

Intelligent Manufacturing Scheduling Optimization Based on Genetic Algorithm and MES

Zheng Xu¹ and Jiancong Wang²

¹ Lecturer and Oujiang Distinguished Professor, School of Business, Wenzhou University, Wenzhou, 325035, China

² Associate Professor, School of Business, Henan University, Kaifeng, 475000, China, E-mail: tongxunzuozhe8866@126.com (corresponding author).

Production Management

Received November 4, 2025; revised May 18, 2026; July 15, 2026; accepted October 4, 2026

Available online October 20, 2026

Abstract: Against the backdrop of intensified global manufacturing competition and the deep advancement of Industry 4.0, production scheduling, as a core link in efficient operations within intelligent manufacturing, faces challenges that traditional methods can no longer meet, such as delayed data acquisition and insufficient dynamic response. Therefore, a scheduling model for Industry 4.0 intelligent manufacturing based on a Genetic Algorithm (GA) and a Manufacturing Execution System (MES) is proposed. During the process, the particle swarm algorithm was used to optimize the Genetic Algorithm's parameters serially, thereby reducing complexity. At the same time, the ant colony algorithm was integrated to optimize key processes, improving the model's stability and convergence and establishing a scheduling optimization model that integrates data collection, rapid processing, and reasonable allocation. The experimental results show that the inventory turnover rate of the intelligent manufacturing scheduling model constructed in this study has increased by 3.24%, 4.58%, and 6.17%, respectively, compared to the control model's. Meanwhile, the on-time delivery rate reaches 92.13% and 91.75% across two datasets, both above 91%. The task delay rates are 7.69% and 8.67%, showing significant advantages over the comparison models at 10.45% and 11.75%, respectively. These results indicate that the proposed model can achieve efficient allocation of production resources and dynamic responsiveness, thereby improving production line efficiency and offering a new approach to intelligent manufacturing scheduling.

Keywords: Ant colony optimization (ACO); genetic algorithm (GA); hybrid metaheuristics; intelligent manufacturing; manufacturing execution system (MES); scheduling optimization.

Copyright © Journal of Engineering, Project, and Production Management (EPPM-Journal).
DOI 10.32738/JEPPM-2025-257

1. Introduction

In the context of increasingly fierce global manufacturing competition, Industry 4.0 intelligent manufacturing has become a core driver of transformation and upgrading in the manufacturing sector (Sun et al., 2023). Production scheduling, a key component of production management, plays a crucial role in intelligent manufacturing and is critical to efficient operations (Wang et al., 2024). Traditional manufacturing scheduling methods confront challenges including delayed data acquisition, heavy reliance on manual intervention, slow response times, and poor coordination, which render them inadequate for meeting dynamic production demands (Qin et al., 2023). The Manufacturing Execution System (MES) manages people, machines, materials, methods, and the environment in real-time, linking the planning and control layers. It enables the visualization of production processes, improves efficiency, and provides quality traceability, offering essential support for intelligent transformation (Mohamed et al., 2024). The Genetic Algorithm (GA) simulates selection, crossover, and mutation mechanisms of biological evolution to optimize solutions to problems. In intelligent manufacturing, GA efficiently solves complex issues, such as scheduling generation and resource allocation, providing algorithmic support for intelligent decision-making and system performance improvement in dynamic production environments (Neumann et al., 2024). Therefore, an Industry 4.0 intelligent manufacturing scheduling optimization model based on GA and MES is proposed to improve manufacturing efficiency. The innovation of the study lies in optimizing GA with Particle Swarm Optimization (PSO) during model construction. Iterating particle positions and velocities simplifies parameter adjustment and reduces computational complexity. An elite retention strategy ensures that the best solution from each generation is directly passed to the next, preventing the loss of superior genes and improving the GA's convergence stability and search efficiency. The proposed intelligent manufacturing scheduling optimization model is expected to dynamically adjust scheduling plans in response to changes in production tasks, fluctuations in equipment status, and variations in material

supply conditions, allocate production tasks reasonably, shorten production cycles, and enhance production efficiency.

2. Literature Review

With the advantages of real-time data integration and process visualization, MES has been widely applied in discrete manufacturing industries, such as the automotive and electronics sectors, as well as process industries, including the chemical and pharmaceutical sectors. Park et al. (2024) proposed an agent-based MES to address the inflexibility and poor scalability of traditional manufacturing systems. Experimental results showed that their system had high autonomy and reconfigurability, but its robustness was insufficient in complex scenarios. Guo et al. (2023) addressed issues of poor real-time performance and accuracy in traditional enterprise production systems and proposed an AI-based MES system. However, the system sub-component is constrained by the middleware during data transmission, making it challenging to ensure real-time data transmission. GA, with its advantages of adaptive global search and parallel exploration of multiple solutions, has been widely applied in workshop scheduling, neural network weight optimization, and parameter optimization in engineering design. Many scholars have conducted in-depth research on GA. Kuster et al. (2023) proposed a multi-objective optimization framework based on GA, which integrates objectives such as energy consumption, peak reduction, and manufacturing span to enhance the efficiency of industrial production scheduling. However, it needs to increase the probability of obtaining the global optimal solution by setting a variable mutation rate for the GA and implementing random restarts. Guzman et al. (2023) proposed a heuristic algorithm combining GA and mixed-integer linear programming to optimize production and distribution plans in the supply chain, achieving global coordination from production scheduling to logistics delivery. Its universality for cross-industry supply chains still required further validation. Nwanwe et al. (2024) proposed an optimization framework that combines artificial neural networks and a multi-objective GA to maximize harvest yield while minimizing energy consumption. However, the framework strongly depended on the training data, and its generalizability decreased when the data were insufficient.

Intelligent manufacturing scheduling optimizes the allocation of production resources and the assignment of tasks through smart technologies. Intelligent scheduling plays a pivotal role in enhancing efficiency and minimizing costs, finding wide application in various production scenarios in both discrete and process manufacturing industries. Niu et al. (2023) proposed a multi-task chained scheduling model based on support vector machines for scheduling automatic guided vehicles. Compared with traditional methods, the model's connection span and overload ratio were improved by 20.0% and 8.5%, respectively. However, its adaptability to dynamic task fluctuations is insufficient, and the adjustment time for relatively stable scenarios has increased significantly. Yang et al. (2022) proposed a scheduling and reconfiguration model based on deep reinforcement learning and the Advantage Actor-Critic algorithm to address delay issues in intelligent scheduling systems. Their model improved efficiency by 57.43% over the iterative greedy algorithm, with a decision time of only 1.47ms. However, the system's data characteristics were manually defined, which prevented autonomous learning and feature extraction. Zhang et al. (2022) addressed the conflict between optimization efficiency and decision response time in scheduling and proposed a real-time scheduling method based on reinforcement learning and digital twins. Their approach demonstrated better adaptability and learning ability than traditional methods, but did not account for device heterogeneity or unexpected failures. Jin et al. (2025) introduced task privacy levels and encryption techniques to improve the efficiency of task scheduling in edge-cloud collaborative computing and proposed a scheduling method based on an improved Artificial Bee Colony algorithm. The results show that this method can reduce task execution delay by 31.13%. Li et al. (2022) employed an adaptive scheduling algorithm to optimize task allocation and path planning in production workshops, resulting in a 21.7% improvement in overall task completion efficiency. However, its performance is superior in more specialized scenarios but offers no advantage in stable scenarios.

In summary, many scholars have made progress in optimizing intelligent manufacturing scheduling, but limitations remain in terms of comprehensiveness and the intelligence of optimization performance. Therefore, this study proposed an intelligent manufacturing scheduling model based on GA and MES. It is expected to respond quickly to dynamic events, adjust production plans and scheduling schemes promptly, and enhance production efficiency.

