International Journal of Industrial Engineering, 31(3), 483-505, 2024

DIGITAL TWIN-ORIENTED COLLABORATIVE OPTIMIZATION OF PROCESS PLANNING AND SCHEDULING IN A FLEXIBLE JOB SHOP

Zhaoming Chen[1, 2, *], Jinsong Zou[3], and Wei Wang[4]

[1]Chongqing University
Chongqing, China

[2]Chongqing school
University of Chinese Academy of Sciences
Chongqing, China
*Corresponding author's email: zhaomingc_sc@163.com

[3]Chongqing Institute of Green and Intelligent Technology
Chinese Academy of Sciences
Chongqing, China

[4]College of Computer Science and Engineering
Chongqing University of Technology
Chongqing, China

Process planning and scheduling are two crucial components in flexible manufacturing systems. To address the challenge of information interaction and sharing during the process planning and scheduling stage of parts, a digital twin-oriented approach is proposed. The objective is to optimize the maximum makespan while accommodating fluctuations in the job shop site. Firstly, in the process planning stage, an enhanced genetic algorithm is employed to generate multiple near-optimal process routes. These routes are coded using a four-level coding system, enhancing the efficiency of the planning process. Then, in the production scheduling stage, a hybrid particle swarm optimization algorithm is constructed, considering the characteristics of multi-process routes and the status of shop production resources and production systems. To improve local search ability, various neighborhood structures are utilized. Finally, the proposed method is evaluated through production example simulations and compared with genetic algorithm and particle swarm optimization. The results demonstrate that this method has a quicker convergence rate, shorter execution time, and higher computation precision, which is not only remarkable but also practical for addressing the collaborative optimization of process planning and scheduling in discrete manufacturing systems.

Keywords: Process Planning, Production Scheduling, Collaborative Optimization, Hybrid PSO Algorithm, Variable Neighborhood Search, Digital Twin

(Received on November 20, 2023; Accepted on May 1, 2024)

1. INTRODUCTION

In the modern era of digital and intelligent manufacturing, manufacturing enterprises are confronted with increasingly fierce global competition and the challenge of catering to diversified and personalized customer demands, requiring customized services. The traditional mass manufacturing model falls short of meeting the current requirements for highly efficient and highly flexible production (Ocampo *et al*., 2020). To enhance their competitiveness, enterprises must optimize the manufacturing process, ensuring not only product quality but also high efficiency, low cost, and the ability to swiftly respond to market changes and consumer demand. Within the manufacturing process, two crucial tasks exist in the production workshop: process planning and production scheduling (Rossit *et al*., 2019), which have a profound impact on the overall manufacturing system. Therefore, it becomes imperative to focus on streamlining and improving these essential aspects.

Process planning is a critical stage in manufacturing where the optimal product processing method, machining sequence, and process parameters etc., are determined. Its primary purpose is to generate a process route for each workpiece while

DOI: 10.23055/ijietap.2024.31.3.9823 ISSN 1943-670X

ensuring compliance with design requirements. It's important to note that multiple process routes may exist for a single workpiece, with close consideration given to the availability of manufacturing resources such as machine tools and cutting tools. By providing detailed operational guidance, process planning facilitates the seamless transformation of product design into final parts, serving as the vital link between product design and manufacturing (Steimer and Aurich, 2016; Yunitarini *et al*., 2018).

On the other hand, production scheduling involves the efficient allocation of limited manufacturing resources to different production tasks based on the process planning stage and reasonably schedules processing times for each process, aligning with preset optimization goals (Moreno *et al*., 2017). Therefore, process planning and production scheduling serve distinct functions but are interdependent, with each task impacting and being constrained by the other. Both process planning and production scheduling present formidable challenges as they fall under the category of complex NP-hard problems, becoming increasingly difficult to solve as the problem scale expands (Rad and Behnamian, 2022; Tamssaouet *et al*., 2022). The current research primarily focuses on optimizing process planning and scheduling separately, but there is a relative lack of collaborative optimization between the two. Additionally, there is a need to address how information exchange and sharing can be achieved between process planning and scheduling. This challenge is crucial to promote the digital transformation of the manufacturing industry and enhance the level of intelligent and networked manufacturing processes.

To tackle these challenges and opportunities, this paper introduces digital twin technology into the process of planning and scheduling of job shop. It proposes a collaborative optimization strategy and solution method specifically designed for a digital twin (DT)-oriented framework of process planning and scheduling. The main highlights of the current research can be mentioned as follows:

- Integrating DT technology: To address the problem of information exchange and sharing between process planning and scheduling in flexible manufacturing systems, a collaborative optimization framework for digital twin is proposed to timely respond to manufacturing resource fluctuations in the workshop, to minimize makespan.
- Collaborative optimization strategy: an improved genetic algorithm is utilized to generate multiple near-optimal process routes for the four-layer encoding of the process. Additionally, a hybrid particle swarm optimization algorithm, integrating variable neighborhood search strategy, is designed to enhance the algorithm's local search capability and effectively solve the optimization problem.
- Case simulation verification: case simulation tests are conducted within a virtual scheduling workshop using production cases. The optimization results obtained from the collaborative optimization method are compared with those obtained by traditional algorithms to validate the feasibility and advantages of the proposed method.

The rest of this paper is organized as follows. Related literature is reviewed in Section 2. The collaborative optimization framework based on digital twin is described in Section 3. The hybrid optimization algorithm and its solution process are developed in Section 4. The case study is introduced in Section 5, while the analysis and discussion of this actual case are described in Section 6. Finally, Section 7 presents the main contributions of this research and suggests potential areas for future investigation.

2. LITERATURE REVIEW

According to literature research, remarkable attention to flexible manufacturing processes in both academia and industry has confirmed the importance of collaborative optimization in process planning and scheduling. In the following, we briefly review some recent papers and elaborate on the specific production problems they address.

The solution to scheduling problems was initially proposed in the mid-1950s and has since become a crucial issue due to the widespread implementation of production scheduling in manufacturing environments (Tugba *et al*., 2023). Scheduling is usually based on the results of process planning as a prerequisite and input, closely related to process planning in practical production scenarios (Wen X *et al*., 2020). In traditional manufacturing systems, process planning and production scheduling are often treated as separate entities, managed by different departments, and optimized individually. Typically, the output of process optimization becomes the input for production scheduling. However, this approach considers process planning as a static plan, assuming the constant availability of workshop manufacturing resources. As a result, process planners tend to rely on their experience and opt for familiar equipment, often overlooking the real-time dynamics of workshop equipment during production (Lamini *et al*., 2022). Therefore, the optimal process planning in the initial stage of process design is often compromised by various production constraints during actual implementation. These constraints include order changes, machine failures, raw material shortages, process delays, etc., causing the manufacturing system to be inflexible and seriously affecting the feasibility of the scheduling plan. Relevant investigation shows that approximately 30% of process planning needs to be revised before product manufacturing to adapt to the dynamic manufacturing environment.

Furthermore, the optimization objectives of process planning and production scheduling often differ. Process planning typically focuses on factors such as processing time, production cost, and resource utilization, while the scheduling process must consider product delivery time, customer satisfaction, and the appropriate start time for each process to achieve smooth scheduling and scheduling efficiency. This disparity between objectives further adds complexity to dynamic process planning and production scheduling (Liu *et al*., 2022; Nejad *et al*., 2011). Consequently, it becomes crucial to attain collaborative optimization of process planning and production scheduling. This approach involves simultaneous consideration of the interaction and influence between these two stages, along with effective communication and coordination of information. The benefits of such collaboration are substantial and include improving product quality, reducing production costs, shortening manufacturing cycles, eliminating resource conflicts on the shop floor, and enhancing equipment utilization.

Extensive research has been conducted on the joint optimization of process planning and production scheduling, addressing the complexities inherent in this endeavor. Scholars have highlighted the significance of considering three key sub-problems simultaneously: process flexibility, operational flexibility, and sequence flexibility. This joint optimization problem is more challenging and falls under the category of NP-Hard problems, surpassing the complexity of individual process planning or production scheduling problems (Rossi and Lanzetta, 2020; Jin and Zhang, 2019). Process route flexibility means that some processes of a workpiece can be fulfilled by other alternative processes. Machine flexibility relates to having multiple options for machines that can perform a specific process. This flexibility enables better resource allocation and utilization. Process sequence flexibility refers to the fact that there may be multiple processing sequences for certain processes (Joseph and Sridharan, 2011). To tackle these complex optimization problems, researchers have employed two main approaches: agent-based methods and algorithm-based methods.

Agent-based methods have been extensively employed to tackle the integration of process planning and scheduling problems. Zhang *et al*. (2012) proposed a multi-agent system architecture that combines multiple heuristics to achieve this integration. Fujii *et al*. (2008) presented an integration method based on multi-agent learning, where each machine makes simultaneous decisions on process planning and scheduling. They model these decisions as learning agents using an evolutionary artificial neural network (EANN) to realize accurate outcomes through interaction with other machines. Leung *et al*. (2010) introduced an agent-based ant colony optimization algorithm for integrated process planning and scheduling systems, offering flexible system architecture and responsive fault tolerance. Wong *et al*. (2006) developed an agent-based dynamic integration method for process planning and scheduling, incorporating supervisory control in a hybrid multi-agent system (MAS) to provide superior global performance solutions. Maoudj *et al*. (2019) proposed a distributed multi-agent system (DMAS) for scheduling and control in a robot flexible assembly cell (RFAC). They employed a collaborative method supported by three autonomous control agents (monitoring agent, local agent, and remote agent) to assign and sort the robot tasks, minimizing the maximum completion time. Petronijevi *et al*. (2016) suggested a decentralized decision-making approach based on a multi-agent system under two disturbances: part arrival and machine failure. Their model consisted of part agents, job agents, machine agents, and optimization agents and was validated using AnyLogic software.

Algorithm-based approaches play a crucial role in solving the problem at hand. Yu *et al*. (2015) categorized process planning and scheduling into static and dynamic stages. They combined these stages with the optimization criteria of process planning and scheduling, resulting in a hybrid algorithm that utilized genetic algorithm (GA) and particle swarm optimization (PSO). This approach proved effective in addressing the problem. In a similar vein, Wen *et al*. (2020) designed an improved bee mating optimization algorithm to address the multi-objective integrated process planning and scheduling problem, considering uncertain processing time and delivery time. They conducted various experiments to evaluate the performance of their method. Liu *et al*. (2020) proposed a modified genetic algorithm (MGA) to solve the integrated process planning and scheduling problem by considering the process "OR" network diagram and testing it in an actual case of a non-standard equipment shop. To tackle the distributed process planning and scheduling integration (DIPPS) problem, Zhang *et al*. (2016) introduced an extended genetic algorithm (EGA). They also incorporated a local enhancement strategy involving machine replacement and order exchange to enhance the algorithm's local search ability. In another study, Liu *et al*. (2016) proposed an ant colony optimization (ACO)-based algorithm for integrated process planning and scheduling optimization, which contains not only a scheduling scheme optimization algorithm but also a dynamic emergency handling mechanism and can effectively handle dynamic emergencies. Petrovi *et al*. (2016) proposed a novel algorithm, the natural heuristic ant lion optimization (ALO) algorithm, to address the combined optimization of process planning and scheduling. Their approach was implemented and tested in the MATLAB environment. Overall, these studies contribute to the advancement of algorithm-based methods for solving process planning and scheduling problems.

