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Balancing assembly lines with industrial and collaborative robots: Current trends and future research directions

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ABSTRACT

Assembly-line balancing is a significant issue in production systems. Employing industrial robots as the main production resource was a milestone in developing assembly lines, and emerging Industry 4.0 led industries to build collaborative assembly lines by combining robots and human operator skills. Recently, the majority of research on assembly line balancing has contributed to addressing aspects of utilizing robots in assembly lines and how they can increase line performance. Various models and methods are developed, considering different objectives and performance indicators. Despite the increasing number of studies in this area, a thorough literature review is lacking in identifying gaps, shedding light on research directions, and facilitating future development. This study systematically reviews assembly-line balancing studies targeted at assembly lines with industrial and collaborative robots. Studies are classified based on their objectives and reviewed for their solution method, line layout, and other essential specifications. A descriptive analysis is provided to assist researchers and practitioners in linking different properties of assembly lines to the objectives and applied methodologies. The results show that most studies developed models and solution methods that focused on simultaneously optimizing more than one objective. The review reveals that minimizing the cycle time is the most popular objective, and meta-heuristic algorithms are the dominant solution approaches. It is also observed that balancing assembly lines with collaborative robots has received more attention in the last five years with the emergence of Industry 4.0. The review also highlights gaps in the related literature and provides promising insights for future research.

Nomenclature

Abbreviation	Description
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ALBO	Assembly Line Balancing Optimization
ALBP	Assembly Line Balancing Problem
ALBP-HRC	Assembly Line Balancing Problem with Human-Robot Collaboration
ANN	Artificial Neural Network
B&B	Branch-And-Bound
BA	Bee Algorithm
BDA	Bender's Decomposition Algorithm

(continued on next column)

Nomenclature (*continued*)

Abbreviation	Description
BHEDA	Bound-Guided Hybrid Estimation Of Distribution Algorithm
BS	Beam Search
CMOES	Constraint Multi-Objective Evolutionary Strategy
CP	Constraint Programming
CPA	Cutting Plane Algorithm
CCPA	Chance-Constrained Programming Approach
CS	Cuckoo Search
DA	Dragonfly Algorithm
DE	Differential Evolutionary
DP	Dynamic Programming

(continued on next page)

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Nomenclature (*continued*)

Abbreviation	Description
EDA	Estimation of Distribution Algorithm
ESA	Evolutionary Strategy Algorithm
FEM	Full Enumeration Method
FLC	Fuzzy Logic Controller
GA	Genetic Algorithm
GD	Generational Distance
GLS	Guided Local Search
GP	Goal Programming
GWO	Grey Wolf Optimizer
HMOS	Hybrid Multi-Objective Evolution Strategy
HSA	Harmony Search Algorithm
IBS	Iterative Beam Search
ICS	Immune Clonal Selection
IFPA	Flower Pollination Algorithm
IGD	Inverted Generation Distance
IMABC	Improved Multi-Objective Artificial Bee Colony
IMOHGA	Improved Multi-Objective Hybrid Genetic Algorithm
ICA	Imperialist Competitive Algorithm
INLP	Integer Non-Linear Programming
IP	Integer Programming
ILP	Integer Linear Programming
MA	Memetic Algorithm
MBO	Migrating Bird Optimization
MGA	Modified Genetic Algorithm
MILP	Mixed-Integer Linear Programming
MISOCP	Mixed-Integer Second-Order Cone Programming
MM	Mixed-Model
MOCC	Multi-Objective Cooperative Co-Evolutionary
MOEA/D	Multiobjective Evolutionary Algorithm Based On Decomposition
MOPSO	Multi-Objective Particle Swarm Optimization
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
NSGA-III	Non-Dominated Sorting Genetic Algorithm III
OH	Other Heuristics
PABC	Pareto Artificial Bee Colony Algorithm
PAES	Pareto Archive Evolutionary Strategy
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle Swarm Optimization
RALBP	Robotics Assembly Line Problem
RSA	Restarted Simulated Annealing
SA	Simulated Annealing
SBA	Split-Based Approach
SLR	Systematic Literature Review
SM	Single-Model
VNS	Variable Neighborhood Search
WoS	Web of Science

1. Introduction

The assembly line is a flow-based production system in which the stations, as productive units, are aligned along a material handling device, such as a conveyor, to perform assembly operations. The workpieces are processed while consecutively passing through the station to deliver a complete product at the end of the line (Fathi et al., 2019; Wu et al., 2023). In general, assembly tasks are performed manually, automatically, or a combination of both, and assembly line efficiency is strongly influenced by the optimal allocation of tasks and resources to assembly stations. This issue motivated the emergence of a scientific problem called the assembly line balancing problem (ALBP). The ALBP is concerned with allocating tasks to workstations considering various constraints, such as precedence relationships, cycle time, and other technological and operational limitations. The assembly line balancing (ALB) process influences manufacturing performance and helps systems obtain economic advantages (Boysen et al., 2021).

Automation has recently changed the design of assembly lines from traditional configurations to more flexible and productive settings. This transition is predominantly aligned with developments in the manufacturing industry, shifting from mass production to customization. Advancements in assembly lines and a high level of automation have transformed ALB into a complex task requiring optimization techniques. The assembly line balancing optimization (ALBO) focuses on the optimal distribution of tasks and resources across multiple workstations such that some performance measures are optimized given a set of constraints (Fathi et al., 2018; Nourmohammadi et al., 2019). ALBO is performed by making decisions regarding system capacity (e.g., cycle time, number of stations, and station equipment) and assigning tasks to workstations. The expected outcome of an ALBO is to improve various metrics, such as line efficiency, throughput, cycle time, and flexibility (Wang & Yang, 2017).

Although the ALBP literature is dominated by studies addressing manual assembly lines, the competitive market and the emergence of Industry 4.0 require higher productivity and flexibility to cope with more complex and customized products. Particularly, Industry 4.0 promotes the widespread application of advanced robotic assembly lines to achieve the necessary production flexibility to personalize products based on changing customer preferences (Fathi & Ghobakhloo, 2020; Gualtieri et al., 2023). Intriguingly, the advent of Industry 5.0 is accompanied by a notable emphasis on utilizing advanced robotics to enhance the principles of product personalization and technical assistance. This signifies that the integration of advanced robotic assembly lines is anticipated to become increasingly prevalent and pervasive (Ghobakhloo et al., 2022). Retrospectively, assembly tasks require more repeatability and accuracy than they did a decade ago. Therefore, robots and various automated equipment are more commonly employed on assembly lines to improve flexibility and fulfill the automation requirements of Industry 4.0. Some advantages of assembly robots include performing tasks without exhaustion to keep assembly lines productive, manufacturing good-quality items, providing task safety, and mitigating human labor (Pérez et al., 2020). Human workers are essential resources in assembly lines because their flexibility and adaptability cannot be ignored. Thus, this need for human intervention in assembly lines aligns with the flexible and adjustable automation requirements of Industry 4.0 and drives the industry toward using a combined solution where humans and robots work collaboratively (i.e., human-robot collaboration) (Cai et al., 2022).

The automation requirements of Industry 4.0 have garnered considerable attention in recent years. As a result, industries have implemented platforms that facilitate the integration of collaborative robots, thereby enabling human-robot collaboration (HRC) (Nourmohammadi et al., 2024). Enabling these platforms raised two research problems: (a) the robotic assembly line balancing problem (RALBP), which is being utilized in automated lines with industrial robots; and (b) the assembly line balancing problem with human-robot collaboration (ALBP-HRC), which is being used in assembly lines empowered with collaborative robots. Industrial robots are traditional robotic systems designed for performing specific tasks in a controlled environment. Industrial robots often work independently at a distance from operators and require physical barriers due to safety concerns. In contrast, collaborative robots (i.e., cobots) are designed to work alongside human operators and benefit from advanced safety features and sensors for real-time interaction, enabling them to collaborate closely with humans without the need for barriers. In assembly line balancing problems, industrial and collaborative robots are chosen based on the nature of the assembly tasks, required precision, payload, and the desired level of collaboration with human operators (Grau et al., 2020).

The RALBP is a combinatorial optimization problem dealing with efficiently allocating tasks to workstations on an assembly line. The primary objective of RALBP is to find a balanced distribution of work tasks that could improve relevant performance criteria while considering various operational and technical constraints. The key elements of RALBP include a set of tasks to be performed, precedence relationships among the tasks, a set of workstations available for task execution, robot capabilities, task-specific processing times, and other constraints specific to the assembly process. The ALBP-HRC extends the RALBP by incorporating human workers into the assembly process alongside

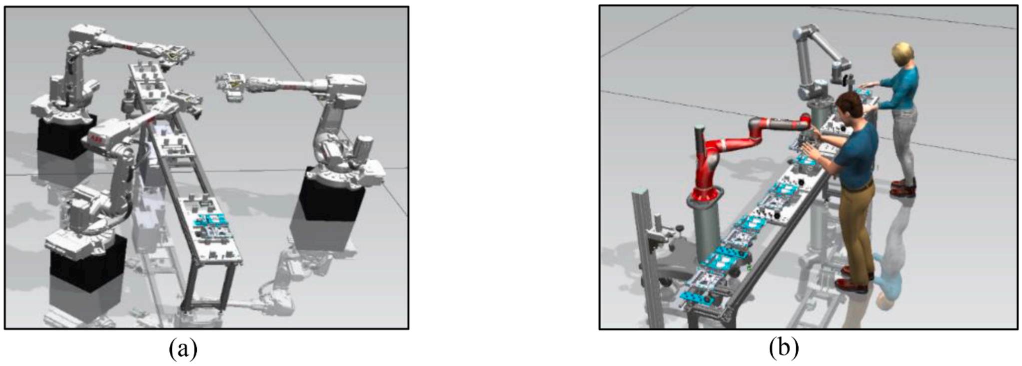


Fig. 1. An illustration of an assembly line with (a) industrial robots and (b) collaborative robots.

robotic resources, which is possible when cobots are available at workstations. ALBP-HRC focuses on the efficient allocation of tasks to both human workers and robots on the assembly line, considering their unique capabilities and collaboration constraints. The basic elements of ALBP-HRC are the same as those for RALBP, with some additional features related to the human worker-specific attributes, such as skill levels that are usually represented as varying processing times. This will also provide the possibility of performing joint tasks by humans and cobots at stations that add new dimensions to the problem, which requires not only the assignment of tasks to stations but also careful scheduling of tasks as human and cobot activities need to be synchronized. Moreover, precedence relationships among tasks should be satisfied not only when assigning tasks to stations but also within each station where humans and cobots work in parallel.

The solution methods used for RALBPs and ALBP-HRC can be interchangeable with certain modifications based on the problem definition. This difference is the result of varied worker types and compatibility, the interaction between humans and robots, safety concerns, and task compatibility to determine which tasks are best suited for robots and which are more appropriate for human operators considering their skills and processing time, and safety aspects, among other factors (Zhang et al., 2023).

This study aims to review existing studies on RALBP and ALBP-HRC due to the industrial shift from manual assembly lines toward lines with industrial and collaborative robots, which we believe is among the first detailed technical surveys in this scope. In addition, this study attempts to differentiate the novelties of each article in the corresponding literature based on their objectives and discuss the value each article proposes based on using different assembly line layouts and solution procedures. A simple illustration of an assembly line with industrial and collaborative robots is shown in Fig. 1.

Although recent review studies on ALBP can be found, this is the first attempt to target RALBP and ALBP-HRC precisely by scrutinizing the relevant research for the problem specification, assembly line layout, solution approaches, and optimization objectives. Boysen et al. (2021) conducted a survey synthesizing the scientific literature on assembly line balancing, encompassing data collection methods, new problem variants, algorithmic advancements, and outlining a future research agenda. Their study mainly provided expert views on existing literature and focused on identifying a future research agenda, thus not detailing the review study's specifics. In a separate analysis, Battaïa and Dolgui (2022) comprehensively examined combinatorial optimization in ALBPs, specifically delving into problem formulations and hybridization with other optimization problems such as process planning, workforce planning, and resource scheduling. Their review offered an overarching view of ALBP literature without reporting specifics of each reviewed paper. Another recent review by Chutima (2022) concentrated on RALBPs until 2019, classifying studies based on layout and the concept of man, machine, material, and method. However, it did not cover ALBP-HRC, which has recently gained prominence with Industry 4.0 and the human-centricity envisioned in Industry 5.0.

While these mentioned recent review studies advanced ALBPs' literature significantly, none conducted a systematic literature review (SLR). Moreover, these previous reviews did not scrutinize existing literature for a unique classification of studies based on optimization objectives, line shape, production specifications (such as assembly resources and production type), and solution approaches. To the best of the authors' knowledge, this current study represents the first SLR targeting RALBP and ALBP-HRC, offering a comprehensive view of existing studies and elucidating detailed aspects of addressed problems, solution methods, and assembly line and production specifications.

The main contribution of this study to the corresponding literature is to systematically review the articles published on RALBP and ALBP-HRC and classify them based on the optimization objectives. Moreover, detailed information on these studies is presented, such as line layout, solution approach, production type (single, multi, or mixed models), and production resources (single or multi-manned/robot). The categorization of studies based on objectives stems from the complex and multi-faceted nature of RALBP and ALBP-HRC, which encompass various dimensions. This complexity necessitates a unique classification system to accommodate the existing literature and support the ongoing progress within the research field for both researchers and practitioners. The primary motivations for the objective-based classification are threefold: Firstly, it provides a structured overview of diverse solution approaches tailored to specific objectives, allowing researchers to comprehensively grasp existing literature trends and identify research gaps. Secondly, it serves as a valuable resource aiding practitioners and decision-makers in manufacturing industries, guiding them toward efficient assembly line balancing strategies based on their main optimization objectives. Lastly, this classification facilitates comprehensive comparative analyses, enabling the assessment of solution methodologies, production model and resources, and line layouts in achieving similar optimization objectives, offering insights into their effectiveness and limitations.

