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MULTI-OBJECTIVE OPTIMIZATION FOR RESOURCE ALLOCATION IN INTELLIGENT MANUFACTURING

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Abstract
As intelligent manufacturing expands globally, efficient resource allocation strategies are critical for optimizing production efficiency, costs, and quality. Although multi-objective optimization algorithms can handle conflicting objectives, traditional approaches struggle with complex manufacturing systems. This research proposes an optimization model integrating an enhanced Non-dominated Sorting Genetic Algorithm II (NSGA-II) with the Fishbone layout for intelligent manufacturing resource allocation. The Fishbone-based model provides efficient decision support, while the enhanced NSGA-II improves solution efficiency and quality. Flexsim simulation demonstrates the practical value of the proposed method in optimizing resource allocation. This work extends the application of multi-objective optimization in intelligent manufacturing and offers a novel tool for resource allocation optimization in the manufacturing industry.
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Key Words: Intelligent Manufacturing, Resource Allocation, Multi-Objective Optimization, Non-Dominated Sorting Genetic Algorithm II, Fishbone Layout, Flexsim Simulation

1. INTRODUCTION

In the contemporary industrial domain, intelligent manufacturing has been acknowledged as an essential means for enhancing production efficiency, reducing costs, and improving product quality [1-3]. With market demands becoming increasingly diverse, traditional production modes struggle to meet the needs of modern manufacturing, necessitating that production resources be allocated and utilized in a more flexible and efficient manner [4, 5]. Multi-objective optimization algorithms, as an effective method for solving resource allocation problems, play a particularly important role in the allocation of resources within intelligent manufacturing. By optimizing multiple objectives simultaneously, a more comprehensive consideration of various constraints and demands during the production process is facilitated, achieving optimal resource allocation [6-8].

The research significance of multi-objective optimization in intelligent manufacturing resource allocation is mainly reflected in its ability to offer an efficient means to balance multiple conflicting objectives, such as cost, time, and quality [9, 10]. In intelligent manufacturing systems, the optimized allocation of resources is directly related to production efficiency and costs, thereby affecting the competitiveness of enterprises [11, 12]. Therefore, exploring effective multi-objective optimization strategies holds significant theoretical and practical value for guiding the rational allocation of resources in intelligent manufacturing systems.

However, despite the potential application value of multi-objective optimization algorithms in intelligent manufacturing resource allocation, existing research methods still exhibit flaws and deficiencies [13, 14]. For example, some algorithms may struggle to converge rapidly to the optimal solution when dealing with complex manufacturing environments, or they may lack flexibility in balancing multiple objectives [15-17]. Moreover, the adaptability and accuracy of existing methods in simulation modelling and practical applications also require improvement [18].

In response to these issues, a new research approach is proposed, encompassing three main aspects: firstly, an optimization modelling for intelligent manufacturing resource allocation based on the Fishbone layout is designed to construct a mathematical model that accurately reflects the demands for intelligent manufacturing resource allocation; secondly, an improved NSGA-II for solving multi-objective models is developed, enhancing the efficiency and quality of solutions through algorithm optimization; lastly, a Flexsim simulation modelling for the optimization of intelligent manufacturing resource allocation is conducted, verifying the effectiveness and practicality of the proposed method through simulation. This research not only contributes to deepening the theoretical application of multi-objective optimization algorithms in intelligent manufacturing resource allocation but also provides effective solutions for actual production, holding significant research value and application prospects.

2. OPTIMIZATION MODELING FOR RESOURCE ALLOCATION IN INTELLIGENT MANUFACTURING BASED ON FISHBONE LAYOUT

An adjustment and optimization of the innovative shelving layout concept proposed by Gue and Meller was chosen for modelling the resource allocation optimization using the Fishbone layout, to better adapt to the complex demands of the intelligent manufacturing environment. This layout introduces a central pick-up and delivery (P&D) point from which two symmetrical, inclined aisles extend, with resource allocation points such as machines, workstations, or storage areas on either side of these aisles arranged perpendicularly, forming a fishbone-like structure. In intelligent manufacturing, this layout not only focuses on the effective utilization of storage space but also pays special attention to the dynamic scheduling and optimization of resources during the production process, as well as to the synergy with the production lines.

