Journal of Intelligent Management Decision
https://www.acadlore.com/journals/JIMD

Optimization of Production Scheduling Through a Multi-Objective Constrained Greedy Model

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Received: 08-01-2024 **Revised:** 09-03-2024 **Accepted:** 09-10-2024

Citation: J. Gao, G. X. Sun, and T. H. Qian, "Optimization of production scheduling through a multi-objective constrained greedy model," *J. Intell Manag. Decis.*, vol. 3, no. 3, pp. 159–174, 2024. https://doi.org/10.56578/jimd030303.

Abstract: The traditional manufacturing sector in China is increasingly challenged by rising labour costs and the diminishing demographic advantage. These issues exacerbate existing inefficiencies, such as limited value addition, high resource consumption, prolonged production cycles, inconsistent product quality, and inadequate automation. To address these challenges, a production scheduling framework is proposed, guided by three key objectives: the prioritisation of high-value orders, the reduction of total processing time, and the earliest possible completion of all orders. This study introduces a multi-objective constrained greedy model designed to optimise scheduling by balancing these objectives through maximum weight allocation, shortest processing time selection, and adherence to the earliest deadlines. The proposed approach incorporates comprehensive reward and penalty factors to account for deviations in performance, thus fostering a balance between operational efficiency and product quality. By implementing the optimised scheduling strategy, it is anticipated that significant improvements will be achieved in production efficiency, workforce motivation, product quality, and organisational reputation. The enhanced operational outcomes are expected to strengthen the core competitiveness of enterprises, particularly within the increasingly complex landscape of pull production systems. This research offers valuable insights for manufacturers seeking to transition towards more efficient, automated, and customer-centric production models, addressing both short-term operational challenges and long-term strategic objectives.

Keywords: Multi-objective constrained greedy model; Comprehensive reward and penalty factors; Production scheduling optimisation; Pull production systems

1 Introduction

Traditional manufacturing is the mainstay of China's manufacturing industry and the foundation of the modern industrial system. China's manufacturing industry has the world's largest scale, the most complete range of categories, the most intact system, and strong international competitiveness, with 80% being traditional manufacturing. It is undeniable that after years of rapid development, traditional manufacturing faces many problems that need to be solved. For a long time, "big but not strong, comprehensive but not refined" have been the prominent labels of China's manufacturing industry, characterized by a frequent overcapacity of low-end production and a lack of high-end supply, with an unstable industrial foundation and weak innovation capabilities. At the same time, facing the challenges of tightening resource constraints and rising factor costs, the comparative advantage of traditional manufacturing is gradually disappearing [1]. Facing the multiple challenges of China's traditional manufacturing industry [2], we adopt a multi-objective optimization strategy aimed at balancing the importance of orders, processing time, and completion time, among other conflicting goals. The goal is to find the optimal solution in a complex production environment, thereby enhancing the overall operational efficiency of the enterprise. Multi-objective optimization is used to solve optimization problems with multiple conflicting objective functions [3, 4]. The core of this strategy is to find a balance between these objectives so that the overall goal can be optimized as much as possible. Multi-objective optimization problems are widely used in various fields, often requiring the optimization of multiple goals, so the best solutions obtained need to meet various constraints, and there may be multiple solutions [5].

To achieve this goal, we introduce the greedy algorithm as a solution tool. In the application of traditional Chinese manufacturing, the greedy algorithm can quickly respond to specific problems, such as in resource allocation and order processing. The greedy algorithm can make the most reasonable decisions under the current information, thereby improving production efficiency and resource utilization efficiency. At the same time, due to its simplicity and efficiency, the greedy algorithm is also suitable for rapid implementation in complex and changing production environments, which has a positive significance for enhancing the overall operational efficiency of enterprises [6–8]. The greedy algorithm is an algorithm based on the greedy strategy. Its core idea is to choose the current optimal solution at each step, hoping to ultimately achieve the global optimal solution. Due to its algorithmic characteristics, the greedy algorithm can break down a problem into multiple sub-problems during the problem-solving process [9]. Each sub-problem is solved using the greedy strategy, and then the solutions to the sub-problems are combined into the solution to the original problem. The advantage of the greedy algorithm is its simplicity and efficiency, making it suitable for solving large-scale problems. However, its shortcomings are also obvious, namely that the greedy strategy may lead to local optimal solutions and fail to achieve the global optimal solution. Therefore, when applying the greedy algorithm, it is necessary to analyze the specific problem to determine whether the greedy strategy is feasible and whether it can achieve the global optimal solution. The greedy algorithm is usually suitable for solving optimization problems, such as minimum spanning tree, shortest path, knapsack problem, etc.

In the transformation process of traditional manufacturing, the integration of lean production models and pull production strategies is particularly crucial. The essence of lean production lies in the elimination of waste, cost savings, and continuous improvement. This production management model emphasizes reducing waste and saving costs in the production process, adopting just-in-time (JIT) process control, emphasizing total quality management, and continuous improvement, thereby achieving comprehensive optimization of the production process [10, 11]. Pull production is essentially a form of lean production. In the mid-20th century, Japan was just recovering from the post-war period and urgently needed to develop manufacturing industries such as automobiles to boost the national economy, but it was constrained by limited resources and weak technical strength. Pull production has caused a significant revolution in the manufacturing industry, promoting the transformation of production models from traditional extensive large-scale production methods to more diverse, small-batch, waste-eliminating, and resource-saving production models [12].

The innovative core of this study lies in the ingenious integration of the concepts of lean production and pull production with greedy algorithms to optimize production scheduling. Greedy algorithms, with their simplicity, efficiency, and ability to handle large-scale problems, have become an ideal tool to address complex production scheduling challenges. They follow the principle of local optimality, choosing the best solution at each step. Although they do not directly pursue global optimality, they coincide with the concepts of immediate response and continuous improvement in lean production and pull production. Through this innovative integration, enterprises can achieve refined production management, quickly respond to market demands, and significantly reduce resource waste. Lean production emphasizes comprehensive quality management and continuous improvement, while greedy algorithms pursue the best local solution at each step. The combination of the two makes production scheduling more flexible and efficient. At the same time, pull production promotes production on demand, and greedy algorithms quickly adapt to this change, effectively reducing overproduction and inventory backlog, significantly improving production efficiency, and enhancing the core competitiveness of enterprises.

In response to the low added value, high resource consumption, low production efficiency, and unstable quality faced by traditional manufacturing in China, this study proposes a multi-objective constrained greedy model, combining various production scheduling strategies and improved reward and punishment factors, aiming to find local optimal solutions and optimize production processes [13]. This model not only significantly improves production efficiency and product quality, reduces resource consumption, and increases product added value, but also promotes the transformation and upgrading of the manufacturing industry, enhances enterprise competitiveness [14], and has a profound strategic significance for promoting the sustainable development of the industry.

2 Model Assumptions and Construction

This paper aims to construct a model for allocating n orders among k parallel machines, determining the processing sequence on each machine. The objective of this model is to meet multiple target requirements while ensuring that the machines are not idle. Specifically, these objectives include:

1). Order importance: The higher the order importance weight W_j the more priority the order should have in being completed.