3. Construction of Intelligent Manufacturing Scheduling Model Based on GA and MES

3.1. Scheduling Algorithm Design Integrating MES and GA

MES is a management information system situated between the enterprise-level planning system and the industrial control system, with a focus on the workshop level (Kilari, 2025). It aims to achieve efficient execution of production plans, optimize the allocation of production resources, and refine production process management through real-time monitoring, data collection, and analysis. This improves production efficiency, product quality, and market competitiveness (Macchi et al., 2023). The MES scheduling process is shown in Fig. 1.

As shown in Fig. 1, after the processing plan is input into MES, production information is generated. On the one hand, production information flows to order management, and after scheduling, is coordinated by the planning control module for process tracking. On the other hand, production information is linked to material management, which is simultaneously connected to processing equipment to ensure the supply of production resources. Process tracking data is fed back to quality control, which collaborates with production scheduling to regulate the production rhythm. The control and management module integrates multi-stage information. It ultimately connects to the control system, forming a closed-loop process that spans from planning and resource allocation to production execution and quality control. In this process, a model for the manufacturing scheduling problem can be established based on equipment quantities, processing steps, and processing times, with the total production cost given by Eq. (1).

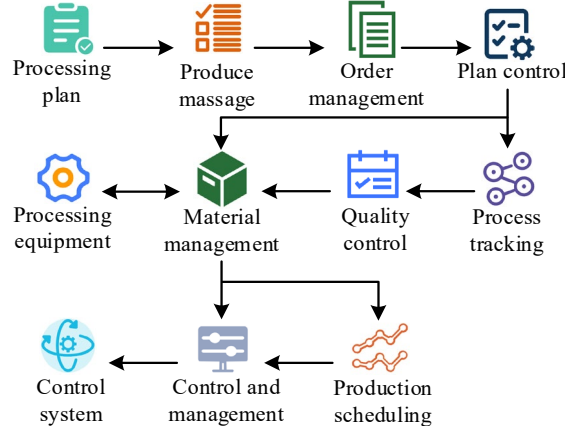


Fig. 1. MES scheduling process diagram

$$F = \sum_{n=1}^i \sum_{m=1}^j \sum_{l=1}^{N_m} x_{n,m,l} \cdot F_{n,m,l} \quad (1)$$

In Eq. (1), F represents total production cost, i represents the quantity of products to be manufactured, j represents the number of product operations, N_m is the number of equipment that can process m simultaneously, n is the product index, m is the operation index, l is the equipment index, and x represents decision factors. The manufacturing time in the scheduling process is expressed in Eq. (2).

$$\begin{cases} W_{(o+1)ml,m+1,k} = \max[P_{(o+1)ml,m,l} \cdot P_{oml,m+1,k}] \\ P_{n,m,l} = W_{n,m,l} + t_{n,m,l} \end{cases} \quad (2)$$

In Eq. (2), W represents the start time of product manufacturing, P represents the end time, o represents the index of equipment processing tasks, k represents the workpiece index, and t represents the product manufacturing time. Constraints during the manufacturing process are expressed in Eq. (3).

$$\begin{cases} \sum_{l=1}^{N_m} x_{n,m,l} = 1 \\ \sum_{l=1}^{N_m} M_{m,l} = i \end{cases} \quad (3)$$

In Eq. (3), M represents the total number of equipment processes. By optimizing the established mathematical model, the optimal manufacturing schedule can be obtained. In solving complex production scheduling problems, multiple feasible scheduling schemes may exist, and traditional algorithms easily fall into local optima. GA evolves multiple initial schedules in parallel, trying different combinations and permutations to find better global solutions. This advantage allows GA to effectively escape local extrema in complex, multi-peak optimization problems, improving solution accuracy and reliability (Yu et al., 2023). However, standard GA only applies crossover, mutation, and selection, which may eliminate high-fitness individuals, causing the best individuals to be lost in the next generation. Therefore, to avoid the problem of traditional GA algorithms losing the current optimal solution during the evolution process, an improved GA (IGA) was developed by introducing an elite retention strategy. The flowchart of the IGA algorithm is shown in Fig. 2.

In Fig. 2, the IGA algorithm first generates an initial population and then calculates individual fitness based on the objective function. If the termination condition is not met, the elite chromosome will be retained as the parent, and its genes will be exchanged to produce offspring that will then replace the parent, forming a new population. This process repeats until convergence. In this IGA, each chromosome represents a scheduling scheme using a process-based encoding approach. Specifically, chromosomes are arranged in the order of processing across all processes and products, with each gene locus corresponding to a process. The order in which the processes appear is the processing order on the machine, thus transforming the solution to the scheduling problem into a chromosome form that can be operated by GAs. Furthermore, the scheduling problem is transformed into a single-objective problem through nondimensionalization, as expressed in Eq. (4).

$$f_q = \begin{cases} \frac{g_q - g_{q\min}}{g_{q\max} - g_{q\min}}, & g_q > 0 \\ 0, & g_q = 0 \end{cases} \quad (4)$$

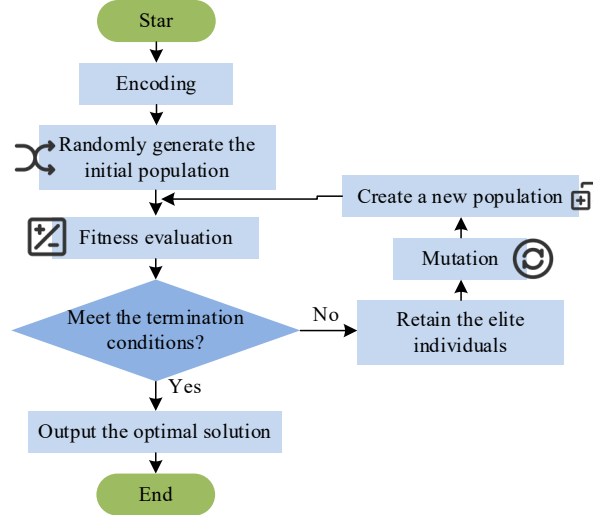


Fig. 2. Optimized IGA flowchart diagram

In Eq. (4), g_q represents the q -th original objective function value. $g_{q\max}$ and $g_{q\min}$ respectively represent the minimum and maximum values of the q -th target in the population. f_q represents the q -th objective function value after nondimensionalization, with a value range of [0,1]. After obtaining the dimensionless objective function value, continue to calculate the fitness of the objective function, as shown in Eq. (5).

$$\begin{cases} F_{it} = \frac{1}{w_1 f_1 + w_2 f_2} \\ w_1 + w_2 = 1 \end{cases} \quad (5)$$

In Eq. (5), F_{it} represents the fitness value of an individual, and the larger its value, the better the solution. w_1 and w_2 represent the weights of the corresponding targets. f_1 and f_2 represent the dimensionless total cost and manufacturing time, respectively. Subsequently, the study employed an elite-retention strategy to preserve the chromosome with the highest fitness value and explored the solution space via crossover operations. The crossover probability P_c is dynamically adjusted based on individual fitness, as shown in Eq. (6).

$$P_c = \begin{cases} P_{c1} - \frac{(P_{c1} - P_{c2})(F_{it} - F_{it,avg})}{F_{it,max} - F_{it,avg}}, & F_{it} \geq F_{it,avg} \\ P_{c1}, & F_{it} < F_{it,avg} \end{cases} \quad (6)$$

