Production Engineering (2025) 19:885–898
https://doi.org/10.1007/s11740-025-01349-8

ORIGINAL PAPER

Enhancing garment manufacturing efficiency through human-centered scheduling

Nengsheng Bao[1] · Xiaoxun Zheng[1] · Yuchen Fan[2] · Alessandro Simeone[2] · Runxuan Bao[3]

Received: 3 December 2024 / Accepted: 29 April 2025 / Published online: 14 May 2025

Abstract

In response to the competitive pressures faced by the garment manufacturing industry, including low production efficiency and poor resource utilization, this research proposes an innovative optimization framework for Garment Flexible Manufacturing Systems (GFMS). The study introduces a novel three-phase scheduling approach that integrates order prioritization, job selection, and workstation matching. This method uniquely combines advanced optimization techniques with human-centric considerations, addressing both production efficiency and worker well-being. The framework employs a priority-based scheduling scheme that dynamically adapts to production demands, while also considering worker skills, historical performance, and ergonomic factors. By incorporating these human elements, the study aligns with Industry 5.0 principles, emphasizing the synergy between technological advancement and human expertise in manufacturing processes. Simulation results demonstrate significant improvements in production efficiency, with a 28% increase in average daily capacity compared to traditional scheduling methods. This research not only enhances production scheduling in the garment industry but also provides a model for integrating human-centric approaches in flexible manufacturing systems, contributing to both operational excellence and sustainable workforce management.

Keywords Garment flexible manufacturing systems (GFMS) · Production scheduling · Human-centric optimization · Industry 5.0 · Efficiency improvement

1 Introduction

The garment industry plays a crucial role in global trade, with particularly significant impact on the Chinese economy through its contributions to employment, income levels, and urbanization [1]. Recent data from China Customs Express show that from January to May 2024, China total exports of textiles and garments amounted to $115.84 billion [2]. However, the industry faces mounting challenges in maintaining competitiveness. The increasing variability in consumer demands requires manufacturers to handle diverse product styles and varying batch sizes efficiently [3]. Additionally, rapid market changes and unpredictable production disruptions have highlighted the limitations of traditional manufacturing systems, which often lack the flexibility to adapt quickly to changing requirements [4]. To tackle these issues, manufacturers have begun exploring more flexible production approaches [5]. The concept of Flexible Manufacturing Systems (FMS) has emerged as a promising solution, offering the capability to handle varying production demands through automated equipment and computer control technologies [6]. This approach has evolved into the Garment Flexible Manufacturing System (GFMS), which specifically addresses the unique requirements of garment production by enabling rapid adjustments and transitions in manufacturing processes while maintaining quality and efficiency [7].

Despite these advances in scheduling optimization, current garment manufacturing systems still face significant challenges in integrating advanced algorithms with practical operational constraints. Most existing scheduling methods focus primarily on mathematical optimization while

✉ Alessandro Simeone
alessandro.simeone@polito.it

1 Intelligent Manufacturing Key Laboratory of Ministry of Education, Shantou University, Shantou, China

2 Department of Management and Production Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, Torino, Italy

3 Guangdong Technion-Israel Institute of Technology, Shantou, China

overlooking the practical constraints and human factors inherent in garment manufacturing. This often leads to suboptimal resource utilization and potential worker dissatisfaction, particularly when systems need to adapt to urgent orders or unexpected machine failures [8]. Garment manufacturing remains a labor-intensive industry where efficient scheduling plays a critical role in meeting delivery timelines and maintaining product quality [9]. Traditional scheduling approaches often rely on mathematical optimization techniques that emphasize resource efficiency but fail to account for real-world constraints such as human variability, skill differences, and unforeseen disruptions like machine failures or urgent order insertions. These oversights frequently lead to suboptimal resource utilization and worker dissatisfaction. This gap is especially pressing in light of the ongoing transition toward Industry 5.0, which emphasizes human-centric, sustainable, and resilient manufacturing systems. Unlike Industry 4.0, which focuses on automation and digitalization, Industry 5.0 envisions a collaborative environment where technology enhances human capabilities rather than replacing them. Xu et al. (2021) describe this shift as a rebalancing of productivity and human well-being [10]. Leng et al. (2021) further highlight the importance of personalized working conditions and collaborative workflows that support workers alongside automated systems [11]. Grabowska et al. (2022) emphasize the growing need to integrate human-centric principles into the design of modern production systems [12].

To address these challenges and align with Industry 5.0 principles, this study proposes a dynamic, human-centric scheduling framework for garment manufacturing systems. The approach integrates quantitative performance metrics with qualitative human factors, enabling real-time adaptation to shifting production conditions. The system also incorporates factors such as work status, experience, and skill levels, enhancing both productivity and responsiveness to workforce variability [13].

The remainder of this manuscript is organized as follows. Section 2 presents a comprehensive review of literature on scheduling algorithms, layout optimization, and human-centric production systems. Section 3 details the proposed three-phase scheduling methodology and its mathematical modelling. Section 4 introduces a case study from a medium-sized garment manufacturing firm, while Sect. 5 discusses experimental results and their implications. Section 6 provides conclusions with a summary of contributions, limitations and recommendations for future research.

2 Literature review

2.1 Evolution of scheduling algorithms in garment manufacturing

The optimization of production scheduling in garment manufacturing has seen significant developments over the years. Initially, metaheuristic algorithms such as genetic algorithms [14], particle swarm optimization [15], ant colony algorithms [16], tabu search algorithms [17], and bee colony optimization [18] were widely employed. These algorithms offer flexibility and adaptability, capable of finding near-optimal solutions for complex optimization problems [19]. Concurrently, heuristic methods like greedy algorithms [20] were used for their ability to quickly find local optimal solutions.

As research progressed, artificial intelligence methods [21] and exact methods such as mixed-integer linear programming [22] and constraint programming [23] gained popularity due to their ability to find optimal solutions for smaller-scale problems within reasonable computational times. The current trend involves combining metaheuristic methods with local search or artificial intelligence techniques to solve scheduling problems [24], aiming to balance solution quality with computational efficiency. However, these algorithmic approaches have several key limitations. First, they often focus solely on mathematical optimization, failing to consider real-world production constraints. Second, the solutions tend to be computationally intensive and difficult to implement in dynamic production environments. Most importantly, these methods typically treat workers as fixed resources, overlooking the variability in human performance and capabilities that significantly impact production efficiency.

2.2 Factory layout optimization and human-machine collaboration

Beyond algorithmic solutions, researchers have explored optimizing factory layouts and enhancing human-machine collaboration to address production challenges in garment manufacturing. These approaches focus on creating adaptable production environments that can effectively respond to changing market demands while maintaining operational efficiency. The integration of layout optimization with collaborative systems has emerged as a key strategy for improving overall manufacturing performance.

Wang [25] introduced an innovative approach by implementing hanging systems in garment production. By using an improved timed Petri net, Wang achieved flexible optimization of multi-task garment production processes. This study demonstrates how novel production line designs can significantly enhance efficiency and flexibility in garment manufacturing. The hanging system allows for easier movement of garments between workstations, reducing handling time and improving overall production flow.

However, personalized customization tends to favor a production model of small batch sizes and multiple varieties, which leads to challenges for hanging assembly lines such as line balancing issues and machine allocation problems during garment changes. The line balancing problem involves optimization of the process routing, which is at the core of pre-production scheduling, and therefore, many scholars are dedicated to solving this issue. In response to the balance optimization problem of the garment assembly line, Liu at al. [26] proposed a multi-objective genetic algorithm aimed at maximizing the efficiency of the assembly line sequencing and minimizing the machine adjustment paths. But the actual production process is subject to real-time constraints, such as worker absences or machine breakdowns, which require immediate adjustments to the workflow distribution.

