

# Exploration of Human–Robot Collaborative Two-Sided Assembly Line Optimization Based on Workload Balancing

Nian Lu \*, Xuan Zhu

School of Economics and Management, Southwest Petroleum University, Chengdu, Sichuan 610500, People's Republic of China

\*Corresponding Author: Nian Lu

---

## ABSTRACT

In the context of Industry 4.0, collaborative robots, as a key enabler of intelligent manufacturing, are increasingly being introduced into assembly environments, forming a novel human–robot collaborative paradigm with workers. This study focuses on the optimal allocation of human–robot collaborative assembly tasks in two-sided assembly line scenarios. A systematic investigation is conducted on assembly line balancing modeling methods incorporating both physical and cognitive workload evaluation mechanisms. On this basis, a multi-objective optimization model is developed with production cycle time, cost, working time, and workload balance as the primary objectives. Furthermore, the conventional Migrating Birds Optimization (MBO) algorithm is extended to a multi-objective framework and enhanced with adaptive improvement strategies to improve solution effectiveness and distribution. The results provide theoretical support and methodological insights for developing human-centric and efficiency-oriented collaborative production systems.

## KEYWORDS

Human–robot collaboration; Workload; Assembly line balancing; Multi-objective optimization; Migrating birds optimization algorithm

---

## 1. INTRODUCTION

In recent years, with the deepening advancement of Industry 4.0, manufacturing systems have been evolving from traditional automation toward higher levels of intelligence. In this process, collaborative robots, as a key enabling technology, have been widely deployed in assembly, material handling, and inspection due to their flexibility, safety, and ability to work alongside humans. This has accelerated the emergence of the human–robot collaborative assembly paradigm [1]. Particularly in two-sided assembly lines for large-scale equipment such as trucks and automobiles, human–robot collaboration demonstrates notable advantages in both efficiency and flexibility [2]. Collaborative robots are a class of robots capable of working jointly with human operators in industrial environments, supporting safe physical human–robot interaction [16]. In a typical collaborative assembly process, robots are assigned repetitive and potentially hazardous tasks, while humans focus on operations requiring flexibility, creativity, and judgment. Through such complementary collaboration, the strengths of both parties are effectively leveraged [9]. According to data from the International Federation of Robotics, the proportion of collaborative robots within the total population of industrial robots has been increasing year by year, highlighting the growing importance of human–robot collaboration in modern production systems.

Two-sided assembly lines, as an important organizational form widely used in the production of large and complex products, offer advantages such as high efficiency, shorter line length, and improved

equipment utilization. Their defining characteristic is the symmetric arrangement of workstations along both sides of the workpiece, where stations exist in pairs and task allocation must consider directional constraints [4]. This configuration is highly suitable for the deployment of human–robot collaboration, as proper task allocation can reduce idle time, minimize material handling, and enhance assembly quality.

Traditional Assembly Line Balancing Problems primarily focus on balancing task processing times and resource allocation, with objectives typically centered on minimizing cycle time or the number of workstations. However, with industrial upgrading and changes in labor structures, increasing attention has been paid to employees' occupational health and fairness. Workload is influenced not only by processing time but also by factors such as posture, operational intensity, and cognitive demands. Therefore, balancing based solely on time allocation is insufficient to meet ergonomic standards [12]. Particularly in human–robot collaborative environments, the same task may be performed by a human worker, a robot, or a combination of both. Different execution modes can lead to variations in processing time, cost, and worker workload [14]. Consequently, task assignment should explicitly consider the selection of collaboration modes and workload evaluation, achieving a dual balance of time and workload [8].

Existing studies predominantly focus on traditional two-sided assembly lines or fully manual/fully automated production systems, with limited attention to assembly line balancing under human–robot collaboration. Moreover, most research adopts cycle time or cost as the primary optimization objectives, often neglecting workload balancing. In addition, collaboration modes are frequently simplified, lacking detailed modeling of task execution logic and collaborative structures, which limits the practical applicability of optimization results. To address these gaps, this paper investigates the assembly task allocation problem under a human–robot hybrid serial collaboration mode. A task workload evaluation model incorporating both physical and cognitive workloads is developed. Furthermore, workload smoothness and working time indicators are introduced, and a multi-objective optimization model integrating cycle time, cost, and human factors is established. Finally, a tailored multi-objective Migrating Birds Optimization (MBO) algorithm is designed to solve the problem, providing theoretical support for the planning and optimization of human–robot collaborative production lines in manufacturing enterprises.