2). Order processing time: The shorter the order processing time D_j, the more it contributes to improving overall production efficiency.

3). Completion time: The earlier the order is completed, the better it meets customer needs in a timely manner.

In the event of conflicts between these objectives, it is necessary to reasonably consider the priority of current objectives and plan the allocation of machines accordingly, designing an efficient production strategy. To achieve these objectives, we introduce a reward and punishment mechanism, which is used to incentivize positive behaviors and penalize negative behaviors in the production process.

There are k unrelated parallel machines $M_i = \{M_1, M_2, \cdots, M_{\mathrm{k}}\}$ in the factory, and the company receives n orders $O_j = \{O_1, O_2, \cdots, O_n\}$ from customers, each with its own order processing time $D_j\,(D_j = \{D_1, D_2, \cdots, D_n\})$, order cut-off time $L_j\,(L_j = \{L_1, L_2, \cdots, L_n\})$, and order importance weight $W_j\,(W_j = \{W_1, W_2, \cdots, W_n\})$. When the delivery date of order O_j is earlier than the order deadline L_j, certain rewards will be generated, and the reward factor of each order is different as $R_j\,(R_j = \{R_1, R_2, \cdots, R_n\})$; however, if the order completion time is later than the order cut-off time L_j will generate a penalty, and the penalty factor for order delay is set to $P_j\,(P_j = \{P_1, P_2, \cdots, P_n\})$.

Through the construction of this model, it is capable of ensuring the satisfaction of multiple objectives, such as order importance, processing time, and completion time, while reasonably allocating resources and optimizing production scheduling. This, in turn, enhances production efficiency and customer satisfaction.

2.1 Model Assumptions

The goal is to distribute tasks among different machines and arrange the execution order of tasks on each machine to maximize profits, which means achieving the highest total reward after deducting all penalties. The solution proposed in this paper is to use a greedy algorithm to find the optimal local solution at each decision point [15]. The greedy model proposed in this paper is based on the following assumptions:

(1) Each machine can only process one order at the same time;

(2) Each order can only be processed by one machine;

(3) Once an order has started processing, it cannot be interrupted and must be completed;

(4) After a machine completes an order, it will immediately prepare to process the next order.

Although these assumptions play a crucial role in building theoretical models, providing necessary simplifications and abstractions to explore the essence of production scheduling problems, we also recognize that in actual production environments, these assumptions may not fully align with the complex and variable real-world situations. Practical dynamic factors such as machine breakdowns, material shortages, and personnel changes present challenges for the practical application of the model, significantly affecting its adaptability and actual effectiveness.

A thorough analysis of these practical constraints reveals that they not only increase the complexity of production scheduling but also demand higher accuracy and reliability from the model. Therefore, how to incorporate these practical constraints into theoretical models and how to effectively address these challenges within the model have become topics worthy of in-depth discussion.

Looking to the future, we anticipate that future research will further expand and deepen the exploration of this field. By comprehensively considering various potential constraints in actual production, we can continuously optimize and improve theoretical models to make them closer to production practice, providing more precise and effective guidance for production scheduling. This will not only help enhance the efficiency and quality of production scheduling but also contribute to the scientific and intelligent advancement of production management.

2.2 Model Construction

In terms of setting the order processing time D_j and the deadline L_j, the model, based on actual production conditions, requires all orders to be completed within 10 working days. This requires that the processing time D_j and the deadline L_j are less than or equal to this range, and that the processing time D_j is less than or equal to the deadline L_j. The constraint formula is shown as Eq. (1):

$$1 \leq D_j \leq L_j \leq 10, \forall j = 1, 2, 3, \cdots, n \tag{1}$$

where, i is the machine index, $i \in (1, 2, \ldots, k)$, j is the order index, $i \in (1, 2, \ldots, \mathrm{n})$, k is the total number of machines, n is the total number of orders, D_j is the processing time of the jth order, and, L_j is the cut-off time of the jth order. Secondly, score the completion of each order as the basis for the subsequent total score of the objective function. The calculation principle of the order score is as follows: assuming that the order O_j is completed before the deadline L_j, it will be calculated based on its lead time, the weight of the order W_j and the reward factor for the order completion of R_j. The calculation formula is shown in Eq. (2):

$$C_+ = (L_j - CC_j + 1) \times W_j \times R_j \quad L_j \geq CC_j, \quad \forall j = 1, 2, 3, \cdots, n \tag{2}$$

where, L_j is the cut-off time of the jth order, W_j is the weight of the jth order, R_j is the reward factor for the completion of the jth order, and CC_j is the actual completion time of the order. Assuming that order O_j is completed later than the deadline L_j, the delay time, order weight W_j and P_j penalty factor for order completion are calculated, the calculation formula is shown in Eq. (3):

$$C_{-} = -W_j \times P_j \quad L_j < CC_j, \quad \forall j = 1, 2, 3, \cdots, n \tag{3}$$

The score CR_j of the jth order is calculated based on the above order completion, as shown in Eq. (4):

$$CR_j = \begin{cases} C_{+} & L_j \geq CC_j \\ C_{-} & L_j < CC_j \end{cases} \quad \forall j = 1, 2, 3, \cdots, n \tag{4}$$

where, CR_j is the score of the jth order. In the application, assume that the enterprise has 6 machines available and a total of 20 orders for the current quarter, i.e. k=6, n=20. Before optimizing the strategy, both reward and punishment factors are set to 1 for the time being, and these factors can be adjusted based on subsequent goals and orders.

Based on the above constraints, the total score of the multi-objective greedy algorithm is set as CR, and the aim is to maximize this score. Therefore, the calculation formula of the objective function is shown in Eq. (5):

$$\max CR = \sum_{j=1}^{n} CR_j \tag{5}$$

3 Multi-Objective Greedy Algorithm-Based Production Scheduling Strategy

3.1 Multi-Objective Strategy Analysis

Multi-objective strategy analysis [16] can assist enterprises in dealing with complex order allocation problems by comprehensively considering the priorities of maximum weight, shortest processing time, and earliest deadline. By constructing a multi-objective greedy optimization model, we can compare the strategy scores under different reward and penalty factor settings, thereby more accurately formulating an allocation strategy that enhances the core competitiveness of the enterprise. The scores for the three strategies—maximum weight priority, shortest processing time priority, and earliest deadline priority—when all four types of reward and penalty factors are set, are shown in Table 1:

Table 1. Scores of four reward and punishment factors for three production scheduling objectives

	Score				
Production Scheduling Objective	**The Reward and Punishment Factor is Equal to 1**	**Process Time D_j Reward and Punishment Factor**	**Time L_j Reward and Punishment Factor**	**Weight W_j Reward and Punishment Factor**	**Combined Reward and Punishment Factors**
Maximum weight	159	58.9	485.85	489	310.13
Shortest processing time	14	53.8	133.8	-5.6	54.6
Shortest cut-off time	127	28.1	257.55	297.8	175.04

According to Table 1, with the goal of maximum weight priority, only the processing time D_j's reward and punishment factor after changing the reward and punishment factor makes the score less than the initial reward and punishment factor 1, and the cut-off time L_j reward and punishment factor, weight W_j reward and punishment factor, and comprehensive reward and punishment factor score are all higher than the initial score. The cut-off time L_j reward and punishment factor score of 485.85 is close to the weight W_j reward and punishment factor score of 489, and the final comprehensive reward and punishment factor score is 310.13. The initial score of the target with the shortest processing time is only 14, and the score of the new weight W_j reward and punishment factor is negative, indicating that when considering the processing time priority, the influence of weight W_j is greatly ignored, resulting in the delay of most of them, and the score is as low as -5.6, which has obvious disadvantages compared with other strategies under the same reward and punishment factor. Among the targets with the shortest processing time, the highest L_j reward and punishment factor score is the optimal score 133.8; In the strategy with the shortest cut-off time, the reward and punishment factor of processing time D_j is only 28.1, which is significantly lower than the initial reward and punishment factor, and the optimal score is weight W_j reward and punishment factor 297.8.