In Eq. (6), P_{c1} represents the preset maximum crossover probability, which is typically set to 0.9. P_{c2} represents the preset minimum crossover probability, usually set at 0.6. $F_{it,max}$ represents the maximum fitness of the current population. $F_{it,avg}$ represents the average fitness of the current population. Then increase the population's diversity through mutation operations. The mutation probability P_m is also dynamically adjusted, similar to the crossover probability, as shown in Eq. (7).

$$P_m = \begin{cases} P_{m1} - \frac{(P_{m1} - P_{m2})(F_{it} - F_{it,avg})}{F_{it,max} - F_{it,avg}}, & F_{it} \geq F_{it,avg} \\ P_{m1}, & F_{it} < F_{it,avg} \end{cases} \quad (7)$$

In Eq. (7), P_{m1} represents the preset maximum mutation probability, typically set to 0.1. P_{m2} represents the preset minimum mutation probability, typically set to 0.01. Finally, the mean squared error was adopted as the loss function, with its specific expression given in Eq. (8).

$$L = \frac{1}{K'} \sum_{k'}^{K'} (y_{k'} - y'_{k'})^2 \quad (8)$$

In Eq. (8), L represents the loss value, K' indicates the number of scheduling tasks evaluated in the iterative process of the pronoun, k' represents the index of the task, $y_{k'}$ represents the actual optimal target value of the task, and $y'_{k'}$ represents the predicted target value in the scheduling scheme. In summary, the real-time data management capability of MES supports dynamic GA optimization, thereby enhancing MES's decision-making through intelligent optimization. Therefore, the MES-IGA intelligent scheduling algorithm is constructed based on MES and IGA, as shown in Fig. 3.

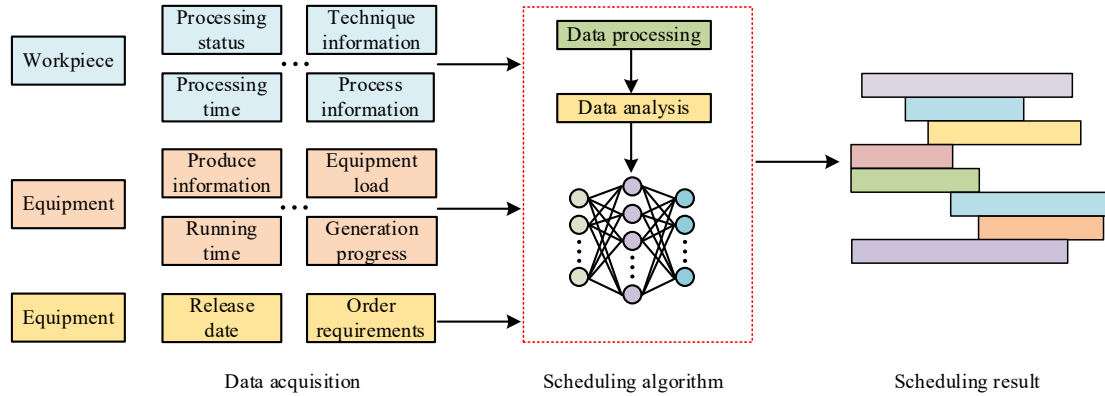


Fig. 3. MES-IGA intelligent scheduling algorithm flow chart

As shown in Fig. 3, the MES-IGA intelligent scheduling algorithm comprises three aspects: data collection, the scheduling algorithm, and the scheduling results. MES collects real-time data, including equipment operation status, material inventory, order demand, and production progress, to provide real-time inputs required for dynamic optimization to IGA. IGA solves the optimal scheduling plan through the chromosome encoding elite retention strategy and crossover mutation operations, presenting it in a Gantt chart format to provide a straightforward process and decision-making basis for intelligent scheduling, and outputs the results to the MES system, which is then executed by the MES system's planning control, process tracking, etc., modules for scheduling. At the same time, MES will track production execution progress in real time and feedback abnormal data, such as equipment failures and process delays, to the IGA module to support dynamic adjustment of the scheduling plan. The mapping diagram between the scheduling scheme and chromosomes is shown in Fig. 4.

As shown in Fig. 4, by unfolding the process tasks to be processed in the left scheduling scheme according to the actual processing order, they are directly mapped to the continuous gene loci of the right chromosome, where each gene locus represents a specific process, thus transforming the scheduling scheme into chromosome encoding that can be processed by GA. An example of partial scheduling results is shown in Table 1.

Table 1. Example of scheduling results

Product Number	Process Number	Machine Number	Start time (h)	End time (h)
P1	1	M1	0.0	2.5
P2	2	M3	2.5	5.0
P3	1	M2	0.0	3.0
P4	2	M2	3.0	6.5

In Table 1, each row represents the scheduling result for a process, including the product number, process sequence, equipment used, and start and end times, which clearly displays the task allocation and time arrangement for each piece of equipment.

3.2. Design of MES-IGA Intelligent Scheduling Model Optimized by PSO and ACO

The constructed MES-IGA algorithm dynamically adjusts manufacturing schedules based on real-time production data from the production line. However, MES-IGA parameter settings rely on experience, and their computational complexity increases with problem dimensionality. Particle Swarm Optimization (PSO) accelerates convergence by simulating swarm intelligence, sharing information among particles, and using a cooperative evolution mechanism. It dynamically adjusts the inertia weight to reduce computational complexity and continuously updates particle positions to improve solution stability (Zaied et al., 2023). The flowchart of the proposed PSO-IGA algorithm is shown in Fig. 5.

In Fig. 5, after inputting the data, PSO-IGA first initializes the particle swarm and determines the initial local and global optimal values, then calculates the fitness of each particle. If the termination condition is not met, update the local optimum, global optimum, and particle velocity and position, and recalculate the fitness. Loop until the termination condition is met before entering the population initialization and iterative calculation of GA, and finally output the optimal solution. This process simulates particle motion in the solution space and adaptively adjusts the search direction based on individual and global optimal experiences. The particle velocity update formula is shown in Eq. (9).