## **2. HUMAN–ROBOT COLLABORATION MODES AND WORKLOAD EVALUATION METHODS**

### **2.1. Classification of Human–Robot Collaboration Modes**

In human–robot collaboration applications, the interaction relationship between humans and robots is commonly categorized into four typical modes: coexistence, synchronization, cooperation, and collaboration [15]. In the coexistence mode, humans and robots operate independently within the same workspace without interfering with each other. In the synchronization mode, both parties work within the same space but execute different tasks in a time-sequenced manner; although tasks are not shared, temporal coordination is required. At the cooperation level, humans and robots may operate simultaneously within a shared task space, with clearly defined task divisions. Collaboration represents the highest level of interaction, where both parties jointly engage in the same task and rely heavily on coordination and information sharing. Some studies further divide human–robot interaction into four stages, with increasing levels of interaction intensity and coordination requirements, evolving from complete physical separation to full collaboration. Building upon this perspective, this study further abstracts three common collaboration modes under typical production logic. A comparative analysis of the characteristics of these three human–robot collaboration modes is presented in Table 1.

### (1) Human–Robot Cooperative Serial Mode

In the human–robot cooperative serial mode, workers and collaborative robots share the same workspace and alternately perform sequential operations on the same task. This mode emphasizes coordinated interaction between humans and robots. Typically, the robot first completes repetitive or heavy-load operations, followed by human workers who perform more complex and fine-grained tasks. While this approach ensures operational safety and reduces workers’ physical workload, the alternating execution may introduce waiting time, resulting in relatively limited overall efficiency. Therefore, it is suitable for scenarios with less stringent cycle time requirements and high precision demands.

### (2) Human–Robot Hybrid Parallel Mode

The human–robot hybrid parallel mode allows robots and workers to perform different tasks simultaneously or collaborate on specific tasks through functional division, demonstrating a high degree of concurrency. The main advantage of this mode lies in fully leveraging the robot’s capability for high-speed repetitive operations and the human’s flexibility and decision-making ability, thereby significantly improving production cycle time and system adaptability. However, the complexity of parallel task scheduling increases substantially, requiring more efficient resource allocation mechanisms and conflict avoidance strategies. This mode is particularly suitable for mixed-model production environments or assembly lines with ample workspace.

### (3) Human–Robot Hybrid Serial Mode

Compared with the previous two modes, the human–robot hybrid serial mode achieves a balance between practical applicability and deployment cost. In this mode, robots and workers are assigned different subsets of tasks, which are executed sequentially according to predefined priorities. The execution flow is clear, and the scheduling complexity remains moderate. Workers can independently handle flexible tasks, while robots are responsible for stable and high-load operations. Additionally, both parties may alternately collaborate on specific tasks. This mode ensures a certain level of operational efficiency while facilitating workspace independence and management. It has been widely adopted in industrial practice and represents the mainstream approach for deploying collaborative robots.

**Table 1.** Comparison of Characteristics of Three Human–Robot Collaboration Modes

Collaboration Mode	Execution Logic	Concurrency	Scheduling Complexity	Space Requirement	Applicable Scenarios
Cooperative Serial	Humans and robots alternately complete the same task	Low	Medium	High	Precision assembly; structurally dense production lines
Hybrid Parallel	Humans and robots simultaneously perform different tasks	High	High	Medium–High	Multi-task parallel operations; high takt-time lines with sufficient workspace
Hybrid Serial	Humans and robots independently or collaboratively execute tasks in sequence	Medium	Medium	Medium	Small- and medium-batch production; flexible assembly lines; conventional industrial assembly environments

## 2.2. Workload Evaluation Methods

Workload is typically decomposed into two dimensions: physical workload and cognitive workload. Physical workload mainly reflects posture and muscular exertion, while cognitive workload represents task complexity and attentional demand. Numerous studies have shown that excessive cognitive workload not only affects attention but also leads to increased electromyographic activity and operational delays [7].