The final score is set based on the three goals, namely the maximum weight priority, the shortest processing time priority, and the shortest cut-off time priority, and the weight factor is introduced for the final score calculation, as shown in Eq. (6):

$$CR = \alpha CR_D + \beta CR_L + \gamma CR_W \tag{6}$$

When designing multi-objective strategies, the maximum weight priority, the shortest processing time priority, and the shortest cut-off time priority are considered comprehensively. Therefore, the weight of the current goal will be increased correspondingly when each goal is emphasized. For example: when the weight is the highest priority, the value of γ is set to 0.6, and the weight factor of the shortest processing time priority and the shortest cutoff time shortest priority is set to 0.2. The other two strategies are the same. The final score and strategy design are shown in Table 2:

Table 2. Comprehensive scores of the three production scheduling strategies

Production Scheduling Policy	The Reward and Punishment Factor is Equal to 1	Process Time D_j Reward and Punishment Factor	Score Cutoff Time L_j Reward and Punishment Factor	Weight W_j Reward and Punishment Factor	Combined Reward and Punishment Factors
Strategy one	123.6	51.72	369.78	351.84	232.01
Strategy two	65.6	49.68	228.96	154	129.79
Strategy three	110.8	39.4	278.46	275.36	177.97

By combining the three production scheduling objectives with the maximum weight priority, the shortest processing time priority, the shortest cutoff time priority, and the four reward and punishment factors, the processing time D_j reward and punishment factor, the cutoff time L_j reward and punishment factor, the weight W_j reward and punishment factor, and the comprehensive reward and punishment factor, three strategies are obtained as shown in Table 2. The highest score of the three strategies is the cutoff time L_j reward and punishment factor. Secondly, the better score is the influence of weight W_j. Both of these strategies give priority to satisfying the needs of customers, and the actual benefits of the company are more in line with the process of solving multi-objective production [9] in this paper. Therefore, in practical application, for the reward and punishment factor, the cutoff time reward and punishment factor L_j can be given priority. When the corresponding order demand is completed before the order cutoff time, the weight W_j reward and punishment factor can be considered to improve the working efficiency of the machine and the timely completion of important orders.

In calculating the order score, the model carefully considers the case of early or late completion and calculates the score accordingly. This calculation is not only based on the time of advance or delay, but also involves order weights and reward and punishment factors. The reward and punishment factors can be adjusted according to the actual production situation and objectives. Taking a launch vehicle manufacturing company in China as an example, as one of China's launch vehicle manufacturing enterprises, its designers systematically decide the supplier of arrow structure, key materials, product packaging, and manufacturing process. Since different types of launch vehicles have different states and correspond to multiple launch bases in China, each launch of each type of launch vehicle is changing, which means that the production process needs to respond to the design requirements in a timely manner, and adjust the product status, material specifications, and manufacturing process.

However, the company has problems in the production process, such as long delivery cycle, low production efficiency, unstable quality, and low automation rate. For example, the number of days in inventory is an indicator of the length of a product's lead time, and its data shows the number of days a company has experienced from the acquisition of inventory, through assembly consumption, to the delivery of the rocket. According to the statistics of the inventory turnover rate of the company in the past 10 years, it is found that the inventory turnover days of the company were relatively stable from 2011 to 2015, and began to show an upward trend after reaching the lowest 213 days in 2017, reaching as high as 326 days in 2021. Figure 1 shows that it is necessary to adjust methods and strategies to reduce the inventory turnover days.

Through the example of a carrier rocket manufacturing company, it can be seen that different weight settings and the adjustment of reward and punishment factors may lead to different scheduling plans.

In practice, companies can advantage from these analysis results to continuously optimize scheduling strategies. By constantly adjusting weights and reward and punishment factors, companies can develop more accurate and efficient scheduling plans that maximize production efficiency and economic benefits while meeting order requirements. This data-driven decision support tool provides a new methodology for production scheduling and helps realize scientific and intelligent production management.

3.2 Greedy Algorithm

After a thorough understanding of the impact of reward and penalty factors on production scheduling strategies, we now explore how to further improve the efficiency of production scheduling through algorithmic optimization. As discussed in Section 3.1, while cutoff time L_j and weight W_j reward and punishment factors perform well in some cases, in practice, the complexity of production scheduling requires a more flexible and dynamic approach to various variations. This is where greedy algorithms can come into play, but we must also recognize that greedy algorithms run the risk of falling into locally optimal solutions.

The basic idea of the greedy algorithm is to start from an initial solution of the problem and proceed step by step, and according to some optimization measure (greedy strategy), each step must ensure that the local optimal solution can be obtained. This paper presents a greedy algorithm based on optimal order allocation, algorithm 1 is as follows:

Algorithm1: Calculate_score (order, orders, machine_load, machine, machines)

Inputs: Order: order, machine load: machine_load, machine identifier: machine, order list: orders, machine list: machines, the list of reward factors for early completion of the order: rewards, the list of penalty factors for late completion of the order: penalties

Outputs: Updated machine load dictionary:machine_load

Method:

(1) Sort orders by the order's deadline L_j;

(2) Initialize a dictionary machine_load with an empty list, used to store the order load on each machine;

(3) Initialize a maximum score max_score to negative infinity;

(4) Sort orders;

(5) For each order, perform the following operations:

1). Traverse the machines list to find the best machine and perform the following operations for each machine:

a. Initialize an estimated completion time last_finish_time;

b. If machine_load[machine] is empty, then last_finish_time = order[Dj]; otherwise, last_finish_time = max(machine_load[machine]) + order[Dj];

c. score calculation: Score calculation based on penalties and rewards;

d. If score $>$ max_score, assign this number to max_score and best_machine;

(6) If machine_load[best_machine] is empty, directly add the order's processing time D_j, otherwise add the estimated completion time last_finish_time + order[Dj] return machine_load and update the load information of the machine at the same time;

(7) End;

Algorithm 1, while maintaining the efficiency of greedy algorithm, enhances its global search ability, helps to evade local optimal solutions, and further improves the efficiency and quality of production scheduling.

