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Research on Management Model Transformation in Manufacturing Enterprises under Intelligent Production Environments

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Abstract Against the backdrop of rapid development in big data and intelligent algorithms, intelligent production environments serve as the forefront of manufacturing enterprises. Under the guidance of artificial intelligence, these environments require precise control and intelligent management of production systems and processes to maximize corporate value. Based on this, a management approach is proposed for intelligent optimization and control in smart factory operations, grounded in the theory of shared value networks. Building on this, by calculating the earliest start time and earliest completion time for workpiece processing, a processing time matrix is derived for each product, thereby establishing a flexible scheduling optimization decision-making model. The simulated annealing genetic algorithm is employed to solve the flexible scheduling optimization decision-making model. The results indicate that the widespread adoption of flexible production and the enhancement of flexible expansion levels can generate a sustained driving effect on the intelligent upgrading of manufacturing, while improvements in technical flexibility levels can only promote the intelligent upgrading of manufacturing in the short term but will significantly inhibit the intelligent upgrading of the manufacturing sector in the medium to long term.

Index Terms Flexible scheduling production; Simulated annealing genetic algorithm; Shared value network; Management model

I. Introduction

As the global consumer market and geopolitical landscape evolve, China's domestic manufacturing sector is undergoing multifaceted transformations [1]. To adapt to these changes, the domestic manufacturing sector is accelerating its transformation and upgrading efforts, driving its own development toward high-end and intelligent directions [2], [3]. Traditional manufacturing enterprises, in the face of the current new circumstances, should seize the opportunity for enterprise upgrading and prioritize technological innovation in the face of numerous risks and challenges [4], [5]. At the same time, when facing industrial and technological trends, it is essential to actively adapt and align with these changes. By leveraging scientific and technological innovation, proactive planning, and the power of innovation, new development engines can be built to embark on the path of upgrading and transformation, fostering new economic growth points [6]-[9]. Therefore, smart manufacturing, as the core of the manufacturing industry's transformation and upgrading, has become the key pathway to driving high-quality development in the manufacturing sector [10].

At present, the manufacturing sector has broken away from traditional development models, adopting innovation-driven, green development, and structural optimization as its basic guidelines, thereby promoting the sector's development toward automation, informatization, and intelligence. By integrating advanced information technology and smart manufacturing technology, it has not only improved product quality and production efficiency but also achieved more optimal resource allocation [11], [12]. Although China's manufacturing sector has made significant progress in the tide of economic development, it still faces uncertainties in market demand, pressure from technological innovation, and challenges in cost control [13], [14]. These factors have intensified industry competition, necessitating an urgent upgrade in management approaches to address the current situation [15]. During the transition from traditional manufacturing to smart manufacturing, the integration of next-generation information technology with manufacturing processes will drive a transformation in smart production management methods. Lean production management provides robust support and assurance for the high-speed, high-quality, and efficient development of the manufacturing sector [16]-[19].

In the manufacturing industry, promoting the establishment of production management models is of critical importance, as it not only identifies shortcomings and bottlenecks in the production environment but also facilitates the achievement of corporate production objectives. Literature [20] indicates that production control in intelligent production environments is inherently decentralized, necessitating the establishment of a manufacturing execution system to facilitate the transformation of traditional enterprise management models. Literature [21] identifies and validates the impact of relevant management behaviors on operational practices in intelligent production environments, thereby measuring and proposing a comprehensive set of management behaviors to help manufacturing enterprises develop management models aligned with their maturity stages. Literature [22] indicates that the integration of information and communication technology with physical production systems is key to achieving more agile production systems in the future. To this end, an Industry 4.0 production system based on the Internet of Things and service environments has been established to support manufacturing enterprises' production processes. Literature [23] designed an intelligent production model for small textile enterprises, effectively addressing order fulfillment issues for SMEs through the establishment of practical tools incorporating intelligent manufacturing and change management methods, thereby enhancing their production service quality. Literature [24] proposed a production management model based on lean principles to enhance manufacturing enterprises' dynamic response capabilities to market changes, maximizing resource utilization and reducing production losses to support intelligent production. Literature [25] emphasizes that intelligent lean production management is an important method for improving production performance and innovation capabilities. By customizing project management models, it ensures business continuity and risk control levels to achieve the effectiveness of enterprise business process management. Literature [26] integrates production management systems with Industry 4.0 technological innovation methods to formulate enterprise intelligent production strategies. By rapidly and flexibly restructuring intelligent production processes, it enhances enterprise operational efficiency and performance levels. Literature [27] investigates the utility of production management systems based on artificial intelligence technology in the intelligent production processes of manufacturing enterprises. This management model leverages the efficient judgment capabilities of artificial intelligence to not only improve the efficiency and productivity of maintenance operations but also enhance crisis awareness in production manufacturing. Literature [28] introduces intelligent production management and control methods based on digital twin technology, which assist enterprises in real-time data collection, organization, and management of manufacturing processes in complex assembly workshops. Literature [29] also points out that digital twin technology applicable to intelligent manufacturing systems has the ability to monitor production status in real time and predict system failures. Its application in enterprise production management has achieved the sustainable development of intelligent manufacturing systems. Therefore, with the support of production management systems, manufacturing enterprises can deeply understand the influencing factors and interrelationships in the quality management process, construct a comprehensive quality control model, and thereby improve production efficiency in intelligent production environments.

Based on the theory of shared value network, this paper proposes a management method for optimization and control in the operation and management of smart factories. On this basis, the optimization decision of flexible operation plan is further proposed, and the processing time matrix of each product is determined by calculating the earliest start time and the earliest completion time of the workpiece. The simulated annealing genetic algorithm is used to solve the flexible operation plan optimization decision model. Then, the mechanism and effect of modern flexible production on the management mode of manufacturing industry are analyzed from three levels: the popularization of flexible production, the level of extended flexibility and the level of technological flexibility. Finally, the actual simulation analysis is carried out on the Matlab software, and a certain simulation diagram and time value are obtained. Through the simulation comparison of the two algorithms and the comparative analysis of machine tool idleness, the excellent scheduling value of the simulated annealing genetic algorithm is obtained.

