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A study of the multi-objective flexible job-shop scheduling model considering human factors

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Abstract: This research introduces a comprehensive multi-objective mathematical model for the flexible job-shop scheduling problem (FJSP), designed to optimise human-machine efficiency and worker health. The model aims to minimise the total production cost while considering the makespan, delivery delay, labour cost, and ergonomic risks. In particular, the assessment of ergonomic risk is performed using the OCRA method, ensuring the health and safety of workers. Due to the nonlinear nature of the model, this study proposes a custom developed genetic algorithm (GA) and artificial bee colony algorithm (ABCA) to find solutions. To verify the accuracy of these two algorithms, we also compared them with an enumeration method in small-scale production scenarios. Numerical experiments validate the effectiveness of the model in balancing production efficiency with worker welfare, providing a holistic and human-centred approach to addressing scheduling challenges in intelligent manufacturing systems.

Keywords: flexible job shop scheduling; intelligent manufacturing; multi-objective optimisation; artificial bee colony algorithm; ABCA; genetic algorithm; GA; ergonomic risk assessment; OCRA method; human factors.

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Biographical notes: Mingjuan Zhao is currently a Doctoral student at Nagoya Institute of Technology. Her research focuses on incorporating human factors into multi-objective optimisation for production scheduling systems. She employs mathematical techniques such as probability distributions and integrals to assess the health risks associated with repetitive worker actions. Through heuristic algorithms and optimisation methods, she addresses complex scheduling constraints and proposes solutions that balance production efficiency, worker health, and economic performance in intelligent manufacturing environments.

Jing Sun is an Associate Professor at Nagoya Institute of Technology. Her research focuses on various issues in management activities, including production systems, supply chain management, and marketing, from the perspectives of efficiency, quality, economic performance, safety, and security.

Specifically, she works on topics such as production and sales systems centred on ERP, supply chain management, mathematical models for deadline risk and multi-period problems, overall optimisation of electricity markets considering renewable energy, and optimisation of supply-demand balance for relief supplies based on time series analysis.

Koichi Nakade is a Professor at Nagoya Institute of Technology, specialising in operations research. His research focuses on modelling and analysing various systems such as production, logistics, and inventory systems using queuing theory and stochastic processes. He works on optimising system performance in terms of waiting times, throughput, and inventory levels. His research also includes developing algorithms to find near-optimal schedules for issues like worker assignment and shift scheduling in production lines.

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1 Introduction

In the context of a highly competitive global business environment, manufacturing companies face significant challenges in minimising production costs while meeting delivery deadlines. As product variety increases and product lifecycles shorten, intelligent production systems must quickly respond to dynamic market demands (Lei et al., 2023), especially the need for rapid production of diverse, low-volume products (Wang et al., 2023).

The flexible job-shop scheduling problem (FJSP) is a key research area for optimising production processes, increasing efficiency, and reducing costs. This topic has received widespread attention in both academic and industrial circles. With the advancement of Industry 4.0, FJSP research increasingly focuses on scheduling flexibility and response speed, while integrating multi-objective optimisation, resource integration, and new technologies to meet rapidly changing production requirements. It is worth noting, however, that despite significant progress in these areas, research incorporating human factors into FJSP remains relatively scarce. As the manufacturing industry continues to prioritise efficiency, worker workloads have increased significantly, leading to frequent safety issues. Despite this, research on worker safety is still lacking, yet these issues are critical and cannot be overlooked. Given the potential risks associated with safety incidents and ergonomic hazards in manufacturing, incorporating ergonomic risk assessment into the FJSP model has become a pressing need.

In production environments, operators frequently perform repetitive tasks, which can lead to musculoskeletal disorders (MSDs). MSDs are typically caused by sudden exertions or prolonged exposure to certain physical factors, such as repetitive motion, force, vibration, or poor posture (2018). These factors mainly affect the neck, shoulders, limbs, and lower back. Work-related musculoskeletal disorders (WMSDs) are prevalent and impose a significant health burden on workers (2018). Furthermore, they indirectly worsen economic outcomes for employers through absenteeism and compensation

claims. For instance, Marcum and Adams (2017) observed that in the USA, compensation for WMSDs accounted for over 40% of all occupational compensation from 1999 to 2013. Additionally, Koukoulaki (2014) emphasised the ergonomic challenges in lean production environments, particularly the risks of musculoskeletal and psychosocial stress.

In order to identify and assess the ergonomic risks in the work environment, this study adopts the OCRA method. The OCRA method, which is recognised for its quantitative assessment of musculoskeletal risks in repetitive tasks, considers factors such as task frequency, intensity, and duration (Occhipinti and Colombini, 2004). This approach facilitates the achievement of a productive and safe work environment for employees.

The main content and innovations of this study are as follows:

- 1 This research extends the traditional FJSP by incorporating worker allocation and constraints, developing a six-dimensional model that encompasses order-item type-item quantity-operation-machine-worker relationships. The scheduling solution aims to minimise total production costs by considering makespan, order tardiness penalties, worker wages, and ergonomic risks.
- 2 To address ergonomic risks, the study integrates the OCRA method into the FJSP model, systematically examining the impact of job allocation and scheduling strategies on worker health. This approach helps identify and mitigate high-risk tasks, optimising workload distribution and sequencing to enhance worker well-being.
- 3 Based on the proposed mathematical model, both a genetic algorithm (GA) and a Hybrid artificial bee colony algorithm (ABCA) were developed. The performance of these algorithms was evaluated and compared through numerical experiments.

In Section 2, we conducted a review of the literature related to FJSP that is pertinent to the objectives of this study, with a particular focus on research concerning order delivery times and human factors. In Section 3, we integrated human factors into the domain of FJSP and developed a multi-objective mathematical model. Section 4 presents a description of the GA based on the mathematical model. Section 5 provides a detailed account of the ABCA, which was derived from the same model. In Section 6, numerical experiments are conducted to compare the proposed ABCA algorithm with the GA. The results demonstrate that the mathematical model effectively balances productivity and worker safety while minimising total costs. Section 7 outlines the application process of the enumeration method. In Section 8, the accuracy of the proposed GA and ABCA algorithms is validated against the enumeration method in small-scale production scenarios. Finally, Section 9 provides a comprehensive summary of the study.

2 Literature review

In order to advance FJSP in a more intelligent and systematic direction, current research has comprehensively addressed various objectives in scheduling systems. In the current make-to-order production environment, the significance of meeting delivery deadlines has notably increased (Zhang and Wu, 2011). Despite the critical importance of on-time delivery for customer service, research focusing on the minimisation of delivery

deadlines in job shop scheduling remains relatively scarce (Essafi et al., 2008). Türkyılmaz and Bulkan (2014) proposed a hybrid algorithm aimed at addressing the FJSP, with the primary objective of minimising total tardiness. The algorithm combines a GA with parallel variable neighbourhood search (VNS). Wang et al. (2023) studied the distributed heterogeneous unrelated parallel machine scheduling problem (DHUPMSP), with the objective of minimising total tardiness (TDD) and makespan. To address this complex combinatorial optimisation problem, the authors proposed a knowledge and Pareto-based memetic algorithm (KPMA).