The existing studies mentioned above primarily focus on optimizing individual process routes, lacking comprehensive integration strategies for process planning and scheduling. Furthermore, most of these solution methods employ a single algorithm, which requires designing different encoding/decoding and updating strategies for specific problems, etc., and easily falls into local optimum. Moreover, with the increase of solutions and search space, the computation time increases sharply, thus making it difficult to find high-quality feasible solutions (Li *et al*. 2020). With the increasing scale of production data and the requirements of dynamic production scheduling, the demand for information exchange and sharing between process planning and scheduling in the production process is becoming increasingly urgent. The emergence and advancement of digital twin technology provide an effective solution for information interaction and fusion between physical entity workshops and virtual scheduling models, which makes it easy to interconnect data between process planning and scheduling. Digital twin technology realizes high-fidelity mapping and synchronous evolution of physical entities through multi-domain, multi-scale, and multi-probability modeling. It adds or extends new capabilities to physical entities through virtual-real interaction feedback, data fusion analysis, and decision iterative optimization between physical entities and virtual models (Ante 2021). The application domains of digital twin technology have been gradually expanded from the initial aerospace field to intelligent manufacturing, smart city, smart building, and other fields, covering all stages of the product life cycle (Lu *et al*., 2019). The development of digital twin technology will drive the future direction of innovations and advancements of the manufacturing model. Liu *et al*. (2021) integrated the advantages of DT and supernetworks to construct a model of feature-process-machine tool supernetwork in the digital twin workshop and simulated and optimized the initial scheduling plan to realize intelligent workshop scheduling.

Fang *et al*. (2019) proposed a new architecture and working principle of the DT-based job shop scheduling model and given a dynamic interactive scheduling strategy. Chen *et al*. (2023) proposed a DT-oriented multi-objective scheduling framework and strategy to solve fuzzy flexible scheduling problems under multiple uncertainties. Zhang *et al*. (2021) proposed a DT-enhanced dynamic scheduling methodology and verified its effectiveness and advantages through a case study of hydraulic valves in a machining job-shop. Mueller *et al*. (2021) proposed a digital twin-based self-learning process planning method using Deep Q Network for small lot-sizes customized production. Sun *et al*. (2023) designed an energy-efficient scheduling strategy based on digital twin. Wang *et al*. (2020) constructed a digital twin-based process planning and scheduling system model, which can accurately guide the actual production process.

In addition, digital twin is combined with advanced production models such as cloud manufacturing continuously improving the level of green and intelligent manufacturing processes. For example, Hung *et al*. (2022) utilized existing cloud manufacturing services to realize digital twin intelligence. Qi *et al*. (2018) analyzed the role of digital twin and big data in smart manufacturing. Park *et al*. (2020) proposed a cloud-based digital twin intelligent manufacturing system. Nguyen *et al*. (2022) constructed a cyber-physical cloud manufacturing system based on digital twin; Coronado *et al*. (2018) used digital twin and cloud computing to develop a manufacturing execution system that can be used for production control and optimization.

In general, digital twin technology can deeply integrate the physical world and informational world within actual production workshops. While several studies have recognized the significance of DT in achieving workshop production scheduling, most of them have primarily focused on frameworks. Further research is needed, particularly in areas such as dynamic scheduling and real-time response. Currently, there is limited literature available that combines DT with process planning and scheduling in job shop. Consequently, there remains a gap between the optimization plans for scheduling and the actual operation of the workshop.

In summary, we have summarized and compared the main methodologies and problem-solving approaches employed in existing literature in Table 1 to visually display the differences among these studies.

Table 1. Summary of the related reviewed studies

References	**Problem statement**	**Optimization objectives**	**Solution method**	**Case study**
Nejad *et al*. (2011)	Multi-jobs in FMS	Job agent's flow time	Multi-agent architecture	7× 10 scheduling scheme problem
Joseph *et al*. (2011)	Multi-flexibility interaction in FMS	Flow time and tardiness of parts	Simulation method	Simulation-based experiment
Zhang *et al*. (2012)	MAS-based dynamic IPPS	Makespan	ACO algorithm	18 parts 24 test bed problems case
Leung *et al*. (2010)	Graph-based IPPS problem	Makespan	ACO algorithm	Simulation studies
Jin *et al*. (2019)	Multi-objective process planning optimization	Total production time and energy consumption	Dynamic programming-like heuristic algorithm	A group of experiments contains 3 cases.
Wen *et al*. (2020)	FMOIPPS	Fuzzy makespan, average customer satisfaction.	MLCO	10 × 5 scheduling scheme problem

References	Problem statement	Optimization objectives	Solution method	Case study
Wong *et al*. (2006)	Agent-based dynamic IPPS	Schedule and allocation selection of manufacturing resources	MAS-based IPPS approaches and evolutionary algorithm	Simulation studies
Maoudj *et al*. (2019)	DMAS for scheduling and controlling	Makespan	Autonomous control agents based cooperative approach	Simulation Computation
Petronijevi *et al*. (2016)	Multi-agent systems-based decision-making	Processing time	Multi-agent methodology	Simulation in Anylogic software
Yu *et al*. (2015)	IPPS with two phases	The flexibility of rescheduling	GA and PSO-based hybrid algorithm	A set of experiments
Zhang *et al*. (2016)	DIPPS	Machine processing and transportation time	EGA	Experimental verification
Fang *et al*. (2019)	Digital twin-based scheduling	Scheduling deviation	Dynamic interactive scheduling strategies	Prototype system verification
Chen *et al*. (2023)	Fuzzy flexible scheduling	Fuzzy makespan, carbon emission	Hybrid PSO with VNS	Enterprise production example
Zhang *et al*. (2021)	DT-based dynamic scheduling	Makespan and total tardiness	DT-enhanced dynamic scheduling methodology	A scheduling process for making hydraulic valves
Liu *et al*. (2022)	MODIPPS	Makespan, machine load, total machine load	MOMA	Experiments contain 11 cases
Rossi *et al*. (2020)	Hybrid AM-IPS problem	Makespan	ACO-based metaheuristics	Hybrid additive/subtractive parts

FMS=flexible manufacturing system, MAS=Multi-Agent Systems, IPPS=integrated process planning and scheduling, FMOIPPS=fuzzy multi-objective IPPS, MLCO=a multi-layer collaborative optimization method, DMAS=distributed multi-agent system, DIPPS=distributed integration of process planning and scheduling, EGA=extended genetic algorithm, VNS=variable neighborhood search strategy, MODIPPS=multi-objective distributed integrated process planning and scheduling, MOMA=multi objective memetic algorithm, AM-IPS=additive manufacturing integration between planning and scheduling, ACO=Ant Colony Optimization

3. DIGITAL TWIN ORIENTED COLLABORATIVE OPTIMIZATION FRAMEWORK

3.1. Problem Formulations and Hypothesis

The collaborative optimization problem of process planning and production scheduling can be described as follows: A set of n different workpieces $\{J_i|i = 1,2,\cdots,n\}$ needs to be processed on a set of m different processing machines $\{M_k|k = 1,2,\cdots,m\}$, each of which contains several optional process routes and processing machines. Each workpiece requires multiple machining processes $O_{ijp}, j \in \{1,2,\cdots,r_i\}, p \in \{1,2,\cdots,p_{ij}\}$, where r_i represents the total process routes number of workpieces J_i, and p_{ij} represent the total process number of the jth process route for workpiece J_i. The processes have priority constraints, and the processing time of each process varies depending on the machine used. The ultimate objective is to determine the most suitable processing machines according to the available manufacturing resources and machining information. Additionally, the optimal processing sequences for each workpiece on the machine and the start processing time of each process need to be determined. This ensures the optimization of certain performance indicators for the whole system, such as the maximum makespan, production cost, total machine load, etc.

To clearly illustrate the process flexibility, operation flexibility, and sequence flexibility of this optimization problem, Zhang *et al*. (2019) utilized a diagram with an "AND-OR" network node, as shown in Figure 1. This diagram shows the processing information for machining two workpieces on four machines. The diagram mainly contains operation nodes and two virtual nodes, "S" and "E" (representing the starting and completion of the operation, respectively). Each operation node provides details such as process ID, available machines, and corresponding processing time. In this diagram, The AND node indicates that the processes connected via the AND link path can be operated while allowing for the exchange of operation orders. On the other hand, the OR node indicates that only one of the OR link paths needs to be traversed. The operation path originating from the AND node (or the OR node) and merging with other paths is called the AND link path (or OR link path). The arrows between nodes indicate the priority of different nodes. A path starting from node S and ending at node E represents an alternative process scheme. For instance, in this figure, process 4 of workpiece 2 must be processed after process 1.

Additionally, process 6 can be processed by either machine 2 or machine 4, with a corresponding processing time is 9 or 12, respectively. While adhering to the priority constraints, various process schemes can be generated by combining different sets of processes, such as: $(1 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 6 \rightarrow 7)$,$(5 \rightarrow 1 \rightarrow 2 \rightarrow 4 \rightarrow 6 \rightarrow 7)$,$(1 \rightarrow 2 \rightarrow 4 \rightarrow 5 \rightarrow 6 \rightarrow 7)$.