This study aims to answer the following research questions (RQ):

RQ1. What objectives are mostly addressed in the literature, and how are these objectives differentiated in RALBPs and ALBPs-HRC?
RQ2. What are the most commonly addressed line layouts in these two research subjects?
RQ3. What solution methods are applied to solve RALBPs and ALBP-HRC?
RQ4. What are the future research opportunities on RALBPs and ALBPs-HRC?

The remainder of this paper is structured as follows. Section 2 formally defines the RALBP and ALBP-HRC, incorporating their assumption and basic mathematical models. Section 3 presents a review methodology to collect, analyze, and report the outcomes of analyzing the corresponding literature. Section 4 reviews the literature identified in RALBPs and ALBP-HRC for their objective(s), line layout, and solution procedure. Moreover, the important assumptions and novelties of each research work are compared with the rest of the literature. Section 5 discusses the results obtained from the review, including a descriptive analysis of the reviewed articles, the determination of knowledge gaps, and suggestions for future research. Finally, Section 6 presents the discussion and conclusions of this study.

2. RALBP and ALBP-HRC

In the classic ALBP, known as simple ALBP (SALBP), a series of assembly tasks are assigned to manual, human-operated workstations along the assembly line. These workstations are interconnected by material handling devices, such as conveyor belts (Fathi et al., 2020). The main goal of SALBP is to evenly distribute tasks among the workstations while adhering to basic constraints such as task precedence relationships, maximum available cycle time, and the number of workstations. The objectives often include minimizing the number of workstations (Type-I) and cycle time (Type-II). Key inputs include task precedence relations and workstation limitations, each task's processing time, the initial number of workstations, and cycle time (Nourmohammadi et al., 2019). No task splitting is allowed, and it is assumed that all workstations are similar in terms of equipment and operator capabilities. Thus, any task can be performed at any workstation. Furthermore, the line is typically envisioned as a paced, straight-shaped line without buffers, having only one human operator per workstation and producing a single-model product.

The inclusion of robots in assembly lines has led to a new variant of ALBP known as robotic ALBP (RALBP). Dealing with the basic RALBP requires not only the inputs necessary for SALBP but also additional details such as robot capabilities, the total number of available robots mainly imposed due to the high robot cost, and the robot's operation time for each task. With technological advancements and the incorporation of cobots in assembly lines, companies now leverage human operators' flexibility and agility alongside robots' reliability and precision. This synergy has introduced new challenges in balancing assembly lines, known as ALBP-HRC. Most assumptions and constraints of RALBP apply to ALBP-HRC, with additional considerations related to the possibility of human and robot collaboration at each workstation that requires sharing tasks within each workstation to ensure the technological requirements imposed by the precedence constraints.

To better clarify the difference between the SALBP, RALBP, and ALBP-HRC, the problems are formally introduced in the next section.

2.1. Problem definition

In the SALBP, an assembly line consists of $i = \{1, \ldots, I\}$ tasks, each with a processing time of t_i, that should be performed by human operators in a set of workstations denoted as $j = \{1, \ldots, J\}$. Tasks have precedence relations $(i, j) \in P$ that must be satisfied when assigning tasks to workstations. If task i is the immediate predecessor of task j, it should be assigned to the same or an earlier station than j. The overall time of a station cannot exceed a maximum allowed time, known as cycle time, T_c. The primary objective of the optimization is to minimize the T_c for a given number of workstations, or vice versa. A detailed explanation of SALBP can be found in Scholl (1999).

In the basic RALBP, the SALBP is extended by deciding on the operator type W={robot (R) or human (H)} at each station, while the processing time of each task i, might differ for each operator type, tiw. However, not all tasks might be feasible for automated or manual execution; therefore, both operator types might not be available for all tasks. A fully robotic line enforces the use of only robots at the workstations. In contrast, in a semi-robotic line, there might be a combination of both, though only one type is allowed per workstation.

ALBP-HRC extends the RALBP by allowing both operator types $W = \{R \text{ and } H\}$ to be assigned to each station, thus enabling human-robot collaboration. This extension adds a new dimension to the problem and necessitates scheduling at each workstation, as humans and robots can work on different tasks at the same workstation. Therefore, precedence relations within a workstation must be preserved by tracking the start and end times of the tasks.

The main assumptions of the classical problem are as follows:

- The assembly line is one-sided, with workstations arranged in a straight line.
- Only one product type is produced on the line, indicating a single model production.
- The maximum number of workstations and the cycle time are predetermined and known.
- The processing time for each task varies depending on the operator type (i.e., human and robot), and these times are known and deterministic.
- Operators from each type (human or robot) are equivalent in terms of capability and speed.
- Each workstation can be configured as follows: only one human (SALBP), either one human or one robot (RALBP), a human and/or a robot (ALBP-HRC).
- A task can only be assigned to one workstation, and splitting tasks between workstations is not allowed.
- Precedence relationships between tasks are established and provided.
- The maximum number of operators for each type (human and robot) is specified.
- Not every operator type can perform every task, and the specific capabilities of each operator type are predefined.
- The assembly line operates as a paced line without buffers.

2.2. Problem formulation

To elucidate the key differences between problem types, this section outlines the mathematical models for basic SALBP, RALBP, and ALBP-HRC. These models serve as references for understanding the primary inputs, decision variables, and constraints of each problem type. It is noteworthy that the models presented here are adapted from Koltai et al. (2021) and modified to suit the purposes of this study.

Each model is formulated to address two common objectives for each basic problem type: minimizing the number of workstations (Type-I) and minimizing the cycle time (Type-II). In total, six models are presented: SALBP-I, SALBP-II, RALBP-I, RALBP-II, ALBP-HRC-I, and ALBP-HRC-II. Considering that some constraints are common among different models, all objectives and constraints are consolidated into equations 1 to 20. The active objective and applicable constraints for each model are designated with the symbol (●). For example, for SALBP-I, the active objective is represented by equation 1, indicating the objective of minimizing the number of workstations (Type-I), and the active constraints are equations 3, 4, 5, 6, 7, and 9.

The terminologies used in the models are listed below, and the functionality of each constraint is explained immediately following the model.

List of notation

Indices	
i, k	Task index $(1, \cdots, I)$
j	Workstation index $(1, \cdots, J)$
w	Operator type index
Parameters	
I	Total number of tasks
J	Maximum number of workstations
t_{iw}	Processing time of task i if performed by operator type w
T_c	Maximum given cycle time
K	Total number of available robots
NH	Total number of available human operators
W	Set of operator types: human (H) and robot (R)
P_i	Set of the immediate predecessors of task i

(continued on next page)

List of notation (*continued*)

Indices	
NA_w	Set of tasks that cannot be handled by operator type w
Decision variables	
x_{ijw}	Binary decision variable: 1 if task i is assigned to workstation j and performed by operator type w; 0 otherwise
l_{jw}	Binary decision variable: 1 if operator type w is assigned to workstation j; 0 otherwise
s_i	Real positive: start time of task i
e_i	Real positive: end time of task i
N	Number of workstations
T	Cycle time

		SALBP		RALBP		ALBP-HRC	
		I	II	I	II	I	II
(1)	$\text{Min}(N)$	●		●		●	
(2)	$\text{Min}(T)$		●		●		●
(3)	$\sum_{j,w} x_{ijw} = 1\ \forall i$	●	●	●	●	●	●
(4)	$\sum_{j,w} j\left(x_{ijw} - x_{kjw}\right) \geq 0\ \forall(i,k)\middle\vert k \in P_i$	●	●	●	●	●	●
(5)	$x_{ijw} = 0\ \forall(i,j,w)\vert i \in NA_w$	●	●	●	●	●	●
(6)	$\sum_i x_{ijw} t_{iw} \leq T_c\ \forall(j,w)$	●		●		●	
(7)	$\sum_j j^* x_{ijw} \leq N \forall(j,w)$	●		●		●	
(8)	$\sum_i x_{ijw} t_{iw} \leq T\ \forall(j,w)$		●		●		●
(9)	$\sum_j x_{ijR} = 0$	●	●				
(10)	$\sum_{i \notin NA_w} x_{ijw} \leq l_{jw}\ \forall(j,w)$			●	●	●	●
(11)	$\sum_w l_{jw} \leq 1\ \forall j$			●	●		
(12)	$\sum_i x_{ijw} \geq l_{jw} \forall(j,w)$			●	●	●	●
(13)	$\sum_j l_{jR} \leq K$			●	●	●	●
(14)	$\sum_j l_{jH} \leq NH$			●	●	●	●
(15)	$e_i \leq T_c\ \forall i$					●	
(16)	$\left(\sum_w x_{ijw}\right)\left(\sum_w x_{kjw}\right)(s_k - e_i) \geq 0\ \forall(i,k,j)\vert i \in P_k$					●	●
(17)	$\left(\sum_w x_{ijw}\right)\left(\sum_w x_{kjw}\right)(s_k - e_i)(s_i - e_k) \leq 0\ \forall(i,k,j)\vert P_i \cap P_k \neq \varnothing$					●	●
(18)	$e_i = s_i + \sum_{j,w} x_{ijw} t_{iw}\ \forall i$					●	●
(19)	$e_i \geq 0; s_i \geq 0\ \forall i$					●	●
(20)	$e_i \leq T\ \forall i$						●

Equations 1 and 2 represent the objective Type-1 (minimizing the number of workstations) and Type-2 (minimizing the cycle time), respectively. Constraint (3) ensures that each task is assigned to only one workstation. Constraint (4) dictates that Task k must not start before task i if k is a successor of i.

Constraint (5) stipulates that a task can only be assigned to an operator type if it is capable of performing the task. Constraint (6) ensures that the total time of tasks assigned to a workstation does not exceed the maximum cycle time for Type-I problems. Constraint (7) calculates the greatest index of an assigned workstation and links it to the objective when addressing the Type-I problem. Constraint (8) ensures that the cycle time equals the sum of the times of the tasks at the most loaded workstation, linking it to the objective function for the Type-II problem. Constraint (9) restricts the assembly line to human operators only for SALBP. Constraint (10) ensures that a task can only be assigned to a station if the appropriate operator type has been assigned to that station. Constraint (11) limits each station to only one type of resource for RALBP. Constraint (12) implies that an operator type is assigned to a station if at least one task that this operator type can handle has been assigned to the workstation. Constraints (13) and (14) ensure that the number of robots and humans assigned to the line does not exceed the maximum number of available robots and human operators, respectively. Constraint (15) ensures that the completion time of tasks assigned to each station is less than the cycle time for the Type-I problem. Constraint (16) maintains precedence relationships between tasks assigned to a workstation with more than one operator. Constraint (17) ensures that for tasks processed in the same station, the start time of a successor task does not precede the end time of its predecessor. Constraint (18) calculates the end time of a task, which is equal to its start time plus its execution time. Constraint (19) is the non-negativity constraint for task start and end times. Constraint (20) ensures that the cycle time is equivalent to the end time of the last task at the most loaded workstation when addressing the Type-II problem.

2.3. Problem extension considering line and production configurations

Over the years, the introduced classical problems have evolved to meet real-world industrial needs by considering various aspects of production. Key characteristics that differentiate production settings include the assembly line layout, the type and number of assembly resources at workstations, and the production model.

The assembly line layouts studied in existing research include straight, U-shaped, parallel, two-sided, and four-sided designs. In a straight-line layout, all workstations are arranged in a serial manner, with assembly tasks assigned from one direction. In contrast, a U-shaped layout allows tasks to be assigned from both sides of the line (Nourmohammadi et al., 2023a). Parallel lines typically consist of duplicated lines, facilitating the execution of parallel tasks. In two-sided lines, tasks are performed on both sides of the conveyor, differing from traditional lines where tasks are confined to one side. This setup means each workstation comprises two sub-stations, often called mated-workstations (Aslan, 2023). The concept of four-sided assembly workstations is highlighted in a recent study by Rabbani et al. (2020). This layout involves arranging workstations in a square or rectangular pattern, enabling access to the assembly object from the left, right, above, and beneath. However, tasks above the assembly object are typically restricted to robots. Four-sided layouts are prevalent in industries producing large, complex products, such as automotive manufacturing (especially for buses and trucks), heavy equipment production, and other sectors where large-scale products necessitate efficient assembly processes.

In terms of resources, there may be one or more assembly resources (human or robot) at each workstation. In manual assembly lines, the term single-manned or multi-manned indicates the allocation of human resources to workstations or tasks. In a single-manned assembly line, one human operator manages the workstation, while in multi-manned assembly lines, multiple human operators are responsible for a single workstation (Chen et al., 2018). In robotic assembly lines, robots replace human operators, leading to the use of the terms single-robot and multi-robot assembly lines (Lopes et al., 2017). Similarly, in assembly lines with human-robot collaboration, where both human operators and collaborative robots (cobots) are present at a workstation, the terminology adapts to single-manned/robot for configurations with one human and one cobot and multi-manned/robot when more operators and/or cobots are involved.

The production type on assembly lines can be classified as single, multi, and mixed models (Nourmohammadi et al., 2023b; Fokkert & Kok, 1997; Becker & Scholl, 2006). A single-model line is dedicated to producing a single product, and the tasks on the line are specific to the assembly of that single product. In multi-model ALBPs, the assembly line is designed to produce different models in large batches, and the tasks on the line may vary depending on the product being assembled. The mixed-model line is more flexible and is designed to produce multiple product variants simultaneously on the same line.