The concept of U-shaped assembly lines has gained attention for its potential to reduce labor costs and improve precision. Li et al. [27] explored U-shaped assembly line balancing involving collaborative robots, effectively reducing cycle times. This approach combines the benefits of compact factory layout with the precision of robotic assistance. However, the high initial investment costs and complex layouts of U-shaped assembly lines may limit their applicability, especially in smaller factories.

Building upon these layout considerations, human-robot collaboration (HRC) has emerged as a promising area in garment manufacturing. Human-robot collaboration is seen as the key to enhancing the flexibility and reconfigurability of modern production systems. To maximize the role of human-robot collaboration, tasks need to be optimally allocated based on available resources [28]. Kousi et al. [29] proposed a multi-level decision-making framework aimed at dynamically balancing work between human operators and robotic resources. This mechanism integrated a multi-criteria decision-making mechanism with the low-level planning modules of mobile robots to achieve effective reconfiguration plans, considering the real-time status of the workshop. However, this may overlook the complexity of integrating the Material Requirements Planning system with other production management systems, and frequent repositioning could lead to data synchronization issues and management confusion. Zhang et al. [30] investigated the integration of collaborative robots in sewing operations, focusing on how robots can assist human workers in tasks requiring high precision or repetitive motions. Their study showed that HRC can lead to improved product quality and reduced worker fatigue, but also highlighted the need for careful task allocation between humans and robots.

While these layout optimization and human-machine collaboration approaches show promise, they face several significant limitations. The high initial investment costs and complex layouts often make implementation impractical, especially for smaller manufacturers. Additionally, these approaches typically require substantial changes to existing factory setups, creating barriers for adoption in established facilities. Furthermore, the focus on physical reorganization often overlooks the potential for improving efficiency through better scheduling and resource allocation within existing layouts.

2.3 Human-centric approaches in production scheduling

Recognizing the crucial role of human workers in garment production, recent research has increasingly focused on human-centric approaches. To reduce the impact of managers' cognitive biases on production planning and the coordination of all related production processes and decisions, a preliminary framework for a human-centered smart manufacturing system has been developed [31], along with initial hypotheses. This concept provides some guidance for subsequent work. Concerned about the planning of tasks and actions between resources, arising from the dynamic interactive environment between workshop operators and machines in real production [32], provided a human-centered assembly line strategy that effectively proposes alternative sequences for task resource allocation, aiming to reduce issues that arise during operator-machine interactions. However, this application is currently used offline, and actual operation remains to be implemented. Gong et al. [33] constructed a mathematical model for an extended flexible job shop scheduling problem incorporating worker flexibility. Their use of a hybrid artificial swarm algorithm with a novel local search strategy enhances computational speed and search capabilities.

Ergonomics and worker well-being have also become important considerations. Fang et al. [34] explored the relationship between the work environment and human physiological parameters, proposing a cyber-physical human-centric system framework. This approach leverages individual thermal comfort to optimize energy consumption while enhancing human comfort as described in the Industry 5.0 paradigm.

Hémono et al. [35] evaluated the effect of rest periods on alleviating physical labor fatigue in flexible job shop scheduling, incorporating ergonomics-based indices to assess task difficulty. Similarly, Aribi et al. [36] proposed a multi-objective optimization method based on non-dominated sorting genetic algorithm, addressing worker fatigue constraints in dynamic flexible job shop scheduling. While these studies make significant strides in considering worker well-being, they often rely on subjective judgments of worker fatigue, lacking more detailed and objective criteria. Furthermore, Araujo et al. [37] utilized ergonomic approaches to detect inappropriate postures in garment workshops, aiming to reduce work-related musculoskeletal disorders.

2.4 Research gaps and opportunities

The literature survey on garment manufacturing scheduling, discussed in detail in the preceding review, indicates several challenges that compromise both the theoretical rigor and practical applicability of existing models. Many studies focus on algorithmic optimization and technical performance while overlooking the systematic integration of objective human performance measures such as worker proficiency, experience, and efficiency. Human factors are either treated as isolated components or assessed using subjective criteria, which limits the reliability and adaptability of these models in fluctuating production environments.

Table 1 Summary of related works and contribution of the proposed approach

Reference	Focus Area	Methodology	Human Factors	Limitations
Zhang et al. [14]	Total energy consumption in flexible job shop	Improved scheduling approach	Not considered	High computational complexity
Nouiri et al. [15]	Distributed optimization	Particle swarm optimization	Not considered	Limited adaptability to worker variability
Wang [25]	Garment flexible productions	Timed Petri Net	Not considered	Does not address dynamic adaptation
Liu et al. [26]	Assembly line balance	Multi-objective genetic algorithm	Not considered	Limited to offline planning
Kousi et al. [29]	Robotic assembly lines	AI-based scheduling	Considered task allocation only	Limited integration with human capabilities
Gong et al. [33]	Worker flexibility	Hybrid artificial bee colony	Considered worker allocation	Lacking comprehensive skill assessment
Fang et al. [34]	Human thermal comfort	Cyber-physical system	Considered ergonomic factors	Limited to environmental factors
Hémono et al. [35]	Resource allocation	Rest break optimization	Considered fatigue	Based on subjective assessments
Proposed approach	Garment manufacturing scheduling	Three-phase dynamic optimization	Comprehensive integration of worker skills, experience, and efficiency	Addresses real-time adaptation while maintaining human well-being

Other approaches propose extensive modifications to production layouts in order to enhance scheduling performance. Although such interventions can yield improvements in theory, their high financial and operational costs render them impractical for widespread implementation. Moreover, prevailing models typically rely on the assumption of static production conditions. This oversimplification does not adequately capture the real-time fluctuations in demand and workforce availability that are characteristic of modern manufacturing settings.

Table 1 provides an overview of these limitations by comparing the key strengths and weaknesses of existing methodologies with the contributions of the proposed framework.

In response to the identified gaps, the proposed approach implements a three-phase dynamic optimization process that fuses objective, data-driven human performance metrics with traditional operational measures. By operating within existing infrastructures and accommodating real-time production variations, this framework offers a more robust and scientifically sound solution to the challenges of garment manufacturing scheduling.

3 Methodology

The efficiency of garment manufacturing systems is influenced by multiple production stages, with sewing operations representing one of the most complex and labor-intensive processes. While the proposed framework can be applied to various production stages, this research work focusses on the sewing stage, where the intricate interplay between human skills and process requirements presents significant optimization opportunities.

As shown in Fig. 1, this study integrates process optimization and technological advancements to improve both operational efficiency and worker involvement across the manufacturing system, with detailed validation performed in the sewing operations.

