in the s^{th} non-dominated sorting level of the j^{th} generation iteration is represented by V_{jsu}, the stratified individual set is:

$$V_{js} = \left\{V_{js1}, V_{js2}, \cdots, V_{jsu}, \cdots, V_{jsv}\right\} \tag{11}$$

Assuming the impact factor of the sampling scale for the s^{th} level population in the j^{th} generation is represented by x_{js}, the calculation formula for the sampling scale of the s^{th} level population is:

$$d_{js} = |V_{js}| \times \beta_{js} \tag{12}$$

The adaptive iteration formula for x_{js} is:

$$\beta_{js} = e^{\sqrt{j} \cdot \frac{1}{2s} - 1} \tag{13}$$

To further enhance the algorithm's performance, especially in the early stages of evolution, uniform distribution-based individual sampling is used for each non-dominated level according to the sampling scale size. As the number of iterations increases, the size of the first non-dominated level gradually increases. Eqs. (3) to (7) ensure that while retaining elite solutions, the population can explore more new random individuals, thereby avoiding premature convergence. Additionally, considering the complexity and dynamically changing environment in dynamic manufacturing resource allocation, this paper introduces an interval population expansion operation in the late stages of the algorithm's evolution. By expanding individuals in sparse intervals, more feasible solutions are provided, widening the search range. This not only increases the diversity of the population but also improves the uniformity of population distribution, promoting the algorithm to more effectively approach the Pareto optimal boundary.

3.2 Interval population expansion strategy

In dynamic manufacturing resource allocation, the coordination and optimization of various resources such as machinery, labour, and materials are typically involved in their dynamic allocation and scheduling. This allocation not only requires consideration of the physical placement but also addresses aspects such as time scheduling, process optimization, and equipment maintenance. Therefore, maintaining the uniformity of population distribution and reducing sparsity is an essential way to improve the Pareto front distribution. During the historical search process, the previous generation accumulated numerous elite individuals, which contain rich potential effective information. Based on this, this paper proposes a population diversity improvement strategy based on interval population expansion. The main idea of interval population expansion is to appropriately supplement the elite population in current sparse intervals with elite individuals from the same intervals of the previous generation, thereby ensuring the uniformity of the PF front.

Specifically, suppose the existing elite individuals' objective function set is represented by $h = \{h_1(A), ..., h_u(A), ..., h_l(A)\}$, and the previous generation's elite individuals' objective function set is represented by $g = \{h_1(A), ..., g_u(A), ..., g_l(A)\}$. For the current population, the crowding distance values of the individuals in the adjacent two generations are calculated according to the crowding distance calculation formula, resulting in the crowding distance value sets $F_h = \{F_{h1(A)}, ..., F_{hu(A)}, ..., F_{hl(A)}\}$ for the current population and $F_g = \{F_{g1(A)}, ..., F_{gu(A)}, ..., F_{gl(A)}\}$ for the previous generation population. Meanwhile, the average crowding distance value F_{ME} of the current elite population is calculated and retained, with the crowding distance value of boundary elite individuals set to 0.

Furthermore, traverse each individual in the current elite population and compare their crowding distance values. If an individual's crowding distance $F_{hu(A)}$ is less than the average crowding distance F_{ME}, that individual is marked as a sparse individual. For sparse individuals, the function interval composed of its neighbouring individuals $[h_{u-1}(A), h_{u+1}(A)]$ is marked as a sparse interval.

Then, traverse each individual $h_u(A)$ in the previous generation's elite population to determine whether its objective value falls within the current sparse interval. If the objective value does not fall within the sparse interval, skip that individual; if it falls within the sparse interval, the individual is treated as an expansion elite individual and added to the current population until all elite individuals from the previous generation have been traversed.