3. Review methodology

This study adopts a systematic literature review (SLR) approach to collect, classify, and analyze articles in the scope of RALBP and ALBP-HRC. This process identifies existing trends, theoretical implications, and future opportunities for balancing assembly lines with industrial and collaborative robots. Employing SLR has the advantage of identifying relevant research works, proposing a selection process, and analyzing the most related publications to address the research

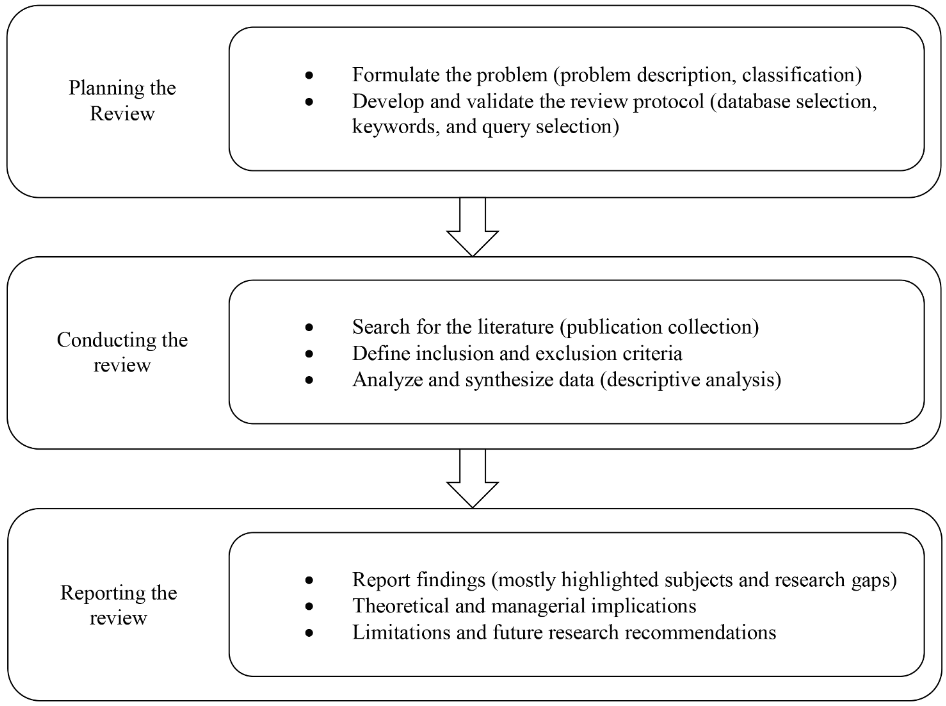


Fig. 2. Steps of SLR.

Table 1
Exclusive criteria proposed in the developed SLR.

Criteria	Description
EXC1	The publication is not written in English
EXC2	The publications whose full text is not accessible or not being accepted in subscription-based or open-access journals
EXC3	The publications in the format of review articles, editorial materials, notes, and meeting abstracts
EXC4	The main theme of the article is not RALBP or ALBP-HRC, and no optimization methodology is applied
EXC5	Merging the articles from both databases and removing duplicate articles (articles that are categorized as ALBP-HRC are removed from the search of RALBP to make a distinction between these two types of problems)

questions mentioned in Section 1. Following the existing SLR guidelines (Xiao & Watson, 2019), the steps conducted for the systematic review in this study are summarized into three phases, as shown in Fig. 2.

In the review planning stage, the main problem was formulated, and different classifications of the problem were addressed to facilitate the keyword selection process. Previous review articles on similar subjects were used to achieve this goal. Subsequently, two scientific databases encompassing the majority of articles were selected, and the search process was performed using a query consisting of relevant keywords. When conducting the review, an initial pool of articles was collected, and different exclusion criteria were defined to refine the pool and extract those that contributed to the subject of the review. After analyzing and synthesizing the final extracted publications, a descriptive analysis was conducted to help the research team identify the knowledge gaps and subjects more frequently addressed in the literature. These classifications and gaps are further reported in the third stage, theoretical implications are derived, and future research perspectives are recommended from the mentioned analysis.

Particularly for a fair and reliable review, the preferred reporting items for systematic reviews and meta-analyses (PRISMA) (Moher et al., 2009) method was adopted to guarantee the reliability of the gathered database (Page et al., 2021). Table 1 lists the exclusion criteria for filtering the initial pool of articles found by searching via queries. The proposed SLR aimed to answer the research questions using descriptive analysis and by analyzing the identified gaps in the literature. Based on the PRISMA method, the adopted SLR approach looks for articles in the context of original research, letters, case studies, and notes published in journals, conference proceedings, or book chapters. The exclusion criteria ensured that the final database contained research articles that were written in English with a centric theme on RALBP or ALBP-HRC.

The following two queries containing keywords related to the utilization of robots in assembly line balancing problems were developed to identify related documents.

- RALBP query: ((robot)OR(robotic))AND((assembly line)AND((balance)OR(balancing)))
- ALBP-HRC query: (((collaborative)OR(collaboration))AND((robot) OR(robotics)))OR((human robot)OR(cobot))AND((assembly line) AND((balance)OR(balancing)))

After using the queries and searching in Scopus and Web of Science (WoS) and filtering the search to topic, abstract, and keywords, the initial pool of articles in each of the databases was obtained. The identified articles were further subjected to the exclusion criteria to shortlist eligible articles for content analysis.

Notably, many articles found using the first query already exist in the pool of the second query. After filtering each article to see if it discusses RALBP or ALBP-HRC, these two categories were differentiated, and the articles found were reviewed in separate sections. In the initial search on WoS conducted in November 2023, 201 articles were found when using the RALBP query, and 191 articles were found when using the ALBP-HRC query. These numbers were 242 and 271, respectively, when searching Scopus. Fig. 3 shows the steps in obtaining the final pool of articles by applying the exclusion and inclusion criteria.

4. Review results and findings

The collected articles on RALBP and ALBP-HRC are reviewed in this section to determine the most frequently addressed objectives, assembly layouts, and a variety of solution methodologies (exact, heuristic, and

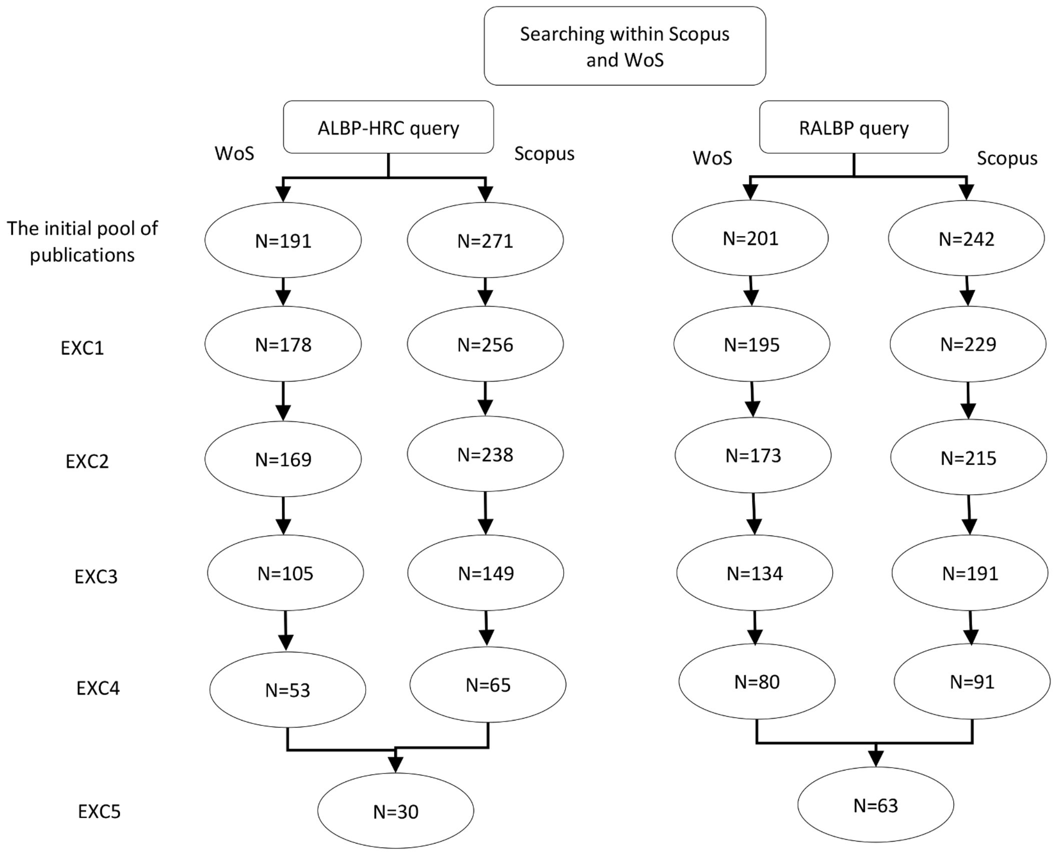


Fig. 3. Article collection and filtering process.

Table 2
The optimization objective(s) considered in the reviewed RALBP and ALBP-HRC studies.

Types of RALBP and ALBP-HRC	Objective
Type I	Min (number of workstations)
Type II	Min (cycle time)
Type C	Min (total cost) – Min (robot cost) – Min (robot setup cost) – Max (total profit)
Type O	Min (workload variance) – Min (makespan) – Max (production rate) – Min (energy consumption) – Min (ergonomic risk) – Min (energy load variance) – Max (seizing components), etc.
Type H	Combination of at least two of the abovementioned objectives

meta-heuristic). In addition, the production type (i.e., single, multi, mixed models) and the assembly resources (i.e., single- or multi-manned/robot) are reported for the reviewed studies. This section contributes to answering RQ1 to RQ3.

The collected articles are classified into tables to visualize the research gaps and possible future developments. Based on the initial search and scanning of all the collected articles, the RALBPs and ALBPs-HRC are grouped into five types based on the objective(s) they aim to optimize, as presented in Table 2. Although the objective function served in this study as the primary criterion for classifying the RALBP and ALBP-HRC literature, other distinctions regarding assembly line layouts, solution methodologies, and production specifications (i.e., types and resources) are reported for each study. This comprehensive approach aims to facilitate in-depth comparisons and enable further classifications within the scope of these analyses.

4.1. Review of RALBP studies

The main differences between classic ALBP (i.e., SALBP) and RALBP are discussed in Section 2. Addressing RALBP requires not only the inputs necessary for SALBP but also additional information about robot capabilities, such as precision, payload capacity, tooling requirements, and operation times for each task-robot combination. Beyond typical constraints for classic ALBP, such as precedence relationships and maximum cycle time, task assignment in RALBP is influenced by factors like task repeatability, precision requirements, quality, and safety concerns. Robot-related costs, including acquisition, operating expenses, and energy usage, are crucial in RALBP and may necessitate additional constraints on budget and energy consumption. Other constraints related to tool availability and robot capabilities are also typical in RALBP. Moreover, balancing objectives might be extended to include minimization of energy consumption, carbon emissions, robot and tool costs, and tool change times, among others. Following the classification presented in Table 2, the published articles identified on RALBP using the explained SLR method are reviewed in this section.

4.1.1. RALBP-type I (RALBP-I)

RALBP-I aims to minimize the number of workstations or robot cells in an assembly line. Assuming only one robot is in each cell, reducing the number of robot cells is equivalent to minimizing the number of workstations. Rubinovitz et al. (1993) pioneered the first mathematical model for RALBP-I. They employed a branch-and-bound (B&B) technique, integrating frontier search methods to determine the optimal number of workstations needed in the assembly line. Considering a simple ALBP, which contains a single product and a single robot in each workstation, the main inputs of the B&B algorithm in this elaboration were the operation times associated with the different types of equipment, their cost, and a set of potential assembly sequences. In another

Table 3
Summary of RALBP-I studies.

Author (s)	Line layout	Solution method		Solution approach	Production				
					Single/multi/mixed model			Assembly resources	
	Straight	Heuristic and Meta-heuristic	Exact		Single	Multi	Mixed	Single-robot	Multi-robot
Rubinovitz et al. (1993)	✓		✓	B&B	✓			✓	
Kim and Park (1995)	✓		✓	ILP, CPA	✓			✓	
Hong and Cho (1997)	✓	✓		SA	✓			✓	
Koltai et al. (2021)	✓		✓	MILP	✓			✓	

study on RALBP-I proposed by Kim and Park (1995), they aimed to minimize the total number of robot cells when precedence constraints of tasks and cycle-time requirements exist. The problem was formulated as an integer linear programming (ILP) model and solved using the strong cutting plane algorithm (CPA) approach to avoid the ineffectiveness of the B&B algorithm for a high number of branches. Subsequently, a study proposed by Hong and Cho (1997) addressed a single-model and deterministic RALBP-I to minimize the number of workstations using a simulated annealing (SA) method. In a recent study, Koltai et al. (2021) developed an efficient MILP addressing the RALBP-I. The authours validated the model and compared it results with other problem types.

A summary of the discussed articles is presented in Table 3. According to this table, both exact and non-exact solution approaches were used in three articles. In addition, all studies assumed that the robot cells were working in a straight assembly line, only one robot was available at each workstation, and a single model product was assembled at the line. Therefore, using other shapes of assembly lines, multi-or mixed-production, and the possibility of using multi-robot at workstations can contribute to the corresponding literature in future works since they can increase the flexibility and productivity of the assembly process. Based on the information collected from the review, most recent research discussing minimizing workstations also considers objectives like minimizing cycle time or energy consumption. Hence, these studies are predominantly categorized under RALBP-H. Moreover, the literature review revealed a shift in recent studies from focusing on minimizing workstations to other objectives, which limited the RALBP-I literature to older studies. However, it is crucial to note that the initial studies within RALBP-I laid the foundation for subsequent research in the broader context of RALBP and ALBP-HRC.