The proposed framework is designed to optimize operational efficiency while systematically emphasizing worker well-being through several integrated strategies. First, it incorporates a workstation assignment algorithm that prevents the consecutive allocation of physically demanding tasks to the same worker, effectively managing workload

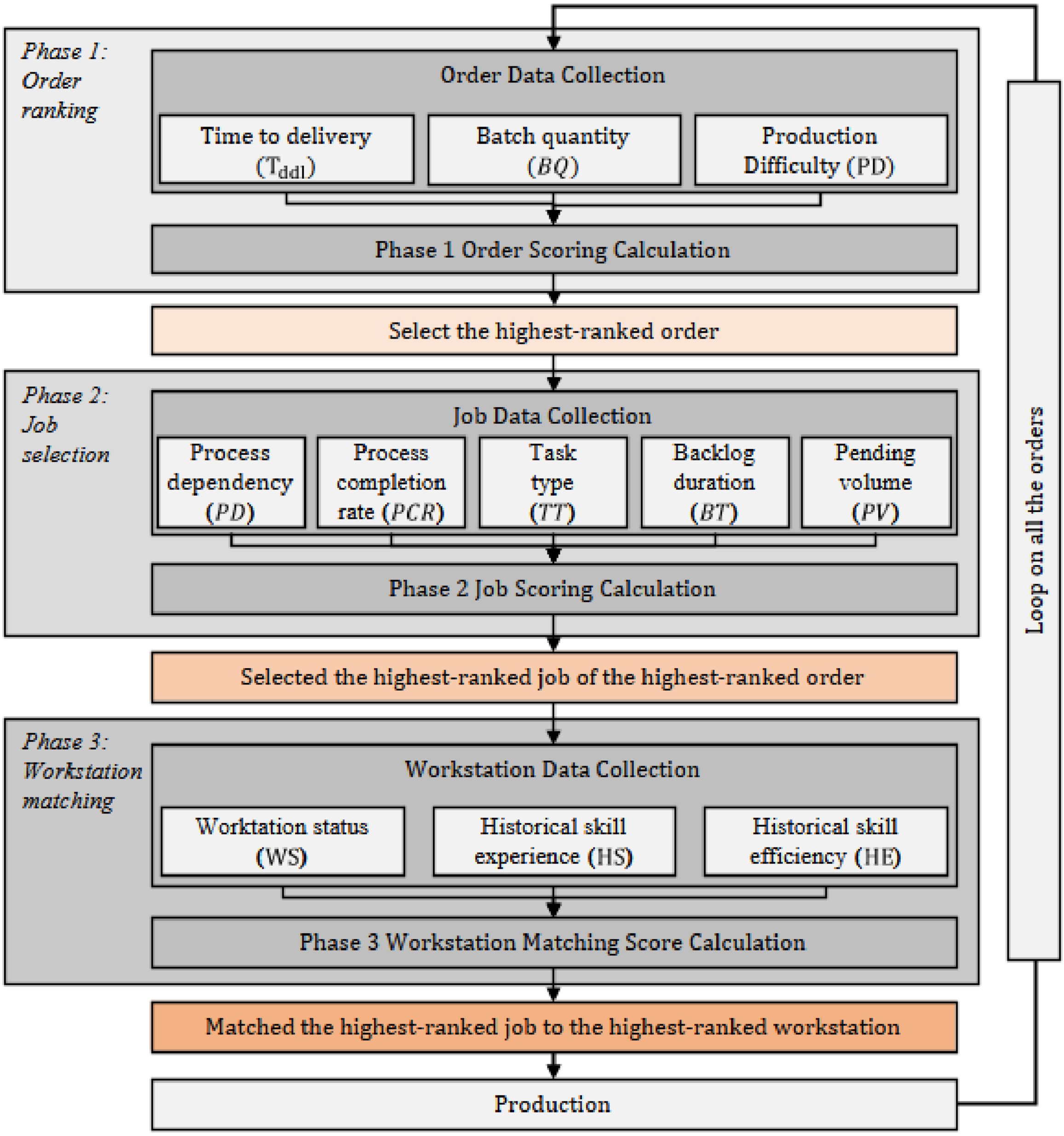

Fig. 1 Methodology flowchart illustrating the three-phase scheduling approach and its components

intensity and minimizing fatigue. Second, the framework strategically utilizes workers' specialized skills, competencies, and personal preferences, which enhances job satisfaction and contributes to sustained productivity. Third, the system includes a dynamic scheduling component updated every 30 s, enabling workers to address unexpected personal needs promptly without causing substantial disruptions to production flow. Finally, regular short breaks are systematically embedded within the production schedule, aligning with ergonomic principles to support workers' physical and cognitive well-being without compromising overall productivity.

3.1 Phase 1: order ranking

In the proposed framework, during Phase 1, the system collects all existing orders based on delivery time, production quantity, and production process difficulty. Orders are prioritized in descending order according to their calculated scores, with the highest-ranked orders selected for further processing. Equation (1) shows how the order score P_{1x} is calculated.

$$P_{1x} = \frac{BQ_x \times PD_x}{(1 + T_{\mathrm{ddl}x})^3} \tag{1}$$

The Equation selects the order x that most urgently needs to be produced among the orders to be produced. Where BQ_x refers to the total number of garments to be produced, PD_x refers to the overall difficulty of the order production process, and $T_{\mathrm{ddl}x}$ refers to the time to delivery. It important to note that the overall difficulty scores of the production process are provided by the production manager based on his/her expertise. This ensures that the assessment of each order complexity is informed by professional judgment and experience, tailoring production priorities to current operational capacities and requirements.

The P_{1x} score range of all the variables involved in the three phases are shown in Table 2. In the table, based on practical considerations, the time range for T_{ddl} is set to 0-100 days; for BQ, the quantity range is set to 1-1000 pieces; as for PD, there are three levels to choose from: simple, moderate, and difficult.

The quantification of these parameters is based on extensive industry experience and empirical studies from industrial partner. The time range for T_{ddl}(0-100 days) reflects typical order completion cycles in garment manufacturing, while the production quantity range (1-1000 pieces) aligns with common batch sizes in medium-sized facilities. The three-level classification of process difficulty (simple, moderate, difficult) was established through consultation with experienced production managers and analysis of historical production data, considering factors such as operation complexity, skill requirements, and error rates.

3.2 Phase 2: job selection

Phase 2 focuses on the systematic selection and sequencing of specific jobs within each production order. After receiving the highest-priority order from Phase 1, this phase evaluates individual manufacturing operations (jobs) within that order. The evaluation process considers multiple factors including process dependencies, completion rates, and resource requirements to assign a comprehensive score to each job. For example, in a shirt production order, operations such as collar assembly, sleeve attachment, and buttonhole creation are individually scored. These scores determine the execution sequence, ensuring that critical operations (such as those with high dependency requirements or approaching completion) are prioritized appropriately. This structured approach ensures that jobs are not only selected based on their individual importance but also scheduled in a sequence that optimizes overall production flow.

Equation (2) shows the job selection process, denoted as P_{2x}.

$$P_{2x} = PD + PCT_x + TT_x + BT_x + PV_x \tag{2}$$

where PD represents the process dependencies and logical sequence of manufacturing processes. Precedence constraints serve two functions. First, they contribute to the calculation of job priority scores through PD. Second, they act as strict constraints that enforce the sequencing of operations. A higher PD score for a job does not override the prescribed order; the scheduling system maintains a precedence graph to ensure that all prerequisite operations are completed before a job is scheduled. For example, in garment assembly, a sleeve attachment operation may receive a high priority but will not be scheduled until both the sleeve preparation and main body assembly are complete.

The parameter PCT_x indicates the production completion rate. This metric quantifies the progress of current orders and enables the prioritization of tasks that are near completion in order to improve overall efficiency [38]; the parameter TT_x, differentiates between tasks requiring multiple operations and those that can be executed in a single step, thereby facilitating optimized resource allocation [39]; the parameter BT_x, measures the duration of task backlog, helping to prevent delays in the production flow. Finally, PV_x captures the pending volume of tasks and supports a balanced workload distribution across the production line [40].

