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Integrated Scheduling Method for Flexible Job Shops Considering Personalized Requirements

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Abstract: In response to the challenges of high-mix low-volume production driven by personalized customization demands, existing research has predominantly focused on single-dimensional improvements, with insufficient comprehensive consideration of dynamic disturbances such as process variations and machine failures derived from customization requirements. To address this gap, this study develops a multi-objective mathematical model that simultaneously minimizes total production costs and makespan by integrating critical dynamic disturbance factors. An improved hybrid algorithm H-IPNSGA-II combining particle swarm optimization (PSO) and non-dominated sorting genetic algorithm-II (NSGA-II) is proposed to solve the model. A case study involving an automotive parts manufacturing enterprise is conducted to validate the proposed methodology. Comparative experiments and sensitivity analysis demonstrate the superior performance of the model and algorithm, providing theoretical support for personalized production scheduling. This research contributes to advancing multi-objective optimization approaches in customized manufacturing environments with complex uncertainties.

1. Introduction

The manufacturing industry has undergone an iterative transformation of production paradigms, evolving from Mass Production (MP) and Mass Customization (MC) to Personalized Production (PP) [1]. Mass Production achieves cost and efficiency optimization through standardization and high-volume production models but struggles to adapt to consumers' diversified demands [2]; Mass Customization relies on modular design and flexible manufacturing systems to provide limited personalized configurations on the premise of cost control[3] [4]; while Personalized Production takes deep customer participation and full-custom production as its core, realizing highly customized goals through technology integration [5] [6]. Currently, Personalized Production has gradually replaced Mass Customization as the mainstream paradigm, with its core appeal being to balance production efficiency and cost-effectiveness while meeting unique customization needs[7] [8], which is more prevalent in the automotive manufacturing industry.

However, traditional job-shop scheduling models are unable to adapt to dynamic demands such as product specification changes and urgent order insertions in personalized production, and are prone to inducing problems like unbalanced equipment loads and disrupted logistics routes, ultimately leading to reduced production efficiency and rising overall costs [9]. As an extended form of the classic Job-Shop Scheduling Problem (JSP) [10], the Flexible Job-Shop Scheduling Problem (FJSP) boasts a core advantage: each operation can be processed on multiple alternative equipments. By simultaneously optimizing job sequencing, equipment assignment, and dynamic uncertainties, it achieves the coordinated improvement of production efficiency, on-time delivery rate, and equipment utilization. Serving as an effective solution to address personalized production, FJSP has become a research hotspot in both academic and industrial circles.

Existing FJSP research still has notable shortcomings: most studies focus on single-objective or local optimization, with insufficient consideration of the coordination of multi-objective constraints [11]; there is insufficient adaptability to scenarios such as dynamic order changes and process specification adjustments derived from personalized demands; traditional algorithms still have room for improvement in balancing solution space coverage, local optimization accuracy, and convergence speed [12]. Based on this, this paper conducts research on the multi-objective integrated flexible job-shop scheduling problem driven by personalized demands, with the main contributions as follows: 1) Integrate personalized constraints such as dynamic order changes and process specification adjustments to establish an integrated "demand-scheduling" multi-objective mathematical model, which accurately maps actual production scenarios; 2) Design a dual-domain encoding of "equipment selection - start time", active decoding and constraint repair mechanisms to ensure process compliance and no equipment conflicts, realizing full coverage of the solution space and feasible solution guarantee; 3) Optimize personalized genetic operations and algorithm fusion architecture to balance global search and local optimization capabilities, improving solution adaptability and efficiency in dynamic personalized scenarios.

2. Literature Review

Research on the Flexible Job-Shop Scheduling Problem (FJSP) mainly focuses on two core dimensions: modeling optimization and algorithm design, and a relatively systematic research system has been formed. However, its adaptability to personalized dynamic scenarios still needs further enhancement.

In terms of modeling, scholars have extended their research from basic problem characterization to complex scenarios: Chan et al. [13] characterized FJSP as an integrated optimization problem of operation assignment and job sequencing under resource constraints, clarifying the core status of joint decision-making; Özgüven et al. [14]introduced process route and planning flexibility to construct a generalized mathematical model; Zhong et al. [12]converted the uncertain problem into a deterministic equivalent problem through chance-constrained programming for the uncertainty of processing time; Ge et al. [15] focused on personalized customization scenarios and conducted research on collaborative scheduling modeling of production and logistics, providing new ideas for demand-driven optimization. Nevertheless, existing models are still insufficient in depicting dynamic constraints derived from personalization (such as order changes and process adjustments).

In terms of algorithm research, metaheuristic algorithms are the mainstream solution methods for FJSP [16]: Genetic Algorithm (GA) and its improved algorithms are the most widely used—Zhang et al. [17]improved the load balancing and robustness of the algorithm through strategy optimization; Moslehi et al. [18] combined Particle Swarm Optimization (PSO) with local search to enhance the solution efficiency of multi-objective problems; Wang et al. [19] developed a multi-objective genetic algorithm based on immune and entropy principles, effectively realizing the coordinated optimization among multiple objectives; Mei et al. [20] integrated an adaptive simulated annealing mechanism into the NSGA-II algorithm to optimize the scheduling performance under low-carbon objectives; Luo et al. [21]adopted a particle swarm algorithm combining multiple strategies, further improving the optimization performance of PSO in scheduling problems. However, traditional algorithms still need to be improved in balancing solution space coverage and optimization efficiency in dynamic personalized scenarios.

In summary, existing research has made remarkable progress in FJSP modeling and algorithms, but there are still shortcomings: first, insufficient consideration of the coordination of personalized dynamic constraints in multi-objective optimization; second, inadequate adaptability of models to personalized scenarios such as order changes and process adjustments; third, the adaptability and optimization efficiency of algorithms in dynamic scenarios need to be improved. Therefore, there is an urgent need to develop an integrated scheduling model and efficient solution algorithm adapted to the dynamic characteristics of personalized production, so as to provide technical support for manufacturing enterprises.

3. Methodology

3.1 Problem Definition

To adapt to the trends of personalized customization and diversified demands in the automotive industry, and to ensure the adaptability and efficiency of scheduling schemes under the Make-to-Order (MTO) production mode, this problem can be described as follows: An automotive functional component supplier undertakes customized production orders, and its production scenario features two core characteristics: “highly personalized” and “demand uncertainty”. Specifically:The set of customized workpieces to be processed in the workshop is defined as $I = \{i|i = 1,2, \dots, I\}$. Each workpiece i corresponds to a unique customized production order and has exclusive processing requirements; the workshop is equipped with multiple processing equipment with differentiated functions, forming an equipment set $M = \{m|m = 1,2, \dots, M\}$ to meet the processing needs of different operations; each workpiece i needs to complete J_i operations following a specific process route, and the total set of operations for all workpieces is $J = \{j|j = 1,2, \dots, J\}$. The actual production scheduling is illustrated in Figure 1.