3.3 Multi-Objective Strategy Analysis Algorithm

In Section 3.2, we introduced the application of the greedy algorithm in the order allocation problem, which achieves rapid resolution through local optimal choices. However, this method may not fully consider the balance of all relevant objectives [17]. Therefore, to more comprehensively solve the production scheduling problem, we need to turn to multi-objective strategy analysis.

The idea of the multi-objective strategy analysis algorithm mainly revolves around how to find an optimal solution or a balanced solution among multiple conflicting or related objectives. By setting weights for the objective functions or using aggregation functions, multiple objectives are merged into one for optimization. Here is an algorithm based on multi-objective strategy analysis, Algorithm 2 as follows:

Algorithm 2: Multi_objective_strategy_analysis (orders, machines)

Inputs: Order list: orders, machine list: machines

Outputs: Machine load situation: machine_load

Method:

(1) Assume orders are already sorted by the deadline L_j; if not sorted, sort first;

(2) Initialize a dictionary machine_load with an empty list, used to store the order load on each machine;

(3) Initialize a list strategy_scores to store strategy scores;

(4) Initialize a dictionary current_times with a value of 0, representing the current time of each machine;

(5) For each order in orders, perform the following operations:

a. Find the machine with the earliest current time as the best_machine;
b. Order allocation, add order to machine_load[best_machine];
c. Add the order's processing time order[Dj] to current_times[best_machine];
d. Initialize time_to_deadline = order[Lj] - current_times[best_machine];
e. If time_to_deadline > 0, score_for_this_order = order[Wj] * time_to_deadline, otherwise, score_for_this_order -order[Wj] *|time_to_deadline|;
(6) Update the overall score, initialize total_score as the sum of all order scores and return;
(7) End;

4 Design of Production Scheduling Strategy

In modern manufacturing, the production scheduling strategy is the key to ensuring that the production process is efficient, flexible, and able to respond quickly to market changes [18]. This chapter will provide an in-depth analysis of how to design production scheduling policies to optimize production scheduling to improve overall production efficiency and customer satisfaction.

The core of production scheduling is to ensure that production activities can meet the needs of downstream customers, while maintaining close collaboration with upstream suppliers. To this end, the establishment of vertical pull and horizontal balance two production lines: (1) Vertical pull: according to the model dimension to establish a pull team, from final assembly to parts to raw materials, step-by-step pull, clear inventory, and issue plans. (2) Horizontal balance: make resource allocation in the workshop dimension, balance plan step by step from final assembly to parts to raw materials, and the production department is responsible for assisting the production unit to coordinate resources among models [19]. Figure 1, as shown, illustrates the specific process.

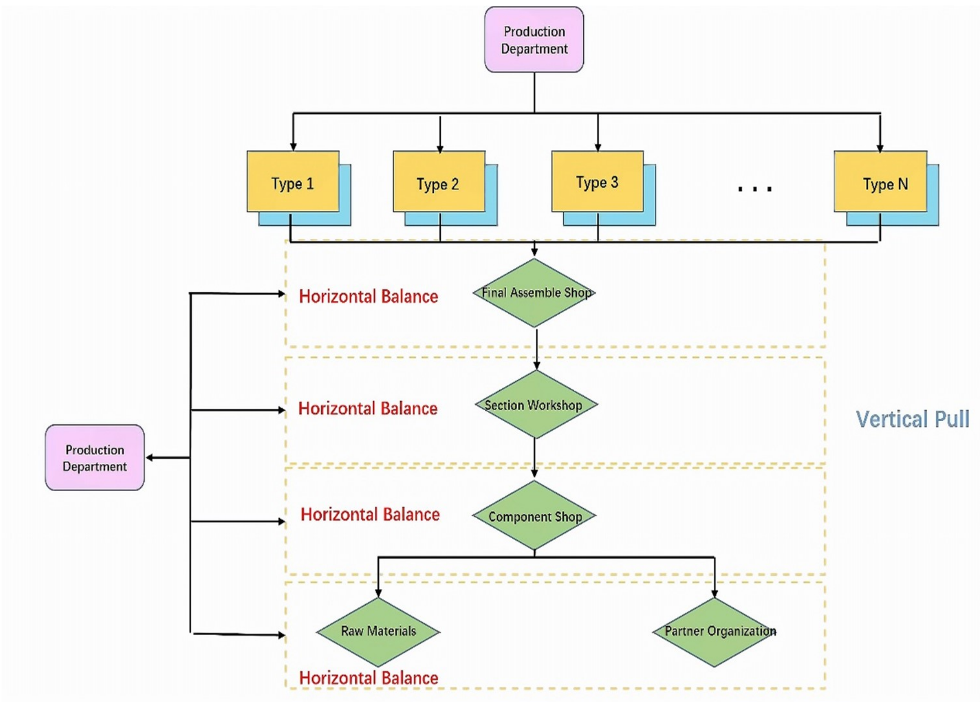


Figure 1. Vertical pull and horizontal balance

In order to further optimize the production scheduling, the production strategy is designed according to the objective function, and the designed production strategy scheme needs to solve three sub-problems: (1) order scheduling, (2) machine allocation, and (3) rewards and penalties for order completion. The details are as follows:

4.1 Order Scheduling

Since there are multiple tasks to be completed, but the number of parts each machine can process is limited, tasks are prioritized according to their delivery dates and the importance of the tasks, with high-priority tasks being produced first to ensure timely delivery. Assuming there are 20 order tasks to be processed in a quarter, taking some orders from 2024 as an example, as shown in Table 3 below.

As shown in Table 3, the machines need to be allocated according to the processing time of the task, and the order scheduling sequence should be allocated according to the processing time D_j, cut-off time L_j, and weight W_j, respectively, as shown in Table 4:

Table 3. Partial order table for 2024

Order Reference	Processing Time D_j	Deadline L_j	Weight W_j
O1	2	6	4
O2	2	7	3
O3	3	8	2
O4	5	9	4
O5	4	6	2
O6	4	7	3
O7	3	7	1
O8	2	7	4
O9	3	9	2
O10	2	6	3
O11	1	5	2
O12	3	6	4
O13	4	8	1
O14	5	9	1
O15	3	7	2
O16	2	10	4
O17	4	6	2
O18	3	5	2
O19	5	7	3
O20	1	5	4