4.1.2. RALBP-type II (RALBP-II)

Levitin et al. (2002) first attempted to address the RALBP-II, aiming at minimizing the cycle time. They solved the problem by a genetic algorithm (GA) that adopts different procedures, such as a local optimization (hill climbing) workpiece exchange procedure, and the best combination of these procedures is tested with a set of randomly

Table 4
Summary of RALBP-II studies.

Author (s)	Line layout				Solution method		Solution approach	Production				
								Single/multi/mixed model			Assembly resources	
	Straight	U-shaped	Two-sided	Parallel	Heuristic and Meta-heuristic	Exact		Single	Multi	Mixed	Single-robot	Multi-robot
Levitin et al. (2002)	✓				✓		GA	✓			✓	
Levitin et al. (2006)	✓				✓		GA	✓			✓	
Gao et al. (2009)	✓				✓	✓	GA, INLP	✓			✓	
Nilakantan and Ponnambalam (2012)	✓				✓		PSO	✓			✓	
Aghajani et al. (2014)			✓		✓	✓	MILP, SA			✓	✓	
Müller et al. (2014)	✓					✓	MILP	✓				✓
Zacharia et al. (2015)	✓				✓		GA	✓			✓	
Nilakantan et al. (2015a)	✓				✓		PSO	✓			✓	
Nilakantan et al. (2015c)	✓				✓	✓	PSO, CS, INLP	✓			✓	
Nilakantan and Ponnambalam (2016)		✓			✓	✓	PSO, INLP	✓			✓	
Li et al. (2016a)			✓		✓	✓	MILP, PSO	✓			✓	
Nilakantan et al. (2017b)	✓	✓			✓		DE	✓			✓	
Çil et al. (2017a)	✓				✓	✓	MILP, BS			✓	✓	
Çil et al. (2017b)	✓				✓	✓	MILP, BS	✓			✓	
Çil et al. (2017c)				✓	✓	✓	MILP, BS	✓			✓	
Lopes et al. (2017)	✓					✓	MILP	✓				✓
Nilakantan et al. (2017c)	✓	✓			✓	✓	INLP, PSO	✓			✓	
Kammer Christensen et al. (2017)	✓				✓		OH		✓		✓	
Li et al. (2018a)			✓		✓		CS	✓			✓	
Borba et al. (2018)	✓				✓	✓	MILP, B&B, BS	✓			✓	
Janardhanan et al. (2019)	✓				✓	✓	MILP, MBO	✓			✓	
Li et al. (2019a)		✓			✓	✓	MILP, MBO	✓			✓	
Li et al. (2019b)			✓		✓	✓	MILP, ABC, MBO	✓			✓	
Sun and Wang (2021)	✓				✓	✓	B&B, EDA	✓			✓	
Koltai et al. (2021)	✓					✓	MILP	✓			✓	
Şahin and Tural (2023)	✓					✓	MILP, MISOCP, CP	✓			✓	
Aslan (2023)			✓		✓	✓	MILP, VNS			✓	✓	
Lahrichi et al. (2023)	✓				✓		SBA	✓			✓	

Table 5
Summary of RALBP-C studies.

Author (s)	Layout (Assembly line)		Objective		Algorithm type		Solution approach	Production				
								Single/multi/mixed model			Assembly resources	
	Straight	U-shaped	Min (total cost)	Max (total profit)	Heuristic and Meta-heuristic	Exact		Single	Multi	Mixed	Single robot	Multi robot
Nilakantan and Ponnambalam (2014)	✓		✓		✓		PSO	✓			✓	
Gultekin et al. (2016)	✓			✓	✓	✓	MILP, OH			✓	✓	
Nilakantan et al. (2017b)	✓	✓	✓		✓		DE	✓			✓	
Pereira et al. (2018)	✓		✓		✓	✓	ILP, MA	✓			✓	
Li et al. (2022a)	✓		✓		✓		BA			✓	✓	
Zhang et al. (2023)	✓		✓		✓		PSO	✓			✓	
Albus and Huber (2023)	✓		✓			✓	ILP	✓			✓	

generated problems. In a later study, Levitin et al. (2006) applied the GA to address the same problem while discussing the feasibility of adopting robots with different processing times, capabilities, and specializations. In later studies on RALBP-II, other assembly line layouts (e.g., two-sided, U-shaped, and parallel) and solution methods were applied to determine how the cycle time could be changed when using different settings.

Mixed-integer linear programming (MILP) has been utilized more than other methodologies to address RALBP-II. Half of the studies within RALBP-II developed and solved the problem using an MILP model. However, other exact methods, such as integer nonlinear programming (INLP) (Gao et al., 2009; Nilakantan & Ponnambalam, 2016; Nilakantan et al., 2015c, 2017c), B&B (Borba et al., 2018; Sun & Wang, 2021), and constraint programming (Şahin & Tural, 2023) have been employed to solve RALBPs-II. Due to the complexity of the problem, even if an exact method or mathematical model has been presented, most studies resorted to meta-heuristic algorithms.The most frequently applied algorithms in RALBs-II are particle swarm optimization (PSO) (Li et al., 2016a; Nilakantan and Ponnambalam, 2012, 2016; Nilakantan et al., 2015a, 2015c, 2017c), GA (Gao et al., 2009; Levitin et al., 2002, 2006; Nilakantan et al., 2015c; Zacharia et al., 2015), SA (Aghajani et al., 2014), artificial bee colony (ABC) (Li et al., 2019b), cuckoo search (CS) (Li et al., 2018a), beam search (BS) (Borba et al., 2018; Çil et al., 2017a, 2017b, 2017c), migrating birds optimization (MBO) (Janardhanan et al., 2019; Li et al., 2019a, 2019b), estimation of distribution algorithm (EDA) (Sun & Wang, 2021), and variable neighborhood search (VNS) algorithm (Aslan, 2023). In recent work, Lahrichi et al. (2023) addressed the RALBP-II and developed a split-based approach, integrating the optimal path algorithm with a metaheuristic algorithm. Şahin and Tural (2023) studied a stochastic RALBP to minimize the cycle time while assigning either a human or robot can be assigned to each workstation. The authors proposed some exact solutions to addressing the problem, namely, mixed-integer second-order cone programming (MISOCP), MILP, and CP.

The review shows that the parallel layout was used in only one study (Çil et al., 2017c) despite its significant impact in increasing the flexibility of the assembly line. In addition, U-shaped and two-sided layouts are not as well studied as straight layouts. Most studies have discussed single-model production, overlooking the variety of product types in the current competitive market. Only one article has discussed multi-manned workstations (Kammer Christensen et al., 2017). Most studies assume that only one resource is available at each workstation to avoid solution complexity. A summary of the reviewed articles is presented in Table 4.

4.1.3. RALBP-type C (RALBP-C)

The profit obtained from implementing robotics in assembly line balancing is an important aspect that can be formulated by quantifying the trade-offs between robot costs, including the investment, setup, and maintenance costs, and the profit obtained by minimizing human intervention in assembly operations. This problem is classified as RALBP-Type C, which aims to minimize costs (Pereira et al., 2018) or maximize profit (Gultekin et al., 2016). The economic dimension of RALBPs was initially explored by Yoosefelahi et al. (2012). Their study aimed to quantify both setup and operational costs associated with robots, while simultaneously seeking to minimize cycle time. However, Nilakantan and Ponnambalam (2014), who adopted four variants of PSO as a solution procedure to minimize the total production cost with a fixed number of workstations, proposed the first study that specifically examined the cost aspect of a RALBP.

In the case of a spot-welding line using robotics, Gultekin et al. (2016) addressed the scheduled unavailability periods in RALBPs. To bring the problem closer to real-world conditions, they included the limited lifetime of tools and analyzed their impact on determining the number of required workstations and task allocation. To solve this problem, they proposed a two-stage heuristic algorithm. Minimizing the total cost was also the objective of Nilakantan et al. (2017b) study, which compared the optimal results for the straight and U-shaped layouts. They applied a DE algorithm to solve the problem and showed that a U-shaped layout usually leads to less cost. Different solution approaches, such as ILP (Albus & Huber, 2023; Pereira et al., 2018), MILP (Gultekin et al., 2016), PSO (Nilakantan & Ponnambalam, 2014; Zhang et al., 2023), and memetic algorithm (MA) (Pereira et al., 2018), have been adopted to solve RALBPs-C.

A summary of RALBP-C, proposed in Table 5, shows that maximizing profit is rarely addressed while quantifying the profit obtained from implementing robots in assembly lines is helpful for managers to measure the workload and number of tasks assigned to workstations. In addition, the effect of other line layouts and multiple robots at workstations on economic efficiency has to be investigated.

4.1.4. RALBP-type O (RALBP-O)

For objectives that do not fall within the existing categorization of RALBPs, another type is proposed (Type O) that encompasses the remainder of articles in RALBPs when they are classified based on their objectives. Daoud et al. (2012) investigated the minimization of seizing components. They devised an MILP model and concurrently applied ACO and PSO algorithms to address the problem. This study assumed that several pick-and-place robots could work in parallel to build an automated assembly line. In a later study by Daoud et al. (2014), they extended their previous work by developing three solution methods based on ACO, PSO, and GA. To enhance the quality of the developed algorithms, they were coupled with guided local search (GLS). They also proposed an exact solution named the full enumeration method (FEM) to assess the quality of their developed algorithms. As robot failures lead to line stoppages and require manual backup operations, Müller et al. (2014) emphasized the possibility of robot failure by proposing a robust

Table 6
Summary of RALBP-O studies.

Author (s)	Layout (Assembly line)			Objective	Algorithm type		Solution approach	Production				
	Straight	U-shaped	Two-sided		Heuristic and Meta-heuristic	Exact		Single/multi/mixed models			Assembly resources	
								Single	Multi	Mixed	Single robot	Multi robot
Daoud et al. (2012)	✓			Max (number of seizing components)	✓	✓	MILP, PSO, ACO	✓			✓	
Daoud et al. (2014)	✓			Max (number of seizing components)	✓	✓	FEM, GA, PSO, ACO	✓			✓	
Müller et al. (2014)	✓			Max (redundancy)		✓	ILP	✓				✓
Nilakantan et al. (2015a)	✓			Min (energy consumption)	✓		PSO	✓			✓	
Nilakantan et al. (2015b)		✓		Min (energy consumption)	✓		PSO	✓			✓	
Müller et al. (2018)	✓			Max (production rate)	✓		GA	✓			✓	
Li et al. (2018b)	✓			Min (makespan)	✓	✓	MILP, SA, GA			✓	✓	
Nilakantan et al. (2018)	✓			Min (energy consumption)	✓		PSO, DE	✓			✓	
Belkharroubi and Yahyaoui (2022)	✓			Min (energy consumption)	✓		CS	✓		✓	✓	
Yadav and Agrawal (2022)			✓	Max (total workload)		✓	MINLP	✓			✓	
Li et al. (2022b)	✓			Min (carbon emission)		✓	MILP	✓			✓	

approach in which the redundancy level of line balancing affects throughput losses. An ILP mode was developed in this study to address the problem while considering the use of multiple robots at each workstation.

Due to the importance of energy in the manufacturing industry, several studies targeted minimizing energy consumption. Nilakantan et al. (2018) and Nilakantan et al. (2015a) addressed this objective in straight assembly lines by developing particle swarm optimization (PSO) and differential evolutionary (DE) algorithms assuming single-model production. Nilakantan et al. (2018) addressed the same problem with the same objective and the same algorithm but for the U-shaped line. Belkharroubi and Yahyaoui (2022) developed a Cuckoo Search (CS) for the same problem while extending it to a mixed-model assembly line. Other considered objectives for RALBP are maximizing the production rate (Müller et al., 2018), minimizing makespan (Li et al., 2018b), maximizing total workload at workstations (Yadav & Agrawal, 2022), and minimizing carbon emission (Li et al., 2022b).

The energy consumption at assembly lines can be minimized in various ways. Focusing on the reviewed studies, all assumed the existence of different robot types with varying energy consumption and distinct processing times for each specific task. However, some studies presumed both the number of workstations and cycle time to be fixed, thereby limiting optimization to the allocation of the most suitable robot to each workstation and assigning the best task to each robot, aiming at the total energy usage minimization (i.e., see the studies reported in Table 6). On the other hand, some studies considered the cycle time as an additional optimization objective alongside energy consumption (see the studies reported in Table 7).These studies calculated energy consumption as the sum of the standby and operation energy consumptions of the workstation, assuming different energy levels during operation and standby modes.

Upon reviewing existing literature, it appears that none of the studies considered the impact of the assembly line layout on energy consumption. Given that total energy consumption is the sum of energy used during the production process and standby period of each specific robot, different layouts can influence the allocation of tasks to workstations, thereby affecting cycle time and, consequently, the idle time of robots. For instance, in a U-shaped line, there is more flexibility in assigning tasks as they can be distributed from both forward and backward directions. Additionally, the possibility of sharing robots between workstations in some layouts could enhance the flexibility of task assignments. This flexibility provides a wider variety of tasks for a robot, influencing task selection and potentially leading to more energy-efficient assignments.

As shown in Table 6, the majority of studies have focused on the minimization of energy consumption, employing various methodologies. It is noteworthy that all studies addressing energy consumption reduction have operated under the assumption of single-robot workstations.