II. Collaborative business processes for smart factory production and operations management

Smart factories represent the forefront of artificial intelligence development, responding to global supply chain competition and new productivity requirements. They achieve pervasive intelligent IoT through the intelligentization of basic equipment and facilities and human-machine intelligent collaboration, and establish a real-time production network with high-speed connectivity among people, machines, and objects through high-speed networks, thereby constructing manufacturing factories with intelligent, flexible, and agile capabilities. At its core, it is supported by a complex cyber-physical system (CPS) that is fully perceptive, effectively regulated, vertically and horizontally integrated, and fully collaborative. At the CPS action layer, leveraging the entire lifecycle of smart factory business processes, it provides lean product design, production, and services guided by overall demand, fully leveraging the technological advantages of big data and industrial internet, such as cloud computing and blockchain. Furthermore, by analyzing the actual smart factory construction pathways of enterprises, this research delves into the management theories and methods for smart factory product design and production, intelligent resource management, and knowledge discovery and service management. Under the guidance of shared value network theory, it achieves the latest research findings in smart factory management theories and methods under the backdrop of smart manufacturing, addressing management bottlenecks in smart factories and facilitating the efficient application of foundational research outcomes in the smart factory domain.

III. Shared value network structure and operating mechanism

Against the backdrop of the new round of technological revolution and global industrial chain optimization, the boundaries of enterprise development have been greatly expanded. Intelligent factory production and operation management are deeply integrated with data and information resources, forming a dynamic value network characterized by collaboration among multiple stakeholders across all stages of the product lifecycle, as well as the sharing and integration of resources, information, and knowledge. Therefore, it is necessary to conduct in-depth research on the shared value network structure and operational mechanisms of intelligent factory production and operation management under the new manufacturing paradigm.

IV. Manage business model innovation and organizational restructuring

Organizational resilience is particularly important for economic stability. Through business model innovation, organizational resilience can be enhanced, helping enterprises gain a competitive edge in a dynamic and ever-changing business environment. Smart factory business models exhibit characteristics such as diversified stakeholders and coordinated value activities. Traditional management teams are no longer suited to current needs, necessitating the establishment of adaptive organizational structures capable of addressing diverse environmental and functional requirements. These structures should leverage flat, virtualized manufacturing platforms as connectors to aggregate resources across the supply chain, fostering new network-based collaborative manufacturing models such as remote customization and off-site production. Therefore, it is essential to focus on exploring management business model innovations based on shared value networks and redefine organizational structures under new business models.

IV. A. Integrated model of product design and production in smart factories

Systematically analyze typical enterprises to identify the common characteristics of product design and production in smart factories for large-scale customization, as well as the differences and challenges in classification and knowledge extraction methods compared to general personalized customization products. Specifically, this can be achieved by analyzing data from different channels—such as external internet users, internal enterprise users, and third parties—in scenarios like product co-creation, to explore matching methods between various types of data (e.g., user behavior, user-generated content, user complaints) and design solutions, thereby establishing a flexible design model for large-scale customization scenarios. Based on theories such as flexible manufacturing, analyze the applicability of delayed manufacturing in the context of large-scale customization in smart factories, as well as the timing and extent of delayed standardization and modularization of components in the design and manufacturing processes, to construct the optimal structure for flexible layout and dynamic response in the large-scale customization production system of smart factories. Drawing on traditional integration theories and models, this study constructs a theoretical framework for an integrated model of product personalization design and production in smart factories from two perspectives—R&D design and manufacturing—and three dimensions—subject, process, and resources. It designs mechanistic models for the key constituent elements and their interrelationships across different dimensions, thereby establishing an integrated model for product design and production in smart factories.

IV. B. Adaptive online design and production network coordination mechanisms for smart factories

Based on different types of manufactured products, identify and construct the attributes, behaviors, interaction rules, and related constraints of the online design and production entities in smart factories. Analyze the forms of interest and demands expressed by customers and upstream and downstream entities in the smart supply chain. Combine blockchain technology with organizational behavior theory, adaptive theory, and other research to design adaptive models and internal and external transaction mechanisms for organizations at various stages of design and production. Construct a static organizational network topology model through social network analysis, and use dynamic network analysis to obtain the complex dynamic relationships between different factors and their impact on organizational structure. Analyze the effectiveness and potential risks of organizational models under different scenarios through computational experiments and other methods, and provide corresponding countermeasures. Construct an enterprise data network space based on the data chain of smart factory products, manufacturing, services, and resources, and analyze the collaborative characteristics of the production and manufacturing network and its role in the co-creation value chain.

V. Intelligent factory production intelligent scheduling and dynamic optimization model

V. A. Enterprise Material Production Management in a Smartly Connected Environment

(1) Relationship between material management and manufacturing Material management mainly involves the digital management of material specifications, types, inputs, and waste generation. Process monitoring and statistics on materials provide a basis for material procurement.

(a) Different products require different specifications of raw materials, and the cutting and usage of raw materials must be calculated. Here, k is the length/weight ratio coefficient.

$$k = \frac{l}{h} \tag{1}$$

(b) Based on data collected on production materials, it is possible to calculate the production material data for each unit of production.

$$q_s = \frac{q_t - q_w}{n} \tag{2}$$

(c) During the production task cycle, statistics on the actual weight of products produced and the weight of scrap are collected to provide data for estimating the weight of scrap. Estimated scrap weight = total weight (sum of the weights of raw materials of various specifications) - product weight (raw material specifications * proportion coefficient), where λ_i is the ratio of consumption per unit product to the length of raw materials of different specifications.

$$E_W = Q_t - \sum_{i=1}^{m} \lambda_i q_i \tag{3}$$

$$\lambda_i = \frac{q_s}{l_i} \tag{4}$$

(2) The compositional framework of information-based material management

In next-generation information technology, the Internet of Things (IoT) is an important component of information technology. While it differs from the concept of the Internet, it can be viewed as an external extension of the Internet in form. The IoT primarily connects devices to the internet through information sensors, chips, infrared sensors, laser scanners, and wireless modules. Through these technologies and devices, it can transmit information about any connected object, enabling dynamic sensing, intelligent identification, and effective management of production processes. Based on IoT technology support, digital management of production materials can be achieved. The bronze-level material management module is primarily composed of two parts: the PC end and the mobile end. The mobile end refers to the collection and statistics of production process data at the production site through IoT, with the data displayed in various modules on the mobile end. The PC end receives data processed on the mobile end and manages material specifications, inventory, and real-time weighing information. The main functions of material management include specification settings, inventory management, material cutting management, real-time weighing, daily scrap management, and project information management. The module structure diagram of material management is shown in Figure 1.