### 2.2.1. Physical Workload Assessment

Rapid Upper Limb Assessment is a widely used posture-based risk evaluation method that enables rapid assessment of potential musculoskeletal disorder risks associated with upper limb postures [5]. It comprehensively considers the angles of the shoulders, elbows, wrists, neck, and trunk, as well as force exertion and repetition frequency, and produces a risk score ranging from 1 to 7 [6].

In this study, posture scores for key task actions are first evaluated using RULA. Subsequently, dynamic energy expenditure (EP) is calculated through an ergonomic simulation platform such as Siemens JACK. A weighting factor for static holding duration, denoted as  $\phi$ , is then introduced to construct the following formulation:

$$PC = \phi \cdot PP + (1 - \phi) \cdot EP \quad (1)$$

This formulation comprehensively captures the combined effects of postural intensity and energy expenditure on workers' physical workload.

### 2.2.2. Cognitive Workload Assessment

Cognitive workload is evaluated using the Task Stiffness model, which transforms factors such as task complexity, information processing requirements, and attentional demand into a quantifiable indicator, denoted as MC. Existing studies have employed methods such as EEG, physiological signals, and the NASA Task Load Index to measure cognitive load [13], demonstrating that high cognitive workload significantly increases electromyographic activity and task completion time. In this study, the stiffness-based approach is adopted to assign each assembly task a corresponding MC value, thereby capturing its cognitive intensity requirements.

### 2.2.3. Integrated Workload Metric

Finally, physical workload and cognitive workload are linearly combined to obtain the integrated workload of each task:

$$WC = PC + MC \quad (2)$$

The WC index is incorporated into the optimization model to smooth task allocation, ensuring that workstations are not only balanced in terms of cycle time but also exhibit similar workload experiences. This contributes to improved overall fairness and ergonomic safety across the entire production process.

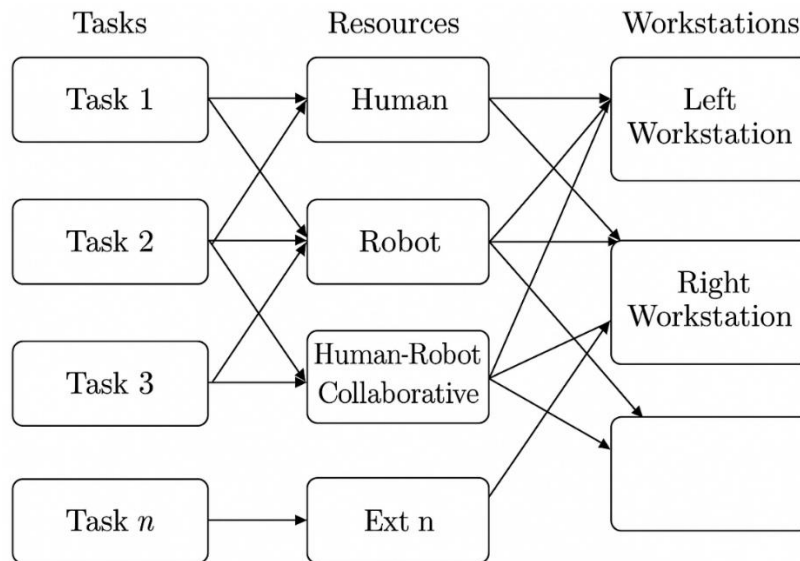
## 3. CONSTRUCTION OF THE ASSEMBLY LINE BALANCING OPTIMIZATION MODEL

### 3.1. Problem Definition and Modeling Background

With the widespread adoption of intelligent manufacturing technologies, collaborative robots are increasingly being introduced into industrial assembly environments, forming a new "human-robot hybrid" assembly system together with human workers. This transformation fundamentally alters the modeling logic, task characteristics, and resource scheduling mechanisms of traditional assembly line

balancing problems. In conventional assembly lines, each task is typically completed by a single resource, with fixed processing times and homogeneous resource capabilities. The primary modeling objective is usually the minimization of cycle time. However, in human–robot collaborative scenarios, each task can be performed by a human alone, a robot alone, or jointly by both. Different execution modes not only result in variations in time and cost but also affect human workload and the utilization efficiency of collaborative resources [11].