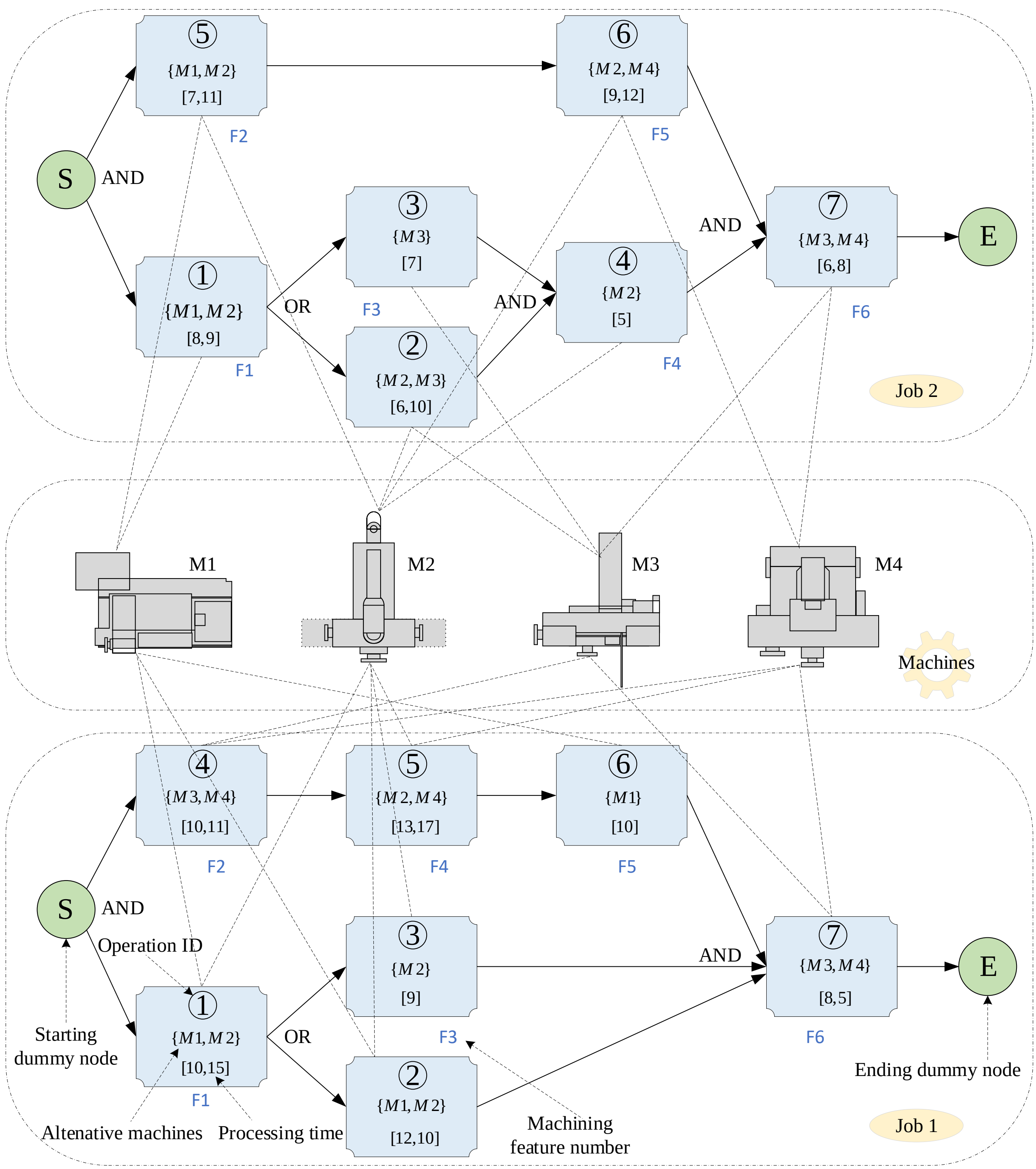


Figure 1. Flexible process plan networks

To combine the solution of the problem with actual production, certain constraints and assumptions should be followed in the machining process (Wang *et al*. 2021):

(1) At the initial moment, all equipment is idle, and all workpieces are available for processing.

(2) Only one process can be processed on a particular equipment at any given time. The next process begins immediately after the completion of the previous process, without any preparation or transfer time.

(3) A workpiece cannot be interrupted during the machining process to process other workpieces.

(4) There is no switching time between two adjacent workpieces on each piece of equipment.

(5) Different workpieces are independent of each other and are of equal priority.

(6) The processing time of each process includes the time required for workpiece movement and loading/unloading adjustment.

(7) The equipment can operate continuously, with an infinite buffer zone between equipment.

Based on the above assumptions, this paper adopts the maximum makespan as the optimization objective. Generally, a shorter maximum makespan implies higher production efficiency and lower manufacturing costs, thus receiving widespread attention in production practice. It can be expressed as:

$$x_{ij} = \begin{cases} 1, & \text{choose the } j\text{th process route of workpiece } J_i \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Decision variables are:

$$min\, F\,(x) = min\{\, max(\, C_{ik})\}, i = 1,2,\cdots,n;\ k = 1,2,\cdots,m \tag{2}$$

$$y_{ijp}^{k} = \begin{cases} 1, & \text{choose the } k\text{th machine for process } O_{ijp} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

The product constraints in the machining process are as follows:

(1) Process constraint: the process$(p+1)$ of$j$thprocess route in workpiece$J_i$should start only after the process$p$is completed. It represents the precedence relationship among various processes of a job, i.e.,

$$x_{ij} y_{ij(p+1)}^{k_1} C_{ij(p+1)}^{k_1} - x_{ij} y_{ij(p+1)}^{k_1} T_{ij(p+1)}^{k_1} \geq x_{ij} y_{ijp}^{k_2} C_{ijp}^{k_2},\ \ k_1, k_2 \in [1, m] \tag{4}$$

(2) Task constraint: the same machine$M_k$can only start another machining task after completing one machining task, i.e.,

$$x_{ij} y_{ijp_1}^{k} C_{ijp_1}^{k} - x_{ij} y_{ijp_1}^{k} T_{ijp_1}^{k} \geq x_{ab} y_{abp_2}^{k} C_{abp_2}^{k}, a, i \in [1, n], b, j \in [1, r_i], p_1, p_2 \in [1, n_{ij}] \tag{5}$$

(3) Process route constraint: each workpiece can only choose one process route, namely:

$$\sum_{j=1}^{r_i} x_{ij} = 1 \tag{6}$$

(4) Machine constraint: a process can only be processed by only one machine from an optional set of machines at a given time, i.e.,

$$M_k \subseteq M_{ijp}, \sum_{k=1}^{m_{ijp}} y_{ijp}^{k} + (1 - x_{ij}) = 1 \tag{7}$$

(5) Completion time constraint: the completion time for each job should be no less than the earliest completion time of

the final processing operation in the $j$thprocess route, i.e.,

$$C_{ik} - x_{ij} y_{ijn_{ij}}^{k} T_{ijn_{ij}}^{k} \geq x_{ij} y_{ij(n_{ij}-1)}^{k} C_{ij(n_{ij}-1)}^{k} \tag{8}$$

The relevant symbols involved in the modeling process and their meanings are shown in Table 2.

Table 2. Meaning of variables and symbols

Symbol	Description	Symbol	Description
i	Index of jobs, $1 \leq i \leq n$	m	The total number of machines
n	The total number of jobs	M	The set of machines, $\{M_1, M_2, \cdots, M_m\}$
J_i	The i_{th} job	k	Index of machines, $1 \leq k \leq m$
J	The set of jobs, $\{J_1, J_2, \cdots, J_n\}$	M_k	The k_{th} machine
r_i	The number of alternative processes of J_i	m_{ijp}	The total number of optional machines for operation O_{ijp}
R_i	The set of optional process plans in job J_i, $\{1,2,\cdots,r_i\}$	M_{ijp}	The set of optional machines for operationO_{ijp}, $\{M_1, M_2, \cdots, M_{m_{ijp}}\}$
R_{ij}	Thej_{th}process plan of job J_i	T_{ijp}^{k}	The processing time of operation O_{ijp} on machine k
j	Index of process plan, $1 \leq j \leq r_i$	C_{ijp}^{k}	The earliest completion time of operation O_{ijp} on machine k
n_{ij}	The total number of j_{th} process plan in job J_i	C_{ik}	The completion time of the i_{th} job on machine k
O_{ijp}	thep_{th} operation in j_{th} process plan of job J_i, $1 \leq p \leq n_{ij}$		

3.2. Collaborative Optimization Framework

With the increasing integration of new-generation information technology and advanced manufacturing technology, the interaction between information systems and physical systems has become more frequent. Digital twin technology, with its virtual-reality mapping and interactive fusion capabilities, has emerged as an effective tool for enhancing the digitalization and intelligence of the manufacturing industry. By leveraging digital twin technology, various aspects such as product design, process flow, and production control can be simulated, optimized, and managed within a virtual environment, catering to the development needs of personalized, service-oriented, and intelligent manufacturing. In the context of the collaborative optimization problem of process planning and production scheduling in a flexible job shop, a collaborative optimization framework is established based on the concept of modular hierarchy. This framework consists of four layers: the physical entity layer, the process planning layer, the digital twin layer, and the scheduling optimization layer. The physical entity layer is the foundation, while the process planning and scheduling optimization layers are controlled by the digital twin layer. This enables data fusion analysis and bidirectional iterative optimization, facilitating on-demand allocation and dynamic adjustment of manufacturing resources. The overall framework is presented in Figure 2.

In the physical entity layer, various physical objects relevant to the flexible job shop are present, including workpieces, raw materials, machine tools, cutting tools, operators, and the workshop environment. It is the carrier for process planning and production scheduling and forms the basis for constructing of the digital twin model.

In the process planning layer, first, comprehensive analysis is conducted on the structural design information, processing technology information, and required manufacturing resource information of the parts. Multiple possible process solutions that meet the technical requirements for each part are formulated. Real-time feedback on manufacturing resource information from the scheduling optimization layer is considered to evaluate and rank these proposed process solutions. The objective is to select several near-optimal process routes that satisfy the current production conditions, considering constraints such as resource load, process flexibility, and manufacturing cost.

Detailed design of the selected process routes is then carried out to specify dimensions, tolerances, machining parameters, etc., for each process. This information is subsequently sent to the scheduling optimization layer, facilitating information interaction and sharing between process planning and scheduling.

In the digital twin layer, a digital twin model of the workshop is created by collecting relevant data from information perception equipment, encompassing part design, processing processes, and manufacturing resources. It mainly includes geometric model, physical model, behavior model, and rule model of the parts. Intelligent optimization algorithms are applied to conduct parallel simulation analysis of process planning data and scheduling data, enabling the simulation of the entire part machining process. Feasibility of the production plan is verified, possible problems in the manufacturing process are predicted, and corresponding improvement measures are suggested, all contributing to collaborative optimization of process planning and production scheduling. The optimized scheduling plan will be fed back to the physical workshop to guide the actual production, ensuring better adaptability and dynamic response.

In the scheduling optimization layer, appropriate machines are assigned to the selected process route, and the optimal start time for each process is determined based on factors such as the work-in-progress quantity and workload of each machine. This layer aims to maximize machine utilization and minimize job completion time. In case of disruptive factors such as machine failures or order changes, the scheduling process promptly assesses and responds to ensure smooth production.