Table 4. Order scheduling sequence

	Processing Time D_j	Deadline L_j	Weight W_j
1	[O4, O4, O4, O4, O4]	[O20]	[O1, O1]
2	[O19, O19, O19, O19, O19]	[O18, O18, O18]	[O8, O8]
3	[O14, O14, O14, O14, O14]	[O11]	[O16, O16]
4	[O5, O5, O5, O5]	[O17, O17, O17, O17]	[O12, O12, O12]
5	[O6, O6, O6, O6]	[O12, O12, O12]	[O20]
6	[O17, O17, O17, O17]	[O1, O1]	[O4, O4, O4, O4, O4]
7	[O13, O13, O13, O13]	[O5, O5, O5, O5]	[O6, O6, O6, O6]
8	[O18, O18, O18]	[O10, O10]	[O10, O10]
9	[O15, O15, O15]	[O7, O7, O7]	[O2, O2]
10	[O3, O3, O3]	[O8, O8]	[O19, O19, O19, O19, O19]
11	[O7, O7, O7]	[O19, O19, O19, O19, O19]	[O5, O5, O5, O5]
12	[O9, O9, O9]	[O15, O15, O15]	[O9, O9, O9]
13	[O12, O12, O12]	[O2, O2]	[O15, O15, O15]
14	[O16, O16]	[O6, O6, O6, O6]	[O3, O3, O3]
15	[O1, O1]	[O13, O13, O13, O13]	[O17, O17, O17, O17]
16	[O2, O2]	[O3, O3, O3]	[O18, O18, O18]
17	[O8, O8]	[O9, O9, O9]	[O11]
18	[O10, O10]	[O4, O4, O4, O4, O4]	[O7, O7, O7]
19	[O11]	[O14, O14, O14, O14, O14]	[O13, O13, O13, O13]
20	[O20]	[O16, O16]	[O14, O14, O14, O14, O14]

4.2 Machine Allocation

If the workshop of the enterprise has a total of 6 machines in the same working condition to work, the current 20 orders need to be reasonably allocated to each machine and ensure that there is no preemption and waste, and according to the above order scheduling situation, the processing time D_j, cut-off time L_j, and weight W_j are considered in order to allocate machines.

First, the machine is allocated according to the processing time D_j, as shown in Table 5:

According to Table 3, it can be seen that all orders are assigned to the corresponding machines, and the order scheduling is only conducted according to the shortest processing time D_j, without considering the problem of the cut-off time L_j, so the order is likely to be overdue. Therefore, it is also necessary to refer to the score of the strategy for evaluation.

Table 5. Assigns machine orders according to the processing time of D_j

Machine Identification Number	Order Sequence
M1	O4, O4, O4, O4, O4, O3, O3, O3, O1, O1
M2	O19, O19, O19, O19, O19, O7, O7, O7, O2, O2
M3	O14, O14, O14, O14, O14, O9, O9, O9, O8, O8
M4	O5, O5, O5, O5, O13, O13, O13, O13, O10, O10
M5	O6, O6, O6, O6, O18, O18, O18, O12, O12, O12
M6	O17, O17, O17, O17, O15, O15, O15, O16, O16, O11

Next, the machines are allocated according to the deadline L_j. At this time, it is important to consider that the order can be completed before the deadline, and the machine allocation situation is shown in Table 6:

Table 6. Assigns machine orders based on cut-off time L_j

Machine Identification Number	Order Sequence
M1	O20, O5, O5, O5, O5, O6, O6, O6, O6, None
M2	O18, O18, O18, O8, O8, O13, O13, O13, O13, None
M3	O11, O10, O10, O19, O19, O19, O19, O19, None, None
M4	O17, O17, O17, O17, O2, O2, O9, O9, O9, None
M5	O12, O12, O12, O15, O15, O15, O16, O16, None, None
M6	O1, O1, O7, O7, O7, O3, O3, O3, None, None

According to Table 6, it can be seen that only part of the orders are assigned to the corresponding machines, and the order scheduling is mainly conducted according to the cut-off time L_j, with the focus on considering the issue of the order not being overdue. After reducing the order delay situation, the corresponding penalty for late occurrence will be reduced and the reward will be increased, which will increase the score of the participating strategy.

Finally, orders are scheduled according to weight W_j, and L_j pays more attention to the size of weight W_j than the cut-off time. At this time, machine allocation is shown in Table 7:

Table 7. Assigns machine orders according to weight W_j

Machine Identification Number	Order Sequence
M1	O1, O1, O10, O10, O9, O9, O9, O18, O18, O18
M2	O8, O8, O2, O2, O15, O15, O15, O11, None, None
M3	O16, O16, O19, O19, O19, O19, O19, O7, O7, O7
M4	O12, O12, O12, O5, O5, O5, O5, None, None, None
M5	O20, O6, O6, O6, O6, O3, O3, O3, None, None
M6	O4, O4, O4, O4, O4, O17, O17, O17, O17, None

The size of the weight W_j indicates the importance of the order. Although the processing time of the order D_j and the deadline time L_j may not guarantee the optimal situation at the same time, the importance of the order will be given priority, and the importance of the order will be completed first.

In the production scheduling, how to arrange and schedule the tasks in the production process reasonably is very important. The greedy algorithm is a common optimization algorithm that achieves the global optimal solution through the local optimal selection of each step. Based on the greedy algorithm principle, this model proposes three strategies: maximum weight first, shortest processing time first, and shortest cutoff time first.

In the maximum weight priority policy, the task with the highest weight is selected first for scheduling to ensure timely completion of important tasks. In the shortest processing time priority strategy, the task with the shortest processing time is selected first for scheduling to shorten the production cycle and improve the production efficiency. In the policy with the shortest deadline, the task with the shortest deadline is selected for scheduling to ensure that the task can be completed within the specified time.

Based on these three strategies, the original orders are prioritized, respectively. The orders are processed according to the principle that the machine preferentially processes those with the longest unused time. The termination condition is the completion of the order processing, or the machine cannot process any remaining order with the remaining unused time. The actual score of different strategies is calculated. When the reward and punishment factors of the three strategies of maximum weight first, shortest processing time first, and shortest cut-off time are all set to 1, the scores are shown in Table 8:

Table 8. Scores of three production scheduling strategies

	Production Scheduling Strategy	Score
1	Maximum weight	159
2	Shortest processing time	14
3	Shortest cut-off time	127

According to the score in Table 8, it can be seen that the shortest processing time is the priority. Although all orders can be reasonably allocated, the final score is only 14 points, which is far lower than the score of the other two strategies. When the reward and punishment factor is 1, the score of the weight first is the best. However, the setting of reward and punishment factors should be further optimized, so the reward and punishment factors should be further adjusted to comprehensively evaluate the score.

4.3 Order rewards and Punishments

The scores of four kinds of reward and punishment factors are set according to the processing time D_j, cut-off time L_j, weight W_j, and three kinds of goals. These factors not only affect the completion of the order, but also may affect each other and produce interactive effects. For example, an order may need to be completed by the deadline due to its high weight in order to receive a higher reward, but it will be penalized accordingly if it is not completed on time. Therefore, the setting of reward and punishment factors needs to reflect these complex relationships.

The reward and punishment factor setting of the processing time D_j: The reward and punishment factor of the processing time is not only related to the processing time itself, but also related to the probability distribution of the current processing time. This setup is designed to encourage shorter processing times and increased production efficiency. Cutoff time L_j reward and punishment factor setting: the cutoff time reward and punishment factor takes into account the urgency of the order. By counting the distribution of deadlines, different levels of rewards and penalties can be set for early or late orders to incentivize timely delivery. Setting the reward and punishment factor of weight W_j: the reward and punishment factor of weight is directly related to the importance of the order. In order to increase the weight gap, the quadratic weight is adopted to set the reward and punishment factor, so that the more important orders will get a greater reward or punishment. Combined reward and punishment factor: the combined reward and punishment factor is a comprehensive consideration of the processing time D_j, cut-off time L_j, and weight W_j. By weighting these factors, it is possible to more fully assess the rewards and penalties for each order. The weighting coefficient is set to reflect the relative importance of different factors in actual production.