Furthermore, human–robot collaborative systems often adopt a two-sided assembly line layout, where resource allocation exhibits spatial symmetry and interdependence, thereby increasing scheduling complexity [10]. To systematically characterize this human–robot hybrid scheduling problem, this study constructs a “task–resource–workstation” mapping structure model, as illustrated in Figure 1.



**Figure 1.** Task–Resource–Workstation Relationship Structure in a Human–Robot Collaborative Assembly Line

Based on the above analysis, this study takes the two-sided assembly line as the research object and focuses on the task allocation problem under the human–robot hybrid serial mode. The objective is to achieve a rational allocation of tasks between human workers and robots while satisfying precedence constraints, directional compatibility, and resource limitations, thereby balancing production cycle time and workload, and optimizing both resource utilization efficiency and human factors experience. To this end, it is necessary to establish an optimization model capable of capturing collaboration structures, workload characteristics, and multi-objective performance.

### 3.2. Modeling Assumptions

To ensure the rationality and feasibility of the model, the following assumptions are made in this study:

- (1) The assembly line under consideration is a single-model, fixed-process two-sided layout;
- (2) Each pair of workstations is allowed to be equipped with one human worker and one collaborative robot, performing different tasks;
- (3) Each task is executed only once, and precedence constraints exist among tasks;
- (4) Each task can be performed using different execution modes (human, robot, or human–robot collaboration), resulting in different processing times and workload levels;
- (5) External disturbances such as equipment failures and material handling buffers are neglected;

(6) Task switching times are not considered, and resources are assumed to be continuously available during the scheduling process.

### 3.3. Parameter Definitions and Decision Variables

Let  $(I = \{1, 2, \dots, n\})$  denote the set of assembly tasks,  $(J = \{1, 2, \dots, m\})$  denote the set of workstation pairs,  $(K = \{L, R\})$  represent the workstation orientation (left and right), and  $(M = \{H, R, C\})$  denote the task execution modes (Human, Robot, and Collaborative, respectively).

The key parameters and decision variables of the model are defined in Table 2.

**Table 2.** Key Parameters and Variables

Symbol	Description
$t_{ijm}$	Processing time required for task $i$ at workstation $j$ under execution mode $m$
$w_{eijm}$	Workload generated when task $i$ is performed under mode $m$
$c_{ijm}$	Cost of performing task $i$ under mode $m$ (including labor, robot, and collaboration costs)
$x_{ijm}$	Binary decision variable; equals 1 if task $i$ is assigned to workstation $j$ and executed under mode $m$ , otherwise 0
CT	Maximum cycle time of the system, equal to the longest processing time among all workstations
WTI	Work time smoothness index (standard deviation of task durations across workstations)
WLI	Workload smoothness index (standard deviation of workload across workstations)

### 3.4. Design of the Optimization Objective Functions

This model simultaneously considers three primary optimization objectives: minimizing cycle time, minimizing cost, and minimizing task imbalance. Accordingly, a multi-objective optimization function is formulated as follows:

(1) Minimization of Assembly Cycle Time  $CT$

$$\min CT = \max_{j \in J} \sum_{i \in I} \sum_{m \in M} x_{ijm} \cdot t_{ijm} \quad (3)$$

(2) Minimization of Resource Cost (CA)

$$\min CA = \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} x_{ijm} \cdot c_{ijm} \quad (4)$$

(3) Minimization of the Comprehensive Smoothness Index (CSI)

$$\min CSI = \alpha_1 \cdot WTI + \alpha_2 \cdot WLI \quad (5)$$

Here, and  $\alpha_1, \alpha_2$  are weighting coefficients used to balance time smoothness and workload smoothness (e.g., 0.5:0.5 or task-specific settings).