Value ranges for these five variables (see Table 3) were established after systematic analysis of historical production data from 2022 to 2024, consultation with production managers and supervisors, and subsequent refinement during a pilot implementation period lasting three months. Sequencing operations require careful attention to the interrelationships between different tasks. Independent operation categories are sequenced separately, whereas dependent tasks within the same category must follow a prescribed order (for example, cutting must precede sewing). Furthermore, sequencing must be maintained within subcategories, such as fabric and lining operations [40]. These dependencies are essential in defining the scoring range for the PD parameter. If precedence constraints are absent and process dependency is not a factor, PD is assigned a value of 1.

Table 2 Summary of basic variables for phase 1: order ranking parameters and their score ranges

Phase	No.	Variable	Description	Score Range
Phase 1 Order Ranking ($\boldsymbol{P_{1x}}$)	1	T_{ddl}	Time to delivery	0-100
	2	BQ	Total number of garments to be produced	1-1000
	3	PD	The overall difficulty of the production process	1 (simple) 2 (moderate) 3 (difficult)

Table 3 Summary of job selection variables showing the scoring criteria for phase 2 parameters

Phase	No.	Variable	Description	Score Range
Phase 2: Job Selection (P_{2x})	1	PD	Process dependency	1 (unrelated) 2 (Same in major categories) 3 (Same in subcategories)
	2	PCT	Process completion rate	1 (completion 51–80%) 2 (completion 21–50%) 3 (completion 0–20%, 81–100%)
	3	TT	Task type	1 (Multi process task) 2 (Single process task)
	4	BT	Backlog duration	1 (backlog = 1–30 min.) 2 (backlog = 31–60 min.) 3 (backlog > 60 min.)
	5	PV	Pending volume	1 (backlog = 1–4 boxes) 2 (backlog = 5–9 boxes) 3 (backlog > 10 boxes)

When a specific sequence is required within the same major category, a value of 2 is assigned; if sequencing is required within a subcategory, the value is set to 3.

The scoring for PCT is designed to reflect production priorities at different stages. Tasks at early stages (0–20% completion) receive higher scores to secure resource allocation for initiation, while tasks with 51–80%completion receive lower scores because they typically represent stable, ongoing processes. Tasks nearing completion (81–100%) receive equivalent priority to avoid delays in order fulfilment. This balanced approach sustains continuous production flow and ensures that both early-stage and near-complete orders receive appropriate attention.

After calculating the scores using Eq. (2), the jobs are sorted in descending order based on their scores. The system then selects jobs for processing starting from the highest-scoring job and moving down the list. This approach ensures that the most critical and urgent tasks are prioritized, allowing for efficient resource allocation by focusing on the most important jobs first.

3.3 Phase 3: workstation matching

Phase 3 is concerned with the strategic allocation of high-priority processes, as identified in Phase 2, to workstations that are most capable of executing them efficiently. This phase ensures that urgent operations are completed in a timely manner.

For clarity in this context, several key terms are defined. A process is a specific manufacturing operation (for example, collar stitching). A job denotes an instance of a process applied to a particular garment order with defined parameters. A task represents a broader category of manufacturing activities that may encompass multiple similar processes.

To accurately account for the operational realities of the garment production environment and to ensure computational tractability, the following simplifying assumptions are adopted:

1) Each machine completes one process at a time and must finish its assigned job without interruption, thereby minimizing quality issues;
2) Processes for different parts can run concurrently, while those for the same part maintain necessary sequential order;
3) Processes commence only when material safety stock reaches a minimum threshold (three baskets), guaranteeing production continuity;
4) Specific processes are assigned to designated machines based on technical specialization;
5) At system initialization, each workstation is paired with corresponding machines and assigned specific workers;
6) Machines operate independently without interdependencies or chain reactions;
7) Each workstation is linked with one or more workers who possess the required skill sets.

These assumptions have several practical implications. The first ensures that once a job is assigned to a workstation, it is completed entirely before a new assignment begins. The second permits parallel processing of garment components (such as sleeves and collars) while preserving essential process order within each component. The material safety stock requirement prevents delays caused by insufficient inputs. Designating specific machines to certain processes mirrors the technical specialization often needed in garment production, such as the creation of buttonholes. Finally, the established pairings between workstations, machines, and workers support an efficient matching of tasks based on both technical capabilities and individual skills.

These assumptions were necessary to ensure computational feasibility while accurately reflecting the production constraints observed at the industrial partner facility.

They provide a structured basis for the workstation matching algorithm, enabling the generation of realistic and implementable solutions that optimize production flow in dynamic environments.

Equation (3) is used to calculate the workstation matching, developed through a synthesis of theoretical scheduling principles [41] and empirical insights from garment manufacturing experts.

$$P_{3x} = WS_x \times (HS_x + HE_x) \quad (3)$$

Where WS_x refers to the status of workstation, HS_x refers to the degree of overlap of historical skills experience, and HE_x refers to the historical skill efficiency.

The station status (WS) scoring reflects both worker presence and machine state, ranging from unmanned (0) to fully idle (3). Historical skill experience (HS) scoring is based on the worker previous experience with similar operations, considering both major categories and subcategories of tasks. Historical efficiency (HE) is determined by comparing the worker past performance records on similar operations, with higher scores assigned to demonstrated higher efficiency levels. The detailed scoring criteria for each parameter are presented in Table 4.

3.4 Dynamic optimization

The goal of scheduling is to achieve the optimal alignment between orders and workstations within a dynamic iteration cycle. A dynamic iteration cycle refers to the system automatically recalculating and updating all orders, jobs, and workstation assignments every 30 s. This matching process involves identifying the most urgent orders and assigning them to the most appropriate workstations along with the necessary processes. The objective is to attain the best performance outcomes within each iteration cycle by:

1) Minimize the maximum completion time for all workstations.
2) Minimize the maximum workload of all machines.
3) Maximize production line balance to avoid overburdened or unbalanced workloads to increase worker productivity.

After each optimization cycle, the system evaluates the outcomes against these objectives. Based on this evaluation, it adjusts the scheduling parameters and priorities for the next iteration. This feedback loop enables the system to respond dynamically to changing production conditions. The results of each iteration guide parameter adjustments for subsequent cycles, allowing the system to adapt to real-time changes in order priorities, workstation availability, and production demands. This reactive approach ensures that the scheduling system can quickly adjust to immediate production needs while maintaining operational efficiency. Unlike learning systems that modify their underlying decision logic, the developed system maintains its core optimization rules while dynamically adjusting scheduling priorities based on current production states.

The 30-second iteration cycle was determined through practical testing in the case study facility, balancing the need for responsive scheduling updates with system stability and computational efficiency. This update frequency allows the system to react to common production variations such as worker availability changes, completion of current tasks, and arrival of new orders, while avoiding excessive adjustments that could disrupt workflow.

To ensure the model matches real production conditions, several practical considerations were incorporated into the optimization process:

– The system accounts for typical production variations such as worker fatigue patterns throughout the day. This is implemented through a time-dependent coefficient that modifies the historical skill efficiency parameter, reducing expected efficiency by 15–20% during afternoon periods (14:00–16:00). The system correspondingly adjusts workstation matching scores, allocating simpler tasks or utilizing higher-skilled workers during these known fatigue periods.