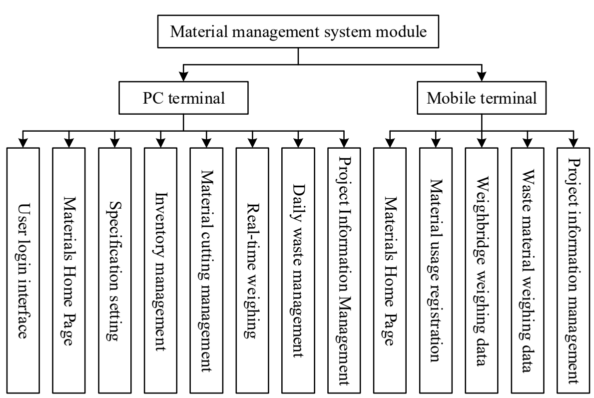


Figure 1: The modular structure of material management

V. B. Construction of a flexible work schedule optimization decision-making model

V. B. 1) Earliest start time for machining workpieces

Based on the principle of dividing decision-making periods, production resource constraints, and minimum batch size restrictions for each period, constraints are established with the objective of minimizing inventory product quantities. This allows for the determination of production batch sizes for various product types within each period. The total production quantity of all product batches within period l is represented as $x_{ji}(j=1,2,...,n+m+u)$.

Without loss of generality, if all components, parts, raw materials, etc., in the product production process structure are collectively referred to as intermediate workpieces, combined with the workshop allocation for workpiece processing and the general product process structure diagram, the simplified product processing hierarchy division is shown in Figure 2.

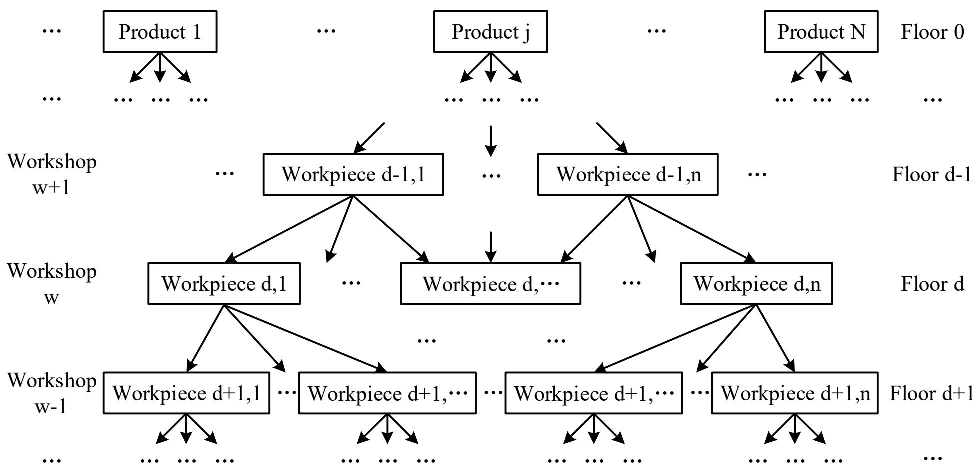


Figure 2: Classification of product processing levels

Workpieces at different levels are processed in different workshops and on different equipment. In this paper, a workpiece at a certain level is assigned to be processed in a corresponding workshop. For example, the workshop corresponding to the d th-level workpiece is workshop w, the $d-1$ th level is the previous level, corresponding to processing in workshop $w+1$, and the $d+1$th level is the next level, corresponding to processing in workshop $w-1$. N_d is the number of workpiece types at level d, and each type of workpiece unit is composed of N_{d+1} types of workpieces from level $d+1$. k_d is the number of processing equipment types in the processing workshop at level d, and the capacity of the same type of equipment can be composed of multiple units. If $N_d > K_d$, it indicates that there will be $(N_d - K_d)$ types of workpieces in workshop w without suitable processing equipment. In this case, corresponding equipment can be added to workshop w. If $N_d < K_d$, it indicates that there will be $(K_d - N_d)$ types of equipment in workshop w that may not be suitable for processing these N_d sets of workpieces, but can be used for processing other workpieces. Therefore, assuming that after appropriate classification and adjustment, $N_d = K_d$.

The calculation basis for the completion time of the d th layer of workpieces required for the l th batch of the j th product in workshop w is the time required to process the n_{d+1} sets of workpieces from the N_{d+1} types of workpieces in the $d+1$th layer among the N_d types of workpieces in that layer in workshop $w-1$ [w-1]. Under the assumption that $N_{d+1} = K_{d+1}$, the time sequence for the completion of these n_{d+1} sets of workpieces in workshop $w-1$ is:

$$\begin{cases} t_{j,d+1,1,1}, t_{j,d+1,1,2}, \cdots\cdots \\ t_{j,d+1,2,1}, t_{j,d+1,2,2}, \cdots\cdots \\ \cdots\cdots \\ t_{j,d+1,k_{d+1},1}, t_{j,d+1,k_{d+1},2}, \cdots\cdots \\ \cdots\cdots \\ t_{j,d+1,K_{d+1},1}, t_{j,d+1,K_{d+1},2}, \cdots\cdots \end{cases} \tag{5}$$

The completion time for the n_{d+1} sets of workpiece assemblies processed in Workshop $w-1$ to meet the processing requirements of the d st-layer workpiece units is $t_{j,d,n} = Max(t_{j,d+1,1,1}, t_{j,d+1,2,1}, \ldots, t_{j,d+1,K_{d+1},1})$. Assuming that the d th-layer n_d th-type workpiece requires $N_{d,n}$ sets for the production of batch product $x_{j,l}$ units, the total demand for this workpiece in the d th layer is $N_{d,n} \times x_{j,l}$. Similarly, the time sequence for completing the set of $d+1$ th-layer workpieces processed in workshop $w-1$ that are required for the N_d types of workpieces in the d th layer is as follows:

$$\begin{aligned}
&\{t'_{j,d,1}, 2\times t'_{j,d,1}, ..., (N_{d,1}\times x_{j,l})\times t'_{j,d,1}\} \\
&\cdots \quad \cdots \\
&\{t'_{j,d,n}, 2\times t'_{j,d,n}, ..., (N_{d,n}\times x_{j,l})\times t'_{j,d,n}\} \\
&\cdots \quad \cdots \\
&\{t'_{j,d,N_d}, 2\times t'_{j,d,N_d}, ..., (N_{d,N_d}\times x_{j,l})\times t'_{j,d,N_d}\}
\end{aligned} \tag{6}$$

The time series of the completion of the complete set of $d+1$ layer workpieces processed in workshop $w-1$ that are required for the d layer N_d types of workpieces mentioned above, that is, the earliest possible start time series for each set of the d layer N_d types of different workpieces in workshop w. Clearly, the earliest possible start time sequence for the first set of the d th layer of N_d types of workpieces for the j th product's l th batch within workshop w is:

$$(t'_{j,d,1}, t'_{j,d,2}, ..., t'_{j,d,n}, ..., t'_{j,d,N_d}) \tag{7}$$

At the same time, the l th batch of the d th layer of workpieces for the $(j-1)$ th product, which is sorted before the j th product, is processed in workshop w within the time K_d different machines in workshop w, i.e., the earliest possible start time for processing the d th layer of the j th product's 1st batch on these K_d different machines, can be arranged in ascending order and expressed as:

$$t'_{(j-1)ld} = (t'_{(j-1),d,1,1}, t'_{(j-1),d,2,1}, ..., t'_{(j-1),d,K_d,1}) \tag{8}$$