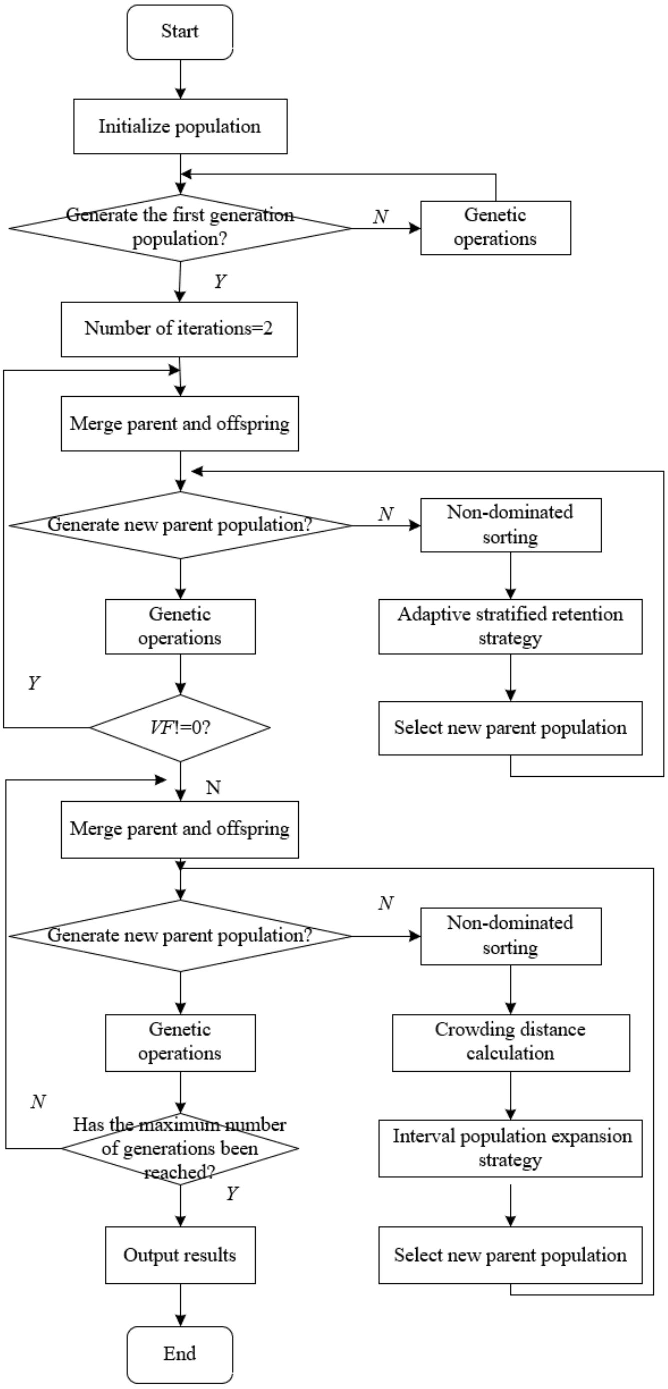


Figure 2: Improved algorithm process.

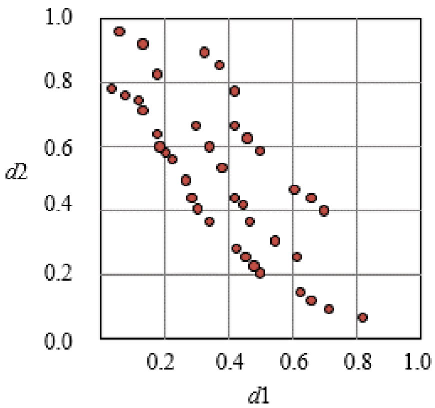
Finally, during the selection of the next generation population, use the new non-dominated sorting to select individuals based on the expanded population. At this point, using the expanded population, a more diverse and balanced Pareto front is obtained.

3.3 Improved algorithm process

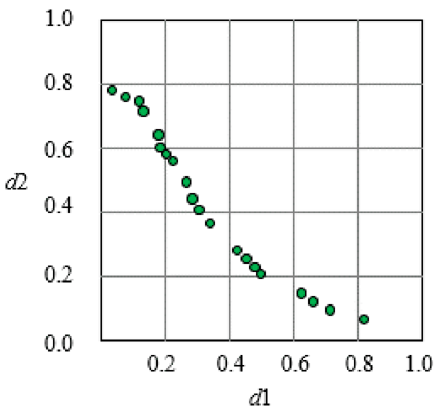
In the multi-objective optimization model for dynamic manufacturing resource allocation, the optimization process requires real-time adjustment of resource allocation and scheduling strategies in a dynamic environment to achieve a balance among objectives such as maximizing equipment utilization, improving production efficiency, and minimizing resource consumption. Fig. 2 shows the improved algorithm process.