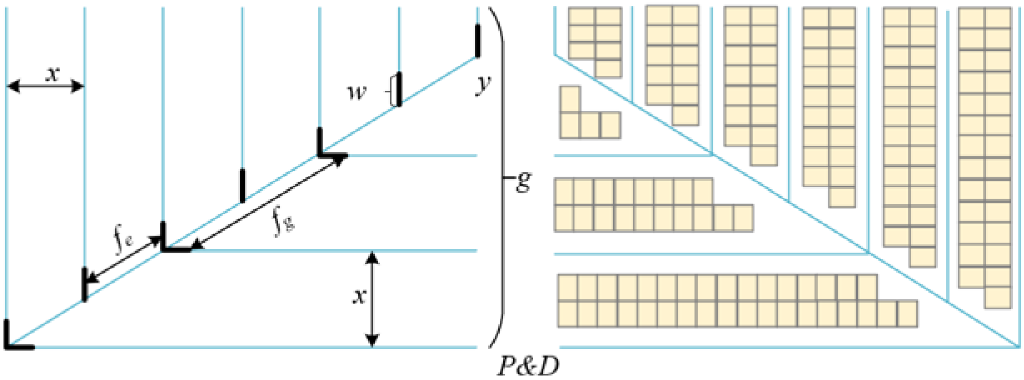

Figure 1: Plan view of the Fishbone layout.

Specifically, a principal aisle inclination of 45 degrees was chosen to optimize paths and improve the efficiency of resource scheduling. This layout model is particularly suitable for optimizing resource allocation in intelligent manufacturing systems by dividing the storage or production areas into four main zones (Zones 1, 2, 3, and 4) and using a counter-clockwise layout strategy with the central P&D point as the core, forming a unique fishbone-like structure. Unlike traditional storage or simple production line applications, the Fishbone layout in this text focuses on the dynamic resource allocation and scheduling problems unique to intelligent manufacturing. Through precise division of areas and logical arrangement of storage positions (storage area number *X*, row number *a*, and column number *b*), a more efficient and adaptable solution is provided for the allocation of machines, layout of workstations, and material flow in intelligent manufacturing systems. Fig. 1 presents the floor plan of the Fishbone layout. By mathematical modelling the relationship between the number of shelf rows *a* and columns *b*, the aim is to achieve optimal resource allocation, effectively shortening the material transfer path. Specifically, with the storage area number represented by X ($X = 1, 2, 3, 4$), the row number represented by a ($a = 1, 2, ..., a_{MAX}$), the column number represented by b ($b = 1, 2, ..., b_{MAX}$), and the maximum shelf column number represented by B, the following relationship between a and b is established:

$$b_{MAX} = \begin{cases} B - \frac{3}{2} \cdot (a-1), a \text{ is an odd number} \\ B - \frac{3}{2} \cdot a + 1, \ \ a \text{ is an even number} \end{cases} \tag{1}$$

In the domain of resource allocation for intelligent manufacturing based on the Fishbone layout, the core challenge of the multi-objective optimization problem (MOP) lies in achieving the maximization of production efficiency and the minimization of costs while maintaining or enhancing product quality. This issue uniquely manifests in the necessity to find an optimal balance among several conflicting objectives, such as resource allocation, scheduling efficiency, and response speed. In intelligent manufacturing systems, efficient resource allocation not only demands short material handling time, thereby enhancing production efficiency, but also seeks to minimize energy consumption and material waste, thus reducing production costs. This typically contradicts the requirements for maintaining high production speeds and high product quality. The optimization model based on the Fishbone layout specifically considers these complex factors within the intelligent manufacturing environment. Through the optimization of resource allocation paths, dynamic scheduling of production resources, and flexible configuration of production processes, the model seeks the best compromise among improving production efficiency, reducing costs, and ensuring product quality. It is assumed that the lower and upper bounds of the variables are represented by $a^M{}_u$ and $a^i{}_u$, respectively. The inequality constraints of the objective functions are represented by $g_j(a_u)$, and the equality constraints by $h_k(x_i)$, with the mathematical description as follows:

$$\begin{gathered} MIN/MAX\ d_l(a_u), l = 1, 2, \dots, L \\ s.t. \begin{cases} h_k(a_u) \geq 0, k = 1, 2, \dots, K \\ g_j(a_u) = 0, j = 1, 2, \dots, J \\ a_u^M \leq a_u \leq a_u^I, u = 1, 2, \dots, v \end{cases} \end{gathered} \tag{2}$$