Thus, the earliest processing start time for different workpieces in the d th layer of the l th batch of the j th product on the K_d different machines in workshop w can be calculated as follows:

$$\begin{cases}
t'_{j,d,1,0} = Max\{t'_{(j-1),d,1,1}, t'_{j,d,1,1}\} \\
t'_{j,d,2,0} = Max\{t'_{(j-1),d,2,1}, t'_{j,d,2,1}\} \\
\cdots\cdots \\
t'_{j,d,K_d,0} = Max\{t'_{(j-1),d,K_d,1}, t'_{j,d,K_d,1}\}
\end{cases} \tag{9}$$

V. B. 2) Earliest completion time for workpiece processing

After determining the earliest processing start time sequence for different workpieces of the d th layer of the l th batch of the j th product on the K_d different machines in workshop w, the processing completion times for different workpieces on the K_d different machines in workshop w can be calculated. Let $t^1_{j,d,1,1}, t^2_{j,d,2,1}, \ldots, t^k_{j,d,k,1}, ..., t^K_{j,d,K,1}$ represent the processing times required for different workpiece units on different equipment k_d, assuming that the processing times for each workpiece unit remain constant, then:

The completion time sequences for workpieces processed on the first type of equipment are:

$$t_{j,d,1,1} = t'_{j,d,1,0} + t'_{j,d,1,1}, t_{j,d,1,2} = t'_{j,d,1,0} + 2\times t'_{j,d,1,1}, ... \tag{10}$$

The completion time series for each set of workpieces processed on the k_d th device are:

$$t_{j,d,k_d,1} = t'_{j,d,k_d,0} + t'_{j,d,k_d,1}, t_{j,d,k_d,2} = t'_{j,d,k_d,0} + 2\times t^1_{j,d,k_d,1}, ... \tag{11}$$

The completion time sequence for each set of workpieces processed on the last piece of equipment is as follows:

$$t_{j,d,K_d,1}=t'_{j,d,K_d,0}+t^1_{j,d,K_d,1},t_{j,d,K_d,2}=t'_{j,d,K_d,0}+2\times t^1_{j,d,K_d,1},\ldots\ldots \tag{12}$$

After summarizing, the time series of the completion of various workpiece sets processed on K_d types of equipment is as follows:

$$\begin{cases} t_{j,d,1,1},t_{j,d,1,2},\cdots\cdots \\ t_{j,d,2,1},t_{j,d,2,2},\cdots\cdots \\ \cdots\cdots \\ t_{j,d,k_d,1},t_{j,d,k_d,2},\cdots\cdots \\ \cdots\cdots \\ t_{j,d,K_d,1},t_{j,d,K_d,2},\cdots\cdots \end{cases} \tag{13}$$

V. B. 3) Product processing time matrix

Based on the above principle, we can calculate the time when all batches of products at level 0 within time period I are processed. The time sequence matrix for each product is shown in Table 1.

Table 1: The time series matrix of the completed processing of each product

j	1	2	···	n	$n+1$	···	$n+m$	$n+m+1$	···	$n+m+u$
PX_{1j}	$t_{1,1}$	$t_{1,2}$	···	$t_{1,n}$	$t_{1,n+1}$	···	$t_{1,n+m}$	$t_{1,n+m+1}$	···	$t_{1,n+m+u}$
PX_{2j}	$t_{2,1}$	$t_{2,2}$	···	$t_{2,n}$	$t_{2,n+1}$	···	$t_{2,n+m}$	$t_{2,n+m+1}$	···	$t_{2,n+m+u}$
⋮	⋮	⋮	···	⋮	⋮	⋮	⋮	⋮	···	⋮
PX_{k_0j}	$t_{k,1}$	$t_{k,2}$	···	$t_{k,n}$	$t_{k,n+1}$	···	$t_{k,n+m}$	$t_{k,n+m+1}$	···	$t_{k,n+m+u}$
⋮	⋮	⋮	···	⋮	⋮	⋮	⋮	⋮	···	⋮
PX_{K_0j}	$t_{K,1}$	$t_{K,2}$	···	$t_{K,n}$	$t_{K,n+1}$	···	$t_{K,n+m}$	$t_{K,n+m+1}$	···	$t_{K,n+m+u}$

V. C. Solving Flexible Job Scheduling Optimization Decision Models

In this paper, the simulated annealing genetic algorithm is used to solve the flexible job scheduling optimization decision model:

Step 1: Determine the initial sample population $P_1(q)$ based on experience.

Step 2: Initialize the sample population P_2 of product sorting π_2 based on $P_1(q)$, and set the competition size (randomly selecting k individuals from the sample population) to $k=1$ [30].

Step 3: If k does not meet the lower-level iteration requirement, repeat Step 2. If q meets the algorithm termination requirement and the lower-level iteration termination condition is satisfied, calculate and select the sample with the optimal fitness value from the sample population P_2, and the algorithm terminates. Otherwise, record the sample population P_2 and proceed to the next step.

Step 4: Calculate the lower-level fitness function for the sample population P_2 saved in Step 3 to determine the sample individual $P_2(q)$ corresponding to the optimal fitness value.

Step 5: Re-initialize the sample population P_1 based on $P_2(q)$, and simultaneously increment the chromosome index q by 1 ($q=q+1$).