### 3.5. Constraint Design

To ensure the feasibility of the model, the following constraints are introduced:

(1) Task Uniqueness Constraint: Each task can be assigned only once to a single workstation, with a definite execution mode:

$$\sum_{j \in J} \sum_{m \in M} x_{ijm} = 1, \forall i \in I \quad (6)$$

(2) Precedence Constraint: Tasks must satisfy the sequential order dictated by the process flow (e.g., Task 2 must be completed after Task 1).

$$start(i_2) \geq finish(i_1), \forall i_1 \rightarrow i_2 \quad (7)$$

(3) Cycle Time Constraint: The total execution time of tasks at each workstation must not exceed the cycle time.

$$\sum_{i \in I} \sum_{m \in M} x_{ijm} \cdot t_{ijm} \leq CT, \forall j \in J \quad (8)$$

(4) Workstation Layout Consistency Constraint: In each workstation pair, the allocation of humans and robots must comply with spatial layout logic and operational intensity limits.

(5) Workload Balance Constraint: Workload among workstations should be as balanced as possible, limiting the range or variance to within a predefined threshold.

$$WLI = \sqrt{\frac{1}{|J|} \sum_j (load_j - \overline{load})^2} \leq \delta \quad (9)$$

(6) Collaboration Mode Selection Logic: For tasks that can be executed in multiple modes, the model must select the combination of resources and execution mode that optimizes workload balance and efficiency.

### 3.6. Analysis of Model Characteristics

The proposed model integrates three key objective dimensions: production efficiency, economic cost, and human factors workload. By seeking a multi-objective Pareto optimal solution among these competing factors, the model exhibits the following characteristics:

- (1) Multi-mode Fusion: Each task offers multiple execution modes, providing significant flexibility for human-robot collaboration.
- (2) Human-Centric Orientation: By incorporating the Rapid Entire Body Assessment (RULA) and the Task Stiffness Method, the model comprehensively evaluates physical ergonomic risks and mental workload, emphasizing health equity in the workplace.
- (3) Spatial Structural Constraints: The model embeds directional layout requirements specific to two-sided assembly lines, ensuring high fidelity to real-world industrial constraints.
- (4) High Scalability: The framework allows for the seamless integration of additional task attributes, making it highly adaptable to complex and evolving industrial scenarios.

In summary, the proposed optimization model establishes a structural foundation for subsequent multi-objective intelligent algorithms. By balancing practicality and scalability, this model serves as a critical link in achieving flexible, efficient, and equitable operations within human-robot collaborative assembly systems.

## 4. DESIGN AND IMPROVEMENT OF MULTI-OBJECTIVE MIGRATING BIRDS OPTIMIZATION ALGORITHM

### 4.1. Principles of Migrating Birds Optimization (MBO)

The Migrating Birds Optimization (MBO) algorithm is a meta-heuristic optimization method inspired by the migratory behavior of bird flocks, first proposed by Duman et al. in 2012. By simulating the formation of a "V-shaped" flight queue and the dynamic shifting of the leader bird during migration, the algorithm emphasizes a balance between information sharing and local search, demonstrating robust global exploration and convergence stability.

Within a flock, the leader bird is responsible for directional guidance, while the remaining individuals perform information propagation and position updates based on their relative coordinates. The leadership role is periodically rotated during migration to prevent the population from becoming trapped in local optima. When mapped onto an intelligent optimization framework, this mechanism is characterized by:

- (1) Local Neighborhood Search: Operations are conducted around the current best solution of an individual.
- (2) Global Directional Control: The search process is guided by the current global best solution.
- (3) Leader Rotation Mechanism: This ensures population vitality and enhances the diversity of the solution space.

While the standard MBO algorithm has been widely applied to single-objective optimization problems, its direct application to human-robot collaborative assembly line balancing, which involves multiple objectives such as efficiency, equity, and cost, remains limited. Consequently, it is necessary to modify and extend the MBO algorithm in terms of encoding schemes, objective handling strategies, and neighborhood structures.

### 4.2. Algorithmic Structural Design for Human-Robot Collaborative Assembly

#### 4.2.1. Segmented Encoding Mechanism

To accommodate the dual decision-making process of task assignment and execution mode selection, this paper adopts a hybrid segmented encoding approach consisting of a "Task Sequence + Mode Matrix":

- (1) Segment 1 (Task Sequence): This segment uses an integer permutation to represent the execution order of tasks, ensuring adherence to precedence constraints.
- (2) Segment 2 (Resource Mode): Each task is assigned a mode label (Human, Robot, or Collaborative), represented by numerical values 0, 1, and 2, respectively.
- (3) Segment 3 (Station Assignment): Utilizing a sequential rotation method, tasks are allocated to either the left or right side of the assembly line based on load-priority rules.