Meanwhile, there is a paucity of literature that considers human factors in the FJSP problem. However, an increasing number of researchers are recognising the impact of human factors on production systems. In the majority of instances, the FJSP that incorporates human factors is designated as the dual resource constrained FJSP (Destouet et al., 2023a). While studying the subproblems of FJSP, namely the sequencing of operations and the assignment of machines to corresponding operations, they have also considered the assignment of workers to corresponding machines. Among them, some studies have considered labour costs (Berti et al., 2021; Gong et al., 2018; Luo et al., 2022). Some studies have indicated that workers may possess varying skillsets, which can influence their efficiency when operating different machinery. This, in turn, can impact task processing times and, subsequently, the overall scheduling optimisation and efficiency (Zheng and Wang, 2016; Tan et al., 2021). In light of the detrimental effects of worker fatigue on efficiency and scheduling, some studies have also investigated the impact of worker fatigue and rest periods (Jaber and Neumann, 2010; Sun et al., 2019). Some papers also point out that workers have varying levels of proficiency with different machines, and the more time a worker spends on a particular machine, the higher their skill level becomes. Therefore, the learning rate of workers also affects scheduling (Wu et al., 2018; Peng et al., 2022).

These studies have incorporated worker factors into FJSP, focusing on the synergistic interaction between machines and workers during machine allocation and scheduling. While these studies consider worker constraints, they have not yet addressed worker safety issues. Various risk assessment methods have been proposed to identify and evaluate ergonomic risks in the work environment. These methods can be classified into four distinct categories:

- 1 Methods for assessing the risk of heavy lifting include the job strain index (JSI-L) (Liles et al., 1984) and the National Institute for occupational safety and health lifting equation (NIOSH-Eq) (WATERS et al., 1993)
- 2 Methods for assessing the risk of awkward postures include the Ovako work analysis system (OWAS) (Karhu et al., 1977), rapid upper limb assessment (RULA) (McAtamney and Nigel, 1993), and rapid entire body assessment (REBA) (Hignett and McAtamney, 2000).
- 3 Repetitive task methods include the occupational repetitive action index (OCRA) (Occhipinti, 1998) and the European assembly worksheet (EAWS) (Schaub et al., 2013).
- 4 Noise assessment methods include the daily noise dose (DND) (Aryanezhad et al., 2009).

Destouet et al. (2023b) reduced ergonomic risks by minimising the maximum OCRA value. In contrast, our study assigns costs to different ergonomic risks and incorporates them into the total production cost, providing a more comprehensive assessment of overall worker health costs. This approach better balances worker health and production objectives in scheduling.

From the above literature review, it can be observed that

- 1 although many current studies on FJSP consider various factors, there is still a lack of research that incorporates order delay penalties and human factors.
- 2 While some FJSP-related studies have considered human factors, they primarily focus on labour constraints, neglecting worker safety issues.
- 3 With the increasing workload and frequent health issues among workers, researchers have proposed various risk assessment methods to evaluate ergonomic risks in the work environment, aiming to prevent risks and ensure worker safety.

Therefore, in this study, we investigate FJSP by incorporating the OCRA method into its mathematical model to address ergonomic risks, considering the low-stress, high-frequency upper limb movements commonly found on manual assembly lines. To clearly differentiate our research from previous studies, we provide Table 1.

Table 1 The differences between the previous studies and our study

<i>Study</i>	<i>Human factors</i>	<i>Delivery</i>	<i>Methods</i>
Zhang and Wu (2011), Essafi et al. (2008), Türkyılmaz and Bulkan (2014), Wang et al. (2023)	×	✓	Annealing algorithm; genetic algorithm; genetic algorithm; memetic algorithm
Berti et al. (2021), Gong et al. (2018), Luo et al. (2022)	✓ (labour cost)	×	Heuristic approach; genetic algorithm; memetic algorithm
Zheng and Wang (2016), Tan et al. (2021)	✓ (Skill)	×	Fruit fly optimisation algorithm; NSGA-II
Jaber and Neumann (2010), Sun et al. (2019)	✓ (Rest)	×	MILP; MOEA
Wu et al. (2018), Peng et al. (2021)	✓ (Learning rate)	×	Genetic algorithm; HDMICA
Destouet et al. (2023)	✓ (Ergonomic risks)	×	NSGA-II
This study	✓ (Ergonomic risks)	✓	Genetic algorithm and artificial bee colony algorithm

3 FJSP model description

This section presents a mathematical model for the FJSP that incorporates considerations related to the workforce. The objective is to develop a model that minimises the total cost of production, which includes four elements: makespan, total order penalty cost, total worker wages, and ergonomic risk. The ergonomic risk is evaluated using the OCRA

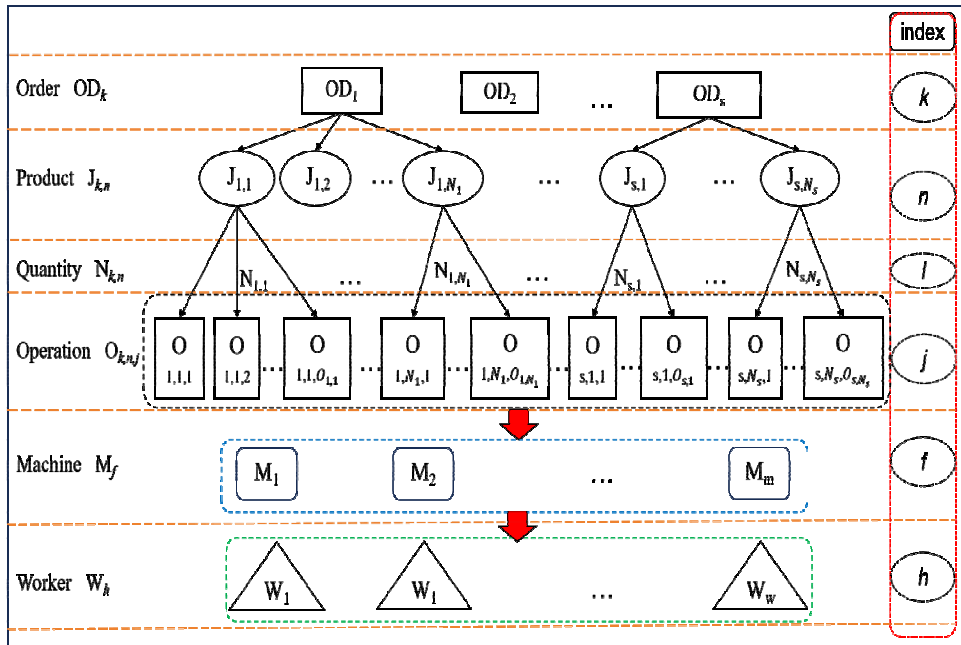
index method. The objective of this multi-objective model is to optimise both production efficiency and workplace safety and health.

3.1 Definition and assumptions

3.1.1 Model description

In this research, we address the FJSP considering worker flexibility and define it as follows: There are OD_k ($k = 1, \dots, s$), each order OD_k consists of N_k products $J_{k,n}$ ($n = 1, \dots, N_k$), and the quantity of each product $J_{k,n}$ is $N_{k,n}$. product $J_{k,n}$ is composed of O_{kn} operations $O_{k,n,j}$ ($j = 1, \dots, O_{kn}$). There are m machines M_f ($f = 1, \dots, m$) and w workers W_h ($h = 1, \dots, w$). Each operation $O_{k,n,j}$ has attributes like the set of possible processing machines $M_{k,n,j}$ and worker set $W_{k,n,j}$, and the processing time is determined by the combination of machine and worker.

Figure 1 Schematic diagram of the model (see online version for colours)



3.1.2 Sub-problems

The scheduling problem is divided into three sub-problems:

- 1 sequencing the operations.
- 2 assigning machines to corresponding operations.
- 3 assigning workers to corresponding machines.

3.1.3 Objective function

The objective of this paper is to minimise the total cost, which is comprised of four sub-objectives:

- 1 The maximum completion time (duration) of a machine: makespan (D_{final}).
- 2 Delay penalties for orders not delivered on time: total penalty for orders (CP_{order}).
- 3 Total wages for workers (C_{worker}).
- 4 Total penalty for ergonomic risk C_{ER} .