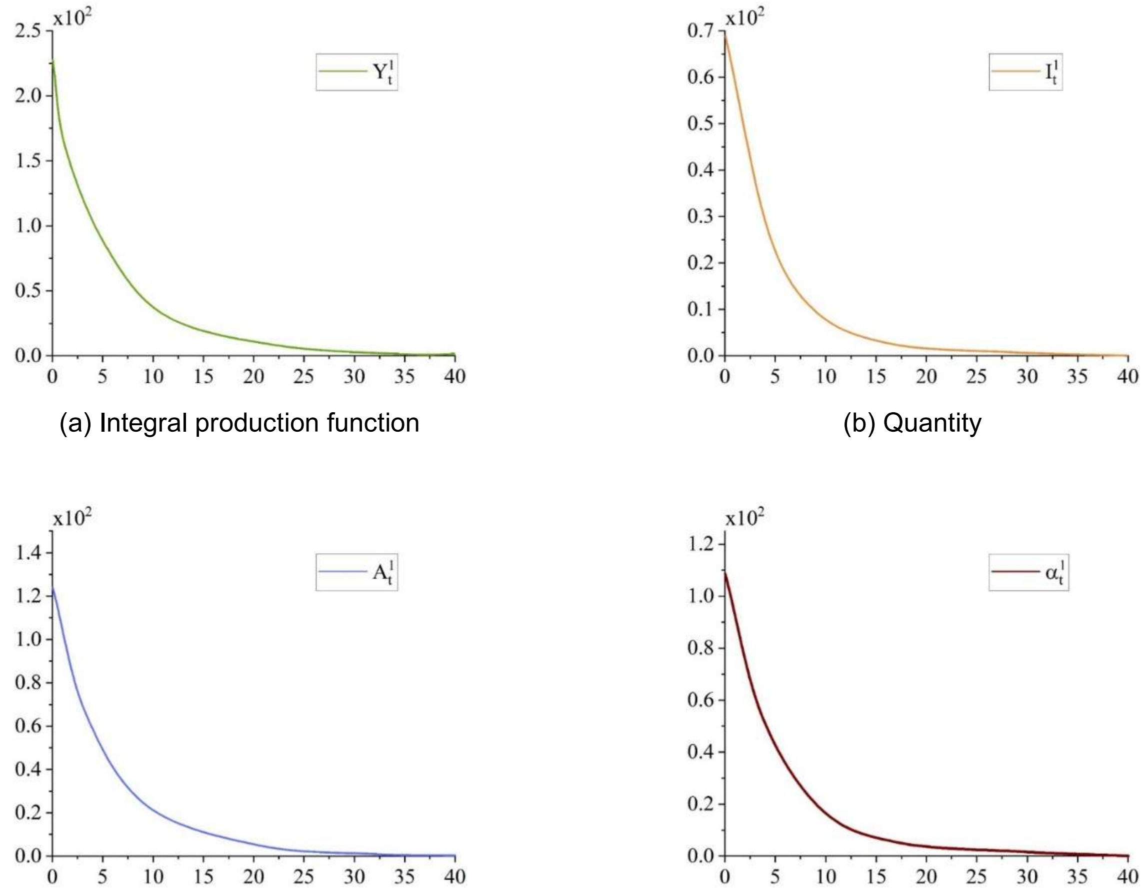
Step 6: Calculate the fitness values of the individuals in the new sample population P_1 using the upper-level fitness function, and identify the sample individual with the optimal fitness value. When the iteration count r reaches the required value, set $P_1(q)$ as the optimal sample individual and continue with Step 2; otherwise, continue with Step 5.

VI. Numerical simulation and impact analysis

This section focuses on exploring the mechanisms and effects of modern flexible production on the intelligent upgrading of manufacturing. Therefore, this section will analyze the impact of flexible production from three perspectives: the prevalence of flexible production, the expansion of flexibility, and the level of technological flexibility.

VI. A. Impact of the widespread adoption of flexible manufacturing

The results of the impact of the degree of flexible production adoption are shown in Figure 3 (a–d represent the overall production function of the manufacturing sector (Y_t^1), the number of intelligent production links in the manufacturing sector (I_t^1), the level of intelligent production technology in the manufacturing sector (A_t^1), and the level of intelligence in the manufacturing sector (α_t)). It can be seen that the increased adoption of flexible production effectively improves the level of intelligent manufacturing in the manufacturing sector, thereby achieving the goal of intelligent upgrading in manufacturing. This is primarily because the widespread adoption of flexible production increases the potential entry pressure from other potential industrial sectors on the manufacturing sector. The manufacturing sector and other potential industrial sectors operate in relatively isolated consumer markets. Therefore, the potential entry pressure faced by the manufacturing sector at this time is not only reflected in the impact of intelligent technologies but also in potential market environment displacement.



(a) Integral production function

(b) Quantity

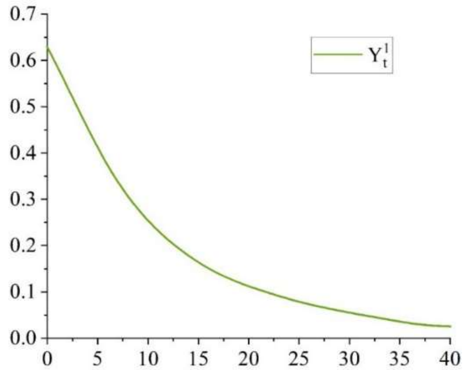
(c) Intelligent technology level

(d) The level of intelligence in the manufacturing industry

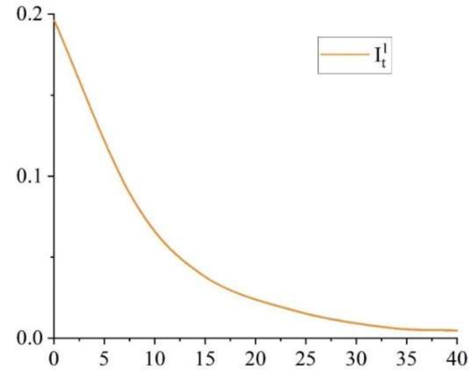
Figure 3: The influence results of the popularization degree of flexible production

VI. B. Impact of increased flexibility

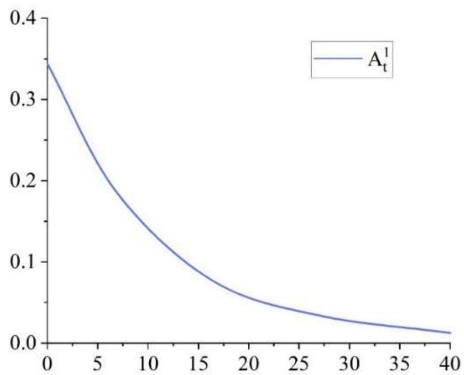
The impact of enhancing the level of extended flexibility is shown in Figure 4 (a–d represent the overall production function (Y_t^1), the number of intelligent production processes in the manufacturing industry (I_t^1), the level of intelligent production technology in the manufacturing industry (A_t^1), and the level of intelligence in the manufacturing industry (α_t)). It can be seen that the improvement in the level of expanded flexibility can promote the intelligent upgrading of the manufacturing industry in the short term. The improvement in the level of expanded flexibility has an impact on the intelligent production technology level A1t and the number of intelligent production processes I1t in the manufacturing industry. In terms of the impact on the level of intelligent production technology in manufacturing (A1t), the improvement in the level of expanded flexibility creates a push effect on A1t. Regarding the impact on the number of intelligent production processes in manufacturing (I1t), the increase in the level of expanded flexibility necessitates that the manufacturing sector implement more comprehensive and complete production process arrangements to control intelligent production processes, thereby establishing effective entry barriers. From the overall impact perspective, whether it is the improvement in the level of intelligent manufacturing technology A1t or the increase in the number of intelligent production processes I1t, these changes ultimately reflect on the level of intelligent manufacturing α_2 and ultimately promote the intelligent upgrading of the manufacturing sector.