4.1.5. RALBP-type H (RALBP-H)

Another type of RALBP, called Type H, is defined when more than one objective is considered. The literature review highlights a study by Yoosefelahi et al. (2012), which pioneered the concept of RALBP-H. Their primary objective was to concurrently minimize cycle time, robot setup, and operational costs. To tackle the intricacies of this challenge, the researchers developed three versions of multi-objective evolution strategies: the constraint multi-objective evolutionary strategy (CMOES), the Pareto archive evolutionary strategy (PAES), and the hybrid multi-objective evolution strategy (HMOS). Another model with the same three objectives and an additional objective of minimizing the sequence-dependent setup cost was presented by Rabbani et al. (2016) when the layout was U-shaped. The authors proposed an MILP, multi-objective particle swarm optimization (MOPSO), and non-dominated sorting genetic algorithm II (NSGA-II) as the solution procedure. The main contribution of this study to the corresponding literature is the proposal of a mixed-model that allows the workstations to assemble a set of similar products when more than a single robot is allowed to perform the assembly task at each workstation. Li et al. (2016b) discussed minimizing energy consumption and cycle time considering the two-sided assembly line layout. They demonstrated that the restarted simulated annealing (RSA) algorithm outperforms the GA in both convergence and spread criteria by developing an RSA approach and comparing the results of this algorithm with those obtained from the GA. Optimizing the cycle time, number of workstations, and total cost was the subject of another work developed by Çil et al. (2016), who developed MILP to solve the problem.

Mitigating carbon emissions in RALBPs has always been an objective

Table 7
Summary of RALBP-H studies.

Author (s)	Layout (Assembly line)					Objectives	Algorithm type		Solution approach	Production				
	Straight	U-shaped	Two-sided	Parallel	Four-sided		Heuristic and Meta-heuristic	Exact		Single/multi/mixed model			Number of resources	
										Single	Multi	Mixed	Single robot	Multi robot
Yoosefelahi et al. (2012)	✓					Min (cycle time), Min (robot setup costs), Min (robot costs)	✓		ESA	✓			✓	
Rabbani et al. (2016)		✓				Min (cycle time), Min (robot costs), Min (robot setup costs), Min (sequence-dependent setup cost	✓	✓	MILP, PSO, NSGA-II			✓		✓
Li et al. (2016b)			✓			Min (cycle time), Min (energy consumption)	✓		SA	✓			✓	
Çil et al. (2016)	✓					Min (cycle time), Min (number of workstations), Min (robot costs)		✓	MILP	✓			✓	
Nilakantan et al. (2017a)	✓					Min (carbon emission), Max (efficiency)	✓		MOCC	✓			✓	
Zhang et al. (2019a)		✓				Min (cycle time), Min (energy consumption)	✓		ABC	✓			✓	
Zhang et al. (2019b)		✓				Min (cycle time), Min (carbon emission), Min (noise emission)	✓		GWO	✓			✓	
Zhou and Wu (2019)	✓					Min (number of workstations), Min (area occupied by stations)	✓		ICS	✓			✓	
Zhou and Wu (2020)	✓					Min (number of workstations), Min (energy consumption)	✓		MOEA/D	✓			✓	
Haotian and Hongjun (2020)	✓					Min (energy consumption), Min (robot cost), Min (smoothness index)	✓		GA	✓				✓
Sun, Wang, and Peng (2020)	✓					Min (cycle time), Min (energy consumption)	✓	✓	MILP, BHEDA	✓			✓	
Rabbani et al. (2020)					✓	Min (number of workstations), Min (operator cost)	✓	✓	MINLP, PSO			✓	✓	
Li et al. (2021a)	✓					Min (cycle time), Min (total cost)	✓	✓	MILP, NSGA-II, ABC	✓			✓	
Khotsaenlee and Chutima (2021)		✓		✓		Min (particulate matter emission), Min (workload variance), Min (energy load variation), Max (corporate tax benefit), Max (efficiency)	✓		NSGA-III	✓			✓	
Zhang et al. (2021)		✓				Min (energy consumption), Min (makespan)	✓		DA			✓	✓	
Chutima and Khotsaenlee (2022)		✓		✓		Max (efficiency), Min (particulate matter emission), Min (workload variance), Min (energy load variation), Max (corporate tax benefit)	✓	✓	MILP, NSTLBO-III	✓			✓	
Chi et al. (2022)						Min (number of workstations), Min (energy consumption)	✓	✓	MILP, SA	✓			✓	
Samouei and Sobhishoja (2023)		✓				Min (cycle time), Min (total cost)	✓	✓	MILP, HSA			✓	✓	

that has been studied along with other objectives, which mainly focus on finding a trade-off between how to make assembly tasks more efficient and how to minimize emissions. The social awareness of this issue is also increasing, and people tend to buy sustainable products with lower carbon footprints. Considering this, minimizing emissions and maximizing efficiency simultaneously were studied by Nilakantan et al. (2017a) in the context of RALBP. They utilized a multi-objective cooperative co-evolutionary (MOCC) algorithm to reduce carbon emissions. They concluded that the bi-objective model solved by MOCC could considerably decrease carbon emissions and increase line efficiency. In a later study, the objective of minimizing emission was observed along with the cycle time minimization and noise emission by Zhang et al. (2019b) when a pareto gray wolf optimization (GWO) meta-heuristic approach was applied. Using evaluation metrics, this approach successfully achieved a trade-off between reducing carbon emissions, noise emissions, and the cycle time for RALBP.

Minimizing the energy consumption was studied along with minimizing the cycle time by Zhang et al. (2019a) who developed a pareto artificial bee colony algorithm (PABC) to deal with U-shaped RALBP. Following the same optimization objectives, Sun et al. (2020)proposed a bound-guided hybrid estimation of distribution algorithm (BHEDA) to tackle the problem. Minimizing energy consumption and the number of workstations were aimed at in another study proposed by Zhou and Wu (2020) when all energy-consuming processes of the assembly line are formulated, and a multiobjective evolutionary algorithm based on decomposition (MOEA/D) is proposed as solution procedures. Targeting the same objectives, Chi et al. (2022) addressed the RALBP and simultaneously optimized the number of workstations and energy consumption. This study solves this problem by developing an MILP model and SA approach.Minimizing the energy consumption was studied along with minimizing the robot cost and smoothness index of the assembly line in another study proposed by Haotian and Hongjun (2020). The smoothness index is used to measure the fluctuation of working hours and is calculated by quantifying the relationship between the working hours of different positions on the assembly line. An improved multi-objective hybrid genetic algorithm (IMOHGA) was developed as a solution procedure. Zhang et al. (2021) conducted a study to minimize energy consumption and make spans simultaneously by using a hybrid multi-objective dragonfly algorithm (DA) for the first time in RALBPs.

The problem of minimizing the number of workstations and the area occupied by each workstation was studied by Zhou and Wu (2019), who used the immune clonal selection (ICS) algorithm to solve this bi-objective problem. The performance of the proposed algorithm was enhanced by an elite strategy and global search. Rabbani et al. (2020) addressed the mixed-model assembly line to minimize the number of workstations and the total cost. This study discussed a four-sided layout to increase the flexibility of the assembly line when operators can work in different directions.They proposed augmented multi-objective particle swarm optimization (AMOPSO) and multi-objective particle swarm optimization (MOPSO). The results showed that AMOPSO provides better solutions (lower cost and fewer workstations).

Minimizing the cycle time and total cost simultaneously was highlighted by Li et al. (2021a). They formulated the problem as a MILP model, developed a hybrid NSGA-II, and improved the multi-objective artificial bee colony (IMABC) algorithm to achieve a set of Pareto solutions for production managers to design the assembly line. This resulted in quantifying a trade-off between cycle time and total costs. Considering the same objectives, Samouei and Sobhishoja (2023) developed an MILP and proposed a harmony search algorithm (HSA) to address the problem while targeting the U-shaped line and mixed-model production. The parallel adjacent U-line (PAUL), a novel layout that increases the assembly line's efficiency, was developed by Khotsaenlee and Chutima (2021) in an RALBP context. Five objectives, such as maximizing efficiency, minimizing particulate matter emission, minimizing workload variance, minimizing energy load variance, and maximizing the value of tax savings, are highlighted in this elaboration. To solve this complex problem with multiple objectives, a non-dominated sorting genetic algorithm III (NSGA-III) was proposed, and its efficiency was compared with other approaches, such as MOEA/D, generational distance (GD), and inverted generation distance (IGD). Chutima and Khotsaenlee (2022) also addressed these five objectives and coped with the complexity of the problem by adopting a novel solution algorithm called non-dominated sorting teaching–learning-based optimization (NSTLBO-III). This algorithm was benchmarked for pareto efficiency with the NSGA-III and MOEA/D approaches.

Most of the articles published in the context of RALBP-H have investigated minimizing the cycle time along with another objective. Moreover, most studies have employed heuristic algorithms to solve the problem. The parallel, two-sided, and four-sided layout has rarely been studied, and there is a lack of research on determining the efficiency of different layouts when optimizing the objective functions. Moreover, more investigations on mixed model production and the use of multi-robots at workstations can help researchers and practitioners examine the problem with insight that contributes more to real-world cases. Table 7 summarizes the studies reviewed in this section.

4.2. Review of ALBP-HRC

Besides the primary differences between RALBP and ALBP-HRC discussed in Section 2, additional distinctions arise from their objectives and constraints. RALBP focuses on fully or semi-automated assembly lines, where each workstation is operated by either a human or a robot. In contrast, ALBP-HRC involves a collaborative environment of human operators and robots sharing a workstation, necessitating a more complex modeling approach to accommodate the capabilities, efficiencies, and coordination of both. While RALBPs primarily aim at assembly line efficiency by minimizing cycle time, reducing workstation numbers, and ensuring workload balance, ALBP-HRC broadens the optimization objectives to include the safety and ergonomic conditions for human operators. It also focuses on task allocation that maximizes the collaboration between robots and human workers toward more sustainable and heumand-centic production. Unique constraints in ALBP-HRC pertain to the capacities and capabilities of both cobots and human workers, often including collaboration constraints to ensure safe and effective interaction. Additionally, ergonomic constraints are usually considered to maintain comfortable working conditions for human

Table 8
Summary of ALBP-HRC-I studies.

Author (s)	Layout (Assembly line)		Algorithm type		Solution approach	Production				
						Single/multi/mixed model			Number of resources	
	Straight	U-shape	Heuristic and Meta-heuristic	Exact		Single	Multi	Mixed	Single manned/ robot	Multi manned/ robot
Koltai et al. (2021)	✓			✓	MILP	✓			✓	
Nourmohammadi et al. (2023a)	✓	✓		✓	MILP	✓				✓

Table 9
Summary of ALBP-HRC-II studies.

Author (s)	Layout (Assembly line)		Algorithm type		Solution approach	Production				
	Straight	U-shaped	Heuristic and Meta-heuristic	Exact		Single/multi/mixed model			Number of resources	
						Single	Multi	Mixed	Single manned/robot	Multi manned/robot
Weckenborg et al. (2020)	✓		✓	✓	MILP, GA	✓			✓	
Çil et al. (2020)	✓		✓	✓	MILP, BA, ABC			✓	✓	
Koltai et al. (2021)	✓			✓	MILP, CP	✓			✓	
Dimény and Koltai (2021)	✓			✓	MILP	✓			✓	
Sikora and Weckenborg (2022)	✓			✓	BDA	✓			✓	✓
Nourmohammadi et al. (2022a)	✓		✓		GA	✓				
Li et al. (2023)		✓	✓	✓	MILP, ABC, MBO	✓			✓	
Mao et al. (2023)		✓	✓	✓	MILP, SA	✓			✓	
Nourmohammadi et al. (2023a)	✓	✓		✓	MILP	✓				✓

workers.

Although the number of published studies in this field is small, all the works were published in the last five years. The increasing number of recent articles indicates that this subject is becoming interesting for both researchers and industrial practitioners. To develop a consistent literature review, the classification proposed in Table 2 was used to review the articles within the scope of ALBP-HRC.

4.2.1. ALBP-HRC-type I (ALBP-HRC-I)

The review showed that ALBP-HRC-I is the least studied problem in the ALBP-HRC literature. The inaugural investigation into this problem type was undertaken by Koltai et al. (2021). In their study, the authors devised an MILP model for a linear and single-model assembly line with the aim of minimizing the number of workstations. In a subsequent study, Nourmohammadi et al. (2023a) introduced a more intricate MILP model for linear and U-shaped assembly lines, permitting the utilization of multiple resources at each workstation.

Considering that ALBP-HRC-I studies are limited, the effect of other line layouts on the number of workstations and considering different production types, multi/mixed-mode, and developing efficient exact and metaheuristics algorithms to handle large size problems are expected. A summary of the relevant studies is presented in Table 8.

4.2.2. ALBP-HRC-type II (ALBP-HRC-II)

Minimizing the cycle time is an objective that can affect all aspects of ALBPs, such as total costs, task allocation, and resource selection. The decision to assign robots or humans to a workstation to minimize the task execution time is influenced by the processing times associated with each option and is subject to constraints related to the number of available robots, robot capability, task compatibility, and other aspects considered in each specific study. The central decision revolves around how tasks are assigned to a workstation and considering whether a task is best suited for a robot, a human operator, or collaborative execution involving both. Moreover, the processing time associated with each option is determined based on the robot type and the level of human skills that are the given inputs.

Weckenborg et al. (2020) pioneered the exploration of this problem type, focusing on minimizing the cycle time of the assembly process. Their study delves into a collaborative environment where a single worker and a single robot are permitted to work simultaneously at each workstation. Employing an MILP model, the study governs the distribution of workload among workers when employing the genetic algorithm (GA) to tackle the problem. The results of a real case study show that substantial cycle time reduction can be gained in a collaborative environment. Using the same approach, Çil et al. (2020) tried to minimize the cycle time of ALBP-HRC by handling the task assignment as well as workers and robots selection. The problem was formulated as an MILP model, and two metaheuristic algorithms, BA and ABC, were proposed. Dimény and Koltai et al. (2021) and Koltai et al. (2021) developed an MILP model to address the basic ALBP-HRC with the aim of minimizing the cycle time.