4. SIMULATION RESULTS AND ANALYSIS

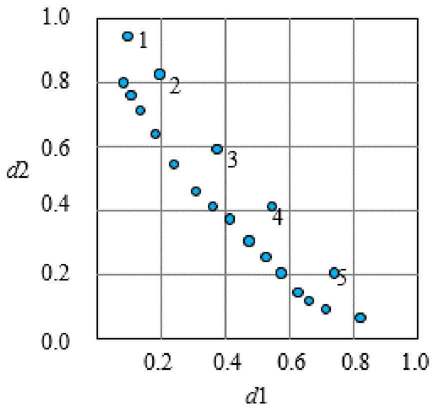
In the experiments targeting the multi-objective optimization model for dynamic manufacturing resource allocation, Fig. 3 shows in detail the screening process when the population evolves to the second generation. Through non-dominated sorting, three non-dominated layers are formed, and the crowding sorting algorithm and the improved adaptive stratified retention strategy are used to select 20 solutions from 40 feasible solutions. The number of feasible solutions retained in each layer is 15 (first layer), 5 (second layer), and 0 (third layer). In Fig. 3 c, the adaptive stratified retention strategy selects 5 solutions (1, 2, 3, 4, 5) from 11 solutions in the second non-dominated layer that are uniformly distributed within a fixed spatial range. In contrast, the results of the crowding sorting algorithm shown in Fig. 3 b indicate that the population distribution is relatively uniform but does not specifically consider the diversity retention between non-dominated layers. Combining the experimental results analysis, the adaptive stratified retention strategy not only retains the overall distribution characteristics of the population but also selectively retains individuals from the second non-dominated layer, improving the diversity and global search capability of the population. Specifically, individual 1 in Fig. 3 c expands the boundary range of the population, while individuals 3, 4, and 5 guide new individuals to evolve towards the sparse parts of the optimal front. This strategy effectively avoids the problem of local convergence of the population, enhances the population's coverage in different objective spaces, and provides a more balanced and diversified solution set for the optimization of dynamic manufacturing resource allocation. Therefore, compared with the traditional crowding sorting algorithm, the adaptive stratified retention strategy has significant advantages in maintaining population diversity and improving global search performance, helping to better meet the complex needs of dynamic manufacturing resource allocation.