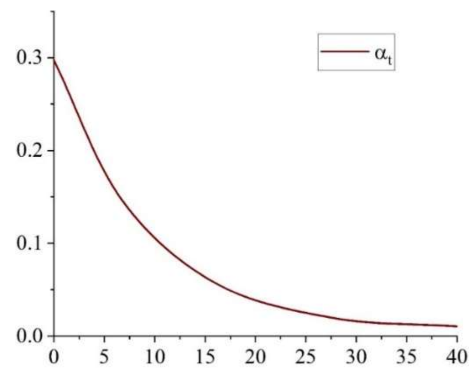
(a) The overall production function



(b) Quantity



(c) Intelligent technology level



(d) The level of intelligence in the manufacturing industry

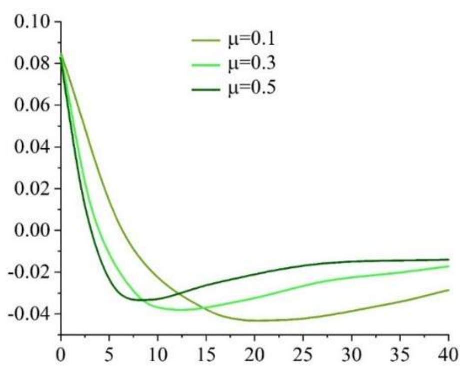
Figure 4: The impact results of the improvement in the level of expansion flexibility

VI. C. Impact of improved technological flexibility

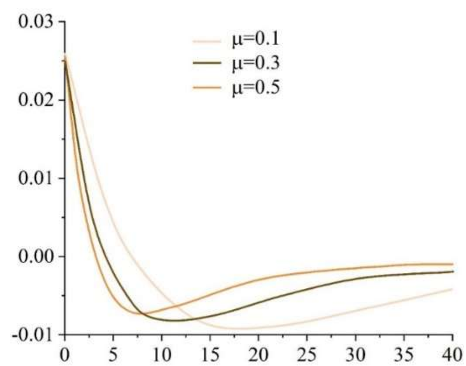
When analyzing the impact of improvements in technological flexibility, it is also necessary to consider the impact of changes in the evolution rate μ and development ceiling η on the results.

(1) The impact of changes in μ on improvements in technological flexibility

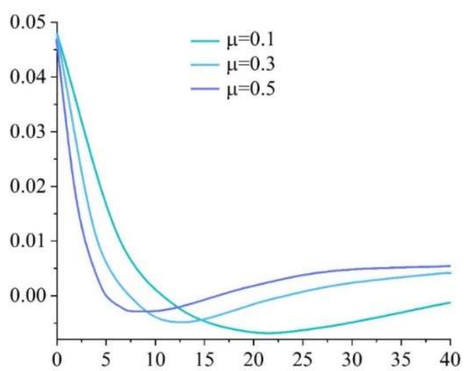
The impact of improvements in technological flexibility levels varies with the evolution rate μ, as shown in Figure 5 (a–d represent the overall production function, the number of intelligent production processes in manufacturing, the level of intelligent production technology in manufacturing, and the overall level of intelligent manufacturing, respectively). Overall, in the short term, the improvement in the level of technological flexibility can achieve the goal of promoting the intelligent upgrading of manufacturing. However, as the level of technological flexibility evolves, once a certain threshold is crossed, the improvement in the level of technological flexibility actually inhibits the progress of manufacturing intelligence α_t to a certain extent. Additionally, as shown in the figure, as the evolution rate μ continues to increase, the threshold inflection point of the level of technological flexibility shows a decreasing trend. This implies that a higher evolution rate weakens the duration of the positive impact of the level of technological flexibility on the intelligent upgrading of the manufacturing industry. From a medium- to long-term perspective, this outcome is not conducive to the manufacturing industry achieving sustained intelligent upgrading. Due to the influence of machine learning mechanisms, the evolution of technological flexibility levels follows an "S"-shaped curve approaching an upper limit, while increases in evolution rate μ make the evolution trend steeper. Specifically, under conditions where evolution rate μ remains constant, as technological flexibility levels increase, other potential industrial sectors can more easily integrate into the production processes of the manufacturing sector. Additionally, since the initial evolution rate is relatively slow and has not yet reached the inflection point where the curve transitions from convex to concave, the coercive effect of the growth in the level of technological flexibility A_t^1 on the level of production intelligence technology dominates at this stage. As shown in the figure, an increase in the level of technological flexibility at t=0 can drive an increase of approximately 0.06 in A_t^1. However, as the threshold inflection point arrives, the growth rate of technological flexibility levels experiences an explosive increase, enabling other potential industrial sectors to quickly replicate the production technologies and processes of the manufacturing sector. Without considering intellectual property protection, these sectors can leverage this advantage to erode the manufacturing sector's market share. This gradually erodes the manufacturing sector's motivation to invest in R&D for intelligent production technologies over the medium to long term. As shown in the figure, after the threshold inflection point, improvements in technological flexibility have a significant negative impact on the change in A_t^1, with an impact magnitude of approximately -0.02. A similar effect is also evident in its impact on the number of intelligent production processes I_t^1 in the manufacturing sector. The short-term technological pressure effect forces the manufacturing sector to more widely deploy intelligent production processes to maintain its excess profits. At this point, an increase of one standard deviation in the level of technological flexibility can bring about a 0.028-unit increase in I_t^1 at t=0. However, with the arrival of the threshold inflection point, the overly rapid growth rate of the level of technological flexibility renders the advantages of intelligent production processes in the manufacturing sector less evident. Therefore, during this phase, the improvement in the level of technological flexibility to some extent inhibits the expansion of intelligent production processes in the manufacturing sector. If the evolution rate of technological flexibility μ is further accelerated under these circumstances, it is evident that as the evolution rate μ continues to rise, the threshold inflection point where technological flexibility transitions from convex to concave will arrive more rapidly.