In the modelling process, to accurately capture the characteristics of intelligent manufacturing systems and the complexity of their resource allocation, thereby supporting the effective resolution of MOPs, a refinement and adjustment of model parameters were undertaken. These parameters include the number of shelf rows, represented by a ($a = 1, 2, ..., a_{MAX}$), reflecting the horizontal distribution of shelves in the Fishbone layout; the number of shelf columns, directly represented by b ($b = 1, 2, ..., b_{MAX}$), indicating the vertical arrangement of shelves; the number of shelf levels, represented by c ($c = 1, 2, ..., c_{MAX}$), used to capture the vertical storage capacity of shelves; the height of a single shelf level, represented by g, related to the vertical movement cost of accessing goods; the identification number of goods, denoted by U_u ($u = 1, 2, ..., u_{MAX}$), used for identifying and managing various materials or products on the production line; the weight of good u represented by l_u, affecting the energy consumption and operation time of material handling equipment; the access frequency of good u denoted by e_u, directly related to the priority strategy for the placement of high-frequency access goods in the optimization model; the horizontal speed of the access equipment represented by N_1, and its vertical lifting speed by N_2, both parameters determining the main components of material access time; the distance travelled by the access equipment in the main aisle denoted by M_1, in the picking aisle by M_2, and the vertical movement distance by M_3. These distance parameters are critical considerations in the optimization process, directly affecting the efficiency and effectiveness of resource allocation across the entire intelligent manufacturing system.

In the optimization modelling for resource allocation in intelligent manufacturing based on the Fishbone layout, maximizing warehousing efficiency has emerged as a critical objective, especially under the multi-objective optimization framework that strives for both production efficiency and reduced operational costs. The realization of this goal relies on prioritizing resources with high access frequencies to be allocated as close as possible to the central P&D point, while resources with lower frequencies are allocated to relatively distant positions. This strategy aims to minimize the total time for resource storage and scheduling, thereby enhancing the warehousing efficiency of the entire intelligent manufacturing system. Specifically, the maximization of warehousing efficiency is achieved through meticulous planning of the one-time movement path for resource storage. This path is divided into three main parts, with each part's impact on warehousing efficiency being carefully considered and optimized to ensure the system's efficient operation.

(i) Movement distance in the main aisle: This part of the path refers to the distance from the central P&D point to the entrance of the row where the designated resource storage location is situated. In the Fishbone layout, owing to its unique symmetrical and inclined design, the movement distance in the main aisle from the P&D point to any storage point is shorter than in traditional linear layouts, which helps reduce handling time and improve warehousing efficiency. The key to optimizing this part of the path lies in the rational arrangement of resources with high access frequencies near the P&D point, to minimize the average movement distance of equipment. The specific expression is as follows:

$$M_1 = \begin{cases} \sqrt{2} \times \left[1 + \frac{3}{2}(a-1)\right] \times m + m, a \text{ is an odd number} \\ \sqrt{2} \times \left[1 + \frac{3}{2}(a-2)\right] \times m + 3m, a \text{ is an even number} \end{cases} \tag{3}$$

(ii) Movement distance within the picking aisle: Once equipment enters the picking aisle, its internal movement distance begins to be calculated. In the Fishbone layout, due to its inclined design, it is possible to approach the target storage location more directly than in traditional parallel layouts, thereby reducing the movement distance within the aisle. This layout optimizes the picking process, especially for resource points located near the "backbone" of the layout, significantly reducing the need for lateral movement. The specific expression is as follows:

$$M_2 = (b-1) \times m \tag{4}$$

(iii) Vertical movement distance: For resources that need to be accessed at different heights, vertical movement distance becomes another important factor affecting warehousing efficiency. In the Fishbone layout, strategically allocating resources with high usage frequencies to lower levels can effectively reduce the need for vertical movement, thereby lowering the total lifting time of the equipment. This tiered resource allocation method further enhances the entire system's access efficiency. The specific expression is as follows:

$$M_3 = (c-1) \times g \tag{5}$$

The objective function for maximizing warehousing efficiency can be further derived as follows:

$$d_1(X,a,b,c) = \left(MIN \sum_{x=1}^{4} \sum_{a=1}^{a_{MAX}} \sum_{b=1}^{b_{MAX}} \sum_{c=1}^{c_{MAX}}\right) \times e_u \times \left(\frac{M_1}{n_1} + \frac{M_2}{n_1} + \frac{M_3}{n_2}\right) \tag{6}$$