3.1.4 Assumptions

- 1 Each machine can perform only one operation at a time.
- 2 Each worker can operate only one machine at a time.
- 3 Each operation can only be performed once on a machine.
- 4 Each operation can only be performed once by a worker.
- 5 No temporary interruptions are permitted after the start of each operation.
- 6 Each operation shall be performed in accordance with the prescribed sequence of operations within the item and shall not be started until the preceding operation has been completed.
- 7 The processing times corresponding to each operation, machine and worker are specified in advance.

3.2 Mathematical model

3.2.1 Decision variables

$x_{k,n,l,j,f,h}$ A binary decision variable that equals 1 if worker h is operating machine f to process operation j for the l^{th} item of product n in order k ; otherwise, it equals 0.

3.2.2 Objective function

Minimise

$$\text{Total cost} = \alpha_1 \cdot D_{final} + CP_{order} + C_{worker} + C_{ER} \quad (1)$$

where

- 1 Makespan D_{final}

$$D_{final} = \max D_{k,n,l,j} \quad (\forall k,n,l,j; k=1, \dots, s; n=1, \dots, N_k; l=1, \dots, N_{kn}; j=2, \dots, O_{kn}) \quad (2)$$

2 Total penalty for orders CP_{order}

$$CP_{order} = \sum_{k=1}^s \left(\max(0, DT_k) \cdot (C_k \cdot 0.05 + CP_k + (DT_k) \cdot C_k \cdot 2 \times 10^{-5}) \right) \quad (3)$$

where

$$DT_k = \max D_{k,n,l,j} - DDL_k \quad (\forall n, l, j; n = 1, \dots, N_k; l = 1, \dots, N_{kn}; j = 2, \dots, O_{kn}) \quad (4)$$

3 Total wages for workers C_{worker}

$$C_{worker} = \sum_{k=1}^s \sum_{n=1}^{N_k} \sum_{l=1}^{N_{kn}} \sum_{j=1}^{O_{kn}} \sum_{f=1}^m \sum_{h=1}^w (x_{k,n,l,j,f,h} \cdot A / t'_{k,n,j,f,h}) \quad (5)$$

where

$$t'_{k,n,j,f,h} = t_{k,n,j,f,h} / D_{time} \quad (6)$$

4 Total penalty for Ergonomic risks C_{ER}

The OCRA index is a method for evaluating and analysing work. It assesses the occupational risk for MSD induced by repetitive activities of the upper limbs. According to the recommended zone risk system for the OCRA index (Occhipinti and Colombini, 2007), we assign the corresponding ergonomic risk unit prices, as shown in equation (9).

$$C_{ER} = \sum_{h=1}^w (\alpha_2 \cdot OCRA_h) \quad (7)$$

where

$$OCRA_h = \frac{\sum_{k=1}^s \sum_{n=1}^{N_k} \sum_{l=1}^{N_{kn}} \sum_{j=1}^{O_{kn}} \sum_{f=1}^m (A \cdot T \cdot x_{k,n,l,j,f,h})}{\sum_{k=1}^s \sum_{n=1}^{N_k} \sum_{l=1}^{N_{kn}} \sum_{j=1}^{O_{kn}} \sum_{f=1}^m [HF \cdot x_{k,n,l,j,f,h} \cdot t'_{k,n,j,f,h}]} \quad (8)$$

$$\alpha_2 = \begin{cases} \alpha_2^{(1)} & OCRA_h \leq 1.5 \text{ (Optimal)} \\ \alpha_2^{(2)} & 1.5 < OCRA_h \leq 3.5 \text{ (Acceptable)} \\ \alpha_2^{(3)} & 3.5 < OCRA_h \leq 4.5 \text{ (Light)} \\ \alpha_2^{(4)} & 4.5 < OCRA_h \leq 9 \text{ (Medium)} \\ \alpha_2^{(5)} & OCRA_h > 9 \text{ (High)} \end{cases} \quad (9)$$

3.2.3 Symbol explanation

- s number of orders
- N_k number of products in order k
- $N_{k,n}$ quantity of product n in order k
- $O_{k,n}$ number of operations for product n in order k

m	number of machines
w	number of workers
$t_{k,n,j,f,h}$	time required for worker h to process operation j of product n in order k on machine f
$M_{k,n,j}$	set of possible machines for operation $O_{k,n,j}$
$W_{k,n,j}$	set of possible workers for machine $M_{k,n,j}$
DDL_k	due date of order k
M	a very large positive number
α_1	unit cost of processing time
α_2	unit cost of OCRA index
C_k	total cost of order k
C_{pk}	loss due to failure to complete order k within the deadline
A	the frequency of actual technical actions (defined as complex movements involving one or more upper limb joints related to upper limb muscle strength) (counts per minute)
HF	coefficient of environmental influence factors, which includes posture, force, repetitiveness, and additional risks associated with the environment
D_{time}	a multiplier used to adjust processing speed
T	cycle time
$D_{k,n,l,j}$	end time of the j^{th} operation for the l^{th} item of product n in order k
$S_{k,n,l,j}$	start time of the j^{th} operation for the l^{th} item of product n in order k
p	Binary variable, taking values of 0 or 1, is used to constrain the sequence of operations on the same machine, ensuring that each machine can handle only one operation at any given time
q	Binary variable, taking values of 0 or 1, is used to constrain the sequence of operations assigned to the same worker, ensuring that each worker can handle only one operation at any given time.

3.2.4 Constraints

1 Operation sequencing

$$S_{k,n,l,j} \geq D_{k,n,l,j-1} \left(\begin{array}{l} \forall k, n, l, j, f, h; k = 1, \dots, s; n = 1, \dots, N_k; l = 1, \dots, N_{kn}; \\ j = 2, \dots, O_{kn}; \end{array} \right) \quad (10)$$

Equation (10) ensures the precedence of operations within the same workpiece, i.e., the start time of operation j must be greater than the end time of the preceding operation $j-1$.

2 Start and end time relationship

$$D_{k,n,l,j} = S_{k,n,l,j} + \sum_{f=1}^m \sum_{h=1}^w (t'_{k,n,j,f,h} \cdot x_{k,n,l,j,f,h}) \quad (11)$$

$$\left(\begin{array}{l} \forall k,n,l,j,f,h; k=1,n,s;n=1,n,N_k;l=1,n,N_{kn}; \\ j=1,n,O_{kn}; f=1,n,m; h=1,n,w \end{array} \right)$$

Equation (11) defines the relationship between the start time $S_{k,n,l,j}$ and the end time $D_{k,n,l,j}$ of each operation. The end time is the start time plus the processing time, determined by the combination of assigned machine f and worker h .

3 Machine availability

$$(S_{k',n',l',j'} - D_{k,n,l,j}) \cdot x_{k,n,l,j,f,h} \cdot x_{k',n',l',j',f,h'} \geq -M \cdot (1-p) \quad (13)$$

$$\left(\begin{array}{l} \forall k,k',n,n',l,l',j,j',f,h,h'; \\ k,k'=1,\dots,s;n,n'=1,\dots,N_k;l,l'=1,\dots,N_{kn}; \\ j,j'=1,\dots,O_{kn}; f=1,\dots,m; h,h'=1,\dots,w; \\ k \neq k' \vee n \neq n' \vee l \neq l' \vee j \neq j'; p \in \{0,1\} \end{array} \right)$$

Equations (12) and (13) ensure that each machine f can handle only one operation at any given time. The formulas achieve this by comparing the start time $S_{k,n,l,j}$ and the end time $D_{k,n,l,j}$ of different operations and using the binary variables $x_{k,n,l,j,f,h}$ and p to prevent any overlap in time.