Bender's decomposition algorithm (BDA) was used in another study presented by Sikora and Weckenborg (2022) when minimizing the cycle time. In their considered problem, collaborative robots can either perform tasks in parallel with a human worker or collaborate with workers on identical tasks.

In an investigation by Li et al. (2023), a U-shaped layout was used under budget constraints that limited the level of application of collaborative robots in assembly lines. They developed an ABC and MBO heuristic to address the complexity of this problem while minimizing the cycle time. Mao et al. (2023) studied collaborative tasks within a U-shaped layout and used the combination of SA and GA problems to optimize the cycle time for a given number of workstations. In a recent study, Nourmohammadi et al. (2023a) developed an efficient MILP for both straight and U-shaped lines while considering the possibility of having multiple assembly resources (i.e., human and robot) at each workstation.

Table 9 shows that all the studies had developed an exact method, while most also proposed a heuristic algorithm to deal with the problem's complexity. Multi-model has not been considered, and mixed-model production and the possibility of using more than one resource on workstations have been only discussed in one study.

4.2.3. ALBP-HRC-type C (ALBP-HRC-C)

As the economic aspects of an ALBP-HRC have become significant in recent years, Weckenborg and Spengler (2019) introduced a cost-effective approach to assembly lines employing collaborative robots. Their article presents an MILP model aimed at minimizing the total cost per assembly cycle. Grounded in real-world scenarios, the study elaborates on how collaborative robots can optimize worker workload. In a separate study, Yaphiar et al. (2019) also investigated strategies for minimizing total costs. They proposed an MILP model to formulate the problem when the total costs are minimized by assigning tasks to workstations and determining which kind of resources (human, robot, or human-robot collaboration) are required to produce various types of products. This study assumed the mixed model production while limiting the number of resources to a maximum of one human and robot at each workstation. Following the same production setting, Samouei and Ashayeri (2019) proposed two MILP models to address the problem. One of the models aimed to minimize the cost only, and the second

Table 10
Summary of ALBP-HRC-C studies.

Author (s)	Layout (Assembly line)		Objectives	Algorithm type		Solution approach	Production				
							Single/multi/mixed model			Number of resources	
	Straight	U-shape		Heuristic and Meta-heuristic	Exact		Single	Multi	Mixed	Single manned/robot	Multi manned/robot
Weckenborg and Spengler (2019)	✓		Min (cost per cycle)		✓	MILP	✓			✓	
Yaphiar et al. (2019)	✓		Min (total cost)		✓	MILP			✓	✓	
Samouei and Ashayeri (2019)	✓		Min (total cost)		✓	MILP			✓	✓	
Nugraha (2021)	✓		Min (total cost)		✓	MILP	✓			✓	
Slama et al. (2023)	✓		Min (total cost)		✓	MILP	✓				✓
Nourmohammadi et al. (2023a)	✓	✓	Min (total cost)		✓	MILP	✓				✓

Table 11
Summary of ALBP-HRC-O studies.

Author (s)	Layout (Assembly line)	Objectives	Algorithm type		Solution approach	Production				
						Single/multi/mixed models			Number of resources	
	Straight		Heuristic and Meta-heuristic	Exact		Single	Multi	Mixed	Single manned/robot	Multi manned/robot
Dimény and Koltai et al. (2021)	✓	Min (number of operators)		✓	MILP	✓			✓	
Dimény and Koltai (2023)	✓	Min (number of operators)		✓	MILP, CP	✓			✓	
Caporale et al. (2023)	✓	Min (makespan)		✓	ILP	✓			✓	

model aimed to minimize both the cost and cycle time. Another cost-oriented study considering single-model production was proposed by Nugraha (2021), who aimed to reduce the total cost by assigning the best resources to workstations and the best tasks to resources. Slama et al. (2023) and Nourmohammadi et al. (2023a) addressed the ALBP-HRC and developed an MILP model for minimizing the total cost of the assembly line while allowing more than one robot and human at each workstation. In the former study, the authors also considered the stochastic nature of task times that human operators perform. This has been one of the first attempts to consider the uncertainty in processing time when dealing with ALBP-HRC.

All the studies that aimed to minimize the cost have been addressed by developing MILP models. Moreover, all the studies, except one, focused on straight assembly lines. However, considering multi- and mixed-model production while allowing multiple resources at the workstation has not been investigated. The reviewed articles are summarized in Table 10.

4.2.4. *ALBP-HRC-type O (ALBP-HRC-O)*

Pioneering a new approach, Dimény and Koltai et al. (2021) introduced an MILP model targeting ALBP-HRC, with the primary objective of reducing the number of operators. In this formulation, the number of workstations remained fixed, but the study focused on optimizing the workforce by potentially decreasing the number of workers. Building on this work, Dimény and Koltai (2023) further explored the same problem, proposing an efficient CP model alongside the MILP approach. This study represented one of the earliest efforts to devise and apply an exact solution method for ALBP-HRC. Advancing the field, Caporale et al. (2023) recently developed an ILP model tailored to minimize the makespan in addressing the problem.

The review shows that all the studies in this category have focused on developing an exact solution to optimize the problem. In addition, only the straight-line shape was considered while assuming a single model production and single resource at each station. Table 11 presents a summary of articles of this type.

4.2.5. *ALBP-HRC-type H (ALBP-HRC-H)*

Introducing a multi-objective perspective, Dalle Mura and Dini (2019) presented an article focusing on minimizing assembly line costs, the number of operators, and energy load variation simultaneously. By integrating these objectives, the study sought to enhance the efficiency of RALBP while also improving the ergonomic working conditions of highly skilled workers. This was achieved by distributing tasks based on individual physical capabilities and the level of collaboration with robots. To tackle large-scale configurations in industries, the authors employed a genetic algorithm (GA). Addressing cycle time and total cost was the subject of other studies suggested by Samouei and Ashayeri (2019) and Li et al. (2021b). Both studies developed an MILP model, and the latter also proposed an MBO algorithm to solve the bi-objective mathematical model and obtain high-quality Pareto solutions. The outcome of this study illustrates that applying MBO to solve the model results in higher computational performance compared with NSGA-II, SA, and multi-objective artificial bee colony (MOABC) approaches. Minimizing ergonomic risk and cycle time concurrently in ALBP-HRC problems is a novel issue addressed by Stecke and Mokhtarzadeh (2021) for the first time. They proposed three solution approaches based on MILP, CP, and BDA and analyzed the efficiency of the algorithms and the changes in cycle time and ergonomic risk when robots are immobile

Table 12
Summary of ALBP-HRC-H studies.

Author (s)	Layout (Assembly line)		Objectives	Solution method		Solution approach	Production				
	Straight	Two-sided		Heuristic and Meta-heuristic	Exact		Single/multi/mixed model			Number of resources	
							Single	Multi	Mixed	Single manned/robot	Multi manned/robot
Dalle Mura and Dini (2019)	✓		Min (total cost), Min (number of operators), Min (energy load variation)	✓		GA	✓			✓	
Samouei and Ashayeri (2019)	✓		Min (cycle time), Min (total cost)		✓	MILP			✓	✓	
Li, Janardhanan, and Tang (2021b)	✓		Min (cycle time), Min (total cost)	✓	✓	MILP, MBO	✓			✓	
Stecke and Mokhtarzadeh (2021)	✓		Min (cycle time), Min (ergonomic risk)		✓	MILP, CP, BDA			✓	✓	
Shan et al. (2021)		✓	Min (cycle time), Min (total cost)	✓		NSGA-II	✓			✓	
Dalle Mura and Dini (2022)	✓		Min (total cost), Min (energy load variation)	✓		GA	✓			✓	
Weckenborg et al. (2022)	✓		Min (total cost), Min (maximum energy expenditure)		✓	MILP	✓			✓	
Nourmohammadi et al. (2022b)	✓		Min (cycle time), Min (number of operators)	✓	✓	MILP, SA	✓				✓
Keshvarparast et al. (2022)	✓		Min (maximum physical workload of workers), Min (cycle time)		✓	MILP	✓			✓	
Dimény and Koltai (2022)	✓		Min (number of operators), Min (total workload of the workers)	✓		MILP			✓	✓	
Dalle Mura and Dini (2023)	✓		Min (energy load variation), Min (total cost)	✓		GA			✓	✓	
Rahman et al. (2023)	✓		Min (cycle time), Min (energy consumption), Min (ergonomic risk)	✓	✓	CCPA, MA	✓			✓	
Demiralay and Kara (2023)	✓		Min (grippers), Min (number of workstations)		✓	MILP	✓			✓	

and mobile.

Using a two-sided layout in a collaborative assembly line, Shan et al. (2021) discussed a bi-objective model to minimize the cycle time and total costs simultaneously. An NSGA-II approach was used to solve the issue of selecting assembly modes and the allocation of these modes in a sequence of operations. Economic and human factors were the subject of another study proposed by Dalle Mura and Dini (2022), who attempted to minimize the total cost and energy load variance among workers. A multi-objective problem was addressed by considering different factors for the economic aspect (number of workers, workers' skills, equipment installed on workstations, and the number of collaborative tasks) and human factors (energy expenditure of workers, physiological characteristics, job rotations, and the degree of their collaboration with robots). Finally, a GA is employed to solve the problem in which the chromosome structure is based on a tailored encoding method for a particular problem that uses the task-oriented representation for the assembly sequence. In another study, Weckenborg et al. (2022) harmonized the conflicting economic and ergonomic objectives when collaborative robots and exoskeletons can support human workers in their assembly tasks. An MILP model is developed to minimize assembly costs and the highest energy expenditure rates among the workers simultaneously. The model is integrated into a planning approach capable of evaluating the efficient frontier of assembly lines and analyzing the interrelationship between economic and ergonomic criteria.

A recent novel approach proposed by Nourmohammadi et al. (2022b) allows the assignment of more than one resource to each workstation. They developed an MILP model and a neighborhood-search SA, and investigated the advantage of this algorithm over other swarm intelligence algorithms. The objectives considered in this study were minimizing the number of operators and cycle time. Minimizing the maximum physical workload of the assigned workers and mitigating the cycle time were the objectives of another study proposed by Keshvarparast et al. (2022). They highlighted the diversity of the human operators based on their experience level and physical ability. Different solutions from the Pareto front are compared, proving that moving from RALBP toward ALBP-HRC can reduce the cycle time and physical workload. Another study conducted by Dimény and Koltai (2022) compared the total workload of workers when collaborative robots were employed at workstations. They developed an MILP model, which is solved with an advanced interactive multidimensional modeling system (AIMMS) and CPLEX commercial solvers. This approach also analyzed how adding robots to workstations affects the total workload of workers.

Dalle Mura and Dini (2023) employed a GA approach to quantify the ergonomic and cost-efficiency aspects of a mixed-model assembly line, and the effectiveness of this algorithm was measured in a real-world case. It is proven that the objectives are optimized by reducing and smoothing the workers' energy expenditure while performing operations on the assembly line. Rahman et al. (2023) developed a model for ALBP-HRC and solved the complex problem using GA and MA. Addressing the combination of different objectives, such as minimizing cycle time, energy consumption, and ergonomic risk, was the main contribution of this study. In a most recent study, Demiralay and Kara (2023) proposed an MILP to minimize the number of workstations and robot grippers in assembly lines with collaborative robots.

The above review shows that mixed-model and multi-manned

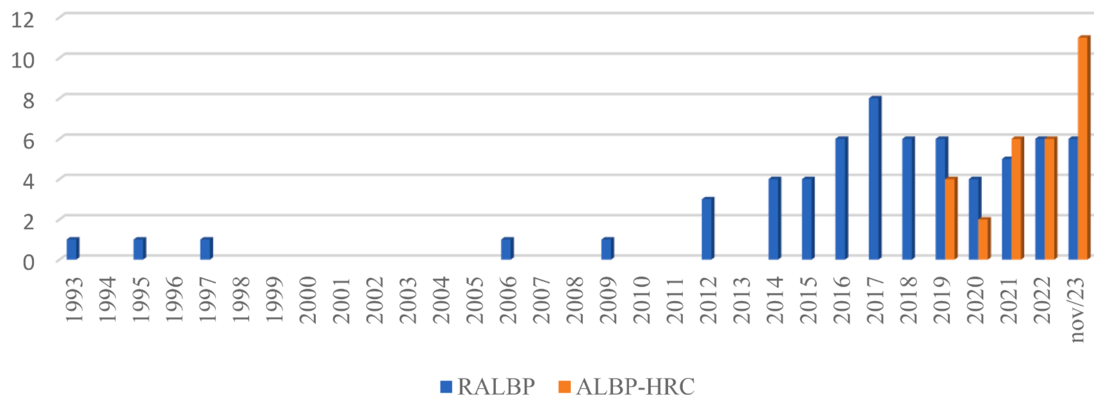


Fig. 4. Year-wise analysis of reviewed articles in the context of RALBP and ALBP-HRC.

