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Analysis of Balancing Solutions for Simple Assembly Lines

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Abstract:

Purpose: Assembly Line Balancing (ALB) is critical to manufacturing efficiency and productivity. It involves assigning tasks to workstations to optimise performance while satisfying task priority and cycle time constraints. The Simple ALBP (SALBP) is a simplified version of the general problem that has received considerable research interest. Many academic works have been published on this topic, using a variety of methods, including exact, heuristic, and metaheuristic approaches. Therefore, the purpose of this research is to present a comprehensive evaluation of the literature on the methods used to solve the SALBP.

Design/methodology/approach: A comprehensive literature review was conducted to identify, select, analyse, and summarise 126 papers on SALBPs. The study started with the selection of relevant keywords. The selected papers were then narrowed down using various criteria.

Findings: The analysis showed that SALBP-1 and SALBP-2 are the most common types, with metaheuristic approaches being the most widely used. Despite extensive research, there is a significant need for studies focusing on SALBPs for multi- and mixed-models, particularly in the context of U-shaped and two-sided lines.

Originality/value: This literature review contributes to the identification of key areas for improvement in the SALBP and provides insight into potential directions for future research.

Keywords: simple assembly line balancing problem, exact method, heuristic method, meta-heuristic method, combinatorial optimisation, artificial intelligence

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1. Introduction

In the context of a highly competitive global market, manufacturers are required to engage in a range of strategies to improve both the efficiency and effectiveness of their production systems (Hager, Wafik & Faouzi, 2017; Priyono, Ijomah & Bititci, 2016). The creation of an efficient assembly line (AL) is considered to be one of the most promising objectives for effective production systems (Abdullah-Make, Ab. Rashid & Razali, 2017). The primary objective of the AL balancing problem (ALBP) is to determine the optimal allocation of tasks to workstations within the production system, while satisfying specific constraints and optimising efficiency by focusing on one or more objectives (Jiao, Jin, Xing, Li & Liu, 2021).

At the line balancing stage, the line configuration is typically referred to as having been selected in a previous decision phase. Each configuration imposes appropriate constraints that must be respected when allocating tasks to workstations. Some common configurations include straight lines (SLs), two-sided lines (TSLs), and U-shaped lines (USLs) (Abdullah-Make et al., 2017; Chutima & Khotsaenlee, 2022).

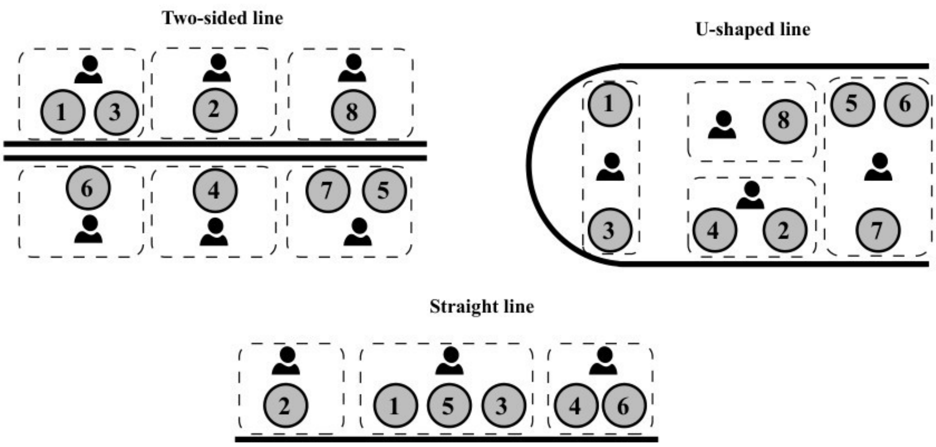

Figure 1. Different types of line layout

Today, line balancing has become one of the most effective tools for adapting the existing production system to evolving product designs or new market conditions. It is also a powerful tool for product customisation (Zamzam & Elakkad, 2021). It is possible to schedule multiple models of a product for production on the same production line, either in a mixed-model (MiM) or multi-model (MuM) mode. In a MiM line, where multiple products are involved, all products are processed simultaneously in a mixed sequence. Conversely, in a MuM line, the production line is dedicated to one product at a time and goes through a set-up process to change to the next product model (Pereira, 2018).