Another key objective is the maximization of shelf stability. The optimization of shelf stability is intended to ensure the safety and efficient operation of the entire production environment. Shelf stability is primarily determined by the weight of the goods and their distribution on the shelves. Therefore, the key to optimization lies in prioritizing the placement of heavier items at the bottom of the shelves and lighter items on the upper levels. The aim is to minimize the sum of the product of the weight of the goods on each shelf level and their height, expressed as:

$$d_2(X,a,b,c) = \left(MIN \sum_{x=1}^{4} \sum_{a=1}^{a_{MAX}} \sum_{b=1}^{b_{MAX}} \sum_{c=1}^{c_{MAX}} \right) \times l_u \times c \times g \tag{7}$$

Compared to traditional storage space allocation optimization, this distribution strategy not only enhances the stability of the shelves, avoiding the risk of tipping due to a high centre of gravity but also considers the objectives of improving warehousing efficiency and reducing operation time in parallel within the multi-objective optimization framework, forming a comprehensive balanced optimization problem. In summary, the multi-objective optimization model for resource allocation in intelligent manufacturing based on the Fishbone layout is as follows:

$$\begin{gathered} d_1(X,a,b,c) = \left(MIN \sum_{X=1}^{4} \sum_{a=1}^{a_{MAX}} \sum_{b=1}^{b_{MAX}} \sum_{c=1}^{c_{MAX}} \right) \times e_u \times \left(\frac{M_1}{n_1} + \frac{M_2}{n_1} + \frac{M_3}{n_2} \right) \\ d_2(X,a,b,c) = \left(MIN \sum_{X=1}^{4} \sum_{a=1}^{a_{MAX}} \sum_{b=1}^{b_{MAX}} \sum_{c=1}^{c_{MAX}} \right) \times l_u \times c \times g \\ s.t. \begin{cases} 1 \le a \le a_{MAX} \\ 1 \le b \le b_{MAX} \\ 1 \le c \le c_{MAX} \\ 1 \le X \le 4 \end{cases} \end{gathered} \tag{8}$$

3. DESIGN OF THE IMPROVED NSGA-II

The enhanced NSGA-II multi-objective model developed in this study addresses the limitations of fixed parameters in traditional genetic algorithms through the adaptive adjustment of crossover and mutation probabilities. This adaptive approach takes into account the uniqueness of the intelligent manufacturing resource allocation problem, where the multi-objective optimization process of resource allocation must not only consider the maximization of resource utilization but also balance factors such as efficiency, cost, and stability. Therefore, in the initial phase of the algorithm, to explore the solution space, a higher crossover probability is employed to increase the diversity of the population and the global search capability. As the algorithm evolves and the population gradually stabilizes with reduced individual differences, the crossover probability is appropriately decreased to protect the genes of superior individuals from being disrupted. At the same time, the mutation probability is increased to maintain the diversity of the population and promote the algorithm's convergence to the global optimum. Especially in the dynamic and complex environment of intelligent manufacturing based on the Fishbone layout, the resource allocation requires the algorithm to have a flexible adjustment mechanism to meet the optimization needs of different stages. The improved NSGA-II dynamically adjusts the crossover and mutation probabilities, allowing the algorithm to adaptively optimize the search strategy at different evolutionary stages, effectively addressing the MOP of intelligent manufacturing resource allocation. This adaptive parameter adjustment mechanism not only improves the search efficiency and quality of the solutions but also enhances the algorithm's capability to handle complex resource allocation problems in intelligent manufacturing. Assuming the initial crossover probability is represented by o_{z0}, the minimum value for the crossover probability by o_{zMIN}, the maximum number of generations by H, the current generation number by gh, the number of objective functions in the optimization problem by l, the maximum value of the u^{th} objective function in the current population by

$MAXP_u$, and the average value of the u^{th} objective function in the current population by MEP_u. The initial mutation probability is represented by o_{l0}, and the minimum value for the mutation probability by o_{lMIN}, then the adaptive formulas are as follows:

$$O_z = \frac{o_{z0} - (o_{z0} - o_{zMIN}) * \frac{h}{H} + \sum_{u=1}^{l} \left(o_{z0} - (o_{z0} - o_{zMIN})^{\frac{MAXP_u}{MEP_u}} \right)}{l+1} \tag{9}$$

$$O_l = \frac{o_{l0} - (o_{l0} - o_{lMIN}) * \frac{h}{H} + \sum_{u=1}^{l} \left(o_{l0} - (o_{l0} - o_{lMIN})^{\frac{MAXP_u}{MEP_u}} \right)}{l+1} \tag{10}$$