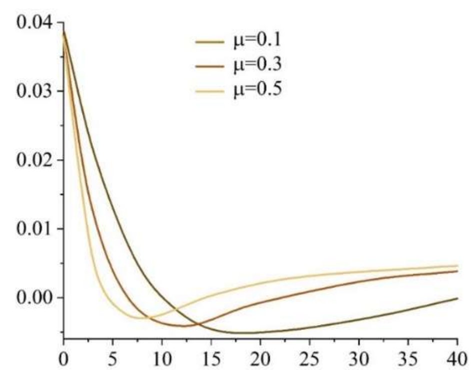
(a) The overall production function



(b) Quantity



(c) Technical level



(d) Level of intelligence

Figure 5: The situation where the impact brought about by the improvement

(2) The impact of changes in η on the improvement of technological flexibility level

The impact of the improvement of technological flexibility level on the upper limit η is shown in Figure 6 (a to d represent the overall production function, the number of intelligent production links in the manufacturing industry, the level of intelligent production technology in the manufacturing industry, and the level of intelligence in the manufacturing industry, respectively). Due to the machine learning characteristics of artificial intelligence, the evolution of the level of technological flexibility follows an “S” curve, where the development ceiling η represents the highest level of technological flexibility that potential industrial sectors can achieve under current technological conditions to successfully integrate into manufacturing production processes. Clearly, changes in the development ceiling η depend on breakthroughs in key core technologies. To simplify the model, this paper sets the development ceiling for the level of technological flexibility. The results show that changes in the development upper limit η do not alter the overall trend of the impact of technological flexibility on the intelligent upgrading of manufacturing. In the short term, an increase in technological flexibility can effectively promote the intelligent upgrading of manufacturing, but from a medium- to long-term perspective, an increase in technological flexibility has a significant inhibitory effect on the intelligent upgrading of manufacturing. However, it is evident that as the upper limit of technological flexibility level development η gradually increases, in the short term, the promotional effect of technological flexibility level on the intelligent level of manufacturing α_t becomes increasingly evident, and the duration of this positive effect also shows a trend of gradual extension.

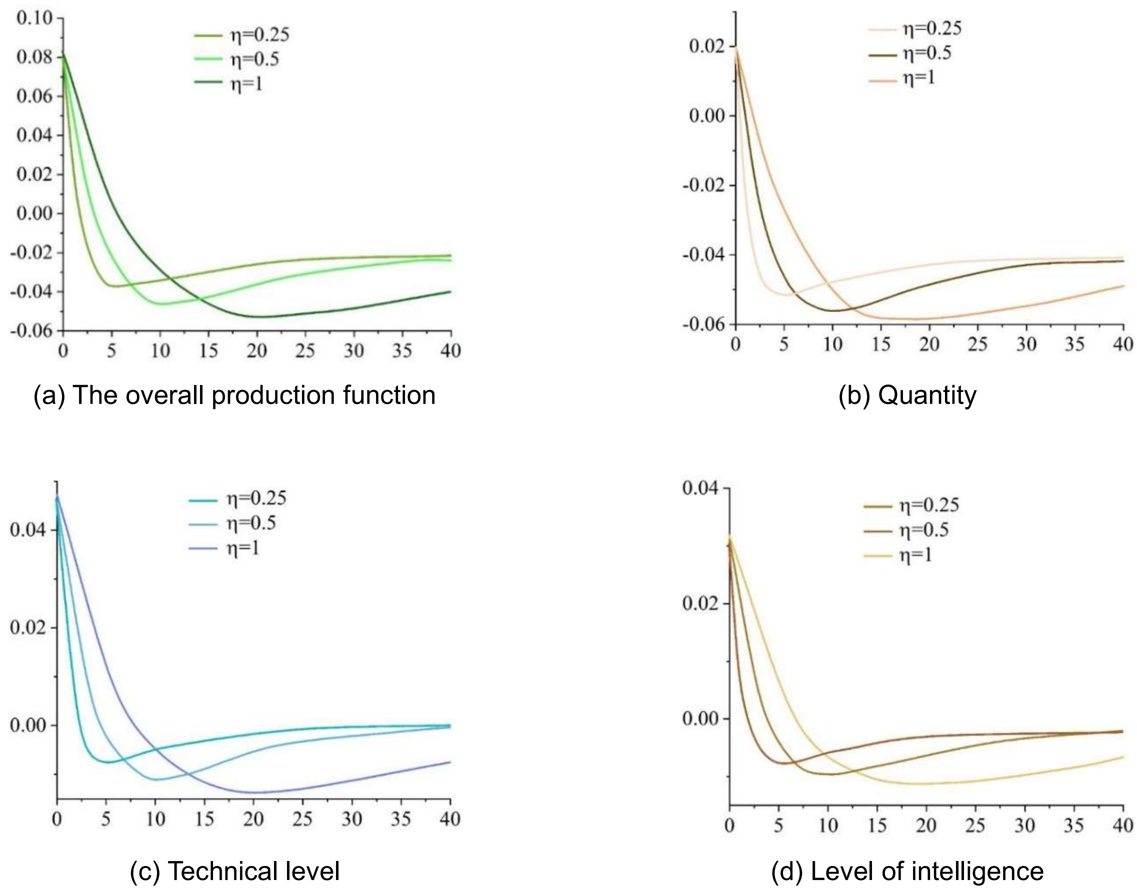


Figure 6: Effect of technological flexibility level improvement

VII. Simulation Applications

The machining task involves all major components of the complete mold frame. The main machining processes are divided into eight sub-processes. To ensure the optimal machining capacity of the eight machines during the process, the manual tool change time required by the machines is ignored. Based on the established model, the results can be obtained through simulation using Matlab R2013a under the machine environment of 8/8/G/Cmax. The simulation results yield a scheduling time diagram, enabling the determination of the optimal scheduling outcome (10 simulations are conducted on the selected data, and the best result from one of the 10 simulations is selected). The parameters for the simulated annealing genetic algorithm are set as follows: Optimization objective: maximum completion time. Iteration count: 500. Mutation probability Pm: 0.35. Mutation transformation logarithm Pc: 4. Simulated annealing initial value: 1000. Simulated annealing final value: 0. These parameters effectively achieve the optimization of the global solution.

VII. A. Particle Swarm Optimization Simulation Scheduling Gantt Chart

The particle swarm optimization scheduling Gantt chart is shown in Figure 7. The machines used to process Workpiece 2 in sequence are Machine 7, Machine 4, Machine 3, Machine 1, Machine 5, Machine 2, and Machine 7, while the original processing machines were 3, Machine 7, Machine 1, Machine 4, Machine 7, Machine 5, and Machine 2. This demonstrates that the particle swarm algorithm can reorder the original sequence of operations. Since the first three operations can be interchanged and the last five operations can be interchanged, the shortest processing sequence can be determined, resulting in a total processing time of 648 minutes. This can be used to optimize the original sequence of operations, thereby improving the overall production process.