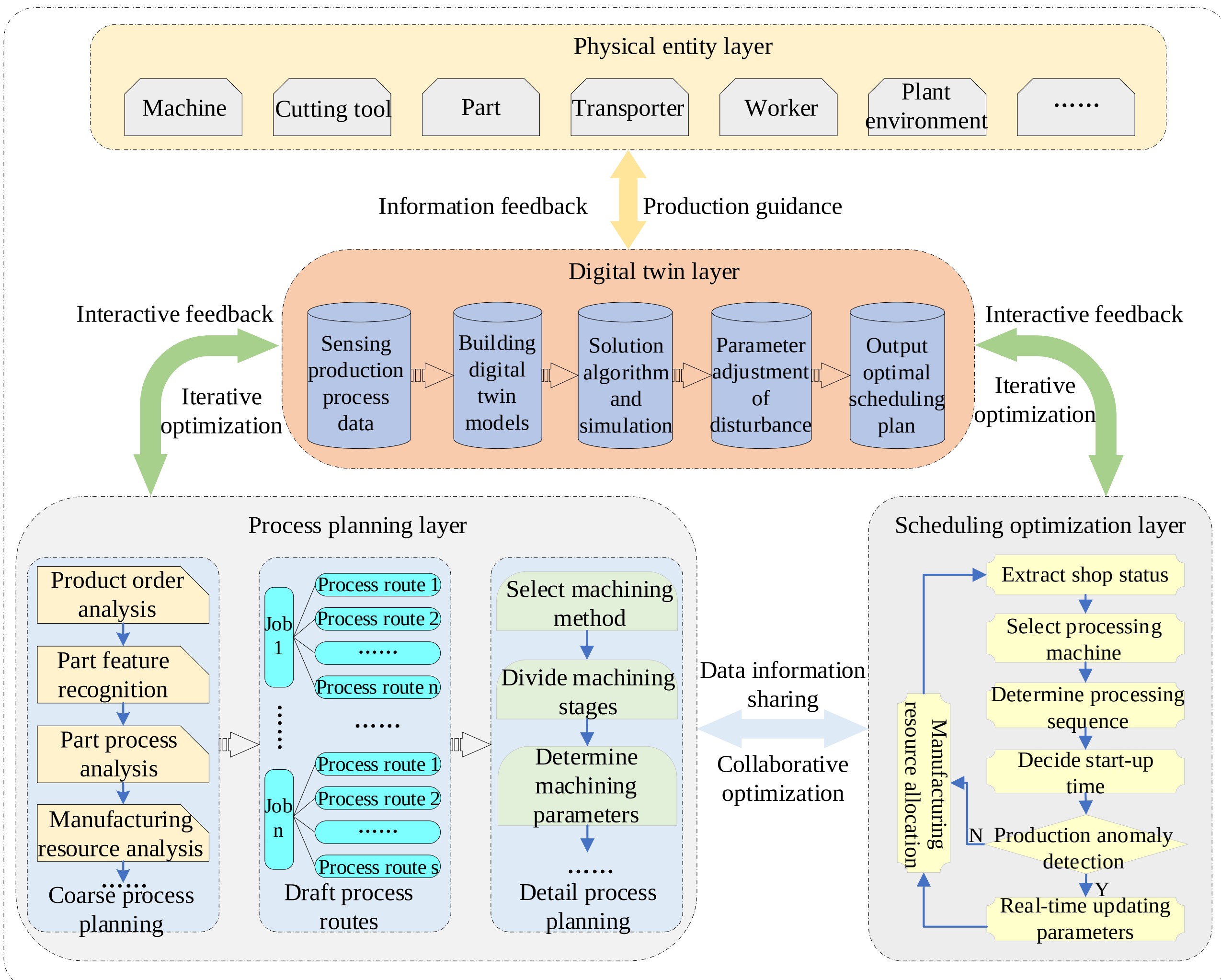


Figure 2. The digital twin-oriented general framework of collaborative optimization

4. GA HYBRID IMPROVED PSO WITH VARIABLE NEIGHBORHOOD (GAHPSOVN) FOR COLLABORATIVE OPTIMIZATION PROBLEM

4.1. Generation of Near-optimal Process Routes

The genetic algorithm (GA) is based on the biological evolution mechanism, using natural rules such as adapt-or-die and survival of the fittest to solve problems through searching and computation. It exhibits features such as global optimization, implicit parallelism, and scalability. However, it suffers from low efficiency and is prone to premature convergence. To address these limitations, an improved crossover strategy is combined with GA to enhance its local search capabilities. The diversity and uniformity of the population in GA are maintained through a random initialization method. The crossover operator is employed to alter the machining sequence of parts, while the mutation operator adjusts the process route of parts. This enables the search for multiple near-optimal process routes of each workpiece, considering the existing constraints imposed by the current manufacturing resources.

4.1.1. Population Initialization

To maintain population diversity in the collaborative optimization problem, a random initialization method is employed. Firstly, the maximum value of the random allocation integer is determined based on the number of workpieces and the total number of machining features of each workpiece. Workpieces are then randomly arranged, with the repetition of a workpiece being equal to the total number of its machining features. Considering the possible priority constraints between different machining features of a workpiece, the constraint adjustment method (Zhang *et al*. 2019) is utilized to assign a random integer to the machining features. The maximum value of these integers corresponds to the total number of machining features. Subsequently, each machining feature is assigned a random number indicating an alternative processing route. Finally, the number of optional machines in each process is taken as the maximum value of the random integer, and the machine number is randomly allocated to each process.

4.1.2. Encoding and Decoding

The process planning stage employs a four-layer encoding method, including job information sting, processing feature information sting, alternative route information sting, and alternative machine information sting. These four layers of information are independent of each other but collectively determine the processing route for a workpiece. Figure 3 illustrates the encoding diagram for the processing information of two workpieces, as depicted in Figure 1. This encoding method effectively captures the operational flexibility, process route flexibility, and machine flexibility in the collaborative optimization process. Moreover, it facilitates the implementation of crossover and mutation operation of GA, enabling dynamic adjustment to the process plan.

2	1	1	2	1	2	1	2	1	2	1	2	Job information string
1	1	3	3	2	4	4	2	5	5	6	6	Machining feature information string
1	1	2	2	1	1	1	1	1	1	1	1	Alternative route information string
2	1	1	1	2	1	2	1	1	2	2	1	Alternative machine information string

Figure 3. Encoding schematic in the process planning stage

In Figure 3, the first line reflects the workpiece information, where different number represents distinct workpiece, and different positions of the same number indicate different machining features. For instance, this line represents 2 workpieces with 6 machining features respectively. The second line reflects the machining feature information, with each number representing the corresponding machining feature number of each workpiece indicated in the previous line. Each feature satisfies the priority constraints. For instance, moving from left to right in this row, the number 1 in position 1 represents the machining feature 1 of workpiece 2, the number 1 in position 2 represents the machining feature 1 of workpiece 1, the number 3 in position 3 represents the machining feature 3 of workpiece 1, and so on. The third line portrays the optional processing route information corresponding to each feature. For example, machining feature 3 of workpiece 1 selects processing route 2, machining feature 3 of workpiece 2 also selects processing route 2, while other machining features choose processing route 1. The fourth line indicates the machine number corresponding to each machining feature of the selected processing route. For instance, moving from left to right, the number 2 in position 1 represents machine number 2 (M2) for the machining feature 1 of workpiece 2 within the processing route 1. The number 1 in position 2 represents machine number 1 (M1) for the machining feature 1 of workpiece 1 within the processing route 1, and so on. When decoding, the processing features of all workpieces are sorted according to the codes in the first and second lines. This yields the following sequence: F21—F11—F13—F23—F12—F24—F14—F22—F15—F25—F16—F26. Subsequently, using the processing route determined in the third line and the machine number selected in the fourth line, the processing machine, processing procedure, and corresponding processing time for each process are finally obtained, as shown in Table 3.

Table 3. Decoding results in the process planning stage

Processing procedure	O_{21}	O_{11}	O_{13}	O_{23}	O_{14}	O_{24}	O_{15}	O_{25}	O_{16}	O_{26}	O_{17}	O_{27}
Selected machine	M_2	M_1	M_2	M_3	M_4	M_2	M_4	M_1	M_1	M_4	M_4	M_3
Processing time	9	10	9	7	11	5	17	7	10	12	5	6

4.1.3. Crossover and Mutation Operations

To adjust and optimize the processing features, alternative routes, and alternative machines of workpieces simultaneously and to obtain multiple near-optimal process routes that adhere to workshop production conditions, the proposed four-layer coding approach requires crossover and mutation operations. Referring to the method of Alzahrani (2019), an improved two-point crossover strategy is adopted to realize the crossover operation. In this strategy, two encoding information are randomly selected from the population. Then, two intersections within the encoding sequence are randomly selected, and the encoding information outside the intersection is copied to the corresponding position in the new coding sequence. This ensures that the newly generated sequence meets the process constraints among features while enabling the parent's desirable genes can be transferred to the offspring as much as possible. The specific process is shown in Figure 4.

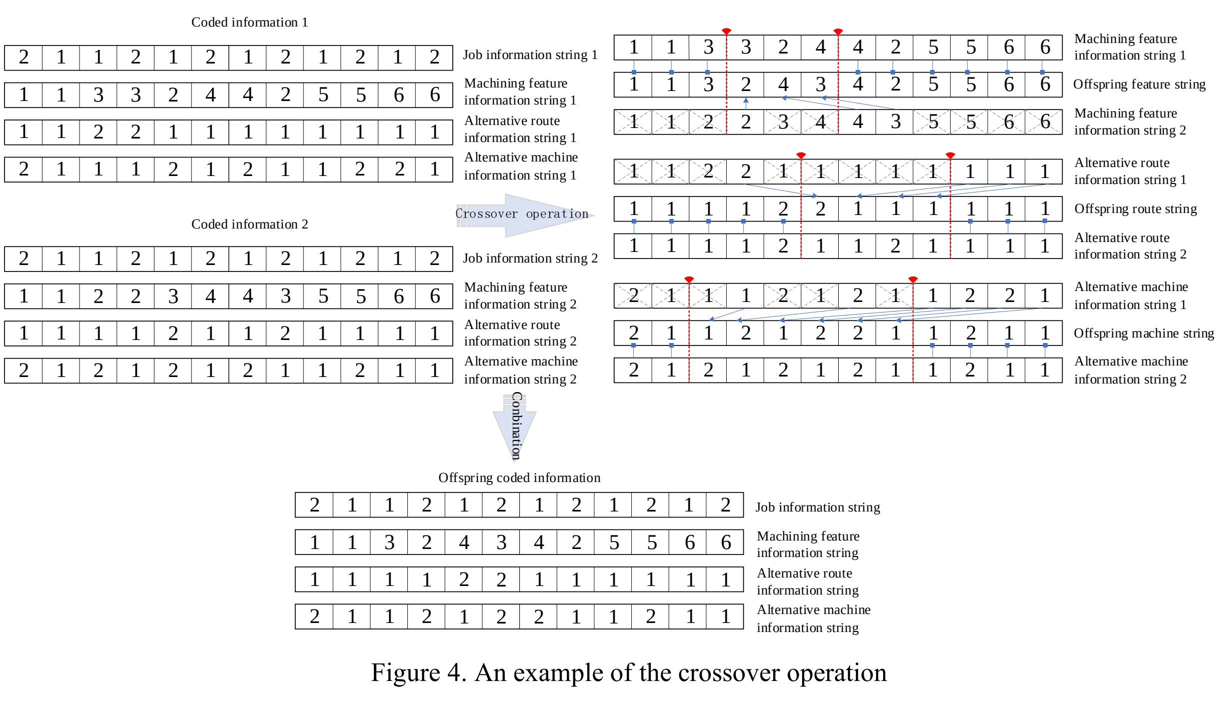


Figure 4. An example of the crossover operation

In this figure, two pieces of coded information (coded information 1 and coded information 2) are randomly selected from the population. The processing feature sequences are extracted from this coded information. Next, 2 intersection points are randomly chosen in the feature sequence, indicated by the red dotted line in the figure. Then, the number sequence from the processing feature information sequence 1 that lies outside the two intersection points is copied into the corresponding position of the offspring feature sequence. Simultaneously, the numbers that match the offspring feature sequence in the processing feature information sequence 2 are sequentially deleted. The remaining numbers in the processing feature information sequence 2 are then inserted into the empty positions of the offspring feature sequence from left to right, resulting in a complete offspring feature information sequence. Similarly, the offspring route sequence and offspring machine sequence are obtained. Finally, this offspring information is combined to create a complete offspring encoded information.