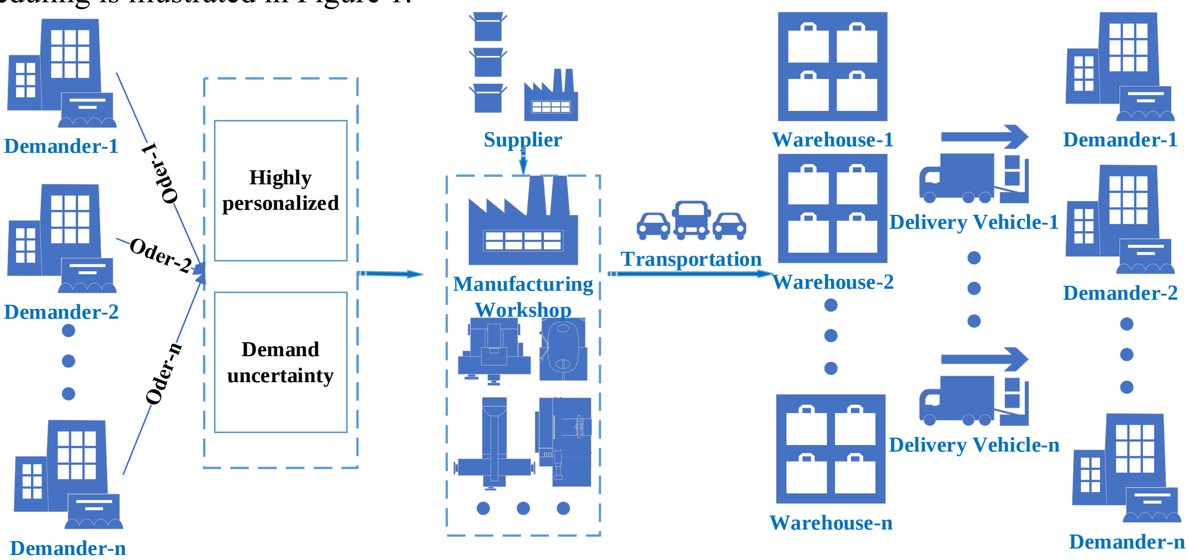

Figure 1 Production Scheduling Schematic Diagram

Based on actual production scenarios and academic modeling standards, this study sets the following assumptions:

(1) The raw material supply is sufficient and meets quality requirements, with no risks of supply

disruptions or quality defects, ensuring production continuity.

(2) The processing of different workpieces can be assigned processing priorities according to order urgency; the operations of the same workpiece follow a strict sequential order, and subsequent operations can only be initiated after the completion of the previous one.

(3) Each operation j can select 1 to 4 suitable pieces of equipment from the equipment set M for processing, which not only guarantees process continuity but also avoids redundancy of equipment resources.

(4) A single piece of equipment can only process one operation of one workpiece at a time, and the processing of the operation cannot be interrupted.

(5) A single workpiece can only undergo one operation on one piece of equipment at a time, with no parallel processing allowed.

(6) The AGV system has no heterogeneous differences and is sufficient in quantity. During transportation, only the unit usage cost, transportation distance cost, and load weight cost are considered, while AGV scheduling conflicts are not taken into account.

3.2 Model Construction and Algorithm Design

Considering the scheduling characteristics of flexible job shops under personalized requirements, a dual-objective optimization system targeting the minimization of total cost and total makespan is constructed. The total cost consists of six types of costs, covering the entire process costs of personalized production. The total makespan is defined as the longest time span from the start of processing to the final completion of all workpieces, which directly reflects the workshop's production efficiency and order response speed, adapting to the rapid delivery requirements of personalized demands. The definitions and value descriptions of key parameters and decision variables involved in the model are shown in Table 1.

Table 1 Meanings and Values of Parameters and Variables

Sets	
i	Set of workpieces, $i = 1,2,\dots,I$
j	Set of operations, $j = 1,2,\dots,J$
m	Set of equipments, $m = 1,2,\dots,M$
v	Set of AGV, $v = 1,2,\dots,V$
parameters	
q_i	Actual production quantity of workpiece i: $q_i \in [q_i^p \times 0.9, q_i^p \times 1.1]$, where q_i^p denotes the demand forecast quantity
t_{ijm}	Processing time of operation j of workpiece i on equipment m: $t_{ijm} \in [t_{ijm}^{\min}, t_{ijm}^{\max}]$
$C_{mcap,m}$	Maximum hourly processing capacity of equipment m : [12,15,18,16,14,10,12,13,14,8,11,9,19,21,23]
P_m	Failure probability per unit overloaded piece count of equipment m : [0.48,0.22,0.16,0.80,0.17,0.86,0.88,0.24,0.15,0.90,0.58,0.82,0.87,0.16,0.75]
C_f^m	Unit fixed cost of equipment m: $C_f^m = 50$ yuan per unit-hour
C_{agv}^v	Unit operating cost of AGV: 45 yuan per unit-hour
C_{mgmt}	Fixed workshop management cost: 100 yuan per hour
$C_{p,ij}$	Unit time production cost of operation j of workpiece i: Varies significantly considering batch size and special operations.
w_i	Unit weight of workpiece i (kg/piece): [6,9,12,10,16,15,8,11,13,4]
$d_{mm'}$	Straight-line distance between different equipment (m)

C_l	Logistics cost per unit weight per unit distance: $C_l = 0.1$ yuan/kg·m
C_{fc}	Unit demand deviation forecast cost: $C_{fc} = 2$ yuan/piece
N_p	Number of forecasts per unit standard cycle: $N_p = 5$
C_d	Unit hourly delay cost per workpiece: $C_d = 15$ yuan/piece-hour
D_i	Normal delivery date; D_i': Urgent delivery date (requiring 12 to 24 hours in advance)
C_m	Unit single failure cost of equipment: $C_m = 200$ yuan per failure
S_{ijm}	Start Processing Time of operation j of workpiece i on equipment (h)
T_i	Total Time for workpiece i to complete all operations (h)
T_{total}	Total Production Cycle (Makespan) (h), $T_{total} = maxT_i$
variables	
z_i	$\begin{cases} 1, Urgent\ order\ requiring\ order\ insertioner \\ 0, otherwise \end{cases}$
x_{ijm}	$\begin{cases} 1, operation\ j\ of\ workpiece\ i\ is\ processed\ on\ machine\ m \\ 0, otherwise \end{cases}$

(1) Fixed Cost (FC): It mainly includes the expenditures of manufacturing equipment, AGVs, and workshop management costs. Its value depends only on the total number of equipment and the total production cycle, and is independent of other dynamic factors in the production process. The details are as follows:

$$FC = \left(\sum_{m=1}^{M} C_f^m + \sum_{v=1}^{V} C_{agv}^v + C_{mgmt} \right) \times T_{total} \tag{1}$$

M denotes the total number of equipment involved in production operations; $T_{\text{total}} = \max(T_i)$ represents the total production cycle (i.e., Makespan), which is the longest time from the start of production to the completion of all tasks. This parameter directly affects the cumulative total of fixed costs throughout the entire production cycle.

(2) Production Cost (PC): It consists of consumable costs and labor costs incurred during the processing of different operations for each workpiece. The formula is as follows, where $J = \sum_{i=1}^{l} J_i$:

$$PC = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{m=1}^{M} C_{p,ij} \times t_{ijm} \times q_i \times x_{ijm} \tag{2}$$

(3) Internal Workshop Logistics Cost (LC): The AGV transportation cost is directly related to the load weight and travel distance.

$$LC = C_l \times \sum_{i=1}^{I} \left[w_i \times q_i \times \sum_{j=1}^{J_i - 1} \sum_{m=1}^{M} \sum_{m'=1}^{M} d_{mm'} \times x_{ijm} \times x_{i(j+1)m'} \right] \tag{3}$$

(4) Flexible Adjustment Cost (FCost): It refers to the adjustment cost arising from deviations between actual demand and forecast demand, covering additional costs incurred in links such as production plan adjustments, inventory strategy changes, and internal logistics and distribution optimization.

$$FCost = C_{fc} \times N_p \times \sum_{i=1}^{I} \left| q_i - q_i^p \right| \tag{4}$$

(5) Delay Cost (DC): Due to dynamic changes in market demand or customers' urgent demands, the job shop may face emergencies. DC is used to measure the cost incurred by the failure to deliver

workpieces on time due to urgent order insertions.

$$DC = C_d \times \sum_{i=1}^{I} \left[q_i \times \max\left(0, T_i - (D_i \cdot (1 - z_i) + D_i' \cdot z_i)\right) \right] \tag{5}$$

$(D_i \cdot (1 - z_i) + D_i' \cdot z_i)$represents the dynamic delivery date of workpiece i, and $max\ (0, T_i$ −dynamic delivery date) is the actual delay time of workpiece i, ensuring that only the costs incurred by delayed deliveries are accounted for.