The first publication on ALBP was by Salveson (1955). Salveson proposed a solution based on linear programming. Subsequently, Baybars (1986a) conducted the initial study to differentiate between the classical and generalised versions of ALBP. The classical version, known as Simple ALBP (SALBP), has attracted considerable attention from researchers. As a result, numerous studies have been devoted to the development of computationally efficient approximations and exact methods for solving the SALB problem (Rekiek, Dolgui, Delchambre & Bratcu, 2002; Scholl & Becker, 2006). Furthermore, with the growing knowledge of the SALB problem, there has been a need for review papers to consolidate and synthesise the results for both academics and practitioners.

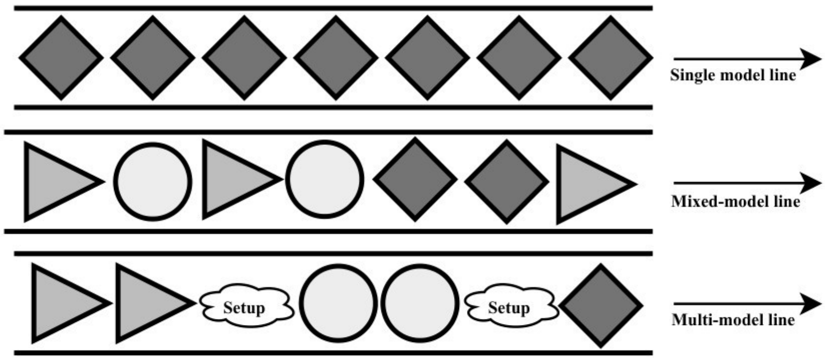

Figure 2. Types of assembly line

This review aims to fill the current gap in the literature by providing a summary of recent advances in the techniques used to solve the types of SALBP. Despite the extensive research on the ALBP (Battaïa & Dolgui, 2022; Boysen, Schulze & Scholl, 2022; Chutima, 2020; El Machouti, Hlyal, Babay & El Alami, 2024a) significant gaps remain in the study of several methods used to solve only the simple version. Therefore, the originality of this review lies in its comprehensive synthesis of recent research on the evolution of SALBP types and methods, providing an integrated perspective that will inform future developments in the field. The remainder of the article is structured as follows: Section 2 presents the basic principles of line balancing, including SALBP classification, multi-objective optimisation, and solution methods. Section 3 provides a summary of the existing work in the literature. Section 4 presents the results and discussion. Section 5 concludes the study and proposes future research directions for SALBPs.

2. Line Balancing: General Principles

For readers unfamiliar with line balancing, this section provides a brief overview of manufacturing flow lines. Further details can be found in (Battaïa & Dolgui, 2013, 2022; Boysen et al., 2022; Eghtesadifard, Khalifeh & Khorram, 2020; Rashid, Hutabarat & Tiwari, 2012; Saif, Guan, Wang, Mirza & Huang, 2014; Sivasankaran & Shahabudeen, 2014).

2.1. Number of Products or Models

In the literature, the following types of lines are often distinguished according to these specific criteria. Figure 2 shows the categorisation of lines based on the degree of similarity between the models produced on the line.

- Single-model (SiM) lines represent a classic configuration that produces a single model of a given product category. In this specific case, both task time and precedence constraints can be observed through a singular precedence graph (Saif et al., 2014).
- MiM lines combine many models of the same basic product that have comparable manufacturing processes and are produced simultaneously on the same line. The precedence diagrams of all product models are combined to determine the precedence relationship in a MiM line (Van Zante-de-Fokkert & De Kok, 1997).
- MuM lines are used in the assembly of a variety of products in batches. A batch line is utilised when there are several discrete items or product families that have significant variations in the manufacturing process (Van Zante-de-Fokkert & De Kok, 1997).