Like the crossover operation, the mutation operation involves adjusting the processing features, alternative route, and the alternative machine of workpieces simultaneously. It can serve to help the algorithm avoid premature convergence and escape local optima, and the detail is as follows. Firstly, two positions are randomly selected within the offspring's coded information, which is generated from the crossover operation. The information at these positions is then exchanged. During this process, it is necessary to check the priority constraints to ensure the validity of the mutation. Then, the mutation is applied to the alternative route information. It means that a position is randomly chosen from the set of positions that contain multiple processing routes. This selected position is then replaced with other routes in the route set.

Finally, the mutation operation is performed on the alternative machines. A position that contains multiple alternative machines is randomly selected, and it is replaced by other machines in the machine set. This process is depicted in Figure 5.

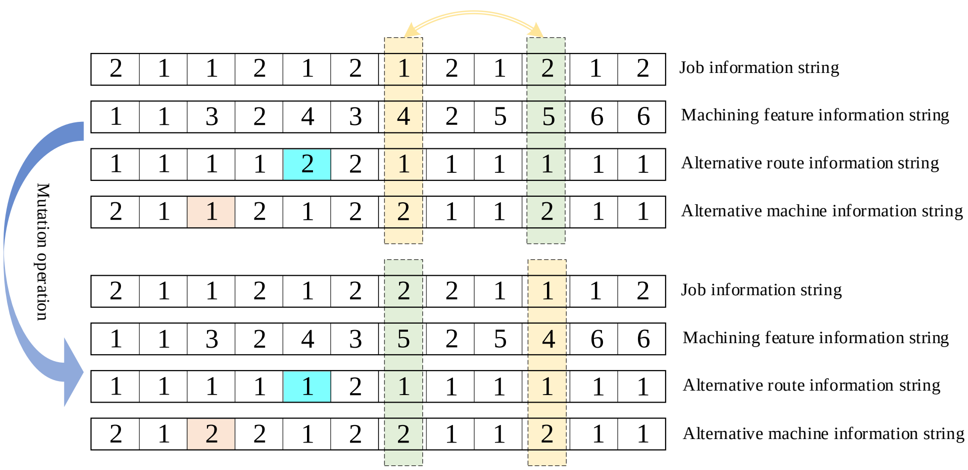


Figure 5. An example of the mutation operation

In this figure, firstly, the machining feature 4 of workpiece 1 is swapped with the machining feature 5 of workpiece 2. The corresponding alternative routes and alternative machines are also exchanged simultaneously, thus enabling the mutation operation of machining features. Then, the alternative route corresponding to the machining feature 4 of workpiece 1 is randomly selected and replaced. Additionally, the alternative machine linked to the machining feature 3 of workpiece 1 is randomly selected to be replaced. It should be noted that no substitutions are made for machining features that have only one process route or a single optional machine.

In the genetic algorithm, multiple process routes are generated and evaluated based on the minimum completion time as the optimization objective. The fitness value of each individual is calculated using equation (9), where$F(x)$ is the objective function. The individuals are then sorted based on their fitness values. Then, three process routes with larger fitness values are preliminarily selected as near-optimal process routes, which are severed as the input conditions for scheduling optimization. Subsequent optimization and adjustments of scheduling are performed using these near-optimal routes.

$$fitness = \frac{1}{F(x)} \tag{9}$$

4.2. Solving the Production Scheduling Scheme

The fitness value of individuals is calculated according to the multiple near-optimal process routes generated during the process planning stage. This calculation leads to a comprehensive sorting of process schemes. Then, from this sorted list, the top-ranked r individuals are selected to form the initial scheduling population. The selection probabilities for these individuals are based on a predefined set. After that, the hybrid variable neighborhood search method of improved PSO is utilized to enhance the local optimization capability. This approach combines the greedy rule and left-shift strategy (Joo *et al*. 2015) to quickly obtain the optimal target value. As process flexibility is considered in the scheduling optimization process, the operational efficiency and flexibility of the overall system can be improved.

4.2.1. Improved PSO

Particle swarm optimization (PSO) is an intelligent search method that emulates the behavior of a biological colony. It utilizes particles in the search space to represent the solution of the optimization problem. Each particle flies at a certain speed within the search space. Consider a D-dimensional search space with a population of N particles. Each particle has a position and a speed. The position of *i*th particle is denoted as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, and its speed is denoted as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. Additionally, the best point of the individual is denoted as $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$, and the best point of the global is denoted as $P_g = (p_{g1}, p_{g2}, \ldots, p_{gD})$. During the flight, particles dynamically adjust their positions and speeds according to the following formula (Manasrah and Ba 2018):

$$v_{ij}^{(t+1)} = \omega v_{ij}^{(t)} + c_1 r_1 (p_{ij}^{(t)} - x_{ij}^{(t)}) + c_2 r_2 (p_{gj}^{(t)} - x_{ij}^{(t)}) \tag{10}$$

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)} \qquad j = 1,2,\ldots,D \tag{11}$$

where, c_1, c_2 represents the learning factor, t represents the iteration times, r_1, r_2 represents the independent random number in the interval [0,1]; ω represents inertia weight. Additionally, to confine the particle motion within a reasonable search space, the following measures are employed:

$$v_{ij}^{(t+1)} = \begin{cases} v_{max}, & v_{ij}^{(t+1)} > v_{max} \\ -v_{max}, & v_{ij}^{(t+1)} < -v_{max} \end{cases} \tag{12}$$

$$x_{ij}^{(t+1)} = \begin{cases} x_{max}, & x_{ij}^{(t+1)} > x_{max} \\ -x_{max}, & x_{ij}^{(t+1)} < -x_{max} \end{cases} \tag{13}$$

Inertia weight ω plays a crucial role in algorithm convergence. Larger values of ω enhance the global search ability, while smaller ones are beneficial for improving the local search ability (Tang *et al*. 2019). Therefore, to achieve a balance between global search and local search, a nonlinear decreasing adjustment is implemented. This adjustment enables the algorithm to realize wide-scale global search in the initial stage and fine-tuned local search in the later stage. The specific adaptive adjustment formula is as follows:

$$\omega(t) = 0.4 + 0.58\, cos(\frac{\pi}{2} \times \frac{t}{t_{max}}) \tag{14}$$

From formula (10), it is evident that when $c_1 < c_2$, particles tend to move toward the global optimal direction. Otherwise, they tend to move towards the individual optimal direction. Therefore, c_1 is set to decrease linearly and c_2 increases linearly so that the algorithm focuses on global search in the initial stage and transitions to local optimal search as it progresses. The specific adjustments are as follows:

$$\begin{cases} c_1 = c_{1max} - (c_{1max} - c_{1min}) \cdot t/t_{max} & (15) \\ c_2 = c_{2min} + (c_{2max} - c_{2min}) \cdot t/t_{max} & (16) \end{cases}$$

4.2.2. Variable Neighborhood Search Processing Machine

To enhance the local search ability of this algorithm, the variable neighborhood search method is usually employed. This method involves replacing each initial solution with the optimal solution within its neighborhood, thereby achieving local optimization. Referring to Nowicki E's method (Nowicki and Smutnicki 2005), two types of neighborhood structures for local search are constructed as follows: (1) In the alternative machine sequence, randomly select J different processing procedures (to reduce the neighborhood scale, usually $J \leq 5$) for full permutation to change the machining sequence of the workpiece on a particular machine, while the machining sequences of the remaining workpieces remain unchanged. (2) In the alternative machine sequence, two procedures are randomly selected, and their machining sequences on the machine are exchanged while keeping the machining sequences of the rest workpiece intact. In this way, the advantages of different neighborhood structures can be considered, and the problem's solution space can be fully searched. Subsequently, the optimal solution is chosen from the neighborhood range based on the optimization objective. To illustrate this process, consider the machines for two workpieces as depicted in Figure 1. The explicit process is shown in Figure 6. In Figure 6 (a), four different processes are randomly selected for full permutation to obtain multiple possible solutions, and one example solution is provided in this figure. In Figure 6 (b), two processes on machine M2 are selected randomly for exchange, leading to a feasible solution.

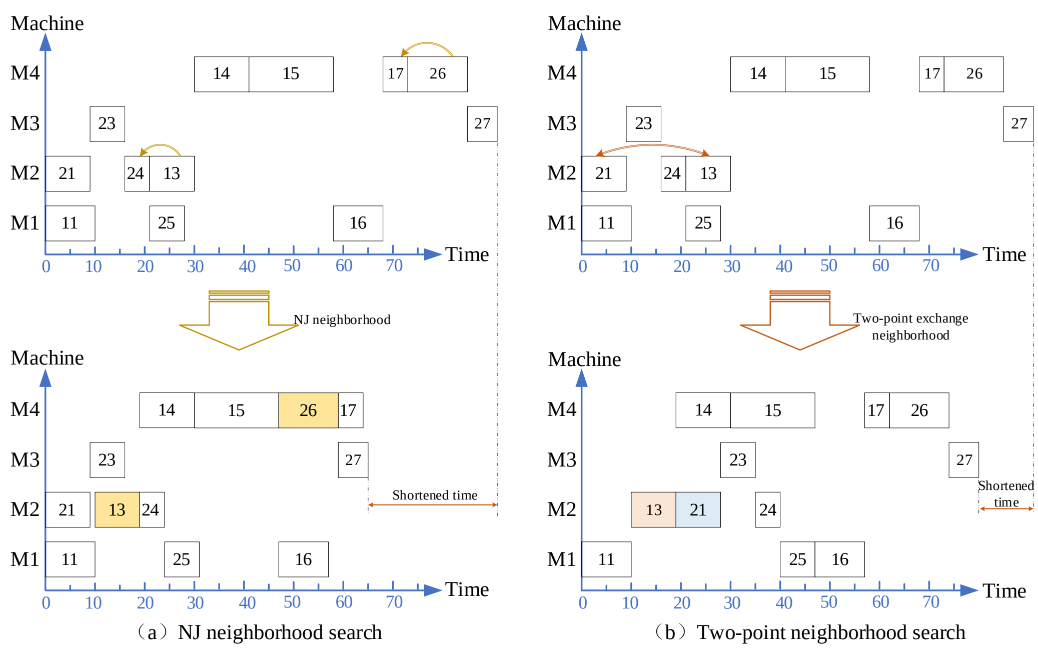


Figure 6. An example of local search processing machine

4.3. Hybrid Optimization Algorithm Flow

The optimization of process planning and scheduling is conducted in a distributed parallel manner, with a focus on collaborative optimization based on DT information sharing. This approach aims to enhance the efficiency and intelligence of production scheduling by driving the scheduling process through optimized process plans. The collaborative optimization process, as presented in Figure 7, consists of three parts: process route optimization, DT information sharing, and scheduling optimization. The main steps of the proposed algorithm are as follows:

Step 1: Initialization. Firstly, initialize the algorithm parameters, such as population size P_s, maximum iterations I_{max}, crossover probability P_c, and mutation probability P_m. And then randomly initialize the process route population.

Step 2: Generation of multiple process routes. The improved genetic algorithm is applied to reproduce, crossover, and mutate individuals in the population to generate multiple possible technological routes.

Step 3: Selection of near-optimal process routes. Based on feedback from the digital twin layer regarding workshop manufacturing resource information, the individual fitness is calculated and sorted. A set of r individuals meeting the current production conditions are selected as near-optimal process routes.