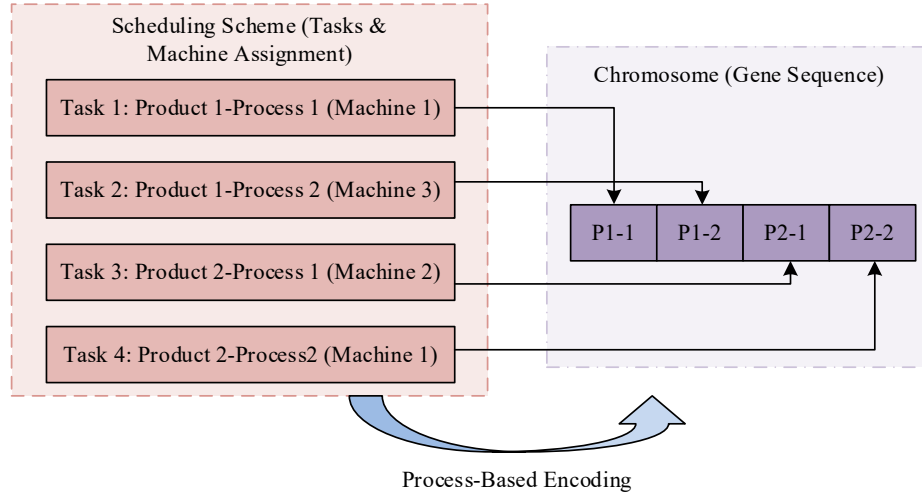


Fig. 4. Schematic diagram of mapping between scheduling scheme and chromosomes

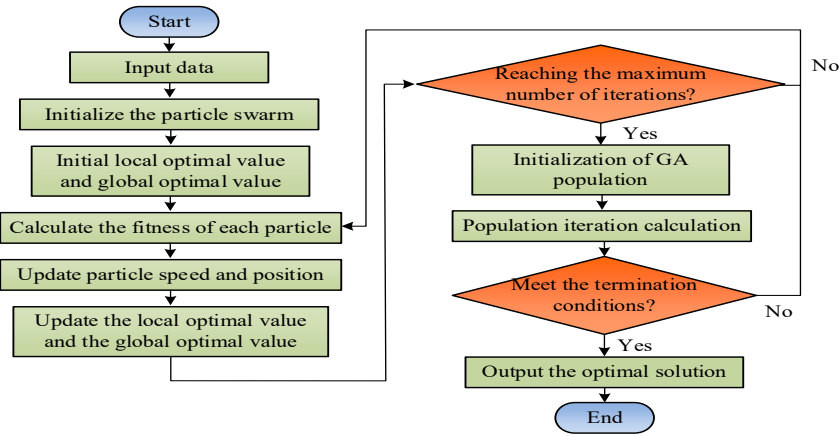


Fig. 5. Schematic diagram of the process of PSO optimizing IGA

$$v_{id}(t+1) = \omega(t) \cdot v_{id}(t) + c_1 r_1 (p_{id} - x_{id}(t)) + c_2 r_2 (g_d - x_{id}(t)) \quad (9)$$

In Eq. (9), $v_{id}(t+1)$ and $v_{id}(t)$ represent the velocity of particle i in the d -th dimension for the $t+1$ -th and t -th generations, $\omega(t)$ represents the inertia weight for the t -th generation, c_1 and c_2 represent individual and global learning factors, r_1 and r_2 represent random numbers uniformly distributed within the range of $[0,1]$, p_{id} represents the individual historical optimal position of particle i in the d -th dimension, $x_{id}(t)$ represents the position of particle i in the d -th dimension for the t -th generation, and g_d represents the global optimal position of the population in the d -th dimension. The particle's position is updated using its velocity, as shown in Eq. (10).

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (10)$$

In Eq. (10), $x_{id}(t+1)$ represents the new position of the $t+1$ -th generation particle. To balance early global search and later local optimization, the inertia weight of PSO uses a linear decay strategy, as shown in Eq. (11).

$$\omega(t) = 0.95 - 0.5 \times \left(\frac{t}{T}\right) \quad (11)$$

In Eq. (11), $\omega(t)$ represents the inertia weight of the t -th generation, t represents the current iteration number, and T describes the total number of iterations. Although PSO-IGA overcomes IGA's dependence on parameters, its local search ability is weak, and it is prone to getting stuck in local optima. Ant colony algorithm (ACO) is a heuristic global optimization algorithm that simulates the foraging behavior of ants and provides robust local optimization capabilities (Liu et al., 2023). Therefore, this study further introduces ACO to improve PSO-IGA, yielding AP-IGA. AP-IGA adopts a serial parallel hybrid architecture, where PSO optimizes the crossover and mutation probability parameters of IGA in series, and then runs in parallel with ACO. Among them, IGA is responsible for the global allocation of production tasks, while ACO is responsible for local path optimization of key processes. The workflow of AP-IGA is shown in Fig. 6.

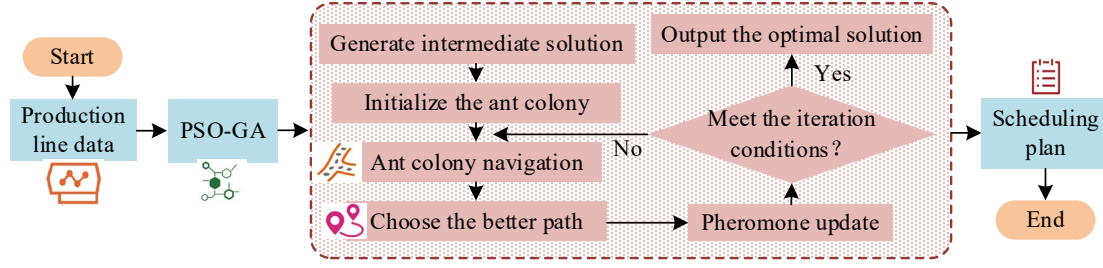


Fig. 6. Schematic diagram of the AP-IGA operation process

In Fig. 6, the ACO algorithm first initializes the ant population and pheromone distribution. Each ant independently constructs feasible solutions based on pheromone concentration and heuristic information, and determines its movement direction based on a combination of factors. After completing one iteration, all ants update the path pheromone according to the quality of the solution. Specifically, high-quality solution paths deposit more pheromones to guide subsequent ants, while pheromones evaporate in proportion to their concentration, preventing premature convergence. Repeat this process until the termination condition is met, ultimately converging to the optimal or approximately optimal solution through a positive feedback mechanism. The transition probability of ants is shown in Eq. (12).

$$Q_{ab}^z(y) = \frac{(\tau_{ab})^\alpha (\eta_{ab})^\beta}{\sum_{s \in b_z(a)} (\tau_{as})^\alpha (\eta_{as})^\beta} \quad (12)$$

In Eq. (12), $Q_{ab}^z(y)$ represents the probability of ant z transitioning from node a to b in the y -th iteration. $\tau_{ab}(y)$ represents the concentration of pheromones on path (a,b) at the y -th round. η_{ab} represents the heuristic factor of path (a,b) . α and β represent the weight coefficients of pheromones and heuristic factors, respectively. $allowed_z(a)$ represents the set of next nodes that ant z is allowed to select at node a . s represents any node in the set. The heuristic factor takes the reciprocal of the path length, as shown in Eq. (13).

$$\eta_{ab} = \frac{1}{D_{ab}} \quad (13)$$

In Eq. (13), D_{ab} represents the distance between nodes a and b . After all ants complete a round trip, update the pheromones on each path according to the update rule shown in Eq. (14).

$$\tau_{ab}(y+1) = (1 - \rho) \cdot \tau_{ab}(y) + \sum_{z=1}^A \Delta \tau_{ab}^z \quad (14)$$

In Eq. (14), $\tau_{ab}(y+1)$ represents the concentration of pheromones on path (a,b) at the $y+1$ -th round. ρ represents the volatility coefficient of pheromones, with a value range of $(0,1)$. A represents the number of ants. $\Delta \tau_{ab}^z$ represents the increment of pheromones left by the z -th ant on path (a,b) . In summary, combining MES and AP-IGA produces the MES-AP-IGA intelligent manufacturing scheduling model, whose structure is shown in Fig. 7.