4 Worker availability

$$(S_{k,n,l,j} - D_{k',n',l',j'}) \cdot x_{k,n,l,j,f,h} \cdot x_{k',n',l',j',f',h} \geq -M \cdot q \quad (14)$$

$$\left(\begin{array}{l} \forall k,k',n,n',l,l',j,j',f,f',h; \\ k,k'=1,\dots,s;n,n'=1,n,N_k;l,l'=1,\dots,N_{kn}; \\ j,j'=1,\dots,O_{kn}; f,f'=1,\dots,m; h=1,\dots,w; \\ k \neq k' \vee n \neq n' \vee l \neq l' \vee j \neq j'; q \in \{0,1\} \end{array} \right)$$

$$(S_{k,n,l,j} - D_{k',n',l',j'}) \cdot x_{k,n,l,j,f,h} \cdot x_{k',n',l',j',f',h} \geq -M \cdot (1-q) \quad (15)$$

$$\left(\begin{array}{l} \forall k,k',n,n',l,l',j,j',f,f',h; \\ k,k'=1,\dots,s;n,n'=1,n,N_k;l,l'=1,\dots,N_{kn}; \\ j,j'=1,\dots,O_{kn}; f,f'=1,\dots,m; h=1,\dots,w; \\ k \neq k' \vee n \neq n' \vee l \neq l' \vee j \neq j'; q \in \{0,1\} \end{array} \right)$$

Similar to the machine availability constraints, equations (14) and (15) ensure that each worker h can handle only one operation at any given time. These constraints compare the operation times assigned to the worker to ensure that there is no overlap in the timing of operations.

5 Unique assignment

$$\sum_{f=1}^m \sum_{h=1}^w x_{k,n,l,j,f,h} = 1$$

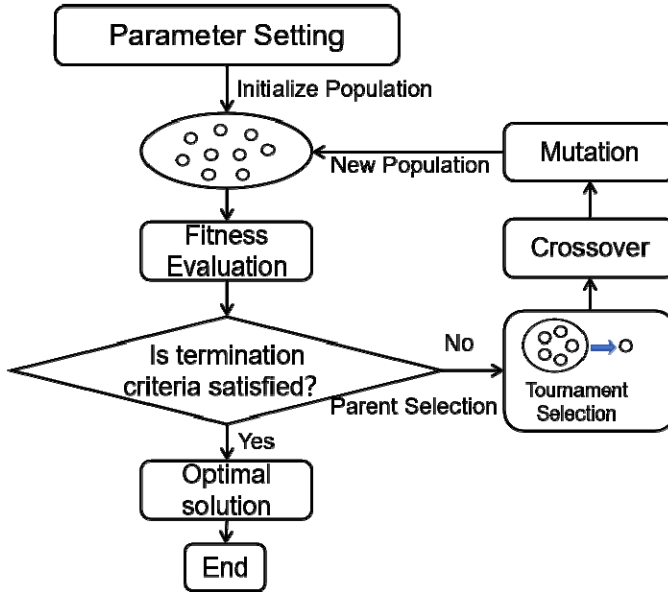
$$\left(\begin{array}{l} \forall k, n, l, j, f, h; k = 1, \dots, s; n = 1, \dots, N_k; l = 1, \dots, N_{kn}; \\ j = 1, \dots, O_{kn}; f = 1, \dots, m; h = 1, \dots, w \end{array} \right) \quad (16)$$

Equation (16) ensures that each operation is assigned to exactly one machine and one worker.

4 Application of genetic algorithm

Given the nonlinear characteristics of this FJSP model, the GA is deemed an appropriate solution method. In Section 4, we examine the implementation of the GA, a heuristic search technique adept at solving complex optimisation challenges, particularly those associated with the FJSP. This algorithm operates by emulating the process of natural selection, effectively refining solutions through successive generations of genetic operations. Figure 2 provides a detailed illustration of this implementation process.

Figure 2 Flowchart of the genetic algorithm



4.1 Chromosome representation

In order to efficiently handle the complexity of scheduling problems, a two-stage encoding strategy is used. The specifics of the encoding method are as follows:

4.1.1 First layer coding: machine and worker assignments

In this layer, a multidimensional array $x_{k,n,l,j,f,h}$ is used to represent the assignment of machines and workers for each operation. Here, k represents the order number, n the product number, l the workpiece number, j the operation number, f the machine number, and h the worker number. If worker h is operating machine f to process operation j for the l^{th} item of product n order k , the corresponding value of $x_{k,n,l,j,f,h}$ set to 1; otherwise, it is 0. This coding approach allows for a clear representation of machine and worker assignments (WA) for each operation.

4.1.2 Second layer coding: execution sequence of operations

The execution sequence of operations is represented using a multidimensional array, $ProcessingOrders\{k\}\{n\}\{l\}\{j\}$. The values k, n, l, j maintain the same meaning as in the first layer of coding, with each element of the array indicating the global execution order of the corresponding operation among all operations. The term ‘all operations’ represents the total sum of all operations across all orders. This quantity is denoted as $\sum_{k=1}^s \sum_{j=1}^{N_k} O_{k,j} \times N_{k,j}$. The execution sequence is determined by a globally unique sequence number. Each operation is assigned a number, and the arrangement of these numbers dictates the execution order of all operations.

To illustrate, if $ProcessingOrders\{1\}\{2\}\{1\}\{3\}$ is equal to 5, it signifies that the third operation of the 1-th item of the second product in the first order is to be executed fifth in the sequence of all operations.

This two-layered coding strategy ensures that during the evolutionary process of the GA, both the machine-WAs and the order of operations can be flexibly adjusted, allowing for the discovery of superior solutions to complex scheduling problems.

4.2 Initialisation of population

4.2.1 Creating a global operation list

First, create a global list of operation coordinates that includes all orders, tasks, workpieces, and operations. Each operation has a unique coordinate to ensure that all scheduling combinations are covered.

4.2.2 Assigning unique sequence numbers

Generate a globally unique sequence number for each operation and randomly shuffle these numbers. These numbers are used to represent the operation sequence (OS) for each individual, ensuring diversity within the population.

4.2.3 Machine and worker selection strategy

When generating the initial population, each operation needs to be assigned an appropriate machine and worker. The steps for selecting suitable resources are as follows:

- 1 Filtering available machines and workers: first, retrieve the available machines and workers for each operation from the data.

- 2 Calculating selection probabilities: calculate the selection probability for each resource based on its current usage. Resources with lower usage frequencies are given higher selection probabilities to promote fair utilisation and population diversity.
- 3 Random selection: randomly select a machine and a worker for the current operation based on the calculated selection probabilities.

4.3 Parent selection

This section examines the process of parental selection through the tournament selection mechanism employed within our GA. Tournament selection is a technique that identifies superior individuals within randomly chosen subgroups of the population. This process is instrumental in preserving diversity while propelling the genetic inheritance of high-quality solutions, thus mitigating premature convergence and fostering expansive exploration of the search space.

4.4 Crossover mechanism

The study employs a uniform crossover (Syswerda, 1989) technique that allows each gene to independently inherit characteristics from either parent with equal probability. This approach generates a single offspring from a pair of parents, ensuring a balanced genetic transfer from the parents and encouraging the combination of new traits, thereby preserving genetic diversity.

4.5 Mutation mechanism

Mutation serves as a mechanism to introduce variations in the individuals' operational assignments and sequences, thereby probing new solutions within the search space.

- Mutation of operation assignments: this entails selecting a gene location (k, n, l, j, f, h) , clearing the current assignment, and then reassigning new machine and worker combinations from the pool of available resources.
- Mutation of OSs: the sequence numbers of two selected operations are swapped. In order to maintain the feasibility of the schedule, only the internal sequence within the related item is readjusted. This process ensures the maintenance of genetic diversity while guaranteeing the viability of the scheduling solutions.
- Through such mutations, our algorithm sustains a rich genetic pool and enhances the probability of unearthing viable, high-fitness schedules in the complex landscape of job-shop scheduling problems.