Step 4: Scheduling optimization. Depending on the selected r near-optimal process routes, the scheduling population is initialized. The hybrid particle swarm algorithm is employed to search for the individual optimal value and the global optimal value of the population, with the maximum makespan as the objective.

Step 5: Termination condition discrimination. If the scheduling process meets the termination conditions, the current optimal scheduling plan and corresponding process route of each workpiece are outputted. If not, the individual position and speed are updated using the iterative formula of the hybrid particle swarm algorithm, and the optimization process returns to Step 4.

Step 6: Production condition evaluation. The scheduling optimization scheme is evaluated to determine whether it meets the on-site production conditions. If so, the optimal scheduling plan is outputted. If not, the scheduling optimization process continues.

Step 7: Virtual verification and analysis. In the virtual space, the optimal scheduling plan and process route of workpieces are simulated and verified to ensure they meet the product requirements. If so, the relevant parameters are fed back to the physical workshop to guide the actual production process. If not, the process planning stage is revisited to re-optimize the process plan.

Step 8: Information storage. The optimal scheduling plan and process route information of each workpiece are updated in the database to give a reference for subsequent product design updates and optimization.

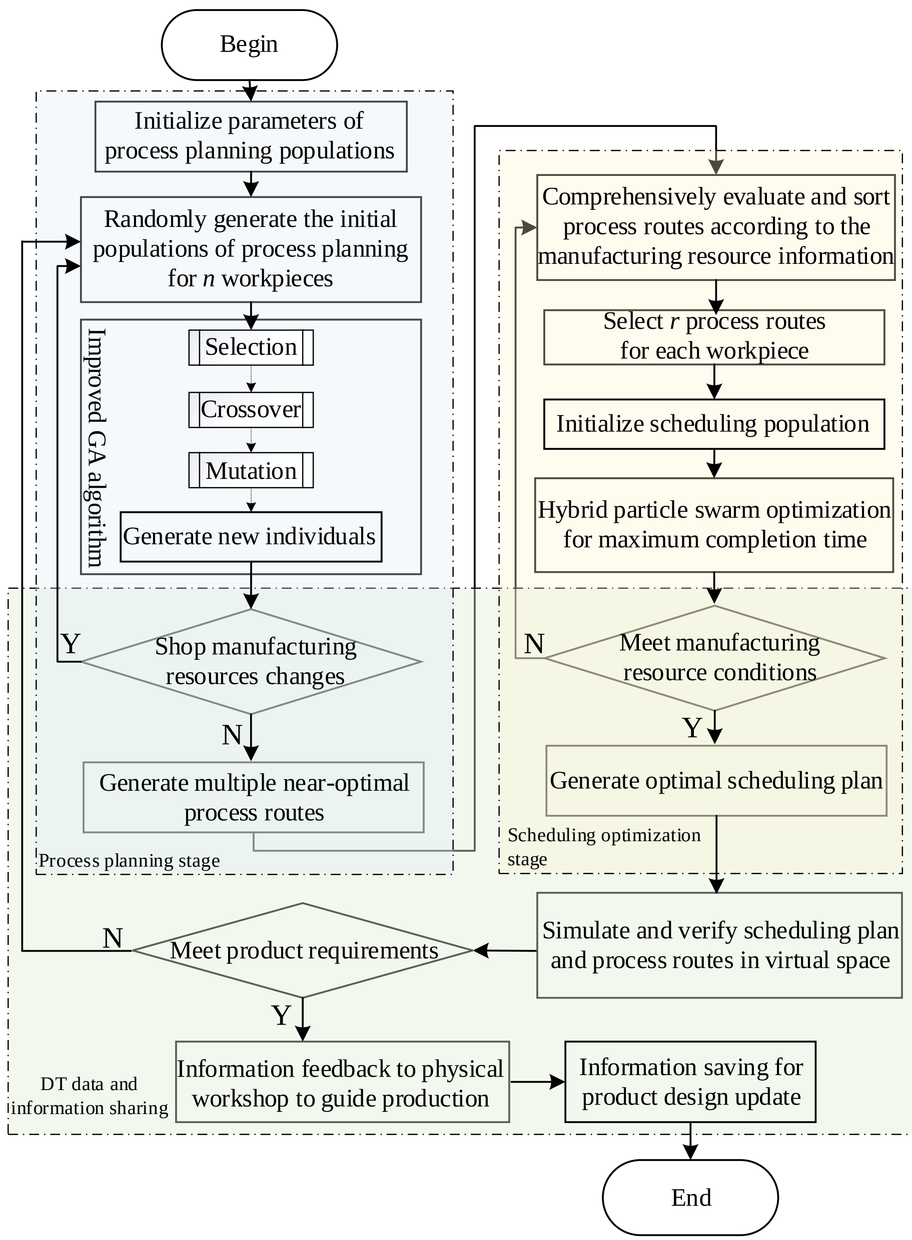
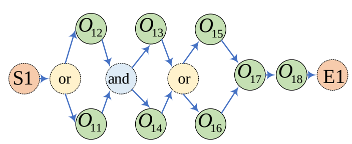
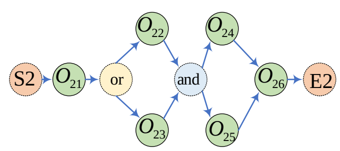
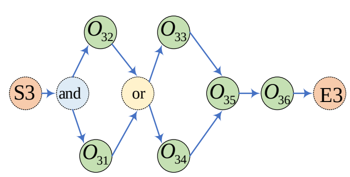
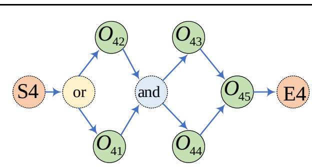
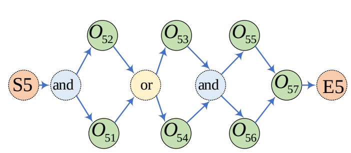


Figure 7. Workflow of collaborative optimization for digital twin

5. CASE STUDY

To demonstrate the feasibility of the proposed method, a production example from a manufacturing enterprise is presented. The production task involves the use of seven sets of equipment to process five different workpieces. The equipment includes one ordinary lathe (M1), two CNC lathes (M2, M3), two CNC milling machines (M4, M5), one drilling machine (M6), and one grinding machine (M7). The material of each workpiece is QT400-15. For each workpiece, there are multiple alternative processes available. Relevant process information is provided in Table 4. The data presented in this table are obtained from the actual data, with rounding operations applied to ensure accuracy.

Table 4. Machining information of workpieces

Jobs	Features	Optional procedure	Process network	Optional machine	Processing time /min	Feature constraints
J1	F1	O_{11}		M1/M2/M3	3 / 2 / 2	
		O_{12}		M1/M2/M3	4 / 3 / 2	
	F2	O_{13}		M2/M3	4 / 3	After F1
		O_{14}		M4/M5	2 / 3	
	F3	O_{15}		M4/M5	3 / 3	
		O_{16}		M4	4	
	F4	O_{17}		M6	1	
	F5	O_{18}		M7	4	After F2，F3，F4
J2	F1	O_{21}		M6	2	
	F2	O_{22}		M1/M2	5 / 3	After F1
		O_{23}		M4/M5	4 / 3	
	F3	O_{24}		M4/M5	2 / 3	After F2
		O_{25}		M4/M5	3 / 2	
	F4	O_{26}		M2/M3	2 / 3	
J3	F1	O_{31}		M1/M2	4 / 3	
		O_{32}		M2/M3	3 / 2	
	F2	O_{33}		M2/M3	2 / 3	
		O_{34}		M4/M5	6 / 5	
	F3	O_{35}		M6	1	After F2
	F4	O_{36}		M7	3	
J4	F1	O_{41}		M1/M2/M3	6 / 4 / 4	
		O_{42}		M2/M3	6 / 5	
	F2	O_{43}		M2/M3	6 / 5	After F1
		O_{44}		M4/M5	3 / 5	
	F3	O_{45}		M7	2	After F2
J5	F1	O_{51}		M1/M2/M3	3 / 4 / 3	
		O_{52}		M1/M2/M3	4 / 4 / 3	
	F2	O_{53}		M2/M3	4 / 3	After F1
		O_{54}		M4/M5	3 / 3	
	F3	O_{55}		M4/M5	4 / 5	
		O_{56}		M4/M5	5/ 3	
	F4	O_{57}		M5	3	After F2

According to the above scheduling task information and the workshop manufacturing resource data, a virtual verification model is constructed using Plant Simulation software, as depicted in Figure 8. The optimized process route and production scheduling information from the proposed method are transferred to this virtual verification model. The model allows for the simulation and analysis of the manufacturing process for the workpiece, enabling the evaluation of whether the product design requirements are met. If so, the verified production scheme can then be fed back to the physical entity layer to guide the actual processing of the workpiece.

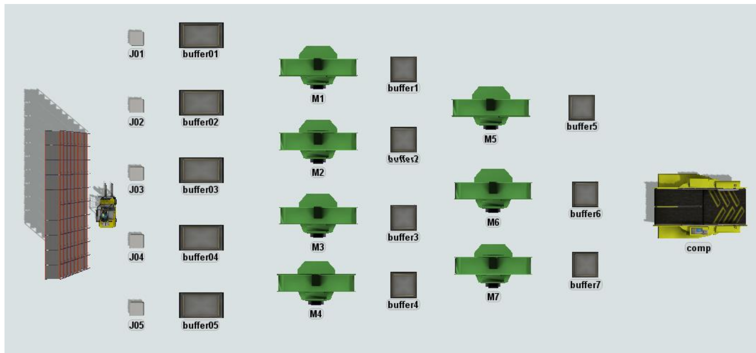


Figure 8. Verification model in virtual space

The proposed optimization method is implemented using MATLAB R2016b on a computer with the following configuration: Windows 7 system, Intel(R)Xeon(R) CPU@3.07GHz, 8GB RAM. Referring to related research results, the parameters are set as follows: the population size N is set to 50, and the crossover probability and mutation probability are set to 0.8 and 0.05, respectively. Additionally, the learning factor $c_1 = c_2 = 2$, and $c2min_{1min}$, $c2max_{1max}$, in the improved PSO. The maximum number of iterations is set to 300. Meanwhile, the results of this method are compared to those of the conventional PSO and GA algorithms to verify the effectiveness of this method.

6. RESULTS ANALYSIS AND DISCUSSION

The convergence curves of the proposed method, as well as conventional GA and PSO, after running independently 20 times, are shown in Figure 9. It can be observed from the convergence curves that as the number of iterations increases, the completion time calculated by all three methods gradually decreases and eventually stabilizes. This indicates that the algorithms are converging towards optimal or near-optimal solutions.

Since the proposed method improves the crossover strategy of GA and the local search strategy of PSO, the solution space distribution is wide, and the particles can quickly explore better regions through global search at the initial search stage. Moreover, the improved learning factor, adaptive weight adjustment strategy, and neighborhood search method contribute to the quick identification of the optimal solution. As a result, the proposed method demonstrates improved convergence compared to the conventional GA and PSO algorithms. It can find the optimal or near-optimal solution in a shorter time, enhancing the efficiency of the optimization process.