(1) Set the reward and punishment factor of processing time D_j. First, make statistics on the distribution of order processing time D_j, as shown in Table 9.

Table 9. D_j distribution of order processing time

Processing Time D_j	1	2	3	4	5
Amount	2	5	6	4	3
Distribution probability	0.1	0.25	0.3	0.2	0.15

Reward factor R_j and penalty P_j factor Settings, the calculation formula is shown in Eqs. (7) and (8):

$$R_j = D_j \times P(R_j) \tag{7}$$

$$P_j = -D_j \times P(P_j) \tag{8}$$

The setting of the reward factor R_j and penalty P_j factors for the processing time D_j is the product of the probability distribution of the processing time D_j and the current processing time.

(2) Setting the reward and punishment factor of the cutoff time L_j. First, the distribution of the order cutoff time L_j is statistically analyzed, as shown in Table 10.

Table 10. L_j distribution of order cut-off time

Deadline L_j	**5**	**6**	**7**	**8**	**9**	**10**
Amount	3	5	6	2	3	1
Distribution probability	0.15	0.25	0.3	0.1	0.15	0.05

The reward factor R_j and penalty P_j factor settings of the cutoff time L_j are calculated by the formulas shown in Eqs. (9) and (10):

$$R_j = L_j \times P(R_j) \tag{9}$$

$$P_j = -L_j \times P(P_j) \tag{10}$$

The setting of the reward factor R_j and penalty P_j factors for the cutoff time L_j is the product of the probability distribution of the cutoff time L_j and the current cutoff time L_j.

(3) Set the reward and punishment factors for weight W_j. First, make statistics on the distribution of order weight W_j, as shown in Table 11.

Table 11. W_j distribution of order weight

Weight W_j	**1**	**2**	**3**	**4**
Amount	3	7	4	6

The weight W_j is not related to the number of order samples, so only the weight problem is considered in the calculation of the reward factor R_j and penalty P_j factor settings. The calculation formula is shown in Eqs. (11) and (12):

$$R_j = \frac{W_j}{5} \times W_j \tag{11}$$

$$P_j = -\frac{W_j}{5} \times W_j \tag{12}$$

The setting of reward factor R_j and punishment factor P_j of weight W_j is related to the power of the second power of weight W_j. The purpose is to increase the weight gap, so that the reward and punishment of more important orders will be greater, which can better motivate employees to improve the work efficiency of orders.

(4) The comprehensive reward and punishment factor, whose setting is based on the above three processing time D_j, cut-off time L_j and weight W_j, is weighted, and the weighting coefficient is set to 0.3. The calculation formula of the comprehensive reward and punishment factor is shown in Eqs. (13) and (14):

$$R_j = 0.3 \times D_j \times P(R_j) + 0.3 \times L_j \times P(R_j) + 0.3 \times \frac{W_j}{5} \times W_j \tag{13}$$

$$P_j = -0.3 \times D_j \times P(R_j) - 0.3 \times L_j \times P(R_j) - 0.3 \times \frac{W_j}{5} \times W_j \tag{14}$$

The comprehensive reward and punishment factor considers the synthesis of processing time D_j, cut-off time L_j, and weight W_j, and then analyzes the comprehensive score of strategies with different reward and punishment factors.

In order to more accurately reflect the theoretical basis and practical background of these reward and penalty factors, it is necessary to further analyze how these factors interact with key performance indicators such as production efficiency, product quality, and customer satisfaction. In addition, by simulating the production scheduling under different reward and penalty strategies, we can better understand the comprehensive mechanism of these factors and adjust the settings of reward and penalty factors accordingly to achieve the best production scheduling effect. This comprehensive approach helps us to understand the impact of reward and punishment mechanisms on the production process more comprehensively, so as to provide more effective production management strategies for actual production enterprises, such as companies.

4.4 Assessment of Rewards and Punishments

In the process of promoting production efficiency and product quality improvement in enterprises, pull production incentive assessment plays a key role. This assessment is guided by "improving quality and efficiency, reducing cost and efficiency, reducing staff, and increasing efficiency", and encourages the workshop to take the initiative and coordination to ensure that the final assembly and pulling projects are delivered according to the planned nodes and the required quantity, and ensure the accurate execution of tasks. Therefore, enterprises need to set up financial support and establish incentive systems to improve the enthusiasm of employees.

In order to achieve this goal, the enterprise has adopted a series of innovative management measures. First of all, the end-user unit and the design unit in the original process are connected in series, and the unit is used to feedback the application situation of the tool to the designer and establish an incentive mechanism to achieve closed-loop management [20] and stimulate the enthusiasm of employees for innovation. Such measures can not only improve the quality of products designed by designers in the product research and development department, improve the pass rate, but also improve the management efficiency by deepening the tracking and understanding of the new tooling by the technical personnel of the using unit. After the production department sends workers for production approval, the progress of the tooling manufacturing task will be automatically synchronized to the user unit, and the user workshop can follow up and supervise the tooling task in time to make timely changes. Figure 2 shows some details.

In order to further stimulate, enterprises have adopted assessment and reward methods, including: (1) The production department needs to define the processing time D_j, cut-off time L_j, and weight W_j in accordance with the order situation every quarter to establish an assessment and reward system with different reward and punishment factors. The production department verifies the total number of people in each unit at the beginning of the year through the reward and punishment factors and the number of parts ordered, defines the amount of incentive quota among the units of the responsibility matrix, and provides feedback to the human resources department. Taking 20 orders in this quarter as an example, 4 reward and punishment factors are shown in Table 12:

Table 12. 4 kinds of reward and punishment factors for 20 orders

Punishment Factors	Order Reward and Punishment Factor Distribution
Process time D_j reward and punishment factor	0.2, 0.2, 0.45, 1.25, 0.8, 0.8, 0.45, 0.2, 0.45, 0.2, 0.05, 0.45, 0.8, 1.25, 0.45, 0.2, 0.8, 0.45, 1.25, 0.05
Cutoff time L_j reward and punishment factor	1.8, 2.45, 3.2, 4.05, 1.8, 2.45, 2.45, 2.45, 4.05, 1.8, 1.25, 1.8, 3.2, 4.05, 2.45, 5, 1.8, 1.25, 2.45, 1.25
Weight W_j reward and punishment factor	3.2, 1.8, 0.8, 3.2, 0.8, 1.8, 0.2, 3.2, 0.8, 1.8, 0.8, 3.2, 0.2, 0.2, 0.8, 3.2, 0.8, 0.8, 1.8, 3.2
Combined reward and punishment factors	1.56, 1.335, 1.335, 2.55, 1.02, 1.515, 0.93, 1.755, 1.59, 1.14, 0.63, 1.635, 1.26, 1.65, 1.11, 2.52, 1.02, 0.75, 1.65, 1.35