a) Non-dominated sorting

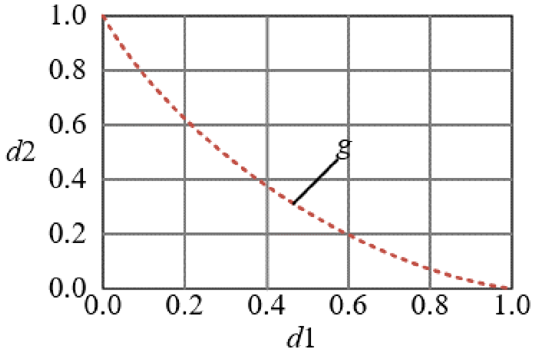


b) Crowding sorting

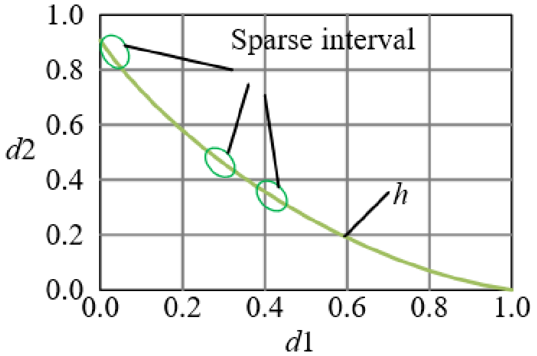


c) The proposed strategy

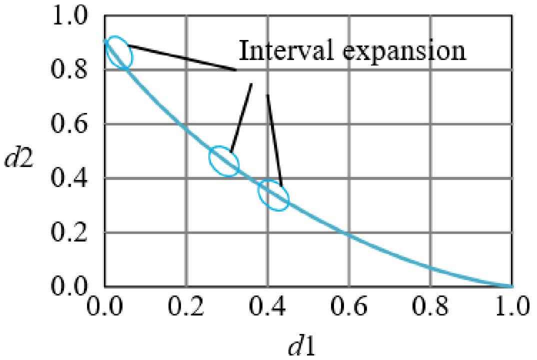
Figure 3: Comparison of selection strategies of different solution algorithms.



a) Previous generation Pareto front



b) Current generation Pareto front



c) Pareto front after interval population expansion strategy

Figure 4: Pareto front situations at different stages of interval population expansion.

By comparing Figs. 4 a and 4 b, it can be observed that although the algorithm generates the current generation Pareto front during the iteration process, its distribution is uneven and not extensive, and it has not yet reached the optimal state. Fig. 4 a shows the Pareto front of the previous generation, while Fig. 4 b shows the Pareto front of the current generation. To solve the problems of uneven distribution and blank intervals in the current generation Pareto front, excellent individuals from the previous generation Pareto front are used to fill these blank intervals. The specific operation is to identify sparse intervals in the current generation Pareto front, such as blank intervals in the second curve, and then select excellent individuals from the corresponding intervals in the previous generation Pareto front to supplement, thereby forming a uniformly distributed and better-converged Pareto front curve as shown in Fig. 4 c. Through this interval population expansion strategy, the experimental results show that the improved NSGA-II algorithm significantly enhances the population's distribution and convergence. This strategy not only solves the problem of uneven distribution in the current generation Pareto front but also accelerates the algorithm's convergence speed, making the Pareto front cover the optimization objective space more comprehensively. Specifically, by supplementing excellent individuals from the previous generation Pareto front, the current generation Pareto front achieves a more uniform distribution, avoids the phenomenon of local convergence, and improves global search capability and diversity. Such improvement in multi-objective optimization for dynamic manufacturing resource allocation can more efficiently find solutions that meet various constraints and optimization objectives, effectively responding to the complexity and dynamic needs of manufacturing resources.

Table I: Comparison of comprehensive evaluation indicator *IGD* values before and after algorithm improvement.

Resource type ID	Before improvement			After improvement		
	Max	Min	Mean	Max	Min	Mean
1	1.12×10^{-2}	8.89×10^{-3}	1.02×10^{-2}	9.62×10^{-3}	6.24×10^{-3}	7.45×10^{-3}
2	2.03×10^{-2}	1.02×10^{-2}	1.36×10^{-2}	1.56×10^{-2}	7.62×10^{-3}	1.12×10^{-2}
3	4.56×10^{-2}	1.21×10^{-2}	2.12×10^{-2}	1.12×10^{-2}	4.72×10^{-3}	8.12×10^{-2}
4	8.23×10^{-3}	5.56×10^{-4}	3.45×10^{-3}	7.12×10^{-3}	8.82×10^{-4}	2.52×10^{-3}
6	2.04×10^{-2}	7.45×10^{-3}	1.42×10^{-2}	1.72×10^{-2}	9.22×10^{-3}	1.22×10^{-2}
7	2.54×10^{-3}	7.12×10^{-4}	1.93×10^{-2}	2.12×10^{-2}	1.02×10^{-2}	1.45×10^{-2}