(6) Equipment Failure Cost (MC) (including maintenance, downtime losses, overload, etc.): It is the cost caused by insufficient production capacity and one of the key indicators to measure the rationality of the scheduling scheme in the job shop of automotive enterprises.

$$MC = C_m \times \sum_{m=1}^{M} \left[P_m \times max\left(0, \sum_{i=1}^{I} \sum_{j=1}^{J} q_i \times x_{ijm} - C_{mcap,m} \times T_m \right) \right] \tag{6}$$

$T_m = \sum_{i=1}^{I} \sum_{j=1}^{J} t_{ijm} \times x_{ijm}$ denotes the total operating time of equipment m. The function of this formula is to accurately identify whether the actual total processing volume exceeds the maximum achievable processing volume. Failure costs will be incurred if it exceeds, otherwise no costs will be generated.

In summary, this paper constructs a dual-objective optimization model. By simultaneously optimizing Total Cost (TC) and Makespan, the dynamic balance between production economy and timeliness can be achieved, adapting to the dual challenges of demand fluctuations and resource constraints. The formula is as follows:

$$min\{TC, Makespan\} \tag{7}$$

$$TC = FC + PC + LC + FCost + DC + MC \tag{8}$$

Constraints:

$$S_{i(j+1)m'} \geq S_{ijm} + t_{ijm} \times x_{ijm}, \forall i, j = 1, \ldots, J_i - 1, m, m' \tag{9}$$

$$S_{i'jm} \geq S_{ijm} + t_{ijm} \times x_{ijm} \ \ or\ \ S_{ijm} \geq S_{i'jm} + t_{i'jm} \times x_{i'jm}, \forall i \neq i', j, m \tag{10}$$

$$t_{ijm}^{min} \leq t_{ijm} \leq t_{ijm}^{max}, \forall i, j, m \tag{11}$$

$$x_{ijm} \in \{0,1\}, S_{ijm} \geq 0, \forall i, j, m \tag{12}$$

Equation (9) represents the precedence constraint of operations. Only when the j-th operation of workpiece i is indeed processed on equipment m (i.e., $x_{ijm} = 1$), $t_{ijm} \times x_{ijm}$ equals the actual processing time. At this point, the start time of the subsequent operation $(j + 1)$ (denoted as $S_{(j+1)m_i}$) must be greater than or equal to the "start time + processing time" of the previous operation. If $x_{ijm} = 0$ (this equipment does not process the operation), the product term is 0, and the constraint is automatically satisfied since $S_{ijm} \geq 0$, without affecting the scheduling of subsequent operations. Equation (10) is the equipment conflict constraint. For the same equipment m, the processing times of different workpieces cannot overlap, and only two feasible sequences exist: either the j-th operation of workpiece i is processed first (the start time of the j-th operation of workpiece i' is greater than or equal to the completion time of the j-th operation of workpiece i), or the j-th operation of workpiece i' is processed first (the start time of the j-th operation of workpiece i is greater than or equal to the completion time of the j-th operation of workpiece i'). The logical "OR" indicates that one of the two sequences must be selected, ensuring the equipment processes only one workpiece at any given time. Equation (11) is the processing time constraint, which ensures the processing duration of any operation fluctuates within a reasonable process range to quickly respond to unforeseen circumstances such as equipment failures. Equation (12) is the variable value constraint. x_{ijm} adopts a 0-1 value rule to indicate whether the operation is being processed, and $S_{ijm} \geq 0$ ensures the start time of any operation is non-negative, guaranteeing the rationality in the time dimension.

3.3 Algorithm Design

This paper integrates the advantages of multi-objective solution sets of NSGA-II with the fast optimization characteristics of PSO to propose the H-MPGA-II algorithm, and its algorithm flow is shown in Figure 2. The core steps and improvements are as follows:

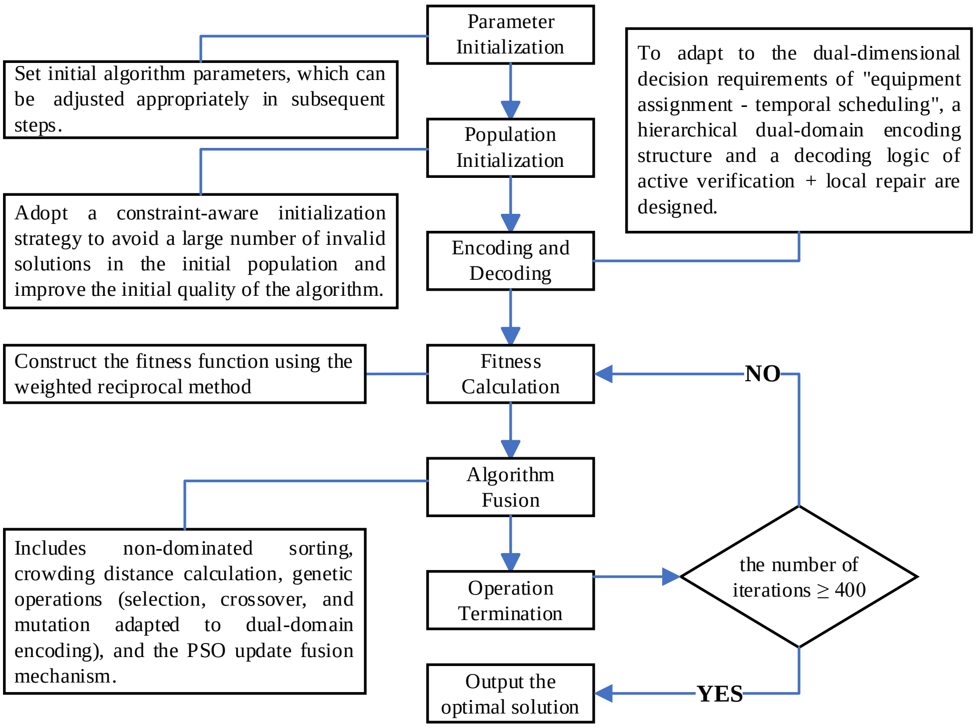

Figure 2 Algorithm Flow

Step 1: Parameter Initialization. Parameter initialization provides prerequisites for subsequent steps such as population initialization, PSO update, and crossover and mutation.

Step 2: Population Initialization. Based on the process constraints of personalized orders and equipment processing capabilities, a constraint-aware initialization strategy is adopted to avoid a large number of invalid solutions in the initial population and improve the initial quality of the algorithm.

Step 3: Encoding and Decoding

(1) To adapt to the dual-dimensional decision requirements of "equipment assignment - temporal scheduling" under personalized demands, a hierarchical dual-domain encoding structure is designed. This encoding method can effectively avoid the mechanical binding of equipment and time sequence, and improve the solution space coverage. As shown inFigure 3: The equipment selection domain indicates whether operation j of workpiece i is processed on equipment m (binary variable).The start time domain indicates the start time of the corresponding equipment m where the equipment selection is 1.For example, "a" indicates that operation 1 of workpiece 1 needs to be processed on M3, and the start time of the equipment is 3.5.