4. FLEXSIM SIMULATION FOR RESOURCE OPTIMIZATION

In the process of resource flow in intelligent manufacturing based on the Fishbone layout, raw materials or semi-finished products start from industrial companies and first enter an automated high-bay warehouse, similar to that of heteromorphic cigarettes but emphasizing dynamic allocation and efficient access of resources in the intelligent manufacturing environment. Subsequently, materials are transferred to a transfer station, where, in the Fishbone layout, emphasis is placed on using optimization algorithms for effective resource allocation to enhance the efficiency of subsequent processing. Then, the materials enter the production line for processing or assembly. After these steps are completed, the finished products are packaged and eventually distributed downstream or to retailers.

(i) Input source

For the logic flow of resource allocation in intelligent manufacturing based on the Fishbone layout, a resource input source model was first constructed. This source is regarded as the automated high-bay warehouse of raw materials or semi-finished products within the intelligent manufacturing system. By setting related parameters and using the "arrival schedule" as the method of arrival, production order data required for the simulation is imported from an Excel spreadsheet. This data includes key information such as the arrival time, quantity, type, and weight of each item. This step simulates the process whereby raw materials or semi-finished products automatically arrive at the production line according to the production schedule in an intelligent manufacturing environment.

Subsequently, in consideration of the potential presence of single or multiple downstream processing points within the intelligent manufacturing system, output methods are set within the simulation model to ensure resources can be efficiently allocated to the next processing stage based on the system's real-time status and processing capacity. In the intelligent manufacturing environment of the Fishbone layout, this often involves complex material handling and distribution logic to ensure materials are quickly and accurately transported to the next process or workstation, thereby maximizing the efficiency and responsiveness of the entire production process. Finally, to enhance the model's visualization and comprehensibility, different types of resources are assigned markers of different colours. This facilitates the rapid identification of various resources during the simulation process and aids in the analysis and optimization of resource flow and allocation strategies within the intelligent manufacturing system.

(ii) Staging area

The setting of a staging area within the model is designed to effectively respond to various resources outputted from the automated high-bay warehouse, such as raw materials or semi-finished products, ensuring they can be swiftly and accurately transported to the next processing station or production line. Therefore, the simulation modelling principle of the staging area needs to precisely simulate the temporary storage, batch processing, and efficient transfer of resources. In this segment, the creation of one or more staging areas is simulated. The function of these areas is to temporarily store resources from upstream and allocate them to the next processing stage according to production demands. The basic parameter settings of the staging area reflect the needs of intelligent manufacturing scenarios, such as the maximum capacity setting, which reflects the system's processing capability limitations, and the application of batch processing modes, which simulates considerations of efficiency and response speed in actual production.

Specific to the demands of the intelligent manufacturing environment, the resource output method of the staging area is also specially configured. To simulate the flow of resources from the staging area to the next processing station, an output setting based on the "first available" principle is adopted, ensuring resources can be quickly transferred along the optimal path. Moreover, considering the variety of different automated handling equipment that may be involved in intelligent manufacturing, the simulation model also includes the use of and scheduling for different handling tools to achieve efficient transportation of resources between processing stations. Through this approach, the design and functionality of the staging area are effectively represented and optimized within the simulation model.

To enhance overall production efficiency and reduce logistics costs, the manual and automated transportation methods within the staging area are meticulously designed. By setting up pre-waiting handling mechanisms in the staging area, significant reductions in idle time for handling tools and manual walking are achieved, further optimizing the production process. In the simulation model, specific triggers and programming logic, such as "on resource available", ensure that after each resource transfer, handling tools promptly return to the staging area awaiting the next dispatch, thereby facilitating the recycling of resources and continuous optimization of the process.