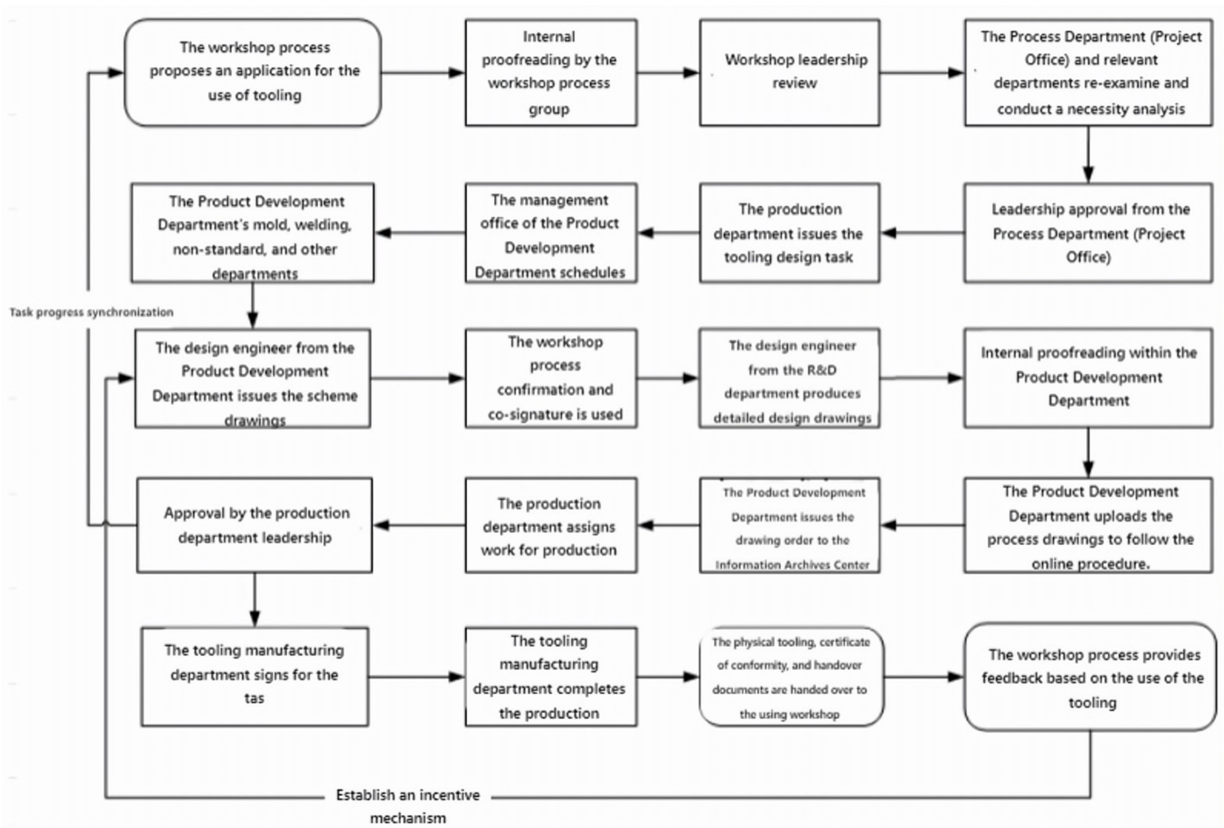
According to different reward and punishment factors to complete the order within the expected time according to 5% of the order quantity × the reward and punishment factor of the current order, 300 yuan/person cap; if the order is not completed within the order deadline, the number of uncompleted order parts x the reward and punishment factor of the current order, 300 yuan/person cap. In order to improve production efficiency, through optimizing the process, improving resource utilization, reducing production costs, and other ways to achieve higher output. It should be noted that when implementing these strategies, enterprises need to comprehensively consider factors such as employee welfare and social responsibility to avoid problems such as excessive employee pressure and increased employee turnover. Enterprises also need to reasonably balance the relationship between cost reduction and efficiency improvement to ensure that product quality and employee stability are not affected while improving efficiency.

(2) In order to maximize the subjective initiative of each workshop, the chain length responsibility system is set up, and the downstream unit (chain length) develops the incentive assessment issuance system for the upstream unit. Chain length system is a new term in the economic field in recent years, to serve as the leader of the chain, by giving full play to the party and government leaders gather internal and external resources, promote the regional development of modern industrial chains, and provide high quality to promote the development of industrial chains. Establish a personalized assessment mechanism between upstream and downstream units, the downstream unit (chain length), formulate an incentive assessment and release system for upstream units, and conduct incentive release according to the system and the implementation of the final assembly pull. At the beginning of each year, each model transmits the annual delivery plan to all levels of chain length units [21]. At the end of each month, the downstream unit will feedback the monthly incentive assessment opinions to the production department, and the production department will collect the monthly incentive information and transfer it to the human resources department for distribution.

(3) Downstream units can control the rhythm of incentive payment according to the actual situation of final assembly and pull, and the incentive payment shall not exceed the total incentive amount of each unit approved by the

production department.

(a)



(b)

Figure 2. Comparison of business management processes before and after optimization: (a) Original tooling service management process; (b) Optimized tooling business management processes

5 Comparison of Effects Before and After Implementation

After the implementation of the above improvement measures, the production situation of a certain model was observed again, and the queuing time, production preparation time, production operation time, and handover time under the new production mode were recorded, as well as the actual start time and actual end time of each step. The results showed that although there was still a certain gap in the completion rate in the sequence, it was obvious that, pull production mode digests historical inventory, releases capacity, and achieves cost reduction and efficiency increase. The production cycle of a certain model has been reduced from the original 285 days to 253 days, as shown in Figures 3 and 4.