This encoding structure preserves the topological logic of the tasks while flexibly representing collaboration modes and spatial layout characteristics. Furthermore, it facilitates subsequent operator manipulations and feasibility recovery.

#### 4.2.2. Non-dominated Sorting Mechanism for Objective Vectors

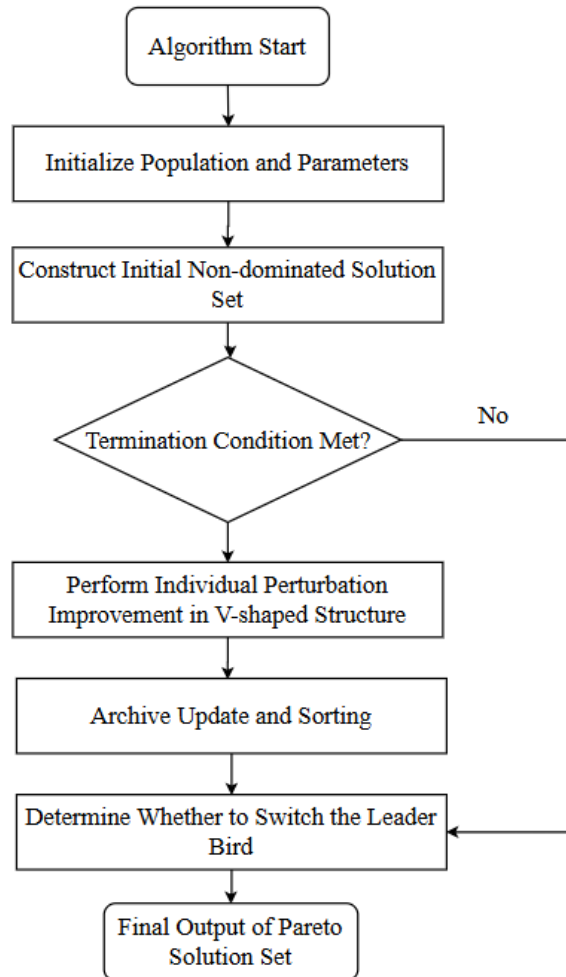
To address the conflicts between multiple objectives, this paper introduces a Pareto non-dominated sorting mechanism based on the NSGA-II framework. Individual migrating birds are stratified according to their objective vectors, and crowding distance is incorporated for selection and retention. The specific procedure is as follows:

- (1) Pareto Sorting: The population is divided into multiple non-dominated fronts using Pareto dominance;
- (2) Crowding Distance Calculation: Within each front, the crowding distance is calculated based on the density of solutions in the objective space;
- (3) Diversity Maintenance: Individuals are selected based on front priority and crowding control to preserve population diversity;
- (4) External Elite Set: An external archive is maintained to record the current set of non-dominated solutions.

This mechanism avoids the limitations of linear weighting methods used in traditional single-objective approaches, thereby enhancing the diversity and adaptability of the resulting solutions.

### 4.3. Procedure and Implementation of the Multi-Objective Migrating Birds Optimization Algorithm

By integrating the aforementioned designs, the overall procedure of the proposed Multi-Objective Migrating Birds Optimization (M-MBO) algorithm is illustrated in Figure 2. The core steps are as follows:



**Figure 2.** Flowchart of the proposed Multi-Objective Migrating Birds Optimization (M-MBO) algorithm

Step 1: Population Initialization and Parameter Setting

First, the algorithmic parameters are defined, including the population size  $N$ , the maximum number of iterations  $T$ , and the leader rotation period  $r$ . Subsequently, multiple individuals satisfying the technological precedence constraints are randomly generated. Each individual is composed of a three-segment encoding: task sequence, execution mode, and workstation mapping, forming the initial population.

#### Step 2: Objective Function Calculation and Non-dominated Sorting

For all individuals in the population, three objective values are calculated: Cycle Time (CT), Resource Cost (CA), and the Comprehensive Workload Balancing Index (CSI). The NSGA-II framework is employed to perform non-dominated sorting and calculate the crowding distance, thereby constructing the Pareto front and the elite archive.