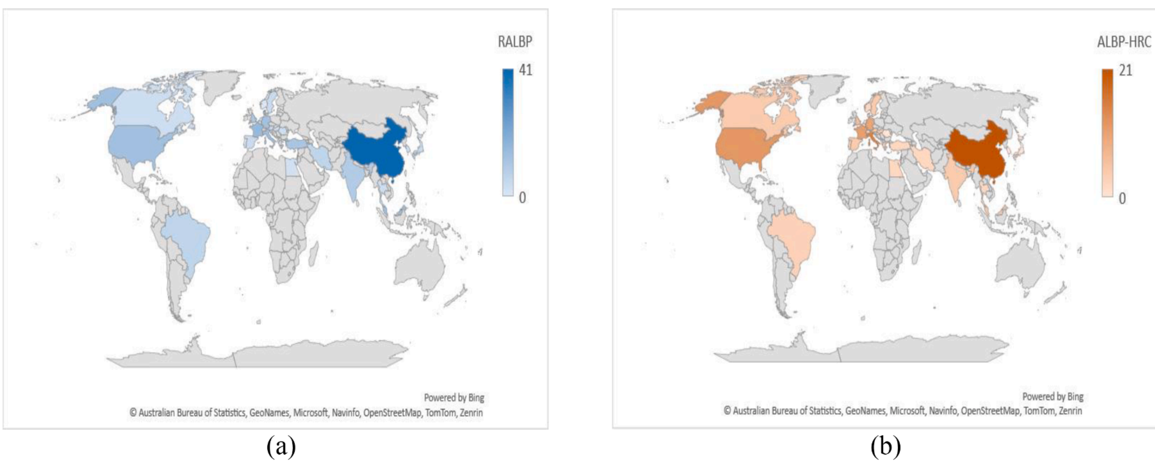


Fig. 5. Country-wise analysis of reviewed articles in the context of (a) RALBP and (b) ALBP-HRC.

assembly lines have rarely been highlighted in the existing studies, while multi-model production has not been addressed. In addition, most authors have built a model based on a straight layout to avoid further complexities when solving the problem. The majority of the papers have also investigated two objectives because increasing the number of independent objectives considerably increases the complexity of the problem. Table 12 summarizes the reviewed studies on ALBP-HRC-H.

5. Discussion

5.1. Review results

The articles reviewed in this survey were analyzed from a demographic perspective, and several graphs were provided to determine the recent trends in RALBP and ALBP-HRC. These graphs can help researchers understand the year-wise trend of the articles published in both scopes, which researchers affiliated with which countries mostly worked on these subjects, which objectives are aimed to be optimized, which layouts are used, and which solution approaches are employed to solve assembly line balancing problems when industrial and collaborative robots are utilized. The analysis and graphical presentation of the review findings provide answers to RQ1 to RQ3. The given analysis also highlights the research gaps by monitoring the problem objectives and thus contributes to responding to RQ4.

The provided analysis includes bibliometric and descriptive. Year-wise and country-wise analyses of reviewed articles are presented and discussed in Figs. 4 and 5, respectively. Analysis of model types and objectives are presented and discussed in Fig. 6. The popularity of line layout for each problem type is analyzed in Fig. 7. Fig. 8 provides an analysis of the product model and production resources. A knowledge gap analysis as per objectives is presented in Fig. 9. An analysis of solution methods for each problem type is presented in Fig. 10.

The number of studies published in RALBP and ALBP-HRC was determined to analyze the number of publications annually. As shown in Fig. 4, the number of published studies on RALBP shows a growing trend since 2014 compared to the past 20 years (from 1993 to 2013), and the number of published studies on ALBP-HRC shows an increasing trend in the past five years. Based on Fig. 4, researchers began addressing HRC in ALBPs in 2019, and with a rising trend, this subject has received considerable attention from scholars in 2023. The reason could be the tendency of scholars to study HRC more than before because of the emergence of Industry 4.0, which encouraged industries to move toward collaborative workstations to increase the flexibility and productivity of assembly lines and allow manufacturing systems to assemble a higher variation of products.

To develop a country-wise analysis, Chinese-affiliated scholars have had the highest contribution in terms of the number of publications in both RALBP and ALBP-HRC, as shown in Fig. 5. Italian, French, and American scholars have also significantly contributed to these two subjects.

Fig. 6 summarizes the problem types (Fig. 6a) and objectives of the reviewed articles (Fig. 6b). According to Fig. 6a, RALBP-II is the most studied type of problem, as minimizing the cycle time is significant for researchers and practitioners owing to its role in mitigating costs, makespan, and energy consumption. As for ALBP-HRC, Type-H received the most significant attention, meaning that most studies tried to optimize more than one objective. Type-H was also the second-most studied problem type of RALBP. Fig. 6b also shows that minimizing the cycle

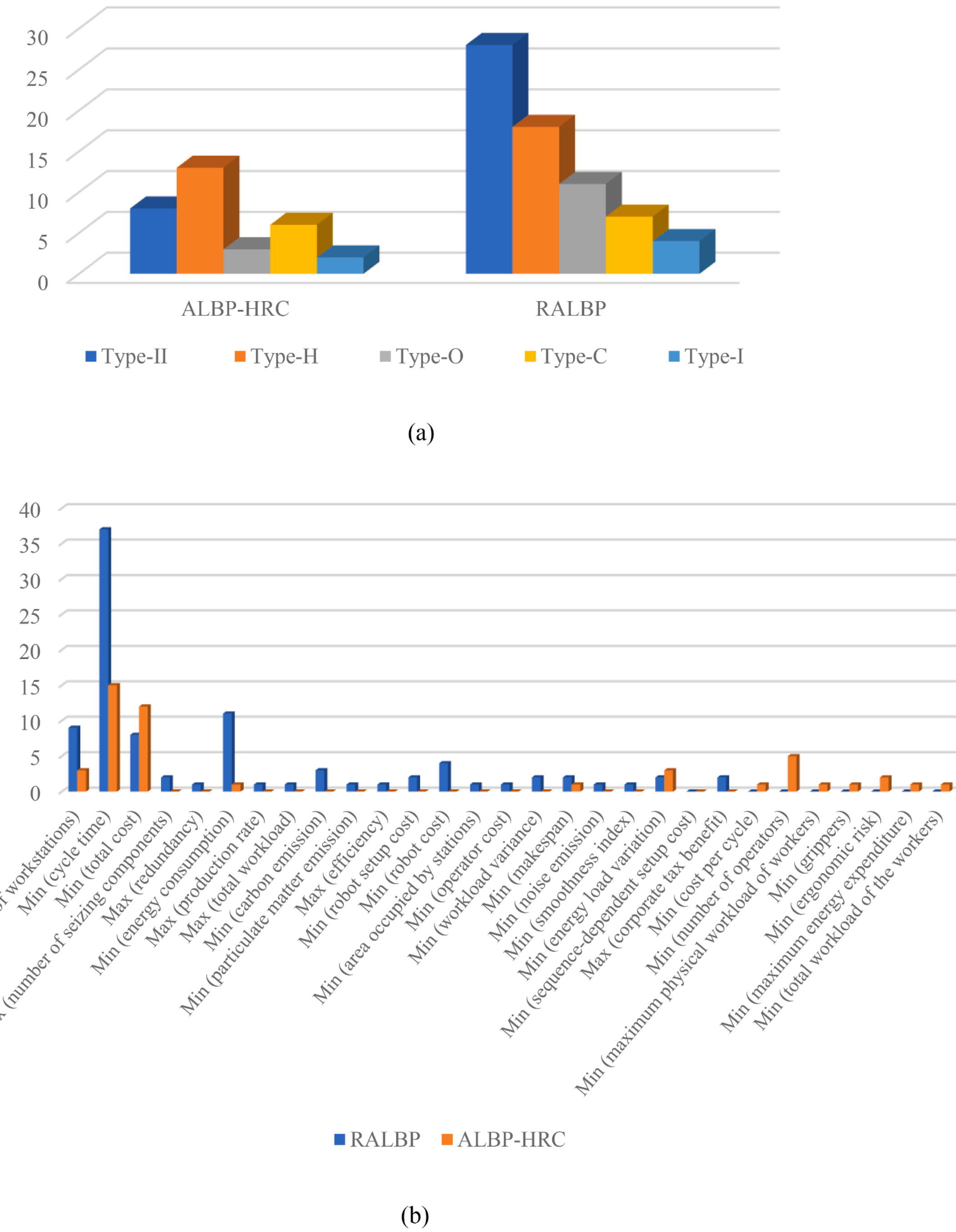


Fig. 6. Distribution of (a) model types and (b) objectives of RALBP and ALBP-HRC.

time is the highest-attended objective for articles published in RALBP and ALBP-HRC. Then, minimizing the total cost, energy consumption, and number of workstations has been given greater consideration compared to others. The ergonomic aspect has not been addressed in RALBPs due to a lack of human intervention in the processes, but it has been studied in the context of ALBP-HRC.

The choice of layout in ALBP significantly influences the efficiency and productivity of the assembly process. Different layouts affect task allocation and workstation efficiency. For example, straight layouts suit sequential workstations for continuous workflow, while U-shaped and parallel layouts accommodate tasks requiring multiple resources (robots or human operators). Line layout also influences cycle time and the number of workstations, with U-shaped lines often requiring fewer workstations compared to straight lines (Fathi et al., 2016). Additionally, logistics considerations are crucial in selecting line layouts, as they impact the time needed for item transfer between workstations. The distribution of layouts in both RALBP and ALBP-HRC is shown in Fig. 7. The majority of articles have investigated a straight assembly line, owing to the increasing complexity of the problem. Then, U-shaped is mostly addressed in both the RALBP and ALBP-HRC. Based on the studied layouts, it is understood that U-shaped and two-sided layouts can increase the efficiency of RALBPs because they lead to combining tasks in the assembly line. For ALBPs-HRC, the U-shaped and parallel layout is promising, as the collaboration of humans and robots is facilitated when defining parallel activities.

Fig. 8 presents the analysis of the reviewed studies based on the product model (single, multi, and mixed-model) and production resource (single, multi-manned/robot). The analysis of the results also

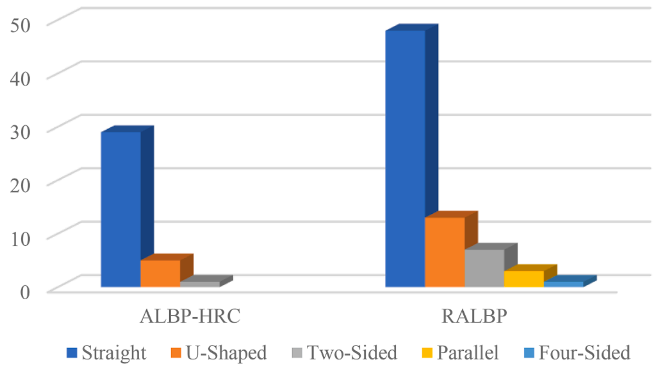


Fig. 7. Distribution of layouts in RALBP and ALBP-HRC problems.

indicates a predominant focus on single-model production for both RALBP and ALBP-HRC, accounting for 82 % of RALBP and 79 % of ALBP-HRC of the reviewed studies. Mixed-model production is less prevalent, representing 18 % of RALBP and 21 % of ALBP-HRC studies. Notably, the multi-model is scarcely represented in RALBP with a single count and is entirely absent in ALBP-HRC, implying that such production setting is rare or less emphasized in current research or applications. The results also reflect a strong focus on single-manned/robot assembly lines in both RALBP and ALBP-HRC studies, with RALBP accounting for 92 % and ALBP-HRC 80 %. Conversely, multi-manned/robots are less frequent, represented in only 8 % of RALBP and 20 % of ALBP-HRC studies, suggesting that collaborative or multi-operator setups are less commonly addressed in these contexts.

5.2. Knowledge gap analysis and future research implications

The analysis presented in this section contributes to the response to RQ4. The review revealed that some prior studies combined different objective types when dealing with RALBP and ALBP-HRC, resulting in multi-objective problems. Although some objectives are frequently combined, others have not received sufficient attention. For instance, the simultaneous optimization of cycle time and energy consumption has been studied in three articles in the context of RALBP. In contrast, energy consumption has not been addressed along with other objectives, such as minimizing emissions or makespan. This is also the case for ALBP-HRC studies when minimizing the total cost along with energy load variation and cycle time is addressed in three articles, while the combination of many other objectives is missed in the corresponding literature. Fig. 9 illustrates the objectives that are combined more frequently in existing RALBP and ALBP-HRC studies.

Fig. 10 suggests an analysis based on the solution method for both RALBP (Fig. 10a) and ALBP-HRC (Fig. 10b), where articles are categorized by their objectives. This figure demonstrates that many studies presented a mathematical model (i.e., linear or non-linear) to address the problem, with MILP being the most popular formulation. However, most studies could only solve small-size problems using the mathematical model and resorted to heuristic algorithms for practical problem sizes, paying less attention to exact algorithms such as B&B, CP, and BDA. The review also shows that highly studied objectives, such as cycle time, energy consumption, and total costs, are optimized using heuristic algorithms because of the complexities raised by optimizing multi-objective models. Fig. 10 also shows that the development of MILP models for Types II and H has been more popular than other problem types for both ALBP-HRC and RALBP. It is evident from this figure that GA and PSO have been applied to a relatively large number of RALBPs as solution procedures, while GA is the most popular algorithm when dealing with ALBP-HRC. The analysis given in Fig. 10 also reveals the lack of application of many other exact and non-exact algorithms for both RALBP and ALBP-HRC.

5.3. Summary of review findings

This study proposes a classification for RALBP and ALBP-HRC based on the objectives of the problem. Such objective-driven classification allows researchers to understand which quantifiable indicators are significant in assembly-line balancing when industrial and collaborative robots are used. An SLR was adopted to review all published articles in the context of RALBP and ALBP-HRC and differentiate them based on their assembly line layouts, solution methodologies, and production specifications. Based on the SLR and underlying analysis, the research questions raised in Section 1 are briefly answered below.

Answer to RQ1: Most RALBP and ALBP-HRC studies aim to minimize the cycle time while minimizing energy consumption, and the cost is the second most frequently addressed objective in RALBPs and ALBP-HRC, respectively. Cost minimization was outlined in eight articles related to RALBP and twelve articles related to ALBP-HRCs, which shows the significance of the economic aspect of ALBPs. The third most popular objective in RALBP and ALBP-HRC studies is minimizing the energy consumption and the number of operators, respectively. In multi-objective studies, minimizing cycle time along with energy consumption and robot cost is mostly applied in RALBPs, while minimizing total cost along with cycle time and energy load variation is frequently addressed in ALBP-HRC.