4.6 Fitness evaluation

In this study, fitness is defined as the total cost, and the objective is to minimise this total cost. In this process, the start time $S_{k,n,l,j}$ of each operation is determined by comparing the completion time of the previous operation (unless the current operation is the first operation of the item), and the last end time of the machine and the worker, based on the acquired genetic information $x_{k,n,l,j,f,h}$ and $ProcessingOrders\{k\}\{n\}\{l\}\{j\}$. The end time

$D_{k,n,l,j}$ of each operation is calculated from the start time $S_{k,n,l,j}$ and the operation duration $t'_{k,n,j,f,h}$.

The start and end times are then used to evaluate the total cost of the proposed solution, which includes the makespan, delay costs, worker's wages, and ergonomic risks. This evaluation quantifies the fitness value of each chromosome in the GA and provides a measure of selection for the next generation.

4.7 Next generation selection

In this section, we describe an elite selection strategy for choosing the next generation within our GA. This method prioritises retaining the highest-performing individuals from a combined pool of parents and offspring, thereby ensuring the perpetuation of superior genetic traits into subsequent generations.

4.8 Termination criteria

- This GA's endpoint: computations cease upon reaching the pre-set maximum number of generations.

This criterion ensures that the algorithm terminates its search within a reasonable timeframe, allowing for the evaluation of the best solution achieved within the specified generational limit.

5 Description of the artificial bee colony algorithm

This section proposes an ABCA based on the model presented in Section 3. The ABCA (Karaboga and Akay, 2009) is a distinctive metaheuristic method specifically devised to address intricate multi-objective scheduling issues. The algorithm emulates the collaborative foraging behaviour observed in bees in their natural habitat. The optimisation process of ABCA is divided into four core phases: initialisation, employed bees, onlooker bees, and scout bees. The flow of the algorithm is shown in Figure 3.

5.1 Coding and decoding

In this algorithm, we have developed a three-layer chromosome coding method that includes OS information, machine selection (MS) information, and worker selection (WS) information. Figure 4 illustrates how this coding method works and shows, for example, that Operator 1 performs operation O1111 on machine 3.

- 1 OS: represents the execution order of operations for each job.
- 2 machine assignment (MA): indicates which machine is assigned to each operation.
- 3 WA: specifies which worker is assigned to each operation.

During the encoding process, the OS chromosome is generated first. Then, for each operation, the corresponding MA and WA chromosomes are determined based on the OS chromosome.

Figure 3 Flowchart of the ABCA algorithm

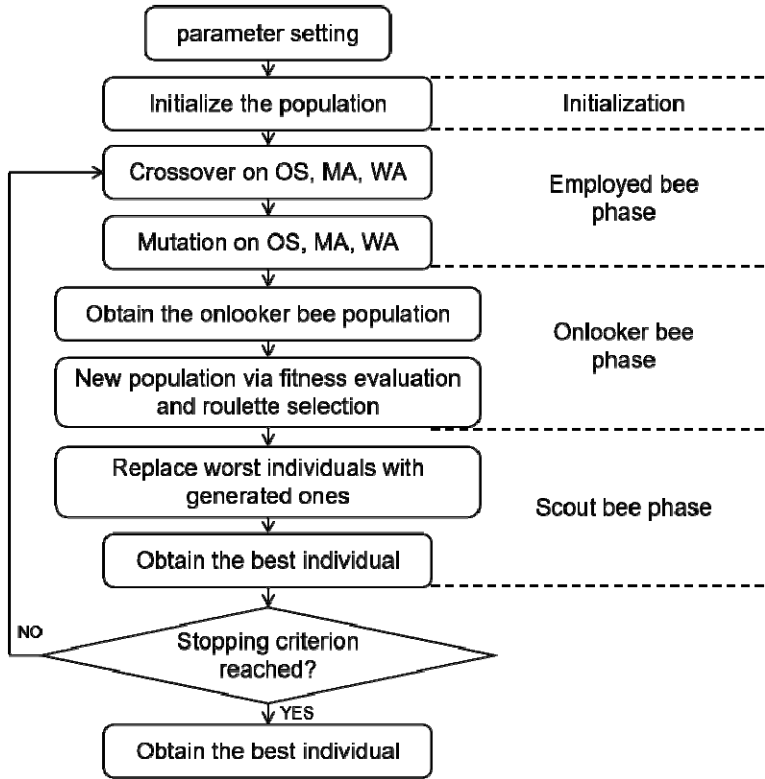
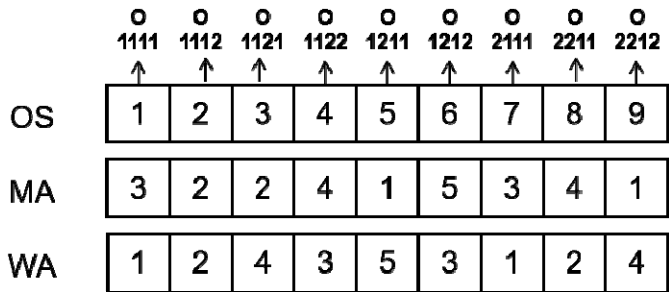


Figure 4 Chromosomes encoding



5.2 Crossover operations

We divide the crossover operation into two parts:

5.2.1 Operation sequence crossover

- 1 First, we determine which positions need to undergo crossover based on a predefined crossover probability.

- 2 For these selected positions, the algorithm randomly selects a set of operations from the OS of the two parent solutions.
- 3 Then, we generate two offspring chromosomes: Offspring 1 replicates the selected operations from Parent 1 in the same order while filling in the remaining operations from Parent 2; Offspring 2 does the reverse, replicating the selected operations from Parent 2 and filling in the remaining operations from Parent 1.

5.2.2 Machine assignment and worker assignment crossover

- 1 A randomly generated set of binary numbers determines which positions in the MA and WA will be exchanged.
- 2 For the selected positions, the corresponding machine and WAs of the two parent solutions are swapped. This operation produces new combinations, thereby exploring a broader solution space.

5.3 Mutation operations

The purpose of the mutation operation is to introduce new gene combinations, thereby exploring more of the solution space and avoiding the algorithm getting stuck in local optima. The specific implementation of the mutation operation is as follows:

5.3.1 Operation sequence mutation

- 1 A mutation probability is set to determine whether the OS should undergo mutation.
- 2 If mutation is required, it is implemented by swapping two randomly selected positions in the OS chromosome. This method can change the order in which jobs are processed, thereby generating a new solution.

5.3.2 Machine assignment mutation

- 1 First, a random position is selected where the MA mutation will be performed.
- 2 For the selected operation, a different machine is randomly chosen from the list of candidate machines, and the chromosome's MA information is updated accordingly.

5.3.3 Worker assignment mutation

- 1 Similarly, a random position is chosen for the WA mutation.
- 2 For the selected operation and machine, a different worker is randomly chosen from the list of candidate workers, and the chromosome's WA information is updated accordingly.

5.4 Onlooker bee selection

The fitness values of all individuals in the current population are calculated, and a roulette wheel selection strategy is applied to choose individuals with higher fitness. The

selected individuals form a new onlooker bee population, replacing the original population with these chosen individuals.

5.5 Scout bee operation

Periodically, a portion of the worst-performing individuals in the population is selected, and these individuals are replaced by randomly generated ones. This step is akin to reintroducing randomness into the population to maintain diversity and prevent the algorithm from getting stuck in local optima.

5.6 Updating the global best solution and termination condition

In each generation, the best individual's fitness value in the current population is recorded. If this value is better than the previously recorded global best solution, the global best solution is updated.