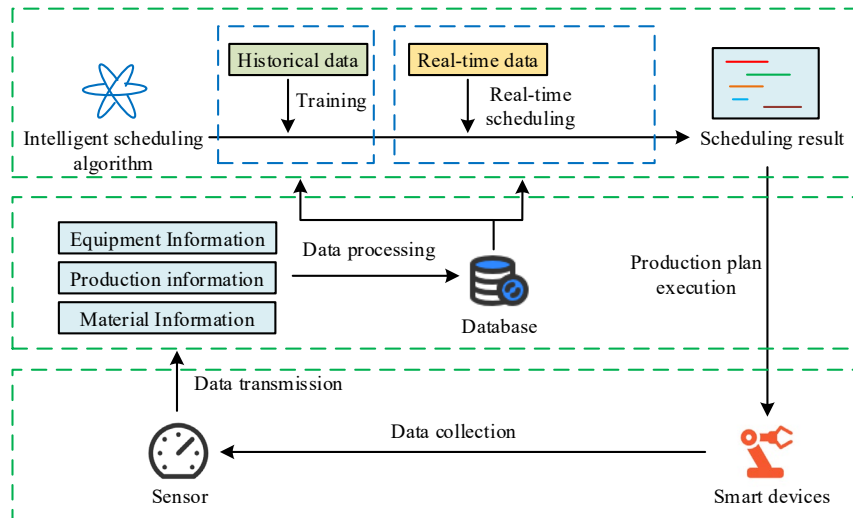


Fig. 7. MES-AP-IGA intelligent manufacturing scheduling model structure diagram

As shown in Fig. 7, MES-AP-IGA collects multidimensional data from MES, including equipment status, production progress, material inventory, and order requirements, thereby supporting model training and scheduling analysis. The data are input into the intelligent scheduling algorithm module. IGA constructs scheduling objective functions based on MES real-time data, and chromosome encoding, elite retention, crossover, and mutation operations achieve global optimization for task allocation and process sequencing. PSO dynamically optimizes IGA parameters by sharing swarm information, thereby reducing computational complexity. ACO optimizes equipment allocation and material paths for critical operations to avoid local optima. The final optimal schedule is presented visually, and operators execute production in accordance with the plan. MES tracks progress in real time and feeds data back into the database, enabling efficient and intelligent manufacturing scheduling.

4. Performance Validation of Intelligent Manufacturing Scheduling Model

4.1. Performance Analysis of MES-IGA Scheduling Algorithm

To evaluate the performance of the MES-IGA scheduling algorithm, comparisons were made with GA combined with Support Vector Machine (SVM), Non-dominated Sorting Genetic Algorithm II (NSGA II), and Multi-Objective Particle Swarm Optimization (MOPSO) algorithms. GA-SVM is widely used in data-driven dynamic scheduling and related areas, but it is highly data-dependent. In contrast, NSGA II excels in the convergence and uniformity of multi-objective solutions through non-dominated sorting and the calculation of crowding degree. It is the international benchmark for multi-objective manufacturing scheduling research, but it still has the drawback of a relatively weak dynamic response. MOPSO exhibits rapid convergence and responds quickly in dynamic scheduling scenarios. These three types of algorithms cover the mainstream research directions, ensuring the comparison is comprehensive and targeted. The experiments were conducted on a system running Windows 10, with an Intel Core i5-12400F CPU @ 2.5 GHz and an NVIDIA RTX 3080 GPU (10GB). The software environment consists of Python 3.9, TensorFlow 2.8, PyTorch 1.12, and the optimization library DEAP 2.3. Parallel computing utilizes four threads, and all experiments are repeated 10 times, with the average value calculated. This study was conducted in two intelligent manufacturing factories in a specific prefecture-level city in China. Factory A is an automotive parts production plant equipped with 86 processing machines and 36752 historical processing records. Factory B is an electronic component production plant equipped with 93 pieces of processing equipment and 49728 historical processing records. This study used its historical processing data to create a test dataset, which was divided into training, validation, and test sets in a 7:2:1 ratio. An example of a partial dataset (the top 5 records of Factory A) is shown in Table 2.

Table 2. Examples of partial dataset

Product Number	Process Number	Equipment Number	Processing time (h)	Material arrival time (h)
P001	1	M1	2.5	0.0
P001	2	M3	1.8	2.5
P002	1	M2	3.0	0.0
P002	2	M1	2.2	3.0
P003	1	M1	1.5	0.0

The four algorithms underwent loss testing, and the results are shown in Fig. 8.

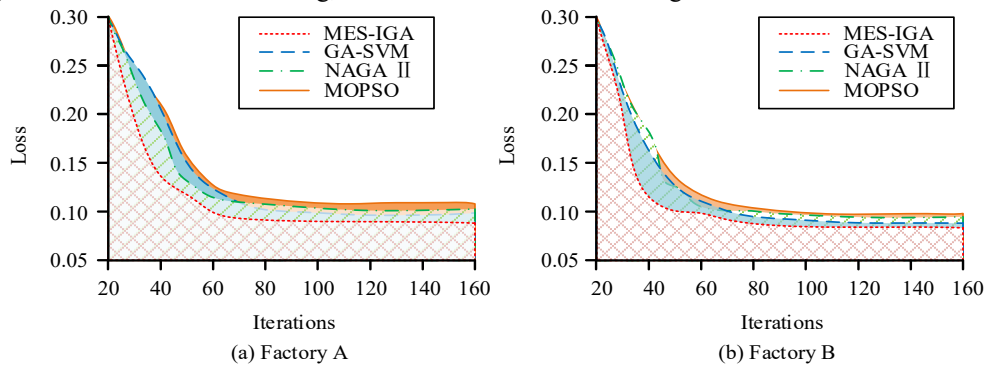


Fig. 8. Comparison of loss value test results

As shown in Fig. 8(a), during testing on the Factory A dataset, when the number of iterations reached 100, the MES-IGA model yielded a loss of 0.094, while GA-SVM and NSGA II recorded losses of 0.11 and 0.12, respectively. Fig. 8(b) shows that during testing on the Factory B dataset, when the number of iterations reached 140, MES-IGA achieved a loss value of 0.092, which was 0.028 lower than that of MOPSO. These results indicate that MES-IGA, which combines MES real-time data support with IGA's global optimization capability, improves the stability of algorithm convergence and solution accuracy, resulting in lower loss values and faster convergence. To further analyze the performance of MES-IGA, eight products were selected to test the production cycle and equipment utilization across the four algorithms. The equipment utilization rate = (actual processing time) or (actual processing time + preventive maintenance time + idle time). Here, the preventive maintenance time is set at 30 minutes per device per day. Results are shown in Fig. 9.

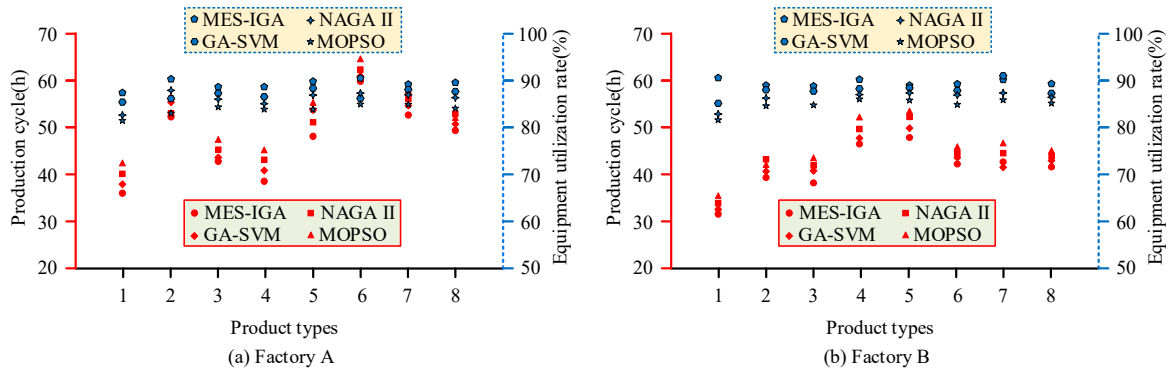


Fig. 9. Production cycle and equipment utilization test results

As shown in Fig. 9(a), during testing on the Factory A dataset, MES-IGA achieved a production cycle of 36.8 h for the first product, with equipment utilization of 87.4%. Fig. 9(b) shows that on the Factory B dataset, MES-IGA produced the fifth product in 46.7 h, 5.6 h shorter than that of NSGA II. Equipment utilization reached 88.3%, 4.2% higher than NSGA II. These results demonstrated that MES-IGA collected real-time data on equipment load and material supply, optimized task allocation through parallel evolution and dynamic scheduling, reduced idle equipment and waiting time, and enabled efficient allocation of production resources across all devices. To further validate MES-IGA performance, four products were selected to test the task delay rate under equipment failure. Results are shown in Fig. 10.