#### Step 3: V-shaped Structure Construction and Role Assignment

The current optimal solution is selected as the "leader bird" based on the non-domination rank and diversity metrics, while the remaining individuals are distributed into the left and right wings according to a V-shaped structure. This structure guides the algorithm in information propagation and local updates through bio-inspired collective collaboration.

#### Step 4: Local Perturbation and New Solution Generation

In each generation, different types of perturbation operators—including task sequence swapping, execution mode switching, and workstation load fine-tuning—are applied to the leader and the wing individuals. This process generates new candidate solutions and enhances the local exploitation capability of the population.

#### Step 5: Update of Non-dominated Solution Set and Elite Archive

The newly generated offspring are merged with the original population. The algorithm then recalculates the non-domination ranks and crowding distances to update the Pareto set and the external elite archive, ensuring the retention of representative non-dominated individuals.

#### Step 6: Periodic Leader Rotation and Flock Restructuring

After every  $r$  generation, a new leader bird is re-selected based on historical contribution or diversity indices, and the V-shaped structure is reconstructed. This mechanism effectively enables the algorithm to escape from local optima and maintains robust global exploration capabilities.

#### Step 7: Termination and Result Output

If the maximum number of iterations  $T$  is reached or the Pareto set remains stable, the algorithm terminates. The current elite archive is then exported as the final non-dominated solution set.

## 5. CONCLUSIONS AND FUTURE WORK

### 5.1. Research Conclusions

Against the backdrop of advancing intelligent manufacturing, traditional assembly lines face multifaceted challenges, including insufficient flexibility, uneven worker workload, and low human-robot collaboration (HRC) efficiency. This study focuses on the two-sided assembly line balancing problem (TALBP) under a human-robot hybrid serial mode, incorporating comprehensive workload assessments. By centering on task assignment and resource scheduling, this research performs systematic modeling and algorithmic optimization, achieving the following pivotal results:

(1) This paper classifies human-robot collaboration modes and identifies the human-robot hybrid serial mode—the most representative in industrial applications—as the primary research focus. Based on a comprehensive analysis of collaborative task flows, station layouts, and coordination mechanisms, the RULA assessment and the Task Stiffness Method are introduced to quantitatively

model physical and mental workloads. This establishes a workload-oriented integrated task evaluation index system, providing a foundation for ergonomic-friendly modeling.

(2) To address practical requirements such as multi-mode task options, two-sided layouts, workload balancing, and cost control, a multi-objective optimization model for assembly line balancing is proposed. Beyond the traditional objective of cycle time minimization, the model incorporates resource cost and workload smoothness, forming a triadic trade-off structure of "Efficiency-Cost-Human Factors." The model utilizes a three-segment encoding scheme (Task–Mode–Station) to accurately represent collaborative flexibility and resource allocation pathways.

(3) Finally, this study extends and structurally improves the Migrating Birds Optimization (MBO) algorithm to develop the M-MBO algorithm specifically for collaborative assembly problems. By integrating non-dominated sorting and crowding distance control, the algorithm achieves a comprehensive search of the multi-objective solution space. Furthermore, the leader rotation and local perturbation strategies enhance convergence stability and the ability to escape local optima.

## 5.2. Limitations and Future Work

While this study provides a systematic exploration of model construction and algorithmic improvements, certain limitations remain, offering space for expansion in future research.

(1) First, the proposed optimization model is currently based on deterministic input parameters and does not account for stochastic factors inherent in production environments, such as robot malfunctions, worker fatigue accumulation, or material supply delays. Future research could incorporate robust optimization or stochastic scheduling mechanisms to enhance the model's resilience to real-world disturbances.

(2) Second, the workload assessment methodology primarily relies on task-level indicators, lacking a dynamic characterization of cognitive fatigue evolution during continuous multi-task operations. Subsequent studies could integrate physiological sensor data with real-time operational records to achieve more granular and dynamic human factors modeling.