Table 4 Workstation matching parameters detailing the scoring system for phase 3 variables

Phase	No.	Variable	Description	Score Range
Phase 3 Workstation Matching ($\boldsymbol{P_{3x}}$)	1	WS	Station status	0 (unmanned) 1 (busy) 2 (production idle) 3 (Fully idle)
	2	HS	Historical skill experience	0 (never done) 2 (done in same major categories) 3 (done in same subcategories)
	3	HE	Historical skill efficiency	0 (not done before) 1 (done before) 2 (second in efficiency) 3 (first in efficiency)

– Task assignments consider practical constraints like physical distance between workstations.
– The scheduling algorithm includes buffer time for material handling and workplace organization.
– Priority adjustments reflect actual production urgency rather than purely mathematical optimization.

These practical considerations help bridge the gap between theoretical optimization and shop floor reality, making the system more applicable in real manufacturing environments. The system collects real-time data through integration with the factory Manufacturing Execution System (MES), receiving workstation status updates, job completions, and order information through Application Programming Interface (API) connections. This integration enables continuous data flow for the 30-second recalculation cycle while allowing manual supervisor inputs when necessary.

4 Case study

In order to validate the proposed framework, an industrial case study is reported in this section, the case study was conducted in collaboration with a medium-sized garment manufacturing company located in Guangdong Province, China. This company specializes in producing a variety of clothing items, including shirts, trousers, and jackets, with a production capacity of approximately 500,000 pieces annually. The company was facing challenges in optimizing its production scheduling, particularly in balancing workloads and meeting tight delivery deadlines. This study utilized ©Tecnomatix Plant Simulation to simulate a fully optimized system incorporating the proposed scheduling model.

Once the production system is initiated, orders are generated automatically, though the order quantity and other details are set variable. System parameters are preset with specific limits: the maximum order size is 1,000 units, with monthly order limits ranging from 100 to 150 units. The system restricts the number of simultaneous orders to a maximum of 10, and each material box can accommodate components for up to 5 processes. During production simulations, order quantity data is randomly generated within these defined limits.

Upon receiving a new order, the system conducts a simulated manual assessment of the workshop capacity to ensure the feasibility of timely delivery. After order confirmation, strategic decisions are made regarding production scheduling. These decisions take into account several factors:

1. Order Size: The total number of units required by the client.
2. Customer Priority and Deadline: The urgency of the order based on the client needs.
3. Production Complexity: The complexity of the garments to be produced.
4. Product Value: The economic value of the order.

For example, an order of 500 units with a three-week deadline, classified as medium difficulty and high value, is assigned an accelerated production slot.

The case study includes four orders, referred to as four different garment styles, namely CED145-CHN0461-B, MBAZ4V-1V92, MDDA3R-1V70, and MJCM7R-1V82, as shown in Fig. 2. The manufacturing processes for these garments do not follow a fixed sequence. Instead, they are divided into various components based on the garment complexity and the specific requirements of each style. For example, the production of the left sleeve, right sleeve, and collar are treated as separate tasks. This variability requires a flexible production scheduling approach to accommodate the diverse and non-linear sequence of operations. Such flexibility allows for the necessary adjustments and reallocation of resources to effectively manage the diverse and often non-linear sequence of operations required by each style.

It is important to note the distinction between a task and a job within the proposed framework. A task refers to a generic manufacturing operation such as sewing or cutting, representing the broader categories of production activities. Conversely, a job denotes a specific instance of a task, characterized by its application to a particular garment component and defined by unique parameters, such as processing time, skill requirements, and quality standards.

Table 5 presents data from the garment production process. Among the key parameters, "Level" uses letters to denote task complexity and importance, where B indicates moderate complexity tasks requiring skilled operators, and C represents basic operations that can be performed by operators with standard training. "Type" categorizes the manufacturing operation method (press, sew, or beat), which directly influences the choice of equipment and operator assignment. The "Hourly Target" is calculated based on standard time measurements and includes allowances for material handling and operator fatigue, providing realistic production goals for each operation.

5 Results and discussion

This section presents and discusses the experimental results from the case study, demonstrating both the initial system state and its dynamic behavior during operation. The results cover order ranking, job selection, and machine matching

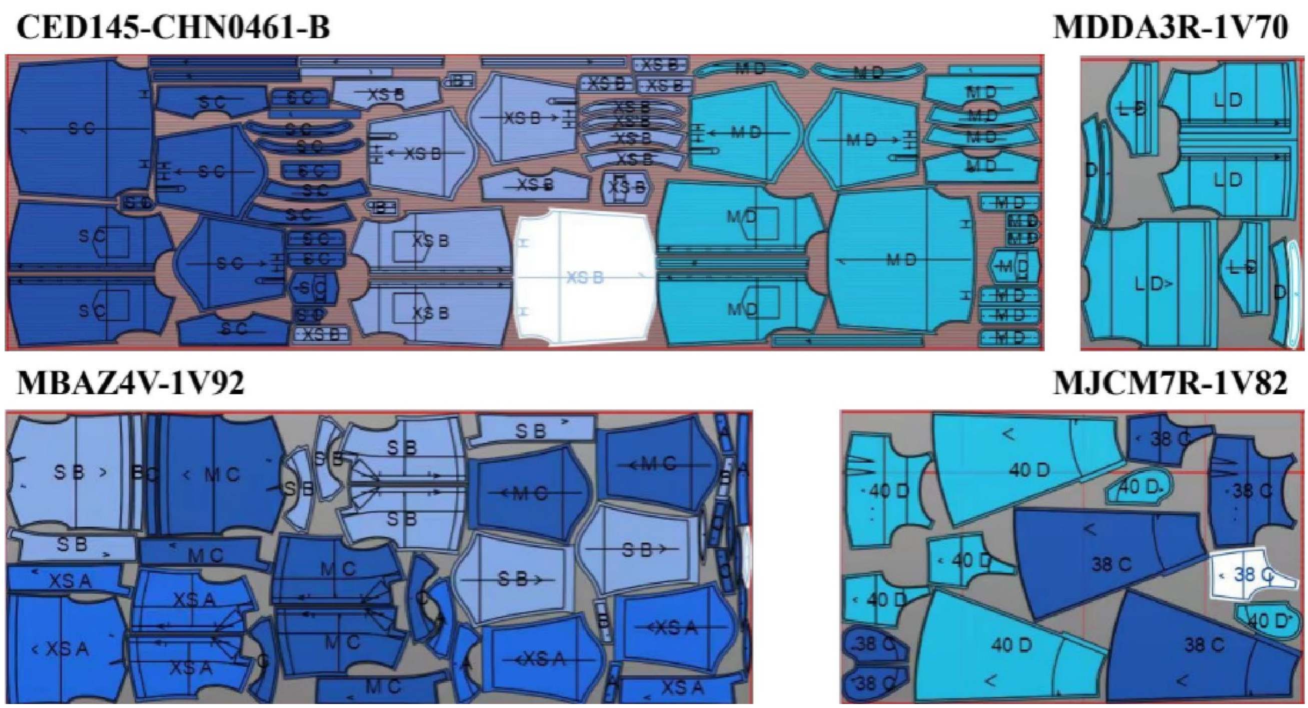

Fig. 2 Sample garment styles used in the case study showing the four different product variants

Table 5 Representative job data from the PJ style illustrating typical production process parameters

No.	Job Name	Detail	Description	Level	Type	Machine	Standard Time	Hourly Target
1	Small components	attach main label with size simultaneously/origin label	diameter 19+	B		computer single	55.31	65
2	Small components	herringbone overlapping button door woven tape	diameter 30 cm*1	B	press	computer single	38.3	94
1	Lining	sewing lining at the back center bone	diameter 41 cm*1	C	sew	regular five-thread	16.76	215
2	Lining	sewing lining at the sleeve bottom bone	diameter 50 cm*2	C	sew	regular five-thread	33.24	108
3	Lining	gathering the lining at the back waist to the shirt hem	diameter 27 cm	C	beat	computer single	51.6	70

phases, with particular attention to how these parameters evolve over time.