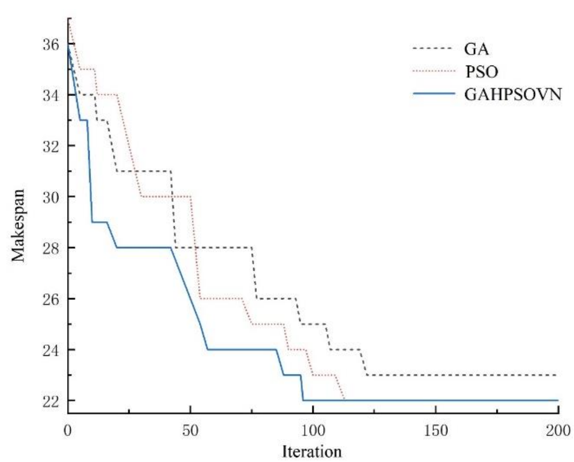


Figure 9. Convergence curves of different algorithm

The comparison of results obtained from the three methods is presented in Table 5. It is evident from the table that all three methods eventually converge to the optimal value of makespan. However, the proposed method in this paper is superior to the other two methods in terms of the average generation, average optimal value, and average operation time. These results indicate the feasibility and superiority of the proposed method. By achieving a lower average generation, the proposed method demonstrates faster convergence to the optimal solution. This efficiency is further reflected in the average operation time, where the proposed method requires less computational time to reach the optimal solution. Moreover, the average optimal value obtained from the proposed method indicates that it consistently yields better solutions compared to the conventional GA and PSO algorithms. Overall, the results comparison demonstrates that the proposed method is not only capable of finding the optimal value of makespan but also offers improved performance in terms of convergence speed and solution quality.

Table 5**.** Results comparison of three methods

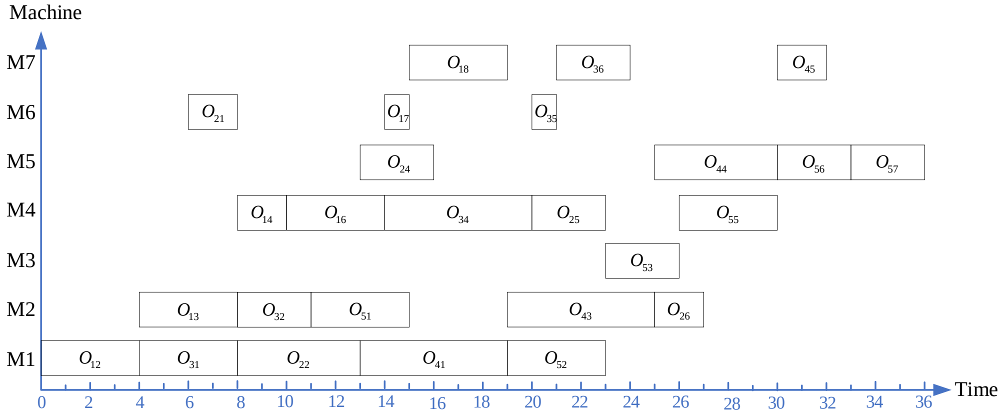
Algorithm	Optimal value	Average generation	Average optimum	Average CPU operation time
GA	22	120.86	22.45	164.13
PSO	22	113.57	22.20	151.72
GAHPSOVN	22	96.32	22.05	130.03

According to the optimization results of the proposed method, the optimal process route is shown in Table 6, and the corresponding scheduling Gantt chart for this process route is depicted in Figure 10. As can be seen from the figure, the scheduling plan depicted in the Gantt chart effectively adheres to the machining feature constraints of workpieces, resulting in a makespan of 22 min. It is 38.89% shorter than the initial data provided by the factory before optimization. The makespan comparison of each workpiece before and after optimization is shown in Figure 11. It clearly illustrates the effectiveness of the optimization process, as the completion time of each workpiece has been significantly shortened. This improvement is conducive to fully utilizing manufacturing resources and reducing production costs. Additionally, it can respond more quickly to changes in orders or urgent order demands, to arrange production plans and scheduling services more flexibly, ultimately leading to improved market competitiveness of enterprises.

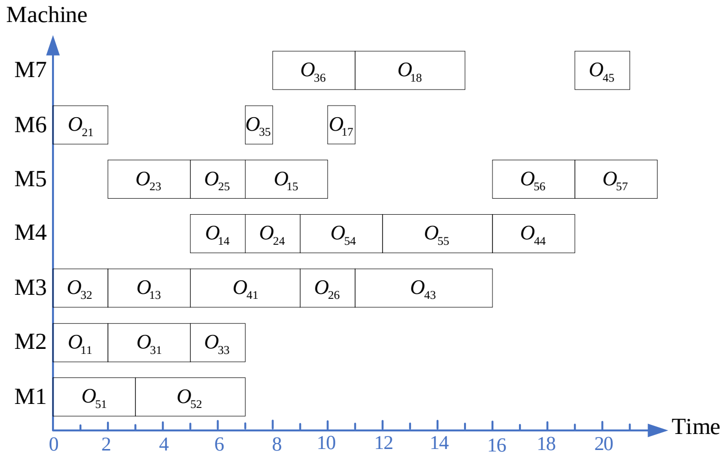
According to the analysis of Figure 10 and Figure 11, it can be observed that before optimization, the initial scheduling plan had relatively scattered the process allocation for each workpiece, leading to an imbalanced machine load. Some processes are centrally concentrated on bottleneck machines, resulting in low overall equipment utilization and increased risk of machine failure. This arrangement also caused delays in completing overall production tasks. After optimization, the proposed method utilizes CNC machining equipment as much as possible to enhance production efficiency. Moreover, the alternative process routes and alternative machines for each workpiece are employed to adjust the starting time and machine allocation for each process. This reduces equipment loss caused by frequent startup and shutdown while improving machine load balancing. The processing time distribution of each process becomes more compact and reasonable, effectively saving processing time and enhancing the flexibility of the machining process. The parameters obtained from this optimization result are applied to a virtual simulation model for machining process simulation. This simulation model provides real-time visibility into the detailed status of the machining process, along with insights into the configuration of workshop manufacturing resources and equipment utilization. This facilitates the reasonable arrangement of different production tasks. The simulation results validate the optimization results, as the makespan obtained from virtual operation also amounts to 22 min. This consistency confirms the stability and reliability of the optimized operation process, offering valuable assistance to the actual processing of the workpiece.

Table 6**.** Optimal process routes of each workpiece

Jobs	Process numbers	Optimal process route	Processing time
J1	6	$O_{11}(M_2) \rightarrow O_{13}(M_3) \rightarrow O_{14}(M_4) \rightarrow O_{15}(M_5) \rightarrow O_{17}(M_6) \rightarrow O_{18}(M_7)$	15
J2	5	$O_{21}(M_6) \rightarrow O_{23}(M_5) \rightarrow O_{25}(M_5) \rightarrow O_{24}(M_4) \rightarrow O_{26}(M_2)$	11
J3	5	$O_{32}(M_3) \rightarrow O_{31}(M_2) \rightarrow O_{33}(M_2) \rightarrow O_{35}(M_6) \rightarrow O_{36}(M_7)$	11
J4	4	$O_{41}(M_3) \rightarrow O_{43}(M_3) \rightarrow O_{44}(M_4) \rightarrow O_{45}(M_7)$	21
J5	6	$O_{51}(M_1) \rightarrow O_{52}(M_1) \rightarrow O_{54}(M_4) \rightarrow O_{55}(M_4) \rightarrow O_{56}(M_5) \rightarrow O_{57}(M_5)$	22



(a) Scheduling plan before optimization



(b) Scheduling plan after optimization

Figure 10. Gantt chart of the scheduling plan

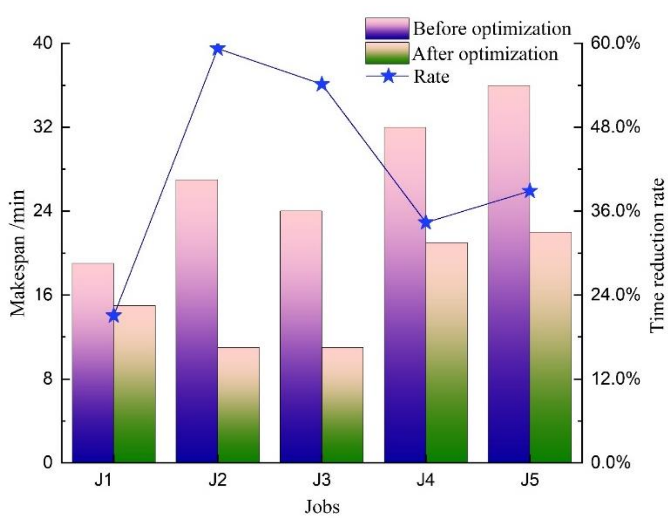


Figure 11. Makespan comparison of workpieces before and after optimization

7. CONCLUSION AND FUTURE RESEARCH

Process planning and scheduling are crucial components of a flexible manufacturing system, and the information interaction between them directly affects the smooth operation of production activities. The collaborative optimization of these two components, combined with digital twin technology, plays a significant role in reducing manufacturing resource conflicts and improving production efficiency, etc. The main work and contributions of this paper are as follows.

Firstly, considering the triple flexibility encountered in the collaborative optimization process, a comprehensive framework of digital twin-oriented collaborative optimization is constructed using a phased multi-level parallel optimization approach. This framework enables efficient and effective optimization of process planning and production scheduling. To address this optimization problem, an innovative GAHPSOVN algorithm is proposed. The algorithm incorporates a multi-dimensional encoding approach and introduces two feasible neighborhood structures. In the process planning stage, an improved genetic algorithm is utilized to enhance searchability and generate a wide range of near-optimal solutions for the process route. These solutions serve as the search space for the scheduling link. Subsequently, a particle swarm algorithm with a variable neighborhood structure is utilized to solve the scheduling plan. This strategy effectively avoids the algorithm falling into local optimal solutions and improves convergence speed. The collaborative operation of process planning and production scheduling effectively enhances the flexibility of the system. Finally, the generated optimal scheduling plan and process route are analyzed and tested in Plant simulation software. The results are compared with those of conventional PSO and GA algorithms to verify the effectiveness of the proposed method.

Since the actual manufacturing system could be affected by various uncertain factors, and optimization objectives can be diverse, the following directions can be tried in future research.

- Consider more complex manufacturing conditions and simulate various interference factors, such as emergency orders, delayed arrival of parts, changes in delivery date, uncertain processing time, equipment failure, and more. This will ensure that the problem solution aligns more closely with the actual production environment.
- Expand the optimization objectives of this problem from single-objective to multi-objective optimization. Additionally, consider environmental and ecological benefits such as energy and resource consumption, environmental impact, as well as carbon emissions, in the manufacturing process. This will lead to more comprehensive and sustainable optimization results.
- Explore more efficient and rapid intelligent algorithms to solve the collaborative optimization problem of process planning and production scheduling. This will promote the digital and intelligent upgrading of the discrete manufacturing industry and facilitate the adoption of advanced technologies.

By pursuing these research directions, the applicability and effectiveness of collaborative optimization in flexible manufacturing systems can be further enhanced, enabling the manufacturing industry to address increasingly complex challenges and achieve higher levels of efficiency and sustainability.