(3) Third, In terms of algorithmic design, although the M-MBO demonstrates capable diversity maintenance and local exploitation, there is still room for improvement in high-dimensional Pareto front control and the clustering quality of solution sets. Future iterations could introduce Estimation of Distribution Algorithms, deep learning-assisted search mechanisms, or reinforcement learning-based intelligent scheduling strategies to further boost solution efficiency and adaptability.

(4) Finally, this study focuses on a single two-sided assembly line and does not address more complex manufacturing structures, such as interlinked multi-line systems or mixed-model production for high-variety products. As the deployment of collaborative robots scales up, the current model could be extended to large-scale intelligent manufacturing scenarios, including multi-line collaborative scheduling and multi-stage assembly system optimization.

## REFERENCES

- [1] Hu, C. Exploration of application models of collaborative robots in industrial production. *Mould Manufacturing*, Vol. 25(6), pp. 243–245, 2025.
- [2] Zhong, W., Li, J., Ge, R., et al. A brief analysis of the application of collaborative robots in automotive final assembly. *China Equipment Engineering*, Vol. (S2), pp. 351–353, 2024.
- [3] Chen, X., Tong, M., & Xiu, S. Application and development of human–robot collaborative robots in the automotive final assembly industry. *Precision Manufacturing and Automation*, Vol. (03), pp.1–4, 2020.
- [4] Guan, M., Yuan, P., & Wang, S. Study on bilateral assembly line balancing problem based on hybrid fruit fly algorithm. *Computer Integrated Manufacturing Systems*, Vol. 31(1), pp.56–66, 2025.
- [5] Lan, Y., Wu, J., Yan, H., et al. Comparative study of bus driver posture risk assessment using OWAS, RULA, and REBA. *Chinese Journal of Industrial Medicine*, Vol. 38(2), pp. 118+125+119–124, 2025.

- [6] Yu, S., Jia, N., Xu, M., et al. Application and comparison of OWAS and RULA posture load assessment methods in the steel industry. *Occupational Health and Emergency Rescue*, Vol. 41(2), pp. 166–171, 2023.
- [7] Biondi, F. N., Cacanindin, A., Douglas, C., & Cort, J. Overloaded and at Work: Investigating the Effect of Cognitive Workload on Assembly Task Performance. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, Vol. 63(5), pp. 813–820, 2020.
- [8] Dalle Mura, M., & Dini, G. Job rotation and human–robot collaboration for enhancing ergonomics in assembly lines by a genetic algorithm. *The International Journal of Advanced Manufacturing Technology*, Vol. 118(9-10), pp.2901–2914, 2021.
- [9] Lee, T. O., Kim, Y., & Kim, Y. K. Two-sided assembly line balancing to maximize work relatedness and slackness. *Computers & Industrial Engineering*, Vol. 40(3), pp.273–292, 2001.
- [10] Mao, Z., Sun, Y., Fang, K., Huang, D., & Zhang, J. Balancing and scheduling of assembly line with multi-type collaborative robots. *International Journal of Production Economics*, Vol. 271, pp.109207, 2024.
- [11] Nourmohammadi, A., Fathi, M., & Ng, A. H. C. Balancing and scheduling assembly lines with human-robot collaboration tasks. *Computers & Operations Research*, Vol. 140, pp.105674, 2022.
- [12] Otto, A., & Scholl, A. Incorporating ergonomic risks into assembly line balancing. *European Journal of Operational Research*, Vol. 212(2), pp.277–286, 2011.
- [13] Ren, B., Zhou, Q., & Chen, J. Assessing cognitive workloads of assembly workers during multi-task switching. *Scientific Reports*, Vol. 13(1), 2023.
- [14] Stecke, K. E., & Mokhtarzadeh, M. (2021). Balancing collaborative human–robot assembly lines to optimise cycle time and ergonomic risk. *International Journal of Production Research*, pp.1–23.
- [15] Wang, L., Gao, R., Váncza, J., Krüger, J., Wang, X. V., Makris, S., & Chryssolouris, G. Symbiotic human-robot collaborative assembly. *CIRP Annals*, Vol. 68(2), pp.701–726, 2019.
- [16] Weckenborg, C., Kieckhäfer, K., Müller, C., Grunewald, M., & Spengler, T. S. Balancing of assembly lines with collaborative robots. *Business Research*, Vol. 13(1), pp.93–132, 2019.