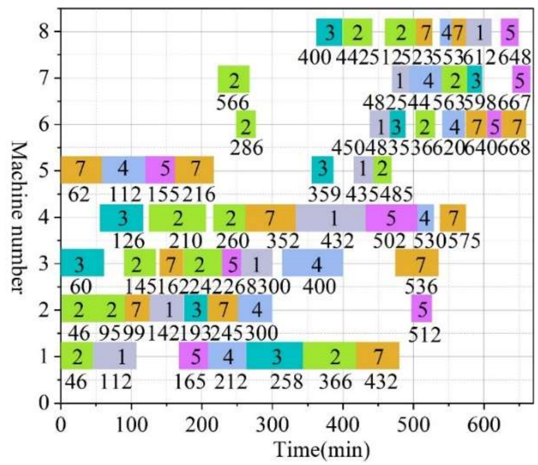


Figure 7: Particle swarm optimization algorithm scheduling

VII. B. Simulation of Genetic Algorithm Simulation Scheduling

The initial population is optimized using a simulated annealing genetic algorithm, yielding the globally optimal solution. During the iterative process, the minimum average flow time is 401 minutes, the maximum completion time is 608 minutes, and the minimum gap time is 812 minutes. The simulated annealing genetic algorithm scheduling Gantt chart is shown in Figure 8. As can be seen from the figure, the workpieces and processes processed by Machine 1 are as follows: 102 Workpiece 1's first process, 404 Workpiece 4's second process, 202 Workpiece 2's third process, 603 Workpiece 6's first process, 505 Workpiece 5's second process, 706 Workpiece 7's third process, 806 Workpiece 8's third process, and 302 Workpiece 3's third process. Among these, the optimal completion time for the simulated annealing particle scheduling algorithm is 615 minutes, which is significantly shorter than the optimal scheduling time of the particle swarm scheduling algorithm. Therefore, it can be concluded that the simulated annealing particle swarm scheduling algorithm outperforms the particle swarm scheduling algorithm in flexible production.

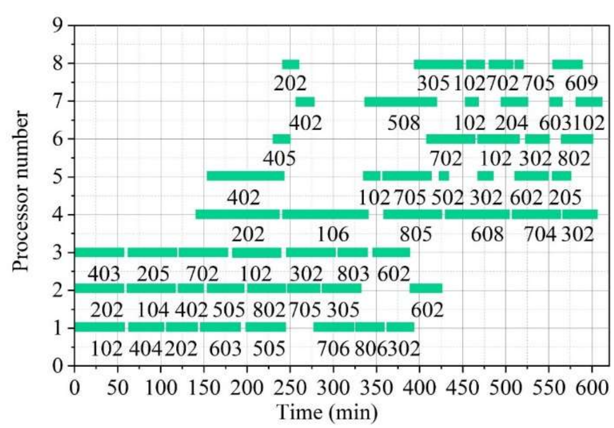


Figure 8: Simulated annealing genetic algorithm scheduling

The particle swarm optimization algorithm machine idle table is shown in Table 2. The total idle time obtained from the table is: Machine 1 took 42 minutes. Machine 2 took 40 minutes. Machine 3 took 32 minutes. Machine 4 took 42 minutes. Machine 5 took 29 minutes. Machine 6 took 31 minutes. Machine 7 took 40 minutes. Machine 8 took 57 minutes, with a total idle time of 313 minutes. After optimization using the particle swarm algorithm, the idle time was improved by 21.5% compared to the original, and the total processing time was reduced by 18.8%.

Table 2: Particle swarm algorithm machine tool idle table

Workpiece	Workpiece 1	Workpiece 2	Workpiece 3	Workpiece 4	Workpiece 5	Workpiece 6	Workpiece 7	Workpiece 8
Machine 1	2	8	3	6	9	3	5	6
Machine 2	1	3	6	9	5	4	8	4
Machine 3	6	7	2	4	2	0	1	10
Machine 4	10	2	4	6	3	2	8	7
Machine 5	3	10	3	2	5	0	2	4
Machine 6	7	3	2	5	0	4	7	3
Machine 7	7	4	9	4	3	9	0	4
Machine 8	6	7	7	6	8	7	8	8

The idle time table for machine tools using the simulated annealing genetic algorithm is shown in Table 3. The total idle time series obtained using the simulated annealing genetic algorithm is as follows: Machine 1 took 39 minutes, Machine 2 took 25 minutes, Machine 3 took 26 minutes, Machine 4 took 42 minutes, and Machine 5 took 24 minutes. Machine 6 took 25 minutes. Machine 7 took 40 minutes. Machine 8 took 58 minutes, with a total idle time of 279 minutes. After calculation, the processing idle time based on the simulated annealing genetic algorithm was 279 minutes, representing a 26.9% improvement in idle time compared to the original method, with a 22% reduction in total processing time. Based on the data in Tables 2 and 3, it can be seen that the optimization results of the simulated annealing genetic algorithm are better than those of the particle swarm algorithm alone. After adopting the simulated annealing genetic algorithm, the overall processing time has significantly improved, and the idle time of machines in scheduling has been greatly reduced, proving the effectiveness of the simulated annealing genetic algorithm in flexible manufacturing systems.

Table 3: Idle table of Simulated annealing Particle swarm algorithm machine tool

Workpiece	Workpiece 1	Workpiece 2	Workpiece 3	Workpiece 4	Workpiece 5	Workpiece 6	Workpiece 7	Workpiece 8
Machine 1	3	3	2	8	8	3	6	6
Machine 2	1	0	6	3	3	1	7	4
Machine 3	2	4	2	4	4	1	1	8
Machine 4	8	6	3	7	4	1	5	8
Machine 5	1	5	0	2	6	1	4	5
Machine 6	5	1	1	3	1	1	4	9
Machine 7	9	8	4	1	3	9	3	3
Machine 8	10	6	5	4	9	9	9	6

VIII. Conclusion

This paper investigates the management models of manufacturing enterprises and proposes optimization and control strategies for their operational management. It also constructs a flexible job scheduling optimization decision-making model. This aims to achieve collaborative, intelligent, flexible restructuring, and mass customization in manufacturing enterprise management, thereby maximizing resource utilization efficiency. The conclusions drawn in the article are as follows:

Improvements in flexibility levels can drive the intelligent upgrading of manufacturing enterprises, while enhancements in technical flexibility levels can only temporarily promote the intelligent upgrading of manufacturing enterprises in the short term, but will significantly inhibit such upgrading in the medium to long term.

In simulation experiments using the simulated annealing genetic algorithm for scheduling, the simulated annealing genetic algorithm reduced idle time by 26.9% and total processing time by 22% compared to the original method. Comparisons show that the optimization results of the simulated annealing genetic algorithm proposed in this paper are better than those obtained using the particle swarm algorithm alone, with a significant improvement in overall time and a substantial reduction in machine idle time, thereby validating the effectiveness of the simulated annealing genetic algorithm in flexible manufacturing systems.

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