Answer to RQ2: More than 70 % of the reviewed articles have built a model based on a straight layout, while 15 % of the articles address a U-shaped layout, which is the next most frequently discussed layout. Other layouts have received less attention despite their potential impact on optimizing the relevant objectives of assembly lines.

Answer to RQ3: Adopting an MILP approach in both RALBP and ALBP-HRC is the most common method for addressing different problems in assembly lines. Among the non-exact algorithms, GA and PSO are applied more frequently in RALBP than in other methodologies. GA

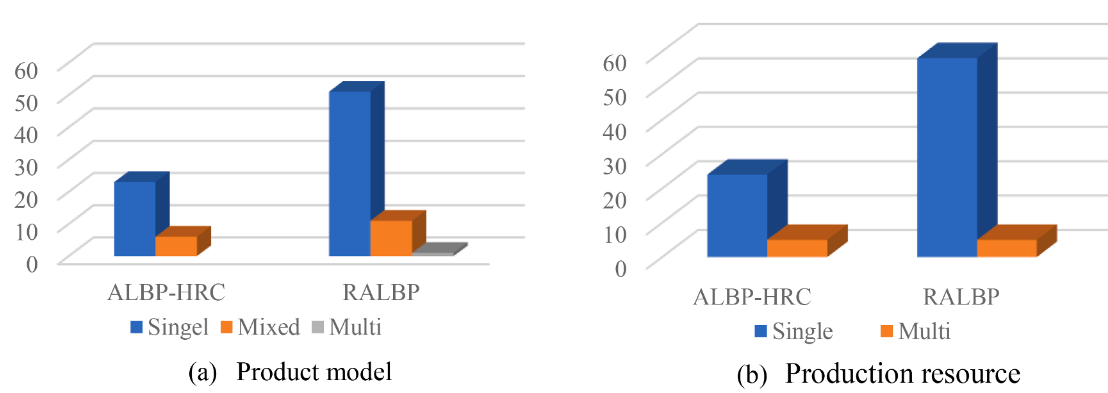


Fig. 8. Single/multi/mixed production model (a) and Single/multi-manned/robot studies.

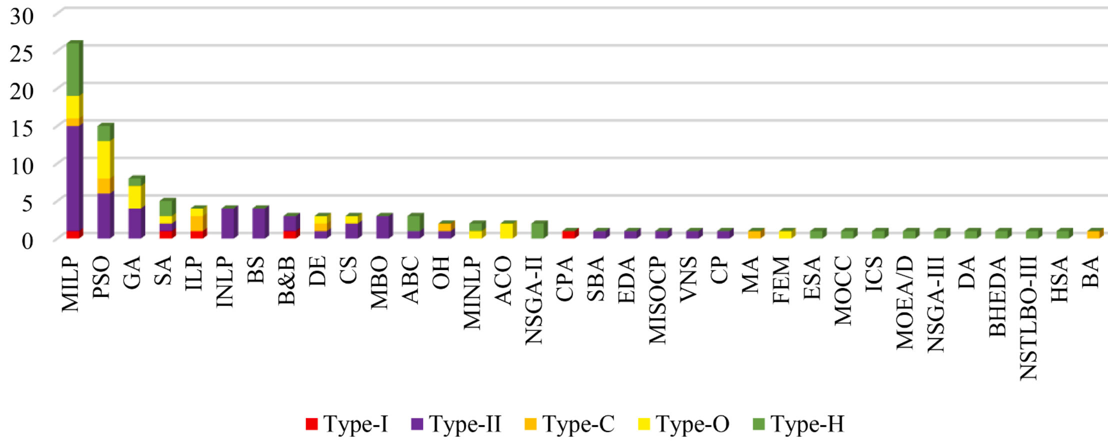
RALBP \ ALBP-HRC	Min (number of workstations)	Min (cycle time)	Min (total cost)	Max (number of seizing components)	Max (redundancy)	Min (energy consumption)	Max (production rate)	Max (total workload)	Min (carbon emission)	Min (particulate matter emission)	Max (efficiency)	Min (robot setup cost)	Min (robot cost)	Min (area occupied by stations)	Min (operator cost)	Min (workload variance)	Min (makespan)	Min (noise emission)	Min (smoothness index)	Min (energy load variation)	Min (sequence-dependent setup cost)	Max (corporate tax benefit)	Min (cost per cycle)	Min (number of operators)	Min (max physical workload of workers)	Min (grippers)	Min (ergonomic risk)	Min (maximum energy expenditure)	Min (total workload of the workers)
Min (number of workstations)																										1			
Min (cycle time)	1		3			1																		1	1		2		
Min (total cost)		2																		3				1				1	
Max (number of seizing components)																													
Max (redundancy)																													
Min (energy consumption)	2	3																									1		
Max (production rate)																													
Max (total workload)																													
Min (carbon emission)		1																											
Min (particulate matter emission)																													
Max (efficiency)									2	1																			
Min (robot setup cost)		2																											
Min (robot cost)	1	3				1						2																	
Min (area occupied by stations)	1																												
Min (operator cost)	1																												
Min (workload variance)										2	2																		
Min (makespan)						1																							
Min (noise emission)		1							1																				
Min (smoothness index)						1							1																
Min (energy load variation)										2	2					2								1					
Min (sequence-dependent setup cost)		1										1	1																
Max (corporate tax benefit)										2	2					2				2									
Min (cost per cycle)																													
Min (number of operators)																													1
Min (maximum physical workload of workers)																													
Min (grippers)																													
Min (ergonomic risk)																													
Min (maximum energy expenditure)																													
Min (total workload of the workers)																													

Fig. 9. Knowledge gap based on the combined objectives for RALBP-H and ALBP-HRC-H.

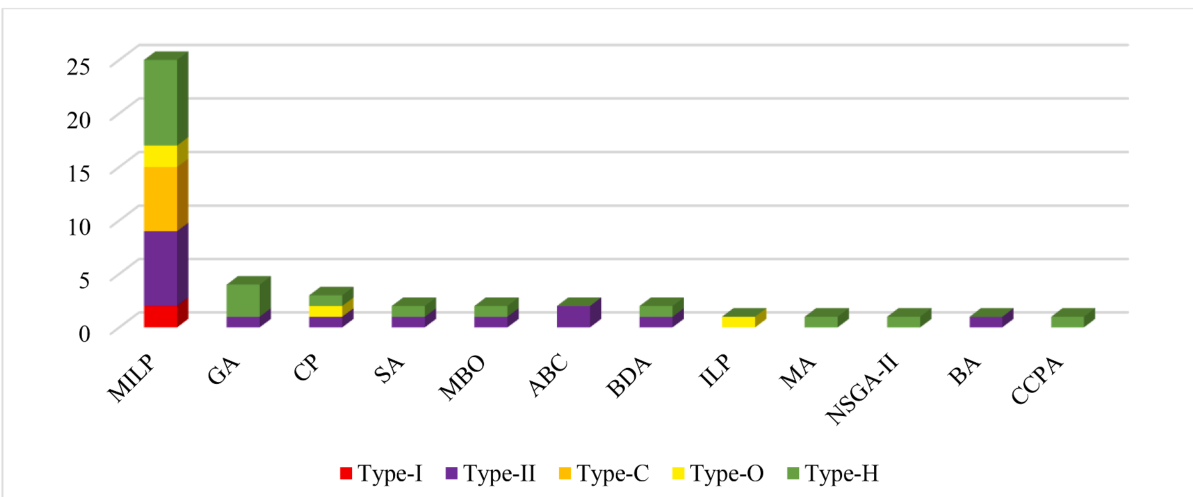
is also the most commonly applied method to solve the ALBP-HRC.

Answer to RQ4: Several knowledge gaps and future research directions are identified based on the outcomes of the present study. Addressing the total cost in ALBP-HRC has mainly been coupled with minimizing energy load variation and cycle time, while it has not been addressed along with important objectives such as energy consumption and economic risks. Minimizing energy consumption is the second most common objective highlighted in RALBPs, whereas it has been addressed in only one study on ALBP-HRC. Despite their potential role in decreasing the assembly cycle time, two-sided, parallel, and four-sided layouts are understudied in the context of ALBP-HRC.

One of the implications of Industry 4.0 in manufacturing systems was employing robots in assembly lines to automate the whole process or a specific part. Robots can be integrated with smart tools and methodologies, such as IoT and big data analysis. From a theoretical perspective, the review performed in this paper helps researchers understand the prevailing RALBP and ALBP-HRC landscapes. Robot type selection is a new idea to be developed by comparing the robots' purchasing and setup costs, maintainability, compatibility, and integration with existing tasks. The number of studies on ALBP-HRC is relatively small compared to that on RALBP, which can be addressed in future works as it is applied in many production systems.



(a)



(b)

Fig. 10. Solution methods for (a) RALBP and (b) ALBP-HRC used for each problem type.

This study helps researchers address topics that have received less attention in RALBPs and make implementation decisions for new systems and practices. For instance, the current review identifies the application of cobots in two-sided and parallel assembly line layouts as a research gap. Moreover, assembly lines with multi-model production have not been investigated in the context of ALBP-HRC, and only one study exists on this production setting for RALBP. Moreover, most studies considered single resources at workstations, leaving room to explore multi-manned/robot assembly lines further.

The consideration of logistics aspects in RALBP and ALBP-HRC, and its influence on line layout selection is an unexplored area that warrants further investigation. For example, line layout can significantly affect total cycle time, especially when workstations are positioned at turns or corners, increasing the time to transfer work to the next workstation. This consideration in line balancing can lead to better task assignments and, consequently, higher line efficiency. Future studies can develop more realistic situations, such as task allocation constraints, or consider the limited capabilities of the robots. In addition, researchers and managers can also test how different types of RALBP and ALBP-HRC can be addressed with the layouts and how the layouts not discussed in the literature can increase the efficiency and productivity of assembly line balancing. Managers and practitioners can also use the results from the corresponding literature to determine which combination of objectives is a priority for their industrial sector and which models, solution procedures, and algorithms can be schematized based on that.

Workplace-related conditions are another issue that has been addressed in a few studies. For instance, minimizing the number of robots or considering more than one assembly resource (i.e., human and robot) is a subject that has been neglected in many publications because of the increasing complexity of the problem. Considering the limited space in assembly stations for robots and workers is another aspect that can be addressed in future studies. Another future development in this contribution is proposing a trade-off between tool costs (robot costs) and the productivity obtained by implementing robotics in ALs. The consideration of robots and workers with different abilities and skill levels is another implication for future studies. Future work can also address machine failures, equipment breakdowns, maintenance time, and processing time uncertainties.

6. Conclusion

Automation has evolved manufacturing systems and affected assembly lines by developing smart manufacturing via robots with multiple capabilities. These robots enable assembly lines in terms of autonomy, flexibility, and transparency, allowing better management of failures in assembly operations by automating the system and mitigating human intervention in assembly tasks. Classifying both RALBP and elaborating ALBP-HRC was the subject of this elaboration, owing to its implications on both efficiency and economic aspects.

This study provides an overview of RALBP and ALBP-HRC by conducting a systematic literature review (SLR). The review primarily focused on identifying the optimization objectives, layouts, production specifications, and solution methods considered in the relevant studies. The SLR is customized to find studies that address assembly line balancing in the presence of industrial and collaborative robots. The review revealed that RALBP has been a subject studied by scholars since 1993, while ALBP-HRC is relatively new and has gained attention since 2019. Three phases of planning, conducting, and reporting the review are developed in this elaboration to collect publications, identify the relevance of the selected items with the corresponding literature, and propose a framework that classifies the publications based on different aspects.

The review result showed that most of the previous studies addressed straight-line assembly lines, while two-sided, parallel, and four-sided assembly lines have scarcely been addressed despite their advantages in increasing the flexibility and efficiency of assembly lines. The review also revealed that most studies aimed to minimize cycle time, total cost, or energy consumption, whereas other objectives (e.g., minimizing carbon emissions) have rarely been addressed. Moreover, most of the developed models have single objectives or two objectives, while three objectives have seldom been outlined. Regarding the solution method, mathematical models and metaheuristic algorithms are widely used to address this problem. The genetic algorithm and particle swarm optimization are the two most commonly used algorithms, whereas MILP is the dominant exact method used to formulate the RALBP and ALBP-HRC. Most studies addressed the single-model production assembly lines and the existence of a single assembly resource (i.e., human or operator) at each workstation, while muli- and mixed-model production and muli-manned/robots at workstations have received little to no attention, leaving an open avenue for future investigation.

The research gaps identified in the solution procedures applied to RALBPs and ALBP-HRC also showed a lack of research on developing exact algorithms. Using exact solution approaches to large-scale problems can be challenging due to the lack of ability to solve the problem in a reasonable time. Researchers can also focus on developing and improving metaheuristic algorithms and combine them with exact algorithms to balance solution quality and computational time. Besides, leveraging the power of parallel and distributed computing systems can help manage computational complexity by breaking down the problem into smaller, manageable subproblems. Moreover, with the advancement in software and hardware, it is now much more possible to address complex problems, such as ALBPs with moderate sizes, using exact solution methods such as constraint programming, decomposition algorithms, and dynamic programming. Researchers and practitioners can use this survey to determine which research scopes can be used for further elaboration, which research areas are missed in the literature, and what new solution procedures (exact or heuristic) can best suit each problem type.

CRediT authorship contribution statement

Masood Fathi: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Arash Sepehri:** Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Formal analysis, Data curation. **Morteza Ghobakhloo:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Mohammad Iranmanesh:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Ming-Lang Tseng:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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