Fig. 10(a) shows that in the Factory A dataset, MES-IGA achieved a task delay rate of 13.4% for the second product, which was 2.2% and 2.8% lower than GA-SVM and MOPSO, respectively. Fig. 10(b) shows that on the Factory B dataset, MES-IGA achieved a task delay rate of 17.5% for the third product, outperforming the other algorithms by a significant margin. This performance benefited from MES real-time monitoring and feedback of equipment failures, allowing IGA to quickly adjust schedules, reallocate tasks, and optimize process sequences to reduce delays.

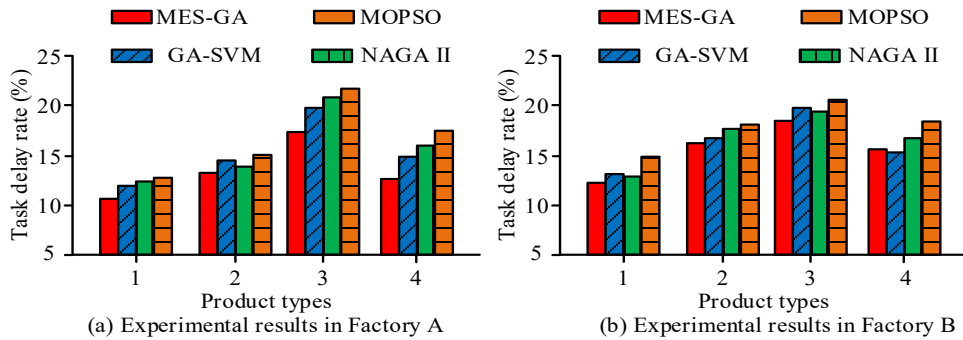


Fig. 10. Task delay rate test results

4.2. Application Analysis of MES-AP-IGA Intelligent Manufacturing Scheduling Model

After validating MES-IGA, the study further evaluated the performance of the MES-AP-IGA model. MES-AP-IGA was compared with GA-SVM, NSGA II, and MOPSO-based smart manufacturing scheduling models. Experiments used historical processing data from two smart factories, C and D, in a northern city of China. To clarify the independent contributions of PSO and ACO to the model performance, a study was conducted using the MES-IGA as the base model. Three sets of ablation experiments were designed, in which either PSO or ACO was removed, or both were retained. The average computing time and inventory turnover rate after 140 iterations were selected for testing. The test results are shown in Table 3.

Table 3. The results of the ablation experiment

Model	Average calculation time (s)	Inventory turnover rate
MES-IGA	18.03	86.45
MES-PSO-IGA	14.25	87.12
MES-ACO-IGA	17.28	89.56
MES-AP-IGA	12.56	91.23

As shown in Table 3, compared with the MES-IGA model, the MES-PSO-IGA model reduced the computation time by 3.78s, but the on-time delivery rate increased by only 0.53%. This indicates that the core value of PSO is to reduce the

computational complexity. The MES-ACO-IGA model achieved a 2.76% increase in on-time delivery rate compared to the MES-IGA model, but the computing time decreased by only 0.75s. This suggests that it mainly optimizes the equipment allocation path for key processes. The MES-AP-IGA model achieved optimal computing time and inventory turnover rate, indicating that PSO and ACO can complement each other and jointly improve the model's overall performance. In addition, the crossover and mutation probabilities in GA are key hyperparameters that affect population diversity and convergence speed. This study examined the impact of various parameter combinations on algorithm performance by controlling the relevant variables. The test results are shown in Table 4.

Table 4. The results of the ablation experiment

Cross probability	Mutation probability	Processing time (s)	On-time delivery rate	Convergence iteration count
0.5	0.01	9.87	89.23	86
0.5	0.03	9.52	89.76	82
0.5	0.05	9.31	90.12	78
0.7	0.01	9.15	90.58	72
0.7	0.03	8.52	92.13	65
0.7	0.05	8.76	91.85	68
0.9	0.01	9.43	88.97	75
0.9	0.03	9.01	89.62	70
0.9	0.05	9.28	88.45	66

As shown in Table 4, the model performed optimally when the crossover probability was between 0.7 and 0.8, and the mutation probability was between 0.03 and 0.05. Within this range, the crossover operation can effectively preserve high-quality genes, while the mutation operation can supplement the population's diversity and prevent premature convergence. However, when the crossover probability is less than 0.6, the frequency of crossover operations is low, the population evolution rate is slow, and the processing time is prolonged. When the mutation probability exceeded 0.05, the population stability was poor, and the processing time fluctuated more significantly. Subsequently, the study selected six products to test the processing times of the four models. The test times are shown in Fig. 11.

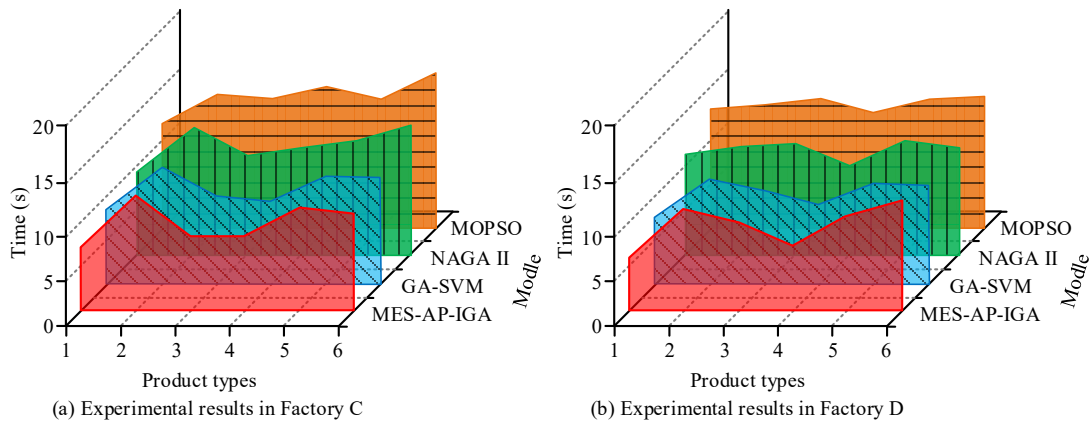


Fig. 11. Processing time test results

Fig. 11(a) shows that in the Factory C dataset, MES-AP-IGA achieved processing times of 7.86s and 9.94s for the first and third products. Fig. 11(b) shows that in the Factory D dataset, MES-AP-IGA attained a time of 12.34 s for the second product, which was 1.86 s and 2.79 s shorter than GA-SVM and NSGA II, respectively. These results indicated that MES-AP-IGA maintained low processing times across different products. By leveraging PSO to optimize GA parameters and reduce computational complexity, and using ACO to enhance local optimization and avoid local optima, the algorithm accelerated the process from data input to optimal solution output. To further analyze MES-AP-IGA, inventory turnover rates were tested. Results are shown in Fig. 12.