5.1 Phase 1: order ranking analysis

While this system updates calculations every 30 seconds to respond to real-time production changes, an initial snapshot of the system state is presented to illustrate the ranking mechanism. Table 5 displays a representative moment in the production schedule, showing key information for each order: the Order Number (ON), quantity, style, and process count. The core' column, calculated using Eq. (1), determines the order priority, with the table sorted in descending order by this score. In practice, these rankings dynamically update based on several factors:

- Completion status of current operations.
- Arrival of new orders.
- Changes in delivery deadlines.
- Worker availability and station status.
- Material availability and production progress.

For example, during the case study monitoring, order priorities typically shifted 3–4 times per hour due to these factors. The highest-priority order, shown in the first row of Table 5, might maintain its position for 15–20 min before being superseded, either due to substantial progress in its completion or the arrival of more urgent orders. This dynamic reallocation ensures the system continuously adapts to changing production conditions while maintaining overall efficiency.

Table 6 Phase 1 scoring results (selected order in the first row)

Order number	Quantity	Product code	Process count	Style	Score
31	566	MDDA3R-1V70	48	PD	0.001396758
10	485	MBAZ4V-1V92	55	PB	0.001355085
51	859	MBAZ4V-1V92	55	PB	0.001350510
24	306	MJCM7R-1V82	63	PJ	0.001340538
142	777	MDDA3R-1V70	48	PD	0.001265215
43	365	MDDA3R-1V70	48	PD	0.001213580
144	106	MBAZ4V-1V92	55	PB	0.001207179
127	935	MDDA3R-1V70	48	PD	0.001162419
28	493	MBAZ4V-1V92	55	PB	0.001123068
90	457	MBAZ4V-1V92	55	PB	0.001100431
46	387	MBAZ4V-1V92	55	PB	0.001097921
48	592	MBAZ4V-1V92	55	PB	0.001073693
66	242	CED145-CHN0461-B	51	PA	0.001066169
112	358	MJCM7R-1V82	63	PJ	0.001043732
122	169	CED145-CHN0461-B	51	PA	0.001028316
27	712	MBAZ4V-1V92	55	PB	0.001009973
134	85	MDDA3R-1V70	48	PD	0.000972748
108	246	MBAZ4V-1V92	55	PB	0.000960937
101	169	MBAZ4V-1V92	55	PB	0.000919531
120	670	MJCM7R-1V82	63	PJ	0.000832963
9	203	CED145-CHN0461-B	51	PA	0.000774384
53	339	MBAZ4V-1V92	55	PB	0.000742553
89	433	MDDA3R-1V70	48	PD	0.000705068
70	296	MDDA3R-1V70	48	PD	0.000628990
6	118	MJCM7R-1V82	63	PJ	0.000606657

In Table 6, the "STYLE" column represents the garment style codes used internally by the manufacturing facility. These codes (PA, PB, PD, and PJ) correspond to different garment categories with specific design characteristics and production requirements. For example, PA refers to casual shirts, PB to formal shirts, PD to trousers, and PJ to jackets. These style designations are important as they correlate with different levels of production complexity and resource requirements, directly influencing the scheduling decisions.

Table 7 Job priority order scores (selected job in the first row)

Job number	Job name	Job time (s)	Score
4	SZDLB016	45.82	13.00
11	SZDQF1563	11.13	12.00
2	SZDXBJ054	19.48	11.00
13	SZDQF310	214.51	11.00
3	SZDXBJ0524	26.01	10.00
6	SZDLB125	71.43	10.00
10	SZDQF306	52.70	10.00
1	SZDXBJ0450	17.71	9.00
5	SZDLB0338	475.71	8.00
9	SZDQF301	182.85	8.00
12	SZDQF208	163.83	8.00
8	SZDQF609	52.92	7.00
7	SZDQF030	159.71	5.00

5.2 Phase 2: job priority order calculation

The highest-scoring order is selected for production, and individual processes within this prioritized order are subsequently ranked based on operational scores computed according to Eq. (2). These processes are sequenced for production in descending order of their operational scores, as detailed in Table 7. This method prioritizes critical processes within the highest-ranked orders, optimizing resource allocation, reducing potential bottlenecks, and accelerating the completion of priority tasks. Consequently, the proposed approach facilitates an efficient and targeted production flow, directly addressing the immediate demands associated with the highest-priority orders.

5.3 Phase 3: workstation matching calculation

The third phase involves workstation matching, where scores are calculated using Eq. (3), considering workstation status (WS), historical skill experience (HS), and historical skill efficiency (HE). The resulting workstation rankings by total score (P3) are presented in Table 8. This approach optimizes resource allocation by pairing critical processes with the most suitable workstations. For instance, workstation SEW-A12, with the highest score of 18 points, indicates optimal readiness and operator skill, whereas ASM-J06, scoring lowest (0 points), suggests a potential need for training or reassignment. High-scoring workstations such as SEW-A12, CUT-B05, and ASM-C08 are thus strategically assigned high-priority processes identified in Phase 2, including "SZDLB016" and "SZDQF1563." By aligning workstation capabilities with specific task requirements, this method ensures efficient utilization of both human and

Table 8 Workstation matching scores (selected workstation in the first row)

Workstation	Station status score	Historical skill score	Historical efficiency score	Total score
SEW-A12	3	3	3	18
CUT-B05	3	2	2	12
ASM-C08	2	3	3	12
FIN-D03	3	3	1	12
PRE-E07	2	3	2	10
PAC-F11	2	2	1	6
QC-G09	2	1	2	6
SEW-H02	1	3	2	5
CUT-I04	1	2	3	5
ASM-J06	3	0	0	0

machine resources, significantly enhancing overall production efficiency.

Beyond integrating the algorithm into day-to-day operations, the study emphasized a continuous improvement process. Regular performance evaluations of the algorithm were conducted to determine its impact on scheduling efficiency, resource utilization, and product quality. These assessments led to periodic adjustments in the algorithm parameters, including variable settings and selection mechanisms, to better align with the dynamic manufacturing environment. Such iterative refinements ensured that the production process remained efficient and responsive to real-time operational demands.

After running this comprehensive simulation model for 150 days, incorporating these practical constraints, the total capacity obtained was 17,929 pieces, with an average capacity of 0.44 pieces per minute, 26.68 pieces per hour, and 640.32 pieces per day. When compared to historical production data under similar operating conditions (accounting for similar disruptions and constraints), this represents a theoretical improvement of 28% over the baseline performance of 500 pieces per day. However, it important to note that actual implementation results may vary due to additional unforeseen factors and the complex interactions between human operators and the production system.