The algorithm stops after a predefined maximum number of iterations. At this point, the retained global best solution represents the optimal solution to the problem.

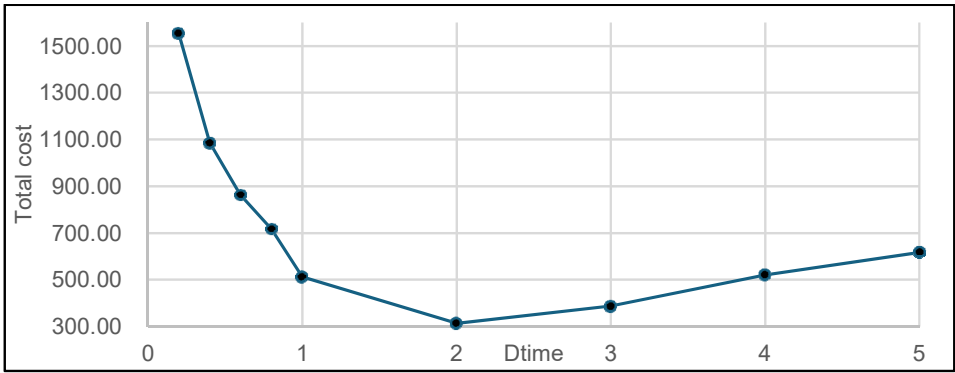
6 Experiments and results

6.1 Experimental setup

In this experiment, solutions were determined using the ABCA proposed in Section 5 and compared with the GA proposed in Section 4. The experiment was conducted on a Windows 10 personal computer (PC) equipped with an Intel i7-9750H (6 cores, 12 threads) and 17 GB of random-access memory (RAM). Based on the combination results obtained by Gong et al. (2019) using the Taguchi method (DOE), we have set the population size, crossover rate, and mutation rate as follows: population size ($\text{pop_size} = 150$), crossover probability ($\text{crossover_rate} = 0.7$), mutation probability ($\text{mutation_rate} = 0.15$) and tournament size ($\text{tournament_size} = 3$), number of selected individuals ($\text{num_selected} = 2$). Additionally, the parameters were set as follows: the number of orders $k = 4$, the number of types of workpieces is $[2, 3, 3, 2]$, the number of machines $m = 5$, and the number of workers $w = 5$. The quantity for each type is as follows: $[3, 2], [1, 3, 2], [2, 2, 1], [2, 2]$. The number of operations for each type is: $[2, 4], [2, 1, 3], [3, 2, 5], [4, 3]$. The delivery deadlines (DDL_k) are $[700, 900, 1,000, 800]$, the order amounts (C_k) are $[150, 100, 150, 150]$, and the penalty fees for delays (CP_k) are $[30, 20, 30, 30]$. $\alpha_1 = 1$, and $\alpha_2^{(1)}, \alpha_2^{(2)}, \alpha_2^{(3)}, \alpha_2^{(4)}, \alpha_2^{(5)}$, were set to 1, 2, 3, 5, 10, respectively.

First, the cycle time (T) was set to 15, the frequency of actual technical actions (A) to 30, and the coefficient of environmental influence factors (HF) to 18. Holding other variables constant, the actual processing speed was adjusted using a D_{time} ranging from 0.2 to 5 in order to investigate the effect of the production speed on the total cost. The experimental results are shown in Figure 5.

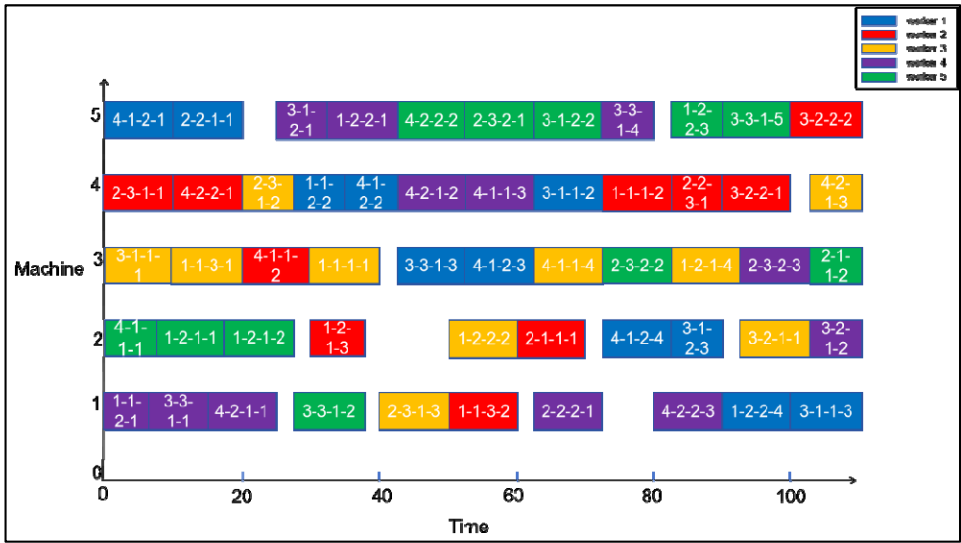
Figure 5 Relationship between total cost and D_{time} (see online version for colours)



Note: ($A = 30$, $HF = 18$).

Figure 5 illustrates that the optimal total cost is achieved when $D_{time} = 2$. Figure 6 depicts the Gantt chart of the production schedule at this point.

Figure 6 Gantt chart of production schedule at minimum total cost at $D_{time} = 2$ (see online version for colours)



A comparison was conducted between the data presented in Figure 5 and the results obtained using the GA, under identical conditions, as illustrated in Table 2. The convergence curves of both the GA and ABCA algorithms were plotted for each case of D_{time} , as illustrated in Figure 7.

Table 2 Comparison of results between different D_{time}

D_{time}	Total cost	D_{final}	CP_{order}	C_{worker}	C_{ER}	Time(s)
0.4	1,085.94	437.50	598.32	46.80	3.33	143.01
0.4	1,167.70	500.00	613.46	50.60	3.64	63.63
0.6	862.83	275.00	504.51	77.70	5.63	144.07
0.6	985.25	375.00	533.10	72.00	5.15	61.66
0.8	715.73	231.25	377.55	98.40	8.54	143.90
0.8	834.91	262.50	466.19	97.60	8.63	63.29
1	511.98	170.00	213.36	113.50	15.12	146.36
1	672.52	225.00	301.91	127.00	18.62	62.74
3	387.63	86.67	0.00	244.50	56.47	145.94
3	532.61	96.67	0.00	327.00	108.95	61.41
5	616.90	52.00	0.00	407.50	157.41	143.65
5	731.95	69.00	0.00	485.00	177.96	62.61

Notes: The gray background colour is indicative of the results yielded by ABCA, whereas the colourless background represents the results obtained by GA.