(2) Decoding is the core link of converting the encoded vector into a feasible scheduling scheme. Targeting the dynamic constraints under personalized demands, a decoding logic of active verification + local repair is designed:Temporal verification: Traverse the start time Sijm of all operations, and verify whether $S_{i(j+1)m'} \geq S_{ijm} + t_{ijm} \times x_{ijm}$ is satisfied. If not, correct S_{ijm} to $S_{i(j+1)m'}$ .Equipment conflict verification: Count the processing task time sequence of each piece of equipment. If there is a conflict where the same equipment processes multiple operations simultaneously, prioritize operations with higher priority, and shift the start time of conflicting operations to the completion time of the previous operation.

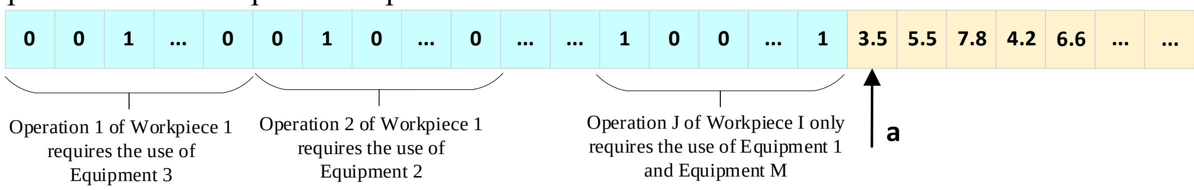

Figure 3 Encoding Mechanism

Step 4: Fitness Calculation. The larger the value, the better the individual, and the higher the chance of becoming a parent individual. Considering that enterprises may attach different levels of importance to the same objective in different periods, the weighted reciprocal method is adopted to construct the fitness function. Among them, ω_1 and ω_2 can be adjusted according to enterprise needs, enabling flexible changes in different priorities:

$$Fit_i = \frac{1}{\omega_1 \cdot TC_i + \omega_2 \cdot Makespan_i} \tag{13}$$

Step 5: Algorithm Fusion. The "individual optimal - global optimal" update mechanism of PSO is integrated into the genetic operations of NSGA-II to improve the algorithm's convergence speed and local optimization ability :

(1) Non-dominated SortingIndividuals in the population are divided into different front levels. The dominance relationship between individuals is determined through pairwise comparison of their objective function values: if individual X is not worse than individual Y in all objectives and better than Y in at least one objective, then X dominates Y. By sequentially selecting non-dominated individuals layer by layer, a Pareto front distribution from Level 1 to subsequent levels is formed, which significantly improves computational efficiency (the maximum number of runs is reduced from $MN^3$to MN^2).

(2) Crowding Distance CalculationFor each objective dimension, the distance difference between adjacent individuals is calculated and normalized. Finally, the sum of distance differences across all dimensions is taken as the crowding distance value of the individual, as shown in Equations (14) and (15). Among them, $\delta_m(i)$denotes the distance difference of individual i in the m-th objective dimension, and $I(i)$ is the crowding distance value. Through crowding distance sorting, individuals with a more uniform distribution are prioritized for retention, which effectively avoids excessive aggregation of the solution set in local areas and enhances the global search ability of the population.

$$\delta_m(i) = \frac{f_m(i+1) - f_m(i-1)}{max f_m(j) - min f_m(j)}, j \in F \tag{14}$$

$$I(i) = \sum_{m=1}^{M} \delta_m(i) \tag{15}$$

(3) Genetic Operations: To adapt to the characteristics of dual-domain encoding, improvements to

genetic operations are required.

1) Selection: The higher the fitness value, the greater the probability of an individual being selected. The roulette wheel selection strategy makes it easier to select high-quality individuals as parent individuals, as shown in Equation (15). Among them, $\sum_{k=1}^{N} Fit_k$ is the total fitness value of the population, and P_i is the selection probability of the i-th individual. First, calculate the Fiti and P_i values of each individual in the population, then generate a random number$i \in [\sum_{k=1}^{i-1} P_k, \sum_{k=1}^{i} P_k]$, the i-th individual is selected as a parent individual. This process is repeated N times until N parent individuals are obtained.

2) Crossover: To avoid infeasible solutions, a dual-domain hierarchical crossover strategy is adopted. For the equipment selection domain: Single-point crossover is used. If all bits of an operation become 0 after crossover, randomly set one equipment bit to 1 to ensure at least one piece of equipment is selected; For the start time domain: Arithmetic crossover is used. The formula for calculating the continuous values at the corresponding positions of two parent individuals is shown in Equation (16). α takes a random value between 0 and 1 to improve population diversity. If the offspring time value is less than 0, it is forced to 0. The specific operation is shown in Figure 4.

3) Mutation:Targeting the dynamics of personalized demands, an adaptive mutation strategy is adopted to improve population diversity, with specific operations shown in Figure 5. For the equipment selection domain: Randomly select a mutation bit and flip its 0-1 value. If there is no suitable equipment for the operation after flipping, re-randomly select a feasible piece of equipment; In the start time domain, a random perturbation strategy is implemented: a random number r within the interval [0, 1] is generated for each continuous value. If $r < P_m$, perform perturbation according to $S'_{ijm} = S_{ijm} + \Delta t$, where $\Delta t \in [0,1]$h. If $S'_{ijm} \leq 0$, set $S'_{ijm} = 0$.

$$FP_i = \frac{Fit_i}{\sum_{k=1}^{N} Fit_k} \tag{16}$$

$$S_{ijm}^{Offspring} = \alpha * S_{ijm}^{Parent1} + (1-\alpha) * S_{ijm}^{Parent2} \tag{17}$$

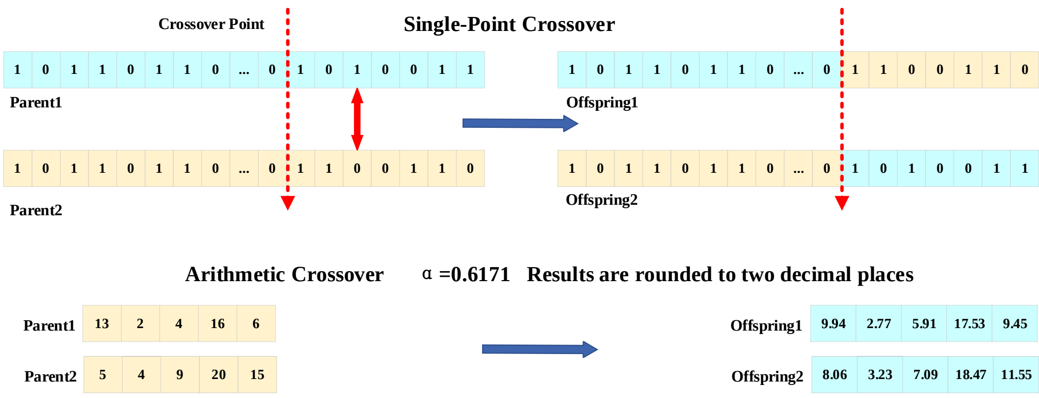

Figure 4 Crossover Operation

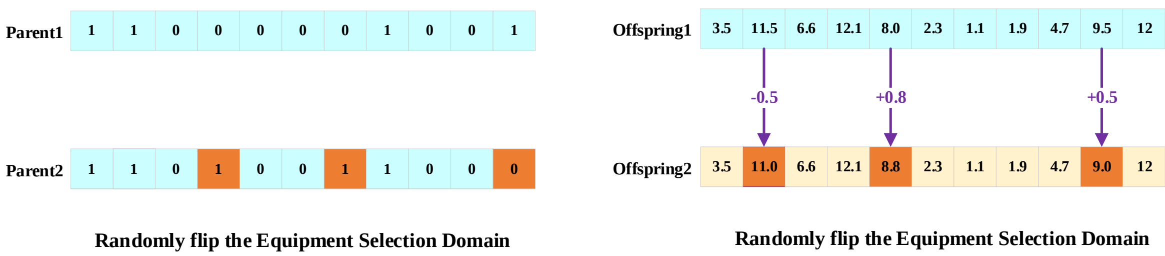

Figure 5 Mutation Operation

(4) Integration of PSO Update Mechanism: After genetic operations, the velocity-position update logic of PSO is introduced to optimize individuals. Specifically, velocity update and position update are performed on the coding vector of each individual in the population in accordance with PSO rules, as shown in Equations (18) and (19):