5.4 Discussion of implementation impact

Implementation of the three-phase scheduling algorithm demonstrated a 28% increase in average daily capacity, underscoring significant quantitative productivity gains and highlighting the effectiveness of incorporating human factors into scheduling decisions. The workstation matching results highlight the importance of incorporating historical worker performance and skill levels for efficient task allocation. Workstations with high historical efficiency scores, such as SEW-A12 with a score of 18, consistently demonstrated superior performance in managing complex tasks. This observation reinforces the validity of integrating worker experience and efficiency into the scheduling algorithm. Additionally, the algorithm integrates fairness mechanisms by monitoring cumulative task complexity and dynamically adjusting workstation matching scores, particularly for workstations repeatedly assigned complex tasks. A 30-second update interval continuously assesses workload intensity, effectively preventing repetitive assignment of physically demanding tasks and ensuring equitable workload distribution aligned with Industry 5.0 principles.

Despite these benefits, the case study also highlighted areas for potential refinement. The current scoring mechanism, although effective, could more precisely capture the nuanced relationship between worker experience, efficiency, and task complexity. Furthermore, the observed variations in workload distribution suggest that there remains room to develop and integrate more sophisticated balancing methods, enhancing the precision of task assignments and further contributing to sustained productivity improvements.

6 Conclusions and future work

This research developed and validated a comprehensive three-phase scheduling framework tailored for small-scale garment production contexts within a Garment Flexible Manufacturing System (GFMS). The proposed framework systematically integrates order prioritization, process sequencing, and workstation matching, addressing fundamental operational challenges typically encountered in garment manufacturing scheduling. Remarkably, the methodology advances traditional production scheduling approaches by explicitly incorporating detailed human-centric considerations, such as worker skills, historical performance, and equitable workload management, alongside operational efficiencies. This integrative strategy provides substantial methodological contributions to the existing body of literature on production scheduling.

Empirical validation demonstrated the practical efficacy of the framework, evidenced by an improvement in terms of average daily production capacity relative to traditional scheduling methods. The explicit consideration of worker competencies and workload fairness significantly contributed to achieving these improvements. However, implementation at a partner manufacturing facility highlighted several limitations, particularly the current scoring system's inadequacies in fully representing variability in machine capabilities and accurately aligning task complexity with worker skill profiles. Furthermore, initial field testing indicated notable discrepancies between simulation-based predictions and observed real-world outcomes. Factors such as informal worker communication, fluctuations in material supplies, unplanned machine downtime, and variability in task setup durations substantially influenced actual productivity, yet proved challenging to accurately simulate. Comprehensive field data analysis is therefore ongoing, aiming to refine the scheduling algorithm, enhance its predictive accuracy, and identify further influential human factors for inclusion.

Future research should focus on addressing these identified limitations. Refinement of the workstation matching algorithm to explicitly include detailed machine-specific parameters, such as processing speed, specialized tooling, and precision capabilities, represents an essential next step. Moreover, exploration of advanced workload balancing methodologies is necessary to enhance task distribution accuracy and system resilience. Finally, further integrating broader human-centric considerations including team dynamics, communication efficacy, leadership impacts, and overall worker well-being would strengthen the practical applicability and theoretical foundation of the scheduling framework, aligning it closely with evolving Industry 5.0 paradigms.

Acknowledgements This work was supported by the 2020 Li Ka Shing Foundation Cross-Disciplinary Research under Grant 2020LKS-FG06D. The authors gratefully acknowledge the Lafeiyi Fashion Co., Ltd. and Junguo Electromechanical Technology Co., Ltd., Shantou, Guangdong, China, for providing the resources and the expertise.

Author contributions Nengsheng Bao (NB) conceived the research framework and led data collection. Xiaoxun Zheng (XZ) optimized methodology and conducted data analysis. Yuchen Fan (YF) contributed to data collection, literature review, and data visualization. Alessandro Simeone (AS) supervised the research process and provided theoretical modifications. Runxuan Bao (RB) designed figures and tables. NB and AS supervised the project. XZ and YF wrote the main manuscript. All authors reviewed, revised, and approved the final version.

Funding Open access funding provided by Politecnico di Torino within the CRUI-CARE Agreement.

Data availability No datasets were generated or analysed during the current study.

Declarations

Declarations of generative AI and AI-assisted technologies in the writing process During the preparation of this work, the authors used ChatGPT in order to improve syntax and grammar. After using this tool/service, the authors reviewed and edited the content as needed and assume full responsibility for the content of the publication.

Competing interests The authors declare no competing interests.

References

1. Hu X, Li M, Huang Y, Jia H (2024) Country-of-Origin or Host-Country effects?? Code-of-Conduct effects? and Labor-Standards compliance in Chinese overseas garment factories: the cases of Cambodia and Myanmar. Sage Open 14. https://doi.org/10.1177/21582440241300863
2. China National Textile and Apparel Council (2024) National Textile and Apparel Exports Maintain Positive Growth from January to May, last accessed 2024/09/11. https://www.cntac.org.cn/zixun/shuju/202406/t20240617_4350948.html
3. Chang R, Zhu S (2022) Probe into the Low-Carbon Economic Environment Challenges and Opportunities of Textile and Garment Export. J Environ Public Health. https://doi.org/10.1155/2022/6043903
4. Shi X, Prajogo D, Fan D, Oke A (2025) Is operational flexibility a viable strategy during major supply chain disruptions? Evidence from the COVID-19 pandemic. Transp Res E Logist Transp Rev 195:103952. https://doi.org/10.1016/j.tre.2024.103952
5. Florescu A, Barabas SA (2020) Modeling and Simulation of a Flexible Manufacturing System—A Basic Component of Industry 4.0. Applied Sciences. 10, 8300 https://doi.org/10.3390/app10228300
6. Florescu A (2020) S.A. Barabas Modeling and simulation of a flexible manufacturing System—A basic component of industry 4.0 https://doi.org/10.3390/app10228300
7. Javaid M, Haleem A, Singh R, Suman R (2022) Enabling flexible manufacturing system (FMS) through the applications of industry 4.0 technologies. Internet Things Cyber-Physical Syst 2:49–62. https://doi.org/10.1016/j.iotcps.2022.05.005
8. Zhang Y, Xu H, Huang J, Xiao Y (2023) Research on multiple constraints intelligent production line scheduling problem based on beetle antennae search (BAS) algorithm. Processes 11:904. https://doi.org/10.3390/pr11030904
9. Choi T-M, Yeung W-K, Cheng E, Yue TC (2018) Optimal scheduling, coordination, and the value of RFID technology in garment manufacturing supply chains. IEEE Trans Eng Manag 65:72–84. https://doi.org/10.1109/TEM.2017.2739799
10. Xu X, Lu Y, Vogel-Heuser B, Wang L (2021) Industry 4.0 and industry 5.0—Inception, conception and perception. J Manuf Syst 61:530–535. https://doi.org/10.1016/j.jmsy.2021.10.006
11. Leng J, Sha W, Wang B, Zheng P, Zhuang C, Liu Q, Wuest T, Mourtzis D, Wang L (2022) Industry 5.0: prospect and retrospect. J Manuf Syst 65:279–295. https://doi.org/10.1016/j.jmsy.2022.09.017
12. Grabowska S, Saniuk S, Gajdzik B (2022) Industry 5.0: improving humanization and sustainability of industry 4.0. Scientometrics 127:3117–3144. https://doi.org/10.1007/s11192-022-04370-1
13. Gong G, Deng Q, Gong X, Liu W, Ren Q (2018) A new double flexible job-shop scheduling problem integrating processing time, green production, and human factor indicators. J Clean Prod 174:560–576. https://doi.org/10.1016/j.jclepro.2017.10.188