Figure 7 Convergence curves of GA and ABCA algorithms (a) $D_{time} = 0.4$ (b) $D_{time} = 0.6$ (c) $D_{time} = 0.8$ (d) $D_{time} = 1$ (e) $D_{time} = 3$ (f) $D_{time} = 5$ (see online version for colours)

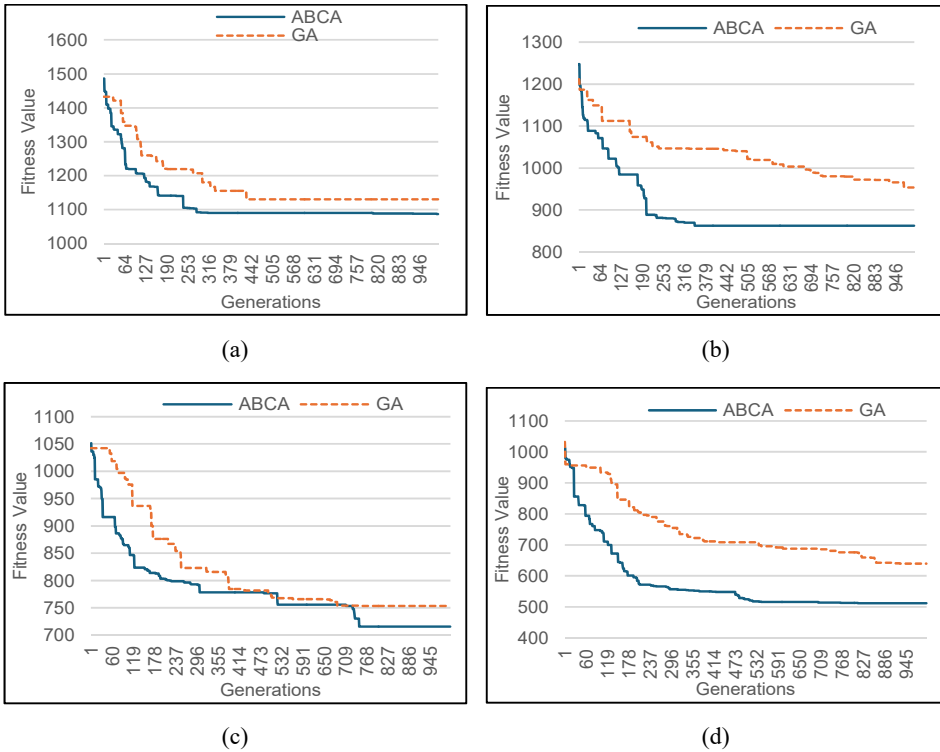


Figure 7 Convergence curves of GA and ABCA algorithms (a) $D_{time} = 0.4$ (b) $D_{time} = 0.6$ (c) $D_{time} = 0.8$ (d) $D_{time} = 1$ (e) $D_{time} = 3$ (f) $D_{time} = 5$ (continued) (see online version for colours)

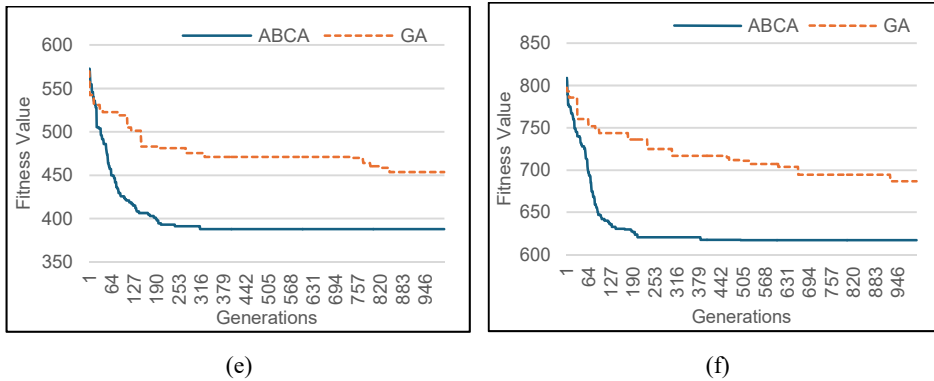
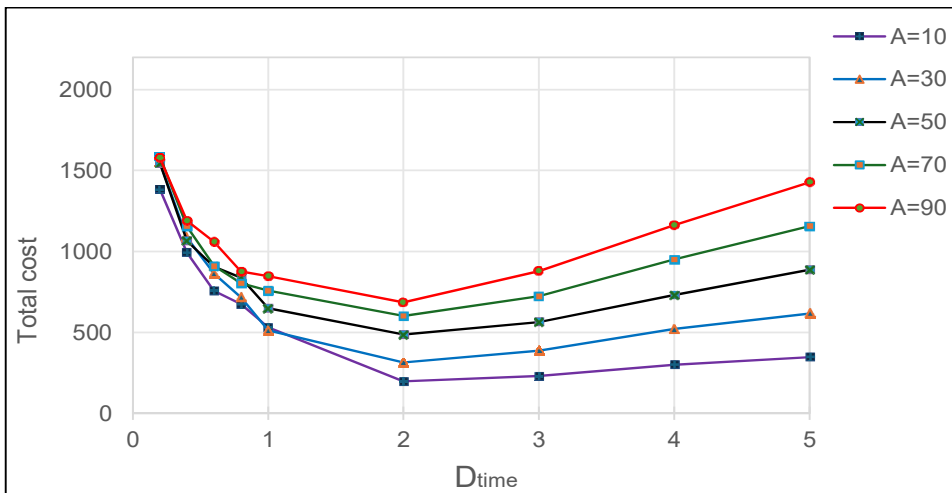


Figure 8 Relationship between change in frequency of actual technical actions (a) and total cost due to D_{time} . (see online version for colours)



Note: $HF = 18$.

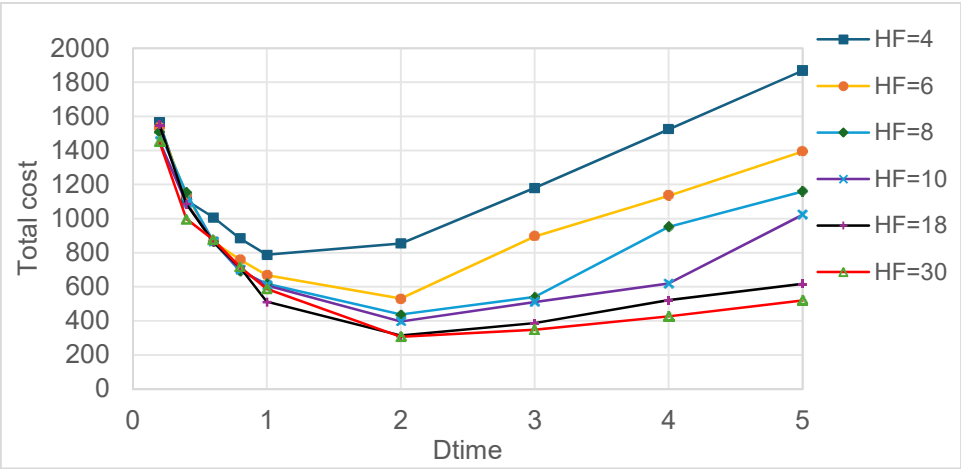
As illustrated in Figure 5, an increase in D_{time} is associated with a decline in total cost, followed by an uptick. Table 2 indicates that as D_{time} increases from 0.2 to 2, the production rate, the makespan D_{final} , and total penalty for orders CP_{order} decrease, while the total wages for workers C_{worker} and total penalty for ergonomic risks C_{ER} increases. Nevertheless, starting from $D_{time} = 2$, the decline in production cycle and total order penalties is less pronounced than the growth in total worker wages and ergonomic risk penalties. This phenomenon is particularly evident as processing speed increases, resulting in a notable rise in the workload for workers, which in turn gives rise to a pronounced surge in health risks and ergonomic risk penalties. As illustrated in Table 2 and Figure 7, the GA exhibits a markedly shorter runtime, approximately half that of the ABCA, under identical conditions. Nevertheless, the ABCA can attain superior solutions with a more rapid convergence rate in comparison to the GA.

In the following section, the range of A was set between 10 and 90 for the experiment with $HF = 18$, and the results were obtained as shown in Figure 8.

As shown in Figure 8, as the actual frequency of action (A) increases, the workload on workers intensifies, leading to an increase in ergonomic risks and related costs, which, in turn, raises the total cost. However, the optimal solution is achieved at the same processing rate, specifically when $D_{time} = 2$.