$$V_{k+1} = w \cdot V_k + c_1 \cdot r_1 \cdot (p_{best} - X_k) + c_2 \cdot r_2 \cdot (g_{best} - X_k) \tag{18}$$

$$X_{k+1} = X_k + V_{k+1} \tag{19}$$

Step 6: Termination Condition.

Determine whether the number of algorithm runs reaches the maximum number of iterations $G_{\max}$. If it is reached, output the optimal solution; otherwise, jump to Step 4 and rerun until the maximum number of iterations is achieved.

4. Case Study

4.1 Data Description

To verify the effectiveness of the proposed algorithm model in practical production scenarios, Enterprise Y is selected as the research case. Enterprise Y is a high-quality auto parts supplier in the industry, which has long undertaken diversified parts demand orders from multiple automobile manufacturers. Its production scheduling scenario is both complex and representative, providing a practical application background for algorithm verification.The research object is the core production workshop of the enterprise. This workshop is equipped with 15 types of processing equipment, including lathes, milling equipments, grinding equipments, boring equipments, CNC equipment tools, EDM equipments, and coordinate measuring equipments (CMMs), which can complete various operations such as turning, shearing, drawing, wire cutting, milling, drilling, argon welding, flanging, mold clamping, as well as inspection, packaging and storage. It is a typical flexible job shop configuration with dual characteristics of operation flexibility and equipment flexibility. Partial production information is shown in Table 2.

Table 2 Data of the FJSP Instance for Enterprise Y

Workpiece No.i	Quantity q_i	Due DateD_i	Optional Equipment M	Processing Time Interval of Each Equipment $t_{ijm} \in [t_{ijm}^{\min}, t_{ijm}^{\max}]$
job1	250	10	1,2,3	[0.37, 0.44, 0.39]-[0.43, 0.50, 0.44]
			6,7	[0.98, 0.91]-[1.24, 1.18]
			8,9	[0.53, 0.59]-[0.66, 0.73]
			4	[0.45]-[0.53]
			10,11,13	[0.20, 0.21, 0.205]-[0.235, 0.24, 0.23]
			11,12	[0.46, 0.41]-[0.58, 0.51]
			13,14,15	[0.26, 0.24, 0.25]-[0.315, 0.28, 0.275]
job2	500	48	1,2,3,4	[0.42, 0.41, 0.43, 0.44]-[0.48, 0.47, 0.51, 0.48]
			6,7,8	[0.34, 0.38, 0.36]-[0.43, 0.50, 0.44]
			9	[0.59]-[0.78]
			5	[0.87]-[1.15]
			10,11	[0.21, 0.22]-[0.26, 0.25]
			12	[0.52]-[0.64]
			13,14	[0.26, 0.25]-[0.33, 0.31]
job3	600	55	2,3,4	[0.50, 0.56, 0.54]-[0.59, 0.67, 0.64]
			6,7,8,9	[0.51, 0.55, 0.58, 0.60]-[0.63, 0.68, 0.72, 0.72]
			8,9	[0.71, 0.65]-[0.91, 0.81]

			1,2	[1.05, 1.13]-[1.32, 1.45]
			10,11,12	[0.21, 0.22, 0.215]-[0.255, 0.25, 0.245]
			11,12	[0.62, 0.72]-[0.80, 0.92]
			13,14,15	[0.32, 0.35, 0.34]-[0.40, 0.43, 0.42]
job4	700	48	2,3,4,5	[0.54, 0.61, 0.49, 0.56]-[0.64, 0.68, 0.59, 0.61]
			6,7	[0.44, 0.49]-[0.54, 0.61]
			8,9	[0.68, 0.76]-[0.85, 0.96]
			4,5	[0.84, 0.89]-[1.06, 1.13]
			10.11	[0.17, 0.175]-[0.20, 0.195]
			12	[0.62]-[0.80]
			13,14	[0.29, 0.30]-[0.365, 0.35]
job5	1900	48	1,2,3	[0.80, 0.80, 0.80]-[1.00, 0.99, 1.00]
			6,7,8	[0.67, 0.71, 0.69]-[0.83, 0.89, 0.86]
			9	[0.91]-[1.24]
			4,5	[0.69, 0.72]-[0.85, 0.85]
			10,11,12	[0.18, 0.185, 0.19]-[0.21, 0.205, 0.21]
			11,12	[1.41, 1.53]-[1.81, 1.98]
			13,14,15	[2.30, 2.48, 2.55]-[3.04, 3.32, 3.25]
job6	1800	72	1,2,3	[0.72, 0.81, 0.76]-[0.90, 1.01, 0.94]
			6,7	[0.60, 0.66]- [0.75, 0.84]
			8,9	[0.39, 0.45]-[0.47, 0.55]
			4,5	[0.43, 0.44]-[0.51, 0.51]
			10,11	[0.24, 0.25]-[0.30, 0.28]
			11,12	[1.40, 1.46]-[1.80, 1.90]
			13,14	[0.90, 0.94]-[1.26, 1.30]
job7	300	24	1,2,3,4	[1.10, 1.13, 1.33, 1.20]-[1.40, 1.43, 1.71, 1.35]
			6,7,8	[0.41, 0.47, 0.42]-[0.49, 0.57, 0.52]
			9	[0.35]-[0.50]
			5	[0.21]-[0.25]
			10,11,12	[0.95, 1.03, 1.07]-[1.22, 1.33, 1.33]
			11,12	[0.98, 1.22]-[1.24, 1.58]
			13,14,15	[1.10, 1.16, 1.20]-[1.53, 1.46, 1.43]
job8	600	24	2,3,4	[0.69, 0.78, 0.71]-[0.85, 0.97, 0.89]
			6,7,8	[0.51, 0.56]-[0.63, 0.70]
			8,9	[0.41, 0.43]- [0.51, 0.50]
			5	[0.25]-[0.29]
			10,11	[0.28, 0.29]-[0.36, 0.34]
			11,12	[1.58, 1.61]-[2.06, 2.09]
			13,14,15	[1.11, 1.17, 1.19]-[1.54, 1.55, 1.63]
job9	650	48	2,3,4	[0.75, 0.79, 0.73]-[0.93, 0.98, 0.91]
			6,7,8	[0.58, 0.60, 0.53]- [0.72, 0.76, 0.65]
			8,9	[0.52, 0.54]-[0.64, 0.64]
			1,2	[1.33, 1.75]-[1.71, 2.28]
			10,11	[0.22, 0.23]-[0.26, 0.25]
			11,12	[1.70, 1.67]-[2.22, 2.17]
			13,14	[1.30, 1.72]-[1.83, 2.40]
job10	200	24	1,2	[0.53, 0.56]-[0.63, 0.68]
			6,7	[0.56, 0.62]-[0.69, 0.77]
			8,9	0.185, 0.20]-[0.215, 0.235]
			4,5	[0.034, 0.038]-[0.042, 0.046]
			10,11,12	[0.185, 0.19, 0.195]-[0.215, 0.21, 0.21]
			11,12	[0.40, 0.42]-[0.50, 0.49]
			13,14,15	[0.25, 0.26, 0.27]-[0.31, 0.30, 0.30]

Data Description

(1) Production Quantity: Due to the impact of personalized demands, actual orders are mostly small-batch, making large-scale production difficult. Therefore, the job shop needs to adjust resources to achieve economical production.