In the experimental results, through the comparison of the comprehensive evaluation index *IGD* values in Table I, the performance differences of the solving algorithm before and after improvement under different resource types can be clearly seen. Before the improvement, the *IGD* values of various resource types were relatively high. For example, the average *IGD* value of resource type 1 was 1.02×10^{-2}, with a maximum value of 1.12×10^{-2} and a minimum value of 8.89×10^{-3}. After the improvement, the average *IGD* value of the same resource type decreased to 7.45×10^{-3}, the maximum value dropped to 9.62×10^{-3}, and the minimum value to 6.24×10^{-3}. Similarly, the *IGD* values of other resource types, such as type 2 and type 6, decreased from 1.36×10^{-2} and 1.42×10^{-2} to 1.12×10^{-2} and 1.22×10^{-2}, respectively. This indicates that the improved algorithm can reduce *IGD* values across multiple resource types, improving the distribution quality of the solutions. Particularly, the improvement effect on resource types 3 and 4 was significant, with the average *IGD* values dropping substantially from 2.12×10^{-2} and 3.45×10^{-3} to 8.12×10^{-3} and 2.52×10^{-3}, respectively, demonstrating the superior performance of the improved algorithm in complex resource types.

Table II: Comparison of distribution evaluation indicator *GD* values before and after algorithm improvement.

Resource type ID	Before improvement			After improvement		
	Max	Min	Mean	Max	Min	Mean
1	7.33×10^{-4}	2.34×10^{-4}	2.78×10^{-4}	5.78×10^{-4}	2.78×10^{-4}	4.45×10^{-4}
2	8.75×10^{-4}	4.82×10^{-4}	7.04×10^{-4}	5.56×10^{-4}	2.26×10^{-4}	3.54×10^{-4}
3	2.37×10^{-3}	1.01×10^{-3}	1.52×10^{-3}	8.22×10^{-4}	5.12×10^{-4}	6.63×10^{-4}
4	7.69×10^{-4}	3.56×10^{-5}	3.45×10^{-4}	5.34×10^{-4}	4.48×10^{-5}	1.78×10^{-4}
6	8.34×10^{-3}	4.45×10^{-4}	6.48×10^{-4}	5.72×10^{-4}	2.48×10^{-4}	4.22×10^{-4}
7	3.54×10^{-2}	6.82×10^{-3}	1.93×10^{-3}	2.22×10^{-3}	7.22×10^{-4}	1.45×10^{-3}

Table II compares the *GD* values before and after algorithm improvement, illustrating significant differences in distribution across different resource types. Before improvement, *GD* values for each resource type were relatively high. For example, type 1 had a mean *GD* of 2.78×10^{-4}, with a maximum of 7.33×10^{-4} and a minimum of 2.34×10^{-4}. After improvement, the mean *GD* for type 1 increased to 4.45×10^{-4}, with the maximum and minimum values changing to 5.78×10^{-4} and 2.78×10^{-4}, respectively. Similar trends were observed for other resource types such as types 2 and 6, indicating improved uniformity in solution distribution.

Significant improvements were particularly evident for complex resource types like type 3, where the mean *GD* decreased substantially from 1.52×10^{-3} to 6.63×10^{-4}, demonstrating the superiority of the improved algorithm on such resource types.

5. CONCLUSION

This study investigates the multi-objective optimization problem of dynamic manufacturing resource allocation and proposes an improved NSGA-II algorithm. By carefully analysing the characteristics and requirements of dynamic manufacturing resource allocation, a multi-objective optimization model is established with clear optimization objectives and constraints. To address the complexity and dynamism of the model, enhancements to the traditional NSGA-II algorithm are introduced, including adaptive layered retention strategy and interval population expansion strategy, aimed at improving population diversity and global search capabilities. Experimental results demonstrate that the improved algorithm significantly outperforms its predecessor in terms of convergence evaluation indicators (*U* values) across various resource types, particularly excelling in complex resource scenarios. Furthermore, comprehensive experimental validations including comparative analysis of different solution selection strategies, Pareto frontiers during interval population expansion stages, result point plots, iteration curves, and comprehensive evaluation metrics (*IGD* values, *GD* values, *U* values) substantiate the effectiveness of the proposed algorithm. Overall, the improved NSGA-II algorithm proposed in this study notably enhances the quality and efficiency of solving dynamic manufacturing resource allocation problems, validating its effectiveness in practical applications and underscoring its significant research value.

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