(iii) Scanners and conveyors

The simulation modelling principle of scanners and conveyors within the model is designed to ensure the efficient identification and accurate diversion of resources such as raw materials, semi-finished, or finished products during the production process. This process simulates how scanners in an intelligent manufacturing system can instantaneously recognize various resources passing through and dynamically allocate these resources to the next processing station or handling step based on preset logic. To achieve balanced loading rates across conveyors and ensure the system's efficiency, programming code is specifically employed to implement the resource allocation logic. This allows the system to automatically adjust the flow of resources based on real-time production conditions and the current load on the conveyors, thereby maximizing production efficiency and minimizing downtime. Furthermore, to enhance the system's visualization management and monitoring capabilities, a visualization management platform is integrated into the simulation model. By scripting specific codes, such as custom code executed after the "on process finish" event is triggered, the platform can display in real-time the scanning results and current status of each resource, facilitating operators' clear understanding of the movement of resources throughout the production process. This visual interactive interface not only aids in the quick diagnosis and resolution of potential production issues but also provides an intuitive means to monitor and optimize the operation of the entire intelligent manufacturing system.

5. SIMULATION RESULTS AND ANALYSIS

Through Fig. 2, which displays the changes in the number of iterations and the fitness values for warehousing efficiency, it is evident that with an increase in the number of iterations, both the NSGA-II and the improved NSGA-II proposed in this study exhibit a gradually declining trend in the fitness values for warehousing efficiency. This indicates that both algorithms can effectively optimize the warehousing efficiency problem during the solution process. Specifically, at the initial stage (0 iterations), the fitness values of both algorithms are 204, suggesting identical efficiency at the starting point. As the number of iterations increases to 50, 100, and 150, the fitness values of the NSGA-II decrease to 194, 190, and 181, respectively, while the fitness values of the improved NSGA-II at the same number of iterations are 194, 190, and 185, respectively, showing performance slightly superior to that of the NSGA-II. Upon reaching 300 iterations, the fitness value of the NSGA-II decreases to 150, whereas the fitness value of the improved NSGA-II further decreases to 141. This demonstrates that the improved NSGA-II possesses better optimization capability and higher efficiency over the long-term iteration process.

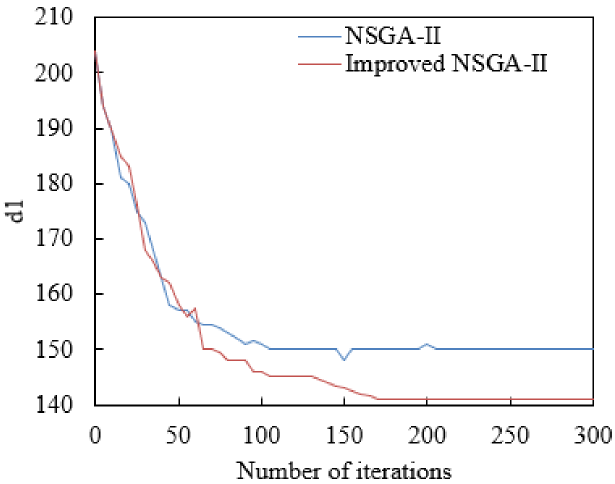

Figure 2: Objective 1: fitness values for warehousing efficiency.

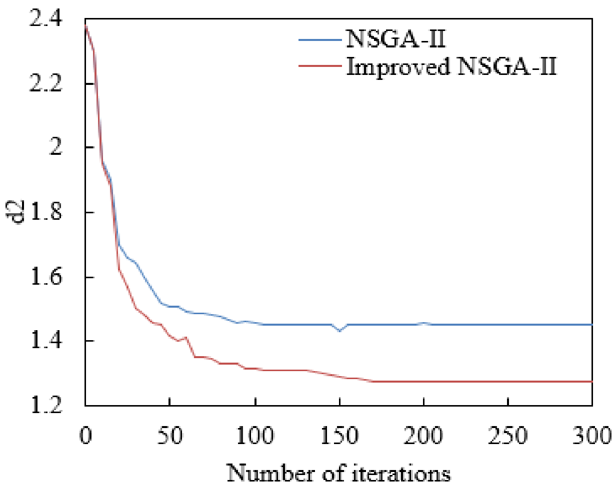

Figure 3: Objective 2: fitness values for shelf stability.