(2) Due Date: Since customers have different demand urgencies for workpieces, there is no linear relationship between the due date and demand volume. In actual production, it is necessary to prioritize satisfying workpieces with shorter due dates to reduce delay costs.

(3) Optional Equipment: Constrained by factors such as equipment production capacity limits, process route dependence, and mold changeover time, some operations can be processed on multiple pieces of equipment (up to 4 units), while others have only one optional piece of equipment available.

(4) Processing Time: Considering factors such as equipment failure rates and equipment performance, the processing time of the same operation varies on different equipment. To reduce production conflicts, the processing duration of any operation is allowed to fluctuate within a reasonable process range, so as to quickly respond to emergencies such as equipment failures.

4.2 Algorithm Experiments

To verify the practical effectiveness of the proposed hybrid algorithm H-MPGA-II in flexible job shop scheduling driven by personalized demands, this experiment takes the standard MOPSO algorithm and standard NSGA-II algorithm as benchmark algorithms, and conducts tests around the core objectives. The experiment designs test instances based on the actual production scenario data of Enterprise Y, which is fully consistent with the problem description and model assumptions mentioned earlier.The experimental environment is configured as follows: Intel (R) Core (TM) i7-8565U CPU @ 1.80GHz (1.99 GHz), 32GB RAM, Dell Windows 10 system. The algorithms are implemented in MATLAB 2023b. All algorithms are run independently 10 times, and then the mean and standard deviation are calculated to eliminate the impact of random errors on the results and ensure the reliability of the outcomes.

4.2.1 Performance Comparison

Combined with the research content of this paper and the parameter configuration experience of previous studies [22], the same parameters are set: population size N=200, crossover probability Pc =0.85, mutation probability Pm=0.5, PSO inertia weight w=0.5, learning factors c1=2.05, c2=2. The algorithms are run 10 times under different iteration numbers, and the results are expressed as mean ± standard deviation (core results + fluctuation range), as shown in Table 3 and Table 4.

Table 3 Comparison of Total Cost Solution Results

Number of Iterations	TC(CNY)Mean ± Standard Deviation		
	MOPSO	NSGA-II	H-MPGA-II
100	1076598.26±2450.32	1054869.85±1890.63	1046458.38±1560.82
200	1054502.81±1980.56	1051955.04±1650.38	1041268.18±1320.65
300	1051684.29±1720.41	1051034.23±1420.52	1038455.80±1150.39
400	1048533.32±1560.78	1049028.83±1280.45	1022822.47±980.56

Table 4 Comparison of Makespan Solution Results

Number of Iterations	Makespan(h)Mean ± Standard Deviation		
	MOPSO	NSGA-II	H-MPGA-II
100	10.98±0.32	10.73±0.26	10.35±0.21
200	10.64±0.28	10.46±0.23	10.33±0.17
300	10.39±0.25	10.43±0.20	9.41±0.14
400	10.31±0.21	10.33±0.18	9.25±0.15

As can be seen from the table data, H-IPNSGA-II demonstrates significant performance advantages at different iterative stages, and its standard deviation is generally smaller than that of the comparison algorithms, indicating better stability:

(1) Total Cost Control Performance: At 400 iterations, the average Total Cost (TC) of H-IPNSGA-II reduces by 2.45% and 2.5% compared with MOPSO and NSGA-II, respectively. The core reason lies in its accurate adaptation to the coupling relationship of multiple costs—through the hybrid search strategy combining PSO and NSGA-II, it synchronously optimizes equipment assignment and processing scheduling, which not only reduces the failure costs caused by equipment overload, but also cuts down the flexibility adjustment costs brought by demand fluctuations.

(2) Makespan Optimization Effect: Similarly, the average Makespan of H-IPNSGA-II shortens by 10.3% and 10.4% in contrast to the comparison algorithms, respectively. The "equipment selection-start time" dual-domain encoding design in this paper avoids the mechanical binding between equipment and tasks in traditional encoding methods, and can more flexibly adapt to the customized process routes of different workpieces, thus reducing the operation waiting time and equipment idle time. It is particularly suitable for the order characteristics of multi-variety and small-batch production in personalized manufacturing.

(3) Iterative Optimization Stability: The performance improvement of H-IPNSGA-II shows a continuous and stable trend. With the increase of iteration times, its standard deviation continues to decrease, approaching the optimal solution gradually with smaller fluctuations. In contrast, the standard MOPSO and NSGA-II algorithms experience optimization stagnation after 200 iterations, where the reduction amplitudes of Makespan and TC are less than 1%, and the standard deviation declines slowly, making it difficult to break through the performance bottleneck further. This also verifies the advantage of the H-MPGA-II hybrid strategy in avoiding premature convergence.

4.2.2 Convergence Comparison

Convergence is a key indicator for measuring the rapid optimization capability of algorithms in dynamic demand scenarios, and the convergence curve reflects the speed and accuracy of algorithms approaching the Pareto optimal solution. Figure 6 and Figure 7 show the convergence curves of the three algorithms in the dimensions of Makespan and total cost, respectively, intuitively presenting the differences in optimization efficiency at different iterative stages.

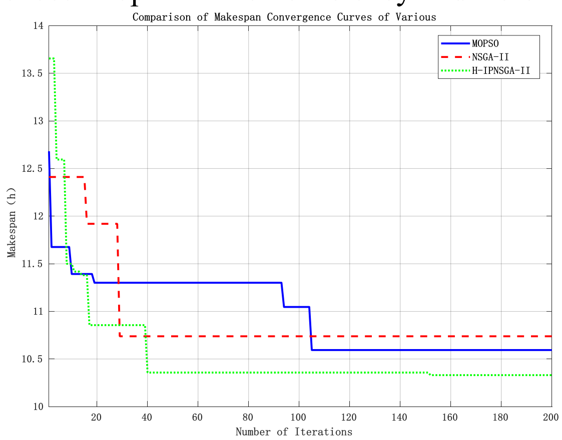

Figure 6 Makespan Convergence Curve

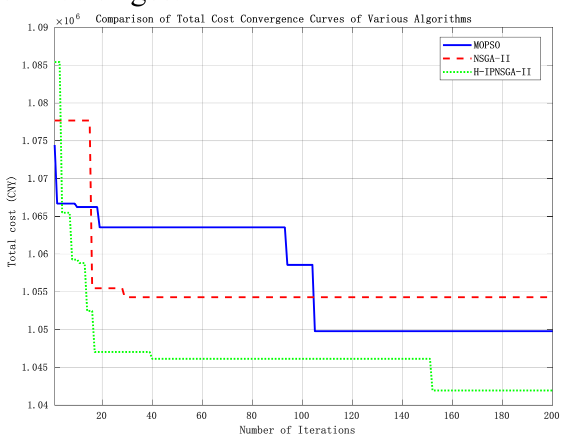

Figure 7 Total Cost Convergence Curve

As shown in the figures, the H-IPNSGA-II algorithm exhibits a much faster early-stage convergence speed than the comparison algorithms, indicating that this algorithm can quickly respond to dynamic demands such as urgent order insertion, thus reducing the time consumed for adjusting scheduling schemes. In addition, the H-IPNSGA-II algorithm does not suffer from premature convergence, and its final convergence value is superior to those of the comparison algorithms. This demonstrates that it can still maintain the accurate exploration of the optimal solution in the later stage of the search process instead of premature stagnation, and thus can effectively meet the sophisticated requirements of multi-objective optimization in personalized production.