14. Zhang Z, Wu L, Peng T, Jia S (2019) An improved scheduling approach for minimizing total energy consumption and Makespan in a flexible job shop environment. Sustain (Switzerland) 11. https://doi.org/10.3390/su11010179
15. Nouiri M, Bekrar A, Jemai A, Niar S, Ammari AC (2018) An effective and distributed particle swarm optimization algorithm for flexible job-shop scheduling problem. J Intell Manuf 29:603–615. https://doi.org/10.1007/s10845-015-1039-3
16. Wei L, He J, Guo Z, Hu Z (2023) A multi-objective migrating birds optimization algorithm based on game theory for dynamic flexible job shop scheduling problem. Expert Syst Appl 227:120268. https://doi.org/10.1016/j.eswa.2023.120268
17. Zhou H, Liu H, Lv C, Zhang C, Shen W (2024) A path relinking with Tabu search algorithm for solving hybrid flow shop scheduling problem considering multiple critical paths. Comput Oper Res 106783. https://doi.org/10.1016/j.cor.2024.106783
18. Yang J, Cui J, Xia X, Gao X, Yang B, Zhang YD (2024) An artificial bee colony algorithm with an adaptive search strategy selection mechanism and its application on workload prediction. Comput Ind Eng 189. https://doi.org/10.1016/j.cie.2024.109982
19. Yang XS, Deb S, Fong S (2014) Metaheuristic algorithms: optimal balance of intensification and diversification. Appl Math Inform Sci 8:977–983. https://doi.org/10.12785/amis/080306
20. Liu ZJ, Sang HY, Zheng CZ, Chi H, Gao KZ, Han YY (2024) An effective multi-restart iterated greedy algorithm for multi-AGVs dispatching problem in the matrix manufacturing workshop. Expert systems with applications. Elsevier Ltd. https://doi.org/10.1016/j.eswa.2024.124223.
21. Shang X (2023) A Study of Deep Learning Neural Network Algorithms and Genetic Algorithms for FJSP. J Appl Math. 1–13 (2023). https://doi.org/10.1155/2023/4573352
22. Fachrizal R, Shepero M, van der Meer D, Munkhammar J, Widén J (2020) Smart charging of electric vehicles considering photovoltaic power production and electricity consumption: A review. eTransportation 4:100056. https://doi.org/10.1016/j.etran.2020.100056
23. Leite AR, Enembreck F, Barthès J-PA (2014) Distributed constraint optimization problems: review and perspectives. Expert Syst Appl 41:5139–5157. https://doi.org/10.1016/j.eswa.2014.02.039
24. Sun K, Zheng D, Song H, Cheng Z, Lang X, Yuan W, Wang J (2023) Hybrid genetic algorithm with variable neighborhood search for flexible job shop scheduling problem in a machining system. Expert Syst Appl 215:119359. https://doi.org/10.1016/j.eswa.2022.119359
25. Wang R (2017) Timed petri net based optimal scheduling for garment flexible productions. J Text Eng Fashion Technol 2. https://doi.org/10.15406/jteft.2017.02.00055
26. Liu J, Lv Y (2023) A Multi-Object genetic algorithm for the assembly line balance optimization in garment flexible job shop scheduling. Intell Autom Soft Comput 37:2421–2439. https://doi.org/10.32604/iasc.2023.040262
27. Li Z, Janardhanan M, Tang Q, Zhang Z (2023) Models and algorithms for U-shaped assembly line balancing problem with collaborative robots. Soft Comput 27:9639–9659. https://doi.org/10.1007/s00500-023-08130-y
28. Charalambous G, Fletcher SR (2022) Trust in industrial Human–Robot collaboration. In: Aldinhas Ferreira MI, Fletcher SR (eds) The 21st century industrial robot: when tools become collaborators. Springer International Publishing, Cham, pp 87–103. https://doi.org/10.1007/978-3-030-78513-0_6.
29. Kousi N, Dimosthenopoulos D, Matthaiakis AS, Michalos G, Makris S (2020) AI based combined scheduling and motion planning in flexible robotic assembly lines. In: Procedia CIRP. pp. 74–79. Elsevier B.V. https://doi.org/10.1016/j.procir.2020.01.041
30. Zhang L, Wang X, Wang H, Li P (2023) A vision-based robotic system following the human upper-limb sewing action. Mech Sci 14:347–359. https://doi.org/10.5194/ms-14-347-2023
31. Kessler M, Arlinghaus JC (2022) A framework for human-centered production planning and control in smart manufacturing. J Manuf Syst 65:220–232. https://doi.org/10.1016/j.jmsy.2022.09.013
32. Evangelou G, Dimitropoulos N, Michalos G, Makris S (2021) An approach for task and action planning in Human–Robot collaborative cells using AI. Procedia CIRP 97:476–481. https://doi.org/10.1016/j.procir.2020.08.006
33. Gong G, Chiong R, Deng Q, Gong X (2019) A hybrid artificial bee colony algorithm for flexible job shop scheduling with worker flexibility. Int J Prod Res 58:1–15. https://doi.org/10.1080/00207543.2019.1653504
34. Fang Y, Lim Y, Ooi SE, Zhou C, Tan Y (2020) Study of human thermal comfort for cyber–physical human centric system in smart homes. Sens (Switzerland) 20. https://doi.org/10.3390/s20020372
35. Hémono P, Sahnoun M, Chabane AN (2023) Optimizing Resource Allocation in the Flexible Job Shop Problem: Assessing the Impact of Rest Breaks on Task Strenuousness Reduction. In: 2023 International Conference on Decision Aid Sciences and Applications (DASA). pp. 320–325 https://doi.org/10.1109/DASA59624.2023.10286783
36. Aribi D, Belkahla Driss O, Haouzi E (2023) H.: Multi-Objective Optimization of the Dynamic and Flexible Job Shop Scheduling Problem Under Workers Fatigue Constraints. In: Proceedings of the 15th International Conference on Agents and Artificial Intelligence. pp. 301–308. SCITEPRESS - Science and Technology Publications https://doi.org/10.5220/0011663800003393
37. Araujo KE, Gonzales AEP, Gutiérrez JAT (2024) Ergonomic Risk Assessment with RULA and OCRA Method in a Garment Workshop. Case Study. In: 2024 15th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT). pp. 92–96 https://doi.org/10.1109/ICMIMT61937.2024.10585653
38. Bruce G (2021) Progress monitoring and control. In: Bruce G (ed) Shipbuilding management. Springer Singapore, Singapore, pp 185–196. https://doi.org/10.1007/978-981-15-8975-1_17.
39. Eger F, Reiff C, Brantl B, Colledani M, Verl A (2018) Correlation analysis methods in multi-stage production systems for reaching zero-defect manufacturing. Procedia CIRP 72:635–640. https://doi.org/10.1016/j.procir.2018.03.163
40. Wang D, Liu X, Hu L, Hu F (2022) Optimization Simulation of Hybrid Assembly Line Production Scheduling in Garment Enterprises. In: 2022 IEEE 6th Information Technology and Mechatronics Engineering Conference (ITOEC). pp. 1375–1379. IEEE https://doi.org/10.1109/ITOEC53115.2022.9734580
41. Chretienne P, Coffman EG Jr., Lenstra JK, Liu Z (1997) Scheduling theory and its applications. J Oper Res Soc 48:764–765. https://doi.org/10.1057/palgrave.jors.2600829

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.