Through the analysis of data on shelf stability fitness values in Fig. 3, it is observed that both the NSGA-II and the improved NSGA-II achieved significant improvements in shelf stability throughout the iteration process. Initially, the fitness values of both algorithms were 2.38, which gradually decreased as the number of iterations increased, indicating optimization of shelf stability. Specifically, as the number of iterations increased to 50, 100, and 150, the fitness values of the NSGA-II decreased to 2.3, 1.96, and 1.9, respectively. Meanwhile, the fitness values of the improved NSGA-II decreased earlier to lower levels, reaching 2.3, 1.95, and 1.88, respectively. Upon reaching 300 iterations, the fitness value of the NSGA-II decreased to 1.45, while the fitness value of the improved NSGA-II further reduced to 1.275, demonstrating that over the long-term iteration process, the improved NSGA-II possesses superior performance in optimizing shelf stability.

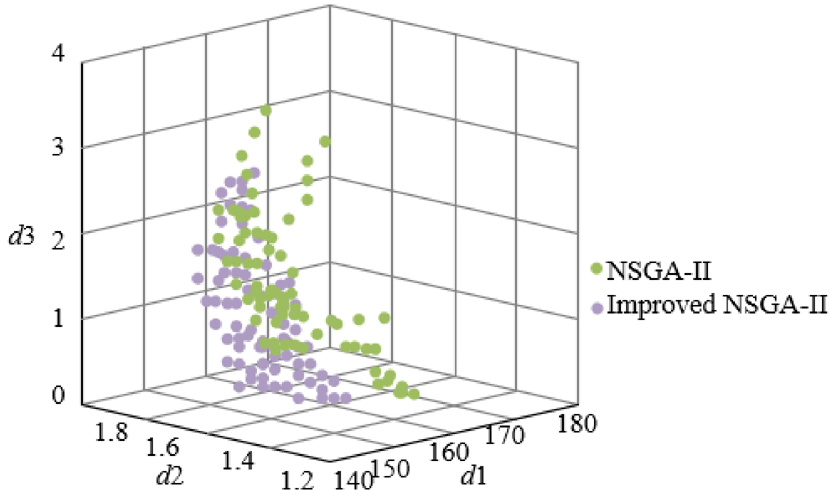

Figure 4: Comparative diagram of the multi-objective Pareto frontier solution set.

In this study, a comparative analysis of the Pareto frontier solution set for the improved NSGA-II and the original NSGA-IIs in addressing the intelligent manufacturing resource allocation problem was conducted. The experimental results depicted in Fig. 4 demonstrate the significant advantages of the improved NSGA-II in solving MOPs. The Pareto solution set obtained by the two algorithms is displayed in a three-dimensional graph, with solutions from the improved NSGA-II represented in green, while those from the original NSGA-II are shown in purple. Observations reveal that the Pareto solution set obtained by the improved NSGA-II not only covers a broader range but also exhibits noticeable improvements in uniformity and distribution of solutions. This extensive and uniform distribution indicates the improved algorithm's excellence in maintaining population diversity, effectively integrating global and local search capabilities to adapt to variable optimization objectives and constraints. The analysis concludes that the improved NSGA-II, with its superior mechanism for maintaining population diversity and a strategy that balances global and local search capabilities, provides a more effective and robust optimization solution for the problem of resource allocation in intelligent manufacturing. The algorithm is not only capable of discovering a broader feasible solution space but also uniformly identifies high-quality Pareto optimal solutions within this space, thereby ensuring the comprehensive performance of the optimization process and the quality of the final solution set.

Table I presents a detailed comparison of the performance of different multi-objective optimization algorithms for intelligent manufacturing resource allocation, based on the hypervolume indicator (*HV*). This indicator reflects the quality of the Pareto frontier solution set obtained by the algorithms, including the distribution, uniformity, and proximity of the solutions to the global optimum. It is observed from the table that the improved NSGA-II significantly outperforms other algorithms in the allocation of raw material resources, achieving a hypervolume value of 0.669, which is notably higher than the performances of NSGA-II, Pareto Envelope-based Selection Algorithm II (PESA-II), and Strength Pareto Evolutionary Algorithm II (SPEA2) algorithms. In the allocation of semi-finished products and resources as well as testing and inspection equipment, the improved NSGA-II also shows competitive performance, although the other algorithms also perform relatively well in these areas. It is noteworthy that all considered algorithms failed to produce effective solutions for the allocation of storage and logistics equipment, possibly indicating the high complexity of this particular problem or the limitations of the algorithms in addressing certain specific constraints. The results for the allocation of production equipment and robots reveal that the performance of each algorithm is similar, yet the improved NSGA-II still holds a slight advantage.