REFERENCES

Alzahrani, J. S. (2019). Multi-objective job shop scheduling under risk using GA. *Science and Education Publishing*, 6:1-12.
Ante, L. (2021). Digital twin technology for smart manufacturing and industry 4.0: a bibliometric analysis of the intellectual structure of the research discourse. *Manufacturing Letters*, 27:96-102.

Chen, Z., Zou, J., and Wang, W. (2023). Digital twin-oriented collaborative optimization of fuzzy flexible job shop scheduling under multiple uncertainties. *Sādhanā*, 48:1-15.

Coronado, P. D. U., Lynn, R., Louhichi, W., Parto, M., Wescoat, E., and Kurfess, T. (2018). Part data integration in the Shop Floor Digital Twin: Mobile and cloud technologies to enable a manufacturing execution system. *Journal of manufacturing systems*, 48:25-33.

Fang, Y., Peng, C., Lou, P., Zhou, Z., and Yan, J. (2019). Digital-Twin-Based Job Shop Scheduling Toward Smart Manufacturing, *IEEE Transactions on Industrial Informatics*, 15:6425-6435.

Fujii, N., Inoue, R., and Ueda, K. (2008). Integration of process planning and scheduling using multi-agent learning. *In Manufacturing Systems and Technologies for the New Frontier: The 41st CIRP Conference on Manufacturing Systems*, 297-300

Hung, M. H., Lin, Y. C., Hsiao, H. C., Chen, C. C., Lai, K. C., Hsieh, Y. M., and Cheng, F. T. (2022). A novel implementation framework of digital twins for intelligent manufacturing based on container technology and cloud manufacturing services. *IEEE Transactions on Automation Science and Engineering*, 19(3):1614-1630.

Jin, L., and Zhang, C. (2019). Process planning optimization with energy consumption reduction from a novel perspective: Mathematical modeling and a dynamic programming-like heuristic algorithm. *IEEE Access*, 7:7381-7396.

Joo, C., Lin, X., and Shroff, N. B. (2009). Understanding the capacity region of the greedy maximal scheduling algorithm in multihop wireless networks. *IEEE/ACM transactions on networking*, 17(4):1132-1145.

Joseph, O. A., and Sridharan, R. (2011). Effects of routing flexibility, sequencing flexibility and scheduling decision rules on the performance of a flexible manufacturing system. *The International Journal of Advanced Manufacturing Technology*, 56(1-4):291-306.

Lamini, C., Benhlima, S., and Ali Bekri, M. (2022). Collaborative Ant Colony Multi-agent Planning System for Autonomous Mobile Robots in a Static Environment. *In The Proceedings of the International Conference on Smart City Applications*, 393:249-265

Leung, C. W., Wong, T. N., Mak, K. L., and Fung, R. Y. (2010). Integrated process planning and scheduling by an agent-based ant colony optimization. *Computers & Industrial Engineering*, 59(1): 166-180.

Li, Y., Li, X., Gao, L., and Meng, L. (2020). An improved artificial bee colony algorithm for distributed heterogeneous hybrid flowshop scheduling problem with sequence-dependent setup times. *Computers & Industrial Engineering*, 147:106638.

Liu, Q., Li, X., Gao, L., and Wang, G. (2022). A multiobjective memetic algorithm for integrated process planning and scheduling problem in distributed heterogeneous manufacturing systems. *Memetic Computing*, 14(2):193-209.

Liu, Q., Li, X., Gao, L., and Li, Y. (2020). A modified genetic algorithm with new encoding and decoding methods for integrated process planning and scheduling problem. *IEEE Transactions on Cybernetics*, 51(9):4429-4438.

Liu, X., Ni, Z., and Qiu, X. (2016). Application of ant colony optimization algorithm in integrated process planning and scheduling. *The International Journal of Advanced Manufacturing Technology*, 84:393-404.

Liu, Z., Chen, W., Zhang, C., Yang, C., and Cheng, Q. (2021). Intelligent scheduling of a feature-process-machine tool supernetwork based on digital twin workshop. *Journal of manufacturing systems*, 58:157-167.

Lu, Q., Parlikad, A. K., Woodall, P., Don Ranasinghe, G., Xie, X., Liang, Z., and Schooling, J. (2020). Developing a digital twin at building and city levels: Case study of West Cambridge campus. *Journal of Management in Engineering*, 36(3):05020004.

Manasrah, A. M., and Ba Ali, H. (2018). Workflow scheduling using hybrid GA-PSO algorithm in cloud computing. *Wireless Communications and Mobile Computing*, 3:1-16.

Maoudj, A., Bouzouia, B., Hentout, A., Kouider, A., and Toumi, R. (2019). Distributed multi-agent scheduling and control system for robotic flexible assembly cells. *Journal of intelligent manufacturing*, 30:1629-1644.

Moreno, E., Rezakhah, M., Newman, A., and Ferreira, F. (2017). Linear models for stockpiling in open-pit mine production scheduling problems. *European Journal of Operational Research*, 260(1):212-221.

Mueller-Zhang, Z., Antonino, P. O., and Kuhn, T. (2021). Integrated planning and scheduling for customized production using digital twins and reinforcement learning. *IFAC-PapersOnLine*, 54(1):408-413.

Nejad, H. T. N., Sugimura, N., and Iwamura, K. (2011). Agent-based dynamic integrated process planning and scheduling in flexible manufacturing systems. *International Journal of Production Research*, 49(5):1373-1389.

Nguyen, T. N., Zeadally, S., and Vuduthala, A. B. (2021). Cyber-physical cloud manufacturing systems with digital twins.

IEEE Internet Computing, 26(3):15-21.

Nowicki, E., and Smutnicki, C. (2005). Some new ideas in TS for job shop scheduling. *Metaheuristic Optimization via Memory and Evolution: Tabu Search and Scatter Search*, 30:165-190.

Ocampo, J., Hernández, J., Márquez, J., and Vizán, A. (2020). The Effect of Process Improvement Practices on Manufacturing Competitiveness of Apparel Factories. *Journal of technology management & innovation*, 15(1):15-26.

Park, Y., Woo, J., and Choi, S. (2020). A cloud-based digital twin manufacturing system based on an interoperable data schema for smart manufacturing. *International Journal of Computer Integrated Manufacturing*, 33(12):1259-1276.

Petrović, M., Petronijević, J., Mitić, M., Vuković, N., Miljković, Z., and Babić, B. (2016). The Ant Lion optimization algorithm for integrated process planning and scheduling. *Applied Mechanics and Materials*, 834:187-192.

Petronijević, J., Petrović, M., Vuković, N., Mitić, M., Babić, B., and Miljković, Z. (2016). Integrated process planning and scheduling using multi-agent methodology. *Applied Mechanics and Materials*, 834:193-198.

Qi, Q., and Tao, F. (2018). Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE Access*, 6:3585-3593.

Rossi, A., and Lanzetta, M. (2020). Integration of hybrid additive/subtractive manufacturing planning and scheduling by metaheuristics. *Computers & Industrial Engineering*, 144:106428.

Rossit, D. A., Tohme, F., and Frutos, M. (2019). Production planning and scheduling in Cyber-Physical Production Systems: a review. *International journal of computer integrated manufacturing*, 32(4-5):385-395.

Bagheri Rad, N., and Behnamian, J. (2022). Recent trends in distributed production network scheduling problem. *Artificial Intelligence Review*, 55(4):2945-2995.

Saraç, T., Ozcelik, F., and Ertem, M. (2023). Unrelated parallel machine scheduling problem with stochastic sequence dependent setup times. *Operational Research*, 23(3):46.

Steimer, C., and Aurich, J. C. (2016). Analysis of information interdependencies between product development and manufacturing system planning in early design phases. *Procedia Cirp*, 50:460-465.

Sun, M., Cai, Z., Yang, C., and Zhang, H. (2023). Digital twin for energy-efficient integrated process planning and scheduling. *The International Journal of Advanced Manufacturing Technology*, 127(7):3819-3837.

Tamssaouet, K., Dauzère-Pérès, S., Knopp, S., Bitar, A., and Yugma, C. (2022). Multiobjective optimization for complex flexible job-shop scheduling problems. *European Journal of Operational Research*, 296(1):87-100.

Tang, H., Chen, R., Li, Y., Peng, Z., Guo, S., and Du, Y. (2019). Flexible job-shop scheduling with tolerated time interval and limited starting time interval based on hybrid discrete PSO-SA: An application from a casting workshop. *Applied Soft Computing*, 78:176-194.

Wang, L., Hu, X., Wang, Y., Xu, S., Ma, S., Yang, K., and Wang, W. (2021). Dynamic job-shop scheduling in smart manufacturing using deep reinforcement learning. *Computer Networks*, 190:107969.

Wang, Y., and Wu, Z. (2020). Model construction of planning and scheduling system based on digital twin. *The International Journal of Advanced Manufacturing Technology*, 109(7):2189-2203.

Wen, X., Li, X., Gao, L., Wang, K., and Li, H. (2020). Modified honey bees mating optimization algorithm for multi-objective uncertain integrated process planning and scheduling problem. *International journal of Advanced Robotic Systems*, 17(3):1-17.

Wen, X., Lian, X., Wang, K., Li, H., and Luo, G. (2020). Multi-layer collaborative optimization method for solving fuzzy multi-objective integrated process planning and scheduling. *Measurement and Control*, 53(9-10), 1883-1901.

Wong, T. N., Leung, C. W., Mak, K. L., and Fung, R. Y. (2006). Dynamic shopfloor scheduling in multi-agent manufacturing systems. *Expert Systems with Applications*, 31(3):486-494.

Yu, M., Zhang, Y., Chen, K., and Zhang, D. (2015). Integration of process planning and scheduling using a hybrid GA/PSO algorithm. *The International Journal of Advanced Manufacturing Technology*, 78:583-592.

Yunitarini, R., Pratikto, P., and Sugiono, S. (2018). An integrated website of electronic data interchange and computer-aided process planning in production outsourcing. *Eastern-European Journal of Enterprise Technologies*, 6(2): 52-60.

Zhang, D. G., Tang, Y. M., Cui, Y. Y., Gao, J. X., Liu, X. H., and Zhang, T. (2018). Novel reliable routing method for engineering of internet of vehicles based on graph theory. *Engineering Computations*, 36(1):226-247.

Zhang, L., Wong, T. N., and Fung, R. Y. (2012). A multi-agent system for dynamic integrated process planning and scheduling using heuristics. In Agent and Multi-Agent Systems. *Technologies and Applications: 6th KES International Conference, Dubrovnik, Croatia*, 309-318.

Zhang, M., Tao, F., & Nee, A. Y. C. (2021). Digital twin enhanced dynamic job-shop scheduling. *Journal of Manufacturing Systems*, 58:146-156.

Zhang, S., Yu, Z., Zhang, W., Yu, D., and Xu, Y. (2016). An extended genetic algorithm for distributed integration of fuzzy process planning and scheduling. *Mathematical Problems in Engineering*, 3:1-13.

Zhang, X., Liu, X., Tang, S., Królczyk, G., and Li, Z. (2019). Solving scheduling problem in a distributed manufacturing system using a discrete fruit fly optimization algorithm. *Energies*, 12(17):3260-3283.