In summary, under the same parameter settings, the algorithm proposed in this paper demonstrates superior multi-objective optimization performance, faster convergence speed and stronger stability in the practical case. The optimal scheduling Gantt chart of this algorithm is shown in Figure 8.

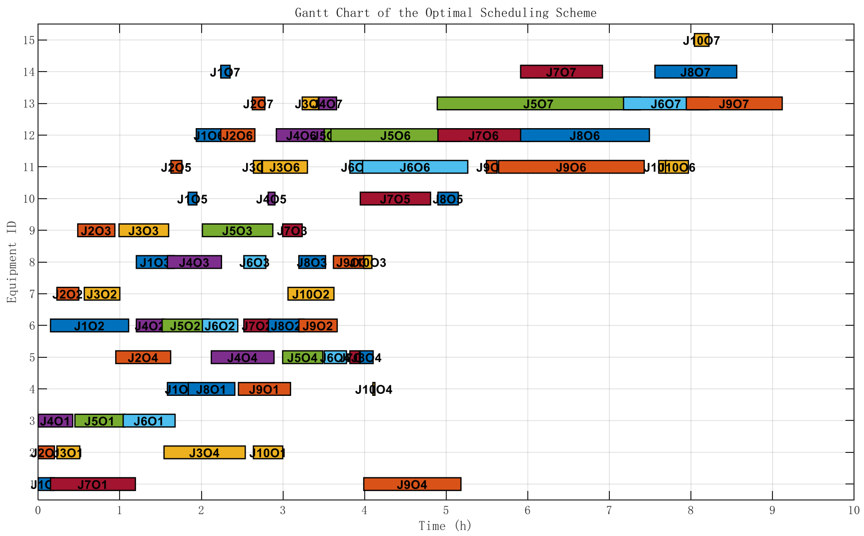

Figure 8 Optimal Scheduling Gantt Chart for the Enterprise Y Instance

4.3 Model Experiments

4.3.1 Result Analysis

The H-IPNSGA-II algorithm is applied to solve the model, and the obtained Pareto front solution set covers scheduling schemes with different objective priorities. Three typical solutions are selected for detailed analysis, as shown in Table 5. Enterprises can flexibly select suitable scheduling schemes according to their own strategic objectives.

Table 5 Scheduling Schemes with Different Priorities

scheme	TC(CNY)	Makespan(h)	FC (CNY)	PC (CNY)	LC (CNY)	$FCost$(CNY)	DC (CNY)	MC(CNY)
1	1024822.47	9.83	11876.35(1.16%)	498235.12(48.62%)	500916.85(48.88%)	6239.80(0.61%)	4567.12(0.44%)	987.23 (0.10%)
2	1132749.17	9.13	13842.51(1.22%)	551237.64(48.66%)	495874.65(43.78%)	6930.23(0.61%)	62345.78(5.50%)	2518.36(0.22%)
3	1098721.33	10.04	12534.68(1.14%)	529457.32(48.20%)	499768.24(45.58%)	6628.08(0.60%)	47823.45 (4.38%)	2209.45(0.20%)

Scheme 1 is Cost-Oriented: Its core advantage lies in significantly reducing delay costs and equipment failure costs through optimized resource allocation. It is suitable for regular production scenarios with accurate demand forecasting and stable orders, where enterprises can achieve economies of scale relying on long-term contracts and stable supply chains.

Scheme 2 is Efficiency-Prioritized: It features the highest total cost yet the shortest production cycle, thus demonstrating significant advantages in scenarios involving urgent order insertion and stringent customer due dates. This scheme maximizes production efficiency by increasing investment in delay costs and equipment maintenance, making it ideal for responding to sudden changes in market demand.

Scheme 3 is Balanced Type: It achieves a trade-off between cost and efficiency in terms of total cost and manufacturing cycle. The proportion of each cost item is relatively balanced, making it applicable to scenarios with moderate demand fluctuations where both operational economy and response speed need to be considered. It provides enterprises with a robust compromise decision option.

Through the multi-dimensional comparison of the Pareto solution set, enterprises can flexibly select suitable scheduling strategies according to order characteristics, market priorities and resource constraints, so as to achieve dynamic balance between personalized demands and production resources.

4.3.2 Sensitivity Analysis

To verify the robustness of the model in uncertain environments, this section focuses on two key parameters—demand fluctuation amplitude and delay cost—to explore the influence law of parameter changes on total cost (TC) and production cycle (Makespan), providing a quantitative basis for enterprise decision-making.

(1) Impact of Demand Fluctuation AmplitudeTaking the average TC and Makespan under the condition of ±5% demand fluctuation amplitude as the baseline, the change ratio of the results under other demand fluctuation amplitudes relative to the baseline value is quantified. The simulation results are shown in Table 6.

Table 6 Simulation Results of Demand Fluctuation

Fluctuation Amplitude	Average TC (CNY)	Average Makespan (h)	Change Rate (vs ±5%)
±5%	1050593.81	9.38	0%
±10%	1058562.80	9.61	TC+0.76%, Makespan+2.45%
±15%	1126848.19	10.35	TC+7.26%, Makespan+10.34%
±20%	1193848.19	11.23	TC+13.64%, Makespan+19.72%

There is a nonlinear positive correlation between demand fluctuation and scheduling objectives. When the fluctuation amplitude is ≤ ±10%, the total cost (TC) and Makespan increase gently (with the change rates both below 3%). The equipment and logistics resources are not saturated, and the fluctuations can be absorbed through dynamic AGV path optimization and adaptive batch adjustment. Exceeding this threshold will lead to equipment overloading, frequent adjustments to production plans, intensified AGV congestion, and a sharp surge in failure and waiting costs. This is consistent with the resource-constrained bottleneck effect of flexible job shops, verifying the model's sensitive response characteristic to fluctuation amplitude.

(2) Impact of Delay CostsAs a key factor affecting enterprise scheduling decisions, changes in delay costs exert an important impact on production scheduling results. Simulation experiments were conducted with different incremental gradients of unit delay cost, as detailed in Table 7.

Table 7 Simulation Results of Delay Cost

Unit Delay Cost (CNY per piece·h)	Average Delay Time (h)	Average TC (CNY)	Delay Cost (Proportion)
10	2.3	1053219.45	8250.06(0.78%)
15	1.2	1184842.47	11239.21(0.95%)
20	0.7	1168527.82	23521.58(2.01%)
25	0.2	1205630.81	37469.32(3.11%)

It can be seen that 15 CNY per piece per hour is the optimal threshold for delay costs. When the delay cost is lower than this value, moderate delays can reduce the risk of equipment overload operation; when it is equal to this value, multi-objective balance can be achieved through operation sequencing optimization; when it is higher than this value, it may be necessary to implement mandatory cycle shortening to offset the substantial delay costs with a small amount of failure costs.