Fig. 12(a) shows that in the Factory C dataset, MES-AP-IGA achieved an inventory turnover rate of 91.23% for the second product, which is 3.24% and 6.17% higher than those of GA-SVM and MOPSO, respectively. Fig. 12(b) shows that in the Factory D dataset, the third product achieved 88.67% with MES-AP-IGA, outperforming GA-SVM at 87.11%. These results demonstrate that MES-AP-IGA, by leveraging real-time MES data and combining PSO-GA global scheduling optimization with ACO-refined resource allocation, dynamically matches production to demand, ensuring efficient resource utilization. To further demonstrate the advantages of MES-AP-IGA, the on-time delivery rate and task delay rate were tested. Results are shown in Table 5.

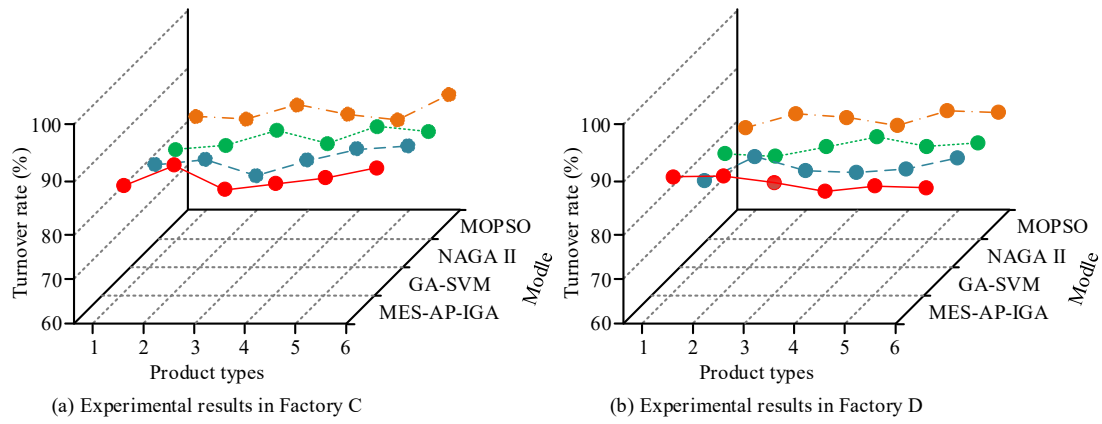
**Fig. 12.** Inventory turnover test results

Table 5 shows that in the Factory C dataset, MES-AP-IGA achieved an on-time delivery rate of 92.13%, significantly higher than GA-SVM and MOPSO, which achieved rates of 88.47% and 85.46%, respectively. The task delay rate of MES-AP-IGA was 7.69%, which is 1.93% lower than that of NSGA II. In the Factory D dataset, MES-AP-IGA achieved 91.75% on-time delivery and 8.67% task delay, outperforming GA-SVM by 3.28% and 0.12%. In the experiment, the t-test indicated that the p-values for the differences between the GA-SVM, NSGA II, MOPSO, and MES-AP-IGA models were 0.024, 0.021, and 0.017, respectively, all of which were statistically significant. Overall, MES-AP-IGA maintained high on-time delivery and low task delay across different factories, effectively improving production line efficiency. To further test the model's practical application, an experiment was conducted at a specific automobile component manufacturing plant. This plant has a total of 109 pieces of production equipment. This study conducted a 3-month pilot production period, with 1 month allocated to parameter debugging and 2 months to official operation. The equipment data, material inventory, and order demands were collected in real time through the MES system. The evaluation results for the model's pilot data are shown in Table 6.

Table 5. The test results of the on-time delivery rate and task delay rate for the four models

Dataset	Model	On-time delivery rate (95% confidence interval, %)	Task delay rate (%)	t-value	p-value
Factory C	MES-AP-IGA	90.21%-93.58%	7.69	-	-
	GA-SVM	86.54%-90.27%	9.57	1.48	0.023
	NSGA II	84.13%-88.52%	9.62	1.55	0.019
	MOPSO	83.27%-87.61%	10.45	2.17	0.016
Factory D	MES-AP-IGA	89.88%-93.14%	8.67	-	-
	GA-SVM	85.33%-89.54%	8.99	1.19	0.024
	NSGA II	84.95%-89.11%	9.42	1.83	0.021
	MOPSO	82.79%-87.03%	11.75	2.46	0.017

Table 6. Test results of the pilot deployment

Evaluation indicators	Before the pilot program	After the pilot program
Equipment utilization rate (%)	82.16	88.47
On-time delivery rate (%)	86.72	92.13
Production defect rate (%)	5.24	2.83

As shown in Table 6, after the model's deployment, the equipment utilization rate at this factory increased from 82.16% to 88.47%, and the on-time delivery rate rose by 5.41%. At the same time, the production anomaly rate decreased from 5.24% to 2.83%, representing a 2.41% reduction. The above experimental results indicate that the MES-AP-IGA model proposed in this study has a stable operational state, can effectively improve processing efficiency, maintain low

computational complexity and demonstrate scalability for large-scale manufacturing scenarios.

5. Conclusion

To address the limitations of traditional manufacturing scheduling methods, such as low production efficiency and limited dynamic adaptability, an Industry 4.0 intelligent manufacturing scheduling model is developed based on GA and MES. PSO and ACO were further applied during model construction to improve stability and convergence. Experimental results showed that across two datasets, MES-IGA achieved losses below 0.095, and its loss curves converged more quickly than those of the comparison models. MES-IGA also maintained equipment utilization above 80%, and overall production cycles were shorter than those of other models. For the second product in the Factory A dataset, MES-IGA achieved a task delay rate of 13.4%, which was 2.2% and 2.8% lower than those of GA-SVM and MOPSO, respectively. Further experiments indicated that the MES-AP-IGA model achieved a processing time reduction of 1.86 s and 2.79 s compared with GA-SVM and NSGA II, respectively, when tested on the Factory D dataset. In the Factory C dataset, MES-AP-IGA achieved an inventory turnover rate of 91.23% for the second product, 4.58% and 6.17% higher than those of GA-SVM and NSGA II, respectively.

Meanwhile, the task delay rate of the MES-AP-IGA model was 1.93% lower than that of the NSGA II model. Through real-time MES data feedback and rapid AP-IGA iteration, the lowest task delay rate can be achieved. Overall, the proposed MES-AP-IGA enables rapid production line scheduling, rational task allocation, and significant improvements in resource utilization and delivery reliability. Based on the research findings, several managerial implications for decision-making can be derived. Firstly, managers can embed MES and IGA algorithms into the production scheduling system to replace traditional manual scheduling or static scheduling, ensuring the stability of critical processes. Secondly, managers can reduce trial-and-error costs by using PSO-optimized parameter settings. In addition, using ACO to dynamically adjust equipment allocation in response to faults or material fluctuations can help reduce task delay rates and improve on-time delivery rates. Despite the significant performance advantages, a 30% increase in computational time was observed in large-scale scenarios in a large-scale scenario involving more than 50 devices. Additionally, the model is relatively sensitive to data quality. When the data missing rate exceeds 15%, the on-time delivery rate drops by 8%. The model is better suited to small- and medium-sized batch production with multiple varieties, but its advantages are not significant in large-scale single-product scenarios. Future research will explore the model's application in larger-scale and more complex manufacturing scenarios, incorporating factors such as carbon emissions, equipment energy consumption, and equipment wear into the multi-objective optimization system. This will continue to enhance the model's performance, enabling it to better meet the sustainable development requirements of Industry 4.0.

Author Contributions

Zheng Xu contributed to investigation, data collection, draft preparation and manuscript editing. Jiancong Wang contributed to methodology, software, validation, analysis and funding acquisition. All authors have read and agreed with the manuscript before its submission and publication.

Funding

The research is supported by the research project "Digital Transformation of Small and Medium-Sized Manufacturing Industries in the Yangtze River Delta," National Office for Philosophy and Social Sciences, Project ID: 19BGL014, Year: 2019.

Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

The authors confirm that no Artificial Intelligence (AI) tools were used in the preparation of this manuscript.

References

- Guo, Y., Zhang, W., Qin, Q., Chen, K., and Wei, Y. (2023). Intelligent manufacturing management system based on data mining in artificial intelligence energy-saving resources. *Soft Computing*, 27(7), 4061-4076. doi: 10.1007/s00500-021-06593-5.
- Guzman O, B. E., Poler, R., and Andres, B. (2023). A matheuristic approach combining genetic algorithm and mixed integer linear programming model for production and distribution planning in the supply chain. *Advances in Production Engineering & Management*, 18(1), 19-31. doi: 10.14743/apem2023.1.454.
- Jin, X., Wang, J., Wang, Z., Wang, G., and Chen, Y. (2025). Joint multi-server cache sharing and delay-aware task scheduling for edge-cloud collaborative computing in intelligent manufacturing. *Wireless Networks*, 31(1), 261-280. doi: 10.1007/s11276-024-03761-x.
- Kilari, S. D. (2025). Artificial intelligence into manufacturing execution systems and supply chain systems. *Direct Research Journal of Engineering and Information Technology*, 13(1), 44-48. doi: 10.26765/DRJEIT708034912.
- Kuster, T., Rayling, P., Wiersig, R., and Pozo Pardo, F. D. (2023). Multi-objective optimization of energy-efficient production schedules using genetic algorithms. *Optimization and engineering*, 24(1), 447-468. doi: doi.org/10.1007/s11081-021-09691-3.
- Li, Z., Sang, H., Pan, Q., Gao, K., Han, Y., and Li, J. (2022). Dynamic AGV scheduling model with exceptional cases in matrix production workshop. *IEEE Transactions on Industrial Informatics*, 19(6), 7762-7770. doi:10.1109/TII.2022.3211507.

- Liu, M., Wei, J. W., Liu, W., and Gong, B. (2023). S-nitrosylation of ACO homolog 4 improves ethylene synthesis and salt tolerance in tomato. *New Phytologist*, 239(1), 159-173. doi: 10.1111/nph.18928.
- Macchi, M., Ragazzini, L., and Negri, E. (2023). A conceptual framework for Digital Twins in production scheduling and control. *IFAC-PapersOnLine*, 56(2), 5661-5666. doi: 10.1016/j.ifacol.2023.10.491.
- Mohamed, M. M. and Alraddadi, A. S. (2024). Agile Factor Flexible Industry 4.0 with MES Manufacturing Execution System Along with ERP Back-End Integration: Ready-Made Garments as a Case Study. *American Journal of Operations Research*, 14(4), 137-150. doi: 10.4236/ajor.2024.144007.
- Neumann, A., Hajji, A., Rekik, M., and Pellerin, R. (2024). Genetic algorithms for planning and scheduling engineer-to-order production: A systematic review. *International Journal of Production Research*, 62(8), 2888-2917. doi: 10.1080/00207543.2023.2237122.
- Niu, H., Wu, W., Xing, Z., Wang, X., and Zhang, T. (2023). A novel multi-tasks chain scheduling algorithm based on capacity prediction to solve AGV dispatching problem in an intelligent manufacturing system. *Journal of Manufacturing Systems*, 68, 130-144. doi: 10.1016/j.jmsy.2023.03.007.
- Nwanwe, O. I., Izuwa, N. C., Ohia, N. P., Kerunwa, A., and Uwaezuoke, N. (2024). Determining optimal controls placed on injection/production wells during waterflooding in heterogeneous oil reservoirs using artificial neural network models and multi-objective genetic algorithm. *Computational Geosciences*, 28(6), 991-1013. doi: 10.1007/s10596-024-10300-2.
- Park, J. and Shin, M. (2024). Manufacturing Execution Framework Based on agent-to-agent Collaboration. *Journal of Korean Society of Industrial and Systems Engineering*, 2024, 47(4): 120-131. doi: 10.11627/jksie.2024.47.4.120.
- Qin, Z., Johnson, D., and Lu, Y. (2023). Dynamic production scheduling towards self-organizing mass personalization: A multi-agent dueling deep reinforcement learning approach. *Journal of Manufacturing Systems*, 68, 242-257. doi: 10.1016/j.jmsy.2023.03.003.
- Sun, M., Cai, Z., and Zhao, N. (2023). Design of intelligent manufacturing system based on digital twin for smart shop floors. *International Journal of Computer Integrated Manufacturing*, 36(4), 542-566. doi: 10.1145/3590163.
- Wang, H., Wang, C., Liu, Q., Zhang, X., Liu, M., Ma, Y., and Shen, W. (2024). A data and knowledge driven autonomous intelligent manufacturing system for intelligent factories. *Journal of Manufacturing Systems*, 74, 512-526. doi: 10.1016/j.jmsy.2024.04.011.
- Yang, S., and Xu, Z. (2022). Intelligent scheduling and reconfiguration via deep reinforcement learning in smart manufacturing. *International Journal of Production Research*, 60(16), 4936-4953. doi: 10.1080/00207543.2021.1943037.
- Yu, S., Li, J., Fang, X., Wang, Y., Wang, J., Xuan, Q., and Fu, C. (2023). Ga-based multipopulation synergistic gene screening strategy on critical nodes detection. *IEEE Transactions on Computational Social Systems*, 11(3), 3839-3850. doi:10.1109/TCSS.2023.3325263.
- Zaied, B. K., Rashid, M., Nasrullah, M., Bari, B. S., Zularisam, A. W., Singh, L., and Krishnan, S. (2023). Prediction and optimization of biogas production from POME co-digestion in solar bioreactor using artificial neural network coupled with particle swarm optimization (ANN-PSO). *Biomass Conversion and Biorefinery*, 13(1), 73-88. doi: 10.1007/s13399-020-01057-6.
- Zhang, L., Yan, Y., Hu, Y., and Ren, W. (2022). Reinforcement learning and digital twin-based real-time scheduling method in intelligent manufacturing systems. *IFAC-PapersOnLine*, 55(10), 359-364. doi: 10.1016/j.ifacol.2022.09.413.



Zheng Xu is a Lecturer and Oujiang Distinguished Professor at the Business School of Wenzhou University, where he also serves as the Chinese Director of the Confucius Classroom at the University of Siena. He earned his Ph.D. in Management Science from Lancaster University, with earlier degrees from Middlesex University and PLA Information Engineering University. He combines a strong background in computer science and management science. His research interests center on SME informatization, information systems and technology (IS/IT) implementation, digital transformation, innovation and entrepreneurship, and e-commerce. He has published over fifteen academic papers and has led four major research projects, including a National Social Science Fund project on the digital transformation of small- and medium-sized manufacturing enterprises in the Yangtze River Delta.



Jiancong Wang is an Associate Professor at the Business School of Henan University and has been teaching and conducting research there since 2011. She earned her Ph.D. in Information Management from Central China Normal University. Her research focuses on innovation systems, e-commerce logistics, SME financing, and technological progress, with extended interests in enterprise informatization and digital transformation. She has published thirteen academic papers in leading journals, including *Scientific Management Research*, *Theoretical Exploration*, *Economic System Reform* and *Applied Mathematics and Nonlinear Sciences*. She has led three major research projects, such as the Henan Provincial Department of Education Humanities and Social Science Project and the Henan University Research Fund Project, and has also participated in several provincial-level and cross-institutional research initiatives. Her work contributes to advancing the understanding of enterprise innovation mechanisms, digital transformation, and e-commerce development in China.