Subsequently, the range of the environmental influence factors (HF) was set between 4 and 30, with a value of the frequency of actual technical actions (A) set to 30, for the experiment. The resulting outcomes are presented in Figure 9.

Figure 9 Relationship between change in environmental influence factors (HF) and total cost due to D_{time} (see online version for colours)



Note: $A = 30$.

As shown in Figure 9, with the increase in HF , the reduction in ergonomic risks and related costs leads to a decrease in total costs. Additionally, as HF increases from 4 to 30, the rate of total cost reduction gradually diminishes. This suggests that after the environmental factor reaches a more desirable range, the influence of human factors on the total cost becomes lower and inhibits the increase of the total cost. In contrast, as environmental factors become poor, they cause human factor costs to rise sharply, along with a sharp increase in total costs.

Figures 8 and 9 demonstrate that both technical movement frequency and environmental factors have a significant impact on human factors costs as well as total costs. For companies, there are two potential avenues for reducing human factors costs: firstly, by controlling posture, strength, repetition, and additional risks associated with the environment; and secondly, by selecting the appropriate frequency of technical movements, thus controlling the costs associated with human factors. This approach allows companies to obtain the best solution to minimise the total cost of ownership.

7 Application of enumeration method

In order to validate the effectiveness of the GA and ABCA, we apply the enumeration method for smaller-scale processing scenarios. This enables a direct comparative analysis with the GA, helping to highlight its advantages and applicability in different settings.

7.1 Description of enumeration method

The Enumerative Algorithm is designed to identify the lowest-cost solution by systematically generating all possible sequences of operations and assigning all possible machines and workers to each operation. This exhaustive approach guarantees the discovery of the globally optimal solution, thereby highlighting its major advantage in terms of solution accuracy. However, the primary drawback of this method is its extremely high time complexity. As the problem size increases, the computational time required grows exponentially, rendering this algorithm impractical for problems of a larger scale.

7.2 Steps of enumeration method

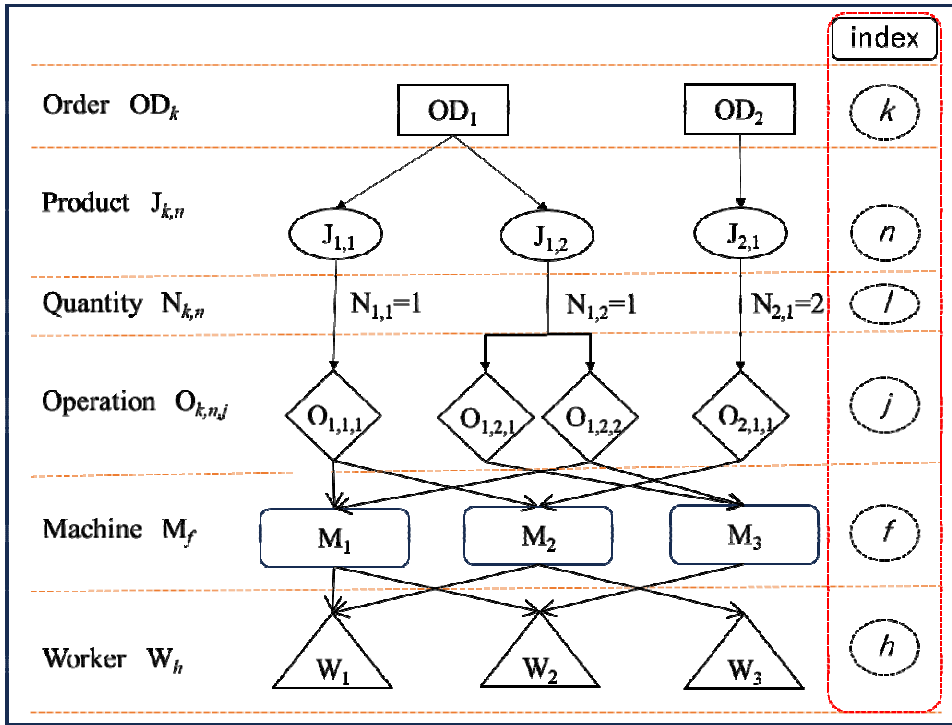
- 1 Initialisation: create an empty set of solutions.
- 2 Generating OSs: generate all possible permutations of OSs.
- 3 Resource allocation: for each permutation, enumerate all possible allocations of machines and workers.
- 4 Validation and storage: check if each allocation satisfies all constraints regarding the sequence of operations and resource allocation for every workpiece. If satisfied, store it as a valid solution.
- 5 Solution evaluation: the cost of each valid solution is calculated, and the one with the lowest cost is selected as the final solution.

8 Comparison of the algorithms with the enumeration method

In order to ascertain the veracity of the proposed GA and ABCA, a comparison will be made with the enumeration method introduced in Section 7, which was developed for use in small-scale production scenarios. The results of a series of experiments conducted using the example in Figure 10 are shown in Table 3.

After comparing the results in Table 3, it was found that the optimal solutions obtained by the ABCA and GA were consistent with those obtained by the enumeration method, validating the accuracy of both algorithms. Additionally, the GA demonstrated a significant advantage in speed, finding the optimal solution in just 1.50 seconds. This indicates that the GA is more efficient in providing solutions of comparable quality, making it particularly suitable for solving small-scale problems and scenarios where time is limited.

Figure 10 An example of model description (see online version for colours)



Note: smaller-scale processing scenarios.

Table 3 Performance comparison of genetic algorithm, artificial bee colony algorithm, and enumeration method

	Execution time (s)	Generation	Total cost	D_{final}	CP_{order}	C_{worker}	C_{ER}
Genetic algorithm	1.50	3	44.75	20.00	0	13.50	11.25
Artificial bee colony algorithm	3.51	3	44.75	20.00	0	13.50	11.25
Enumeration method	17.23	5760	44.75	20.00	0	13.50	11.25

9 Conclusions

This study proposes a multi-objective FJSP model that considers human factors and optimises productivity and total cost while emphasising the importance of worker health and safety. To address the complexity of this problem, this study employed both GA and ABCA and validated the effectiveness of these algorithms through enumeration.

The use of the OCRA index as a criterion for evaluating workers' ergonomic risk ensures workers' health and safety while optimising production scheduling. Based on the results of numerical experiments, the following noteworthy results were obtained:

- 1 For this model, the ABCA algorithm tends to achieve better solutions and is more suitable for large-scale production scenarios, while the GA algorithm has shorter running times, making it more appropriate for small-scale production scenarios.
- 2 Experimental validation indicates that the optimal balance between productivity and worker safety can be achieved by controlling the production speed. This balance is crucial for improving the overall performance and sustainability of the production system.
- 3 The experiments provide multiple solutions for the manufacturing industry to control total costs, especially those related to human factors.

These solutions include improving environmental factors related to posture, strength, repetition, and additional risk, or controlling the frequency of workers' skilled movements, as well as controlling the processing rate.

These findings highlight the importance of considering worker health and safety in production planning decisions and offer a new perspective for the manufacturing industry. While striving for improved productivity and cost-effectiveness, it is imperative to prioritise the well-being of workers, thereby promoting the evolution of manufacturing toward a more humane and sustainable path.

In the future, we will focus on developing and applying multi-objective optimisation algorithms to address the multi-objective FJSP problem that includes human factors. Currently, the ABCA and GA algorithms we employ are single-objective optimisers, and while they have demonstrated certain advantages in handling individual objectives, their capability may be limited when dealing with more complex, multi-objective scenarios. Therefore, future research will aim to introduce and optimise multi-objective algorithms to tackle larger-scale and more complex production scheduling problems. Additionally, future studies will involve the use of larger and more complex problem sets to validate and compare the effectiveness of different algorithms.

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