Table I: Average *HV* values for different multi-objective optimization algorithms in intelligent manufacturing resource allocation.

A population size of 200, three decision variables, and 1000 generations					
Resource type	**Number of decision variables**	**NSGA-II**	**Improved NSGA-II**	**PESA-II**	**SPEA2**
Raw material resources	7	0.456	0.669	0.324	0.521
Semi-finished and resources	12	0.523	0.554	0.536	0.562
Storage and logistics equipment	12	0	0	0	0
Testing and inspection equipment	12	0.556	0.556	0.532	0.366
Production equipment and robots	12	0.176	0.187	0.189	0.186

Table II: Average *DM* values for different multi-objective optimization algorithms in intelligent manufacturing resource allocation.

A population size of 200, three decision variables, and 1000 generations					
Resource type	**Number of decision variables**	**NSGA-II**	**Improved NSGA-II**	**PESA-II**	**SPEA2**
Raw material resources	7	0.578	0.612	0.524	0.545
Semi-finished and resources	12	0.623	0.754	0.612	0.552
Storage and logistics equipment	12	0.195	0.192	0.223	0.189
Testing and inspection equipment	22	0.323	0.466	0.585	0.366
Production equipment and robots	22	0.489	0.787	0.659	0.389

Table II illustrates the performance of different multi-objective optimization algorithms in intelligent manufacturing resource allocation problems, based on the diversity metric (*DM*). The *DM* is utilized to measure the diversity of the solution set, that is, the range and uniformity of solutions in the Pareto frontier solution set. According to the data in the table, the improved NSGA-II exhibits higher diversity metric values in the allocation of most resource types. Particularly in handling the allocation of semi-finished products and resources (0.754) and production equipment and robots (0.787), its *DM* values significantly surpass those of other algorithms. This indicates that the improved NSGA-II can generate a more diverse set of solutions, thereby providing decision-makers with a broader range of choices. In contrast, while other algorithms such as PESA-II and SPEA2 also show good diversity in certain resource types (for example, PESA-II reaches 0.585 in the allocation of testing and inspection equipment), the improved NSGA-II excels overall in maintaining solution set diversity. From these results, it can be concluded that the improved NSGA-II effectively enhances the diversity of the solution set for intelligent manufacturing resource allocation problems through its optimized strategies and mechanisms, thus increasing the likelihood of finding superior solutions. This high degree of solution set diversity is crucial for actual intelligent manufacturing resource allocation, as it means the most suitable resource allocation plan can be selected from a broader optimization solution space based on actual production demands and constraints.

6. CONCLUSION

The research content and outcomes of this study can be summarized as follows: Firstly, a mathematical model for the optimization of resource allocation in intelligent manufacturing based on the Fishbone layout was successfully constructed. This model accurately reflects the needs for resource configuration in intelligent manufacturing. Secondly, an improved NSGA-II for solving multi-objective models was designed and implemented, demonstrating significant improvements in efficiency and quality in optimizing intelligent manufacturing resource allocation. Lastly, the effectiveness and practicality of the proposed methods were validated through Flexsim simulation modelling. The experimental results encompassed evaluations of fitness values for warehousing efficiency, shelf stability, and workload balance, comparative analysis of the multi-objective Pareto frontier solution set, and analyses of the *HV*, *DM*, and spacing metric for different intelligent manufacturing resource allocation multi-objective optimization algorithms, as well as comparisons of algorithmic time efficiency.

Synthesizing the above research content and results, the important conclusion of this study is that the efficiency and effectiveness of intelligent manufacturing resource allocation have been significantly enhanced through the use of the improved NSGA-II, especially in optimizing warehousing efficiency, shelf stability, and workload balance. Moreover, the algorithm also performed well in maintaining the diversity and distribution of the solution set, despite certain limitations in the allocation of specific types of resources. The improvement in time efficiency further enhances the feasibility and appeal of this method in practical applications.

However, the study also has its limitations, particularly in dealing with complex resource types, such as storage and logistics equipment, where the algorithm's distribution metric showed deficiencies. This suggests that future research could focus on further optimizing the algorithm's generality and adaptability to handle more complex and diverse intelligent manufacturing resource allocation scenarios. Additionally, the methods and conclusions of the study could be extended to other similar industrial optimization problems, providing broader impact and contributions to the field of intelligent manufacturing.

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