In summary, there is an obvious interaction effect between the two parameters, and the optimal threshold of delay cost needs to be dynamically adapted in combination with order delivery requirements: if the allowable order delay is ≤ 2.5 h, a threshold of 10 CNY per piece per hour can minimize the total cost (TC); if the delivery requirement is stringent (allowable delay ≤ 1.5 h), a threshold of 15–20 CNY per piece per hour is more suitable, where appropriate increase in delay cost can avoid the sharp surge of failure cost; if near-zero delay is required (allowable delay ≤ 0.5 h), a threshold of 25 CNY per piece per hour can meet the delivery requirement, but additional standby equipment needs to be configured to balance the cost. Overall, dynamic resource adaptation that balances demands and costs is required in actual production.

5. Conclusion

This paper focuses on the personalized demand-driven production scenario with multi-variety and small-batch characteristics. Aiming at the core problems of insufficient adaptation between scheduling schemes and dynamic demands, as well as the difficulty in coordinating multi-objective optimization and full-process cost control in this scenario, a dual-objective integrated scheduling model for flexible job shops is constructed to minimize the total cost and makespan, which comprehensively covers full-process cost elements including production, logistics, and delay costs. The proposed H-IPNSGA-II algorithm organically integrates the fast optimization characteristics of PSO and the multi-objective solution distribution advantages of NSGA-II, providing enterprises with flexibly adaptable Pareto optimal decision-making schemes, and effectively supporting the needs of resource allocation and dynamic response in personalized production.

References

[1] S. J. Hu, "Evolving paradigms of manufacturing: from mass production to mass customization and personalization," Procedia CIRP, vol. 7, pp. 3–8, Jan. 2013, doi: 10.1016/j.procir.2013.05.002.

[2] X. Zhang, X. Ming, Z. Liu, Y. Qu, and D. Yin, "A framework and implementation of customer platform-connection manufactory to service (CPMS) model in product service system," J. Cleaner Prod., vol. 230, pp. 798–819, Sep. 2019, doi: 10.1016/j.jclepro.2019.04.382.

[3] R. Duray, "Mass customization origins: mass or custom manufacturing?," Int. J. Oper. Prod. Manage., vol. 22, no. 3, pp. 314–328, Mar. 2002, doi: 10.1108/01443570210417614.

[4] H. Tieng, C.-F. Chen, F.-T. Cheng, and H.-C. Yang, "Automatic virtual metrology and target value adjustment for mass customization," IEEE Robot. Autom. Lett., vol. 2, no. 2, pp. 546–553, Apr. 2017, doi: 10.1109/LRA.2016.2645507.

[5] C. Turner and J. Oyekan, "Personalised production in the age of circular additive manufacturing," Appl. Sci., vol. 13, no. 8, p. 4912, Jan. 2023, doi: 10.3390/app13084912.

[6] J. Liu, Q. Zhi, H. Ji, B. Li, and S. Lei, "Wheel hub customization with an interactive artificial immune algorithm," J. Intell. Manuf., vol. 32, no. 5, pp. 1305–1322, Jun. 2021, doi: 10.1007/s10845-020-01613-x.

[7] P. Foith-Förster and T. Bauernhansl, "Generic production system model of personalized production," MATEC Web Conf., vol. 301, pp. 19–33, 2019, doi: 10.1051/matecconf/201930100019.

[8] B. K. Barik et al., "Manufacturing paradigms and evolution," in Current Advances in Mechanical Engineering, S. K. Acharya and D. P. Mishra, Eds., Singapore: Springer, 2021, pp. 705–714. doi: 10.1007/978-981-33-4795-3_64.

[9] H. Zhu, Y. Zhang, C. Liu, and W. Shi, "An adaptive reinforcement learning-based scheduling approach with combination rules for mixed-line job shop production," Math. Probl. Eng., vol. 2022, pp. 1–14, Sep. 2022, doi: 10.1155/2022/1672166.

[10] S. Dauzère-Pérès, J. Ding, L. Shen, and K. Tamssaouet, "The flexible job shop scheduling problem: a review," Eur. J. Oper. Res., vol. 314, no. 2, pp. 409–432, Apr. 2024, doi: 10.1016/j.ejor.2023.05.017.

[11] Gu, J., Jiang, T., & Zhu, H. (2021). Multi-objective discrete grey wolf optimization algorithm for energy-saving scheduling in job shop problems. Computer Integrated Manufacturing Systems, 27(8), 2295–2306. https://doi.org/10.13196/j.cims.2021.08.012

[12] Zhong, X., Han, Y., Yao, X., Gong, D., & Sun, Y. (2023). Evolutionary solution method for multi-objective flexible job shop scheduling problem under uncertain processing times. Scientia Sinica Informations, 53(4), 737–757. Retrieved December 03, 2025, from https://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CJFQ&dbname=CJFDLAST2023&filename=PZKX202304006

[13] F. T. S. Chan, T. C. Wong, and L. Y. Chan, "Flexible job-shop scheduling problem under resource constraints," Int. J. Prod. Res., vol. 44, no. 11, pp. 2071–2089, Jun. 2006, doi: 10.1080/00207540500386012.

[14] C. Özgüven, L. Özbakır, and Y. Yavuz, "Mathematical models for job-shop scheduling problems with routing and process plan flexibility," Appl. Math. Modell., vol. 34, no. 6, pp. 1539–1548, Jun. 2010, doi: 10.1016/j.apm.2009.09.002.

[15] Ge, Y., Li, S., & Li, W. (2021). Research on coordinated scheduling of production and logistics in personalized customization workshop. Journal of Nanjing University of Science and Technology, 45(6), 692–699. https://doi.org/10.14177/j.cnki.32-1397n.2021.45.06.007

[16] K. Gao, Z. Cao, L. Zhang, Z. Chen, Y. Han, and Q. Pan, "A review on swarm intelligence and evolutionary algorithms for solving flexible job shop scheduling problems," IEEE/CAA J. Autom. Sinica, vol. 6, no. 4, pp. 904–916, Jul. 2019, doi: 10.1109/jas.2019.1911540.

[17] G. Zhang, L. Gao, and Y. Shi, "An effective genetic algorithm for the flexible job-shop scheduling problem," Expert Syst. Appl., vol. 38, no. 4, pp. 3563–3573, Apr. 2011, doi: 10.1016/j.eswa.2010.08.145.

[18] G. Moslehi and M. Mahnam, "A pareto approach to multi-objective flexible job-shop scheduling problem using particle swarm optimization and local search," Int. J. Prod. Econ., vol. 129, no. 1, pp. 14–22, Jan. 2011, doi: 10.1016/j.ijpe.2010.08.004.

[19] X. Wang, L. Gao, C. Zhang, and X. Shao, "A multi-objective genetic algorithm based on immune and entropy principle for flexible job-shop scheduling problem," Int. J. Adv. Manuf. Technol., vol. 51, no. 5–8, pp. 757–767, Nov. 2010, doi: 10.1007/s00170-010-2642-2.

[20] Z. Mei, Y. Lu, and L. Lv, "Research on multi-objective low-carbon flexible job shop scheduling based on improved NSGA-II," Equipments, vol. 12, no. 9, pp. 590–605, Aug. 2024, doi: 10.3390/equipments12090590.

[21] Luo, Z., Zhu, G., Yang, Z., Wang, Z., & Wu, S. (2024). Multi-strategy particle swarm optimization algorithm for job shop scheduling problem. Computer Integrated Manufacturing Systems, 1–24. https://doi.org/10.13196/j.cims.2023.0611