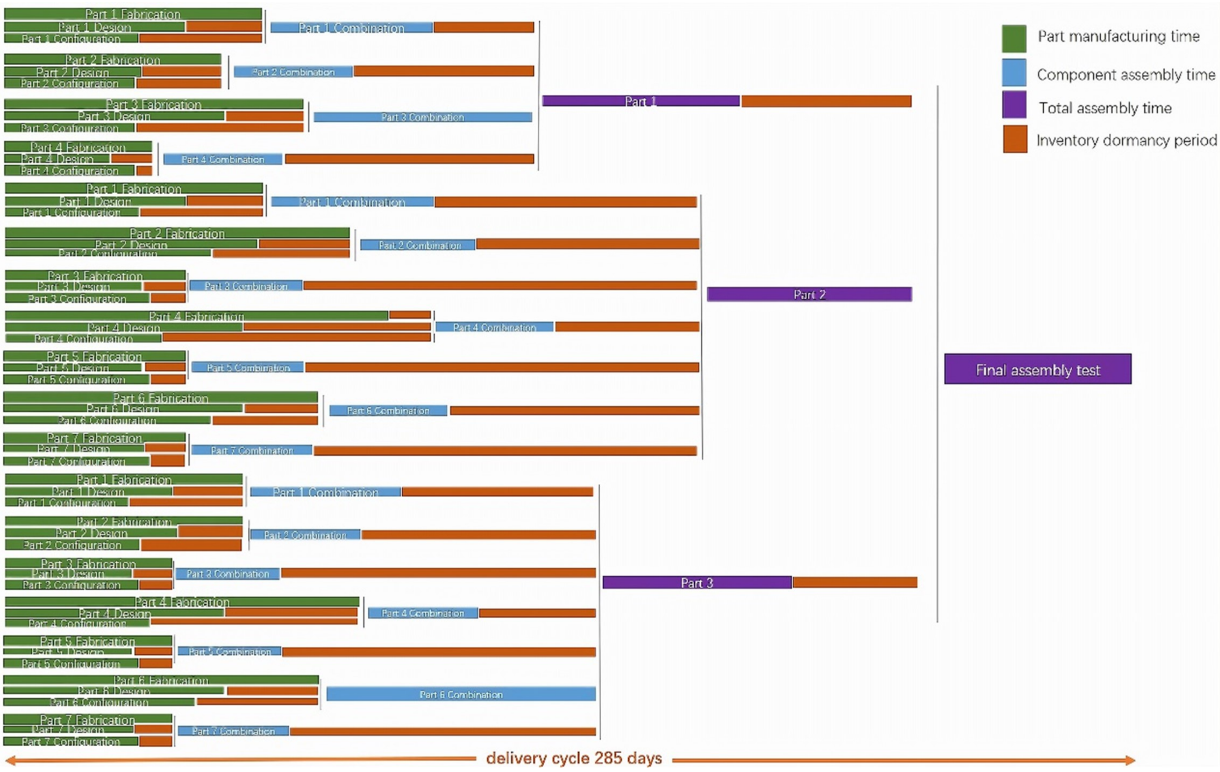


Figure 3. Delivery cycle of a model's original production mode

In addition to shortening the production cycle, the pull production mode also solves the problem that the downstream workshop is often passive waiting and the workshop plan completion rate is low. It reduces cost overhangs and lowers the proportion of stockpiled parts and inactive inventory. In addition, through the upstream and downstream repeated process planning communication, we improve the missing item accuracy, thus enhancing the flexibility of the production line.

In order to further verify the effectiveness of the greedy algorithm-optimized pull production scheduling model, this study compares it with two production scheduling methods: rule-based scheduling and real-time monitoring and adjustment. By comprehensively evaluating key indicators such as production cycle time, inventory level, and planned completion rate, this study found that the pull production model showed significant advantages in multiple dimensions. Compared with rule-based scheduling methods, greedy algorithm-based pull models can respond more flexible to production changes, reduce ineffective production and inventory overruns, and improve production efficiency. Compared with real-time monitoring and adjustment methods, this model reduces the dependence on real-time data through accurate prediction and planning while maintaining a high degree of production flexibility and resource utilization efficiency. These advantages fully prove the excellent performance of the greedy algorithm in optimizing production scheduling and provide strong support for enterprises to improve production efficiency and reduce costs.

In exploring the validity of the greedy algorithmically optimized pull production scheduling model, a comprehensive sensitivity analysis is performed to evaluate its robustness. By accurately simulating the parameter changes in various production scenarios, including but not limited to the increase or decrease of order volume and the adjustment of production capacity, the response mechanism of the model to these dynamic changes is carefully observed. The results show that the pull production model shows good stability and excellent adaptability in various simulation scenarios, which strongly strengthens the scientific basis of the feasibility of the model in the actual production environment.

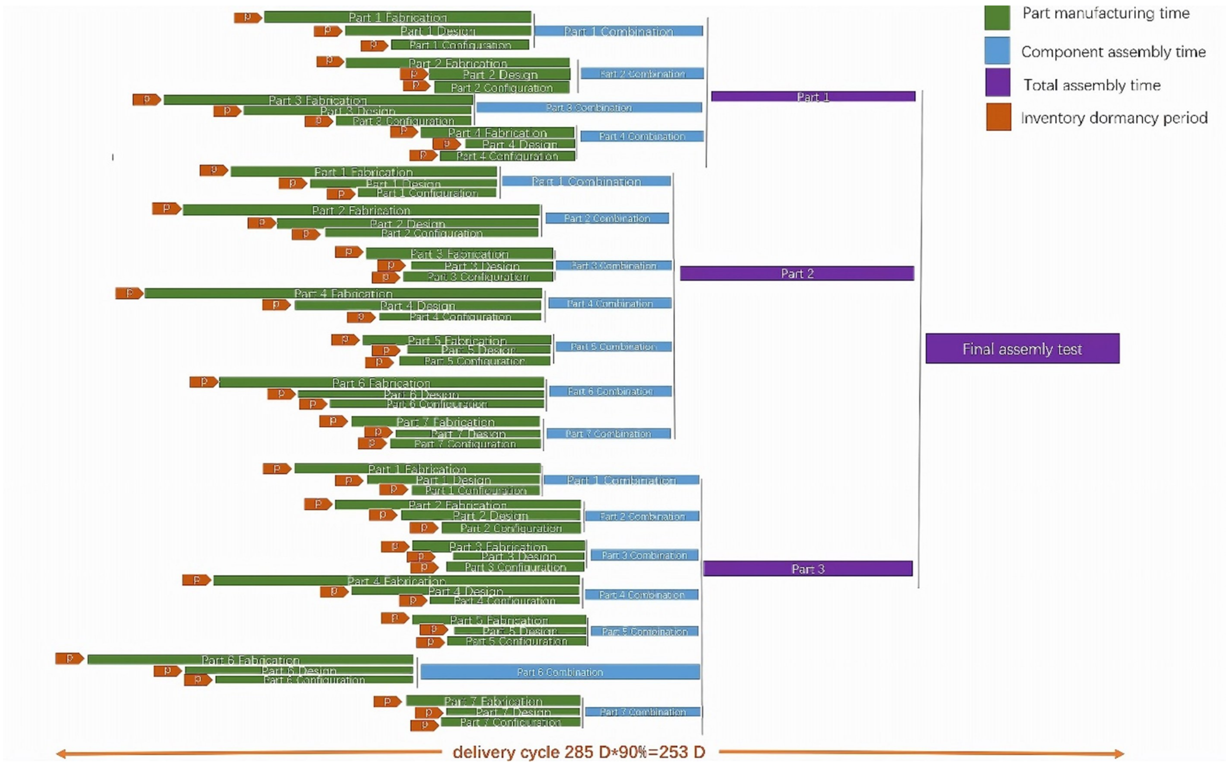


Figure 4. Delivery cycle of a pull production mode

6 Conclusions

The greedy optimization model with multi-objective constraints is used to design the production scheduling strategy, including three objectives: maximum priority of order weight, minimum priority of order processing time, and minimum priority of order cut-off time. Four penalty factors (weight reward and punishment factor, processing time reward and punishment factor, cut-off time reward and punishment factor, and comprehensive reward and punishment factor) are designed according to the order weight, order processing time reward and punishment factor, and three strategies are designed according to the multi-objective, and different reward and punishment factor strategies are applied according to the actual situation to ensure the improvement of production efficiency.

Data Availability

The data supporting our research results are included within the article or supplementary material.

Conflicts of Interest

The authors declare no conflict of interest.

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