The main purpose of implementing different categories of lines in production systems is to meet the multiple and varied requirements of consumers.

2.2. Line Layout

A variety of line configurations can be found in the literature, including SLs, TSLs, and USLs, which are the most frequently used (Gökçen, Ağpak, Gencer & Kizilkaya, 2005). Figure 1 illustrates a selection of line layouts, where the dashed squares correspond to workstations occupied by a single worker. The number of units within each workstation indicates the specific task(s) assigned to that workstation.

- SLs: A series of individual workstations arranged in sequence along a linear conveyor system (Eghtesadifard et al., 2020).
- TSLs: This configuration can be used on either the left or right side. At the same time, the opposite workstations perform identical tasks on the workpiece. The execution of a specific task is constrained to either the left or right side of the line, whereas other tasks are permitted on either side (Abdullah-Make et al., 2017).
- USLs: In this specific configuration, the entry and exit points are located in close proximity to each other. The positioning of workers between the two ends of the line allows them to move from one side to the other. As a result, these workers can manipulate two or more workpieces simultaneously within the same cycle time (Kucukkoc & Zhang, 2015a).

2.3. SALBP Classification

On the other hand, Baybars (1986a) divided the ALBP into two different categories based on their parameters and characteristics: the General ALBP (GALBP) and the SALBP. The SALBP has been the subject of extensive research in the field and, due to its simplified nature, has generated a substantial body of publications. SALBPs are categorised into four different types based on the optimisation objective (Hackman, Magazine & Wee, 1989). The following diagram (Figure 3) shows the purpose of each type of SALBP.

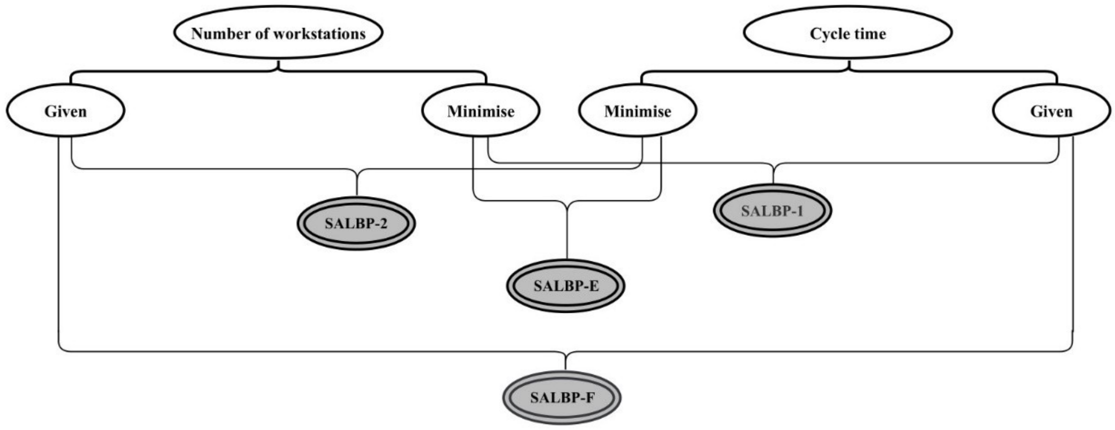

Figure 3. Versions of SALBP

- SALBP-1 distributes work between workstations to minimise the number of workstations M for a fixed cycle time C_T.
- SALBP-2 tries to minimise C_T for a given M.
- SALBP-E represents the most standard type of problem, focusing on maximising line efficiency E while reducing C_T and M due to their interdependence, where $E = \frac{T_{sum}}{M \times C_T}$ and T_{sum} is the sum of all task processing times (PTs).
- SALBP-F is a feasibility issue that determines whether a feasible line balance exists for a given setting of M and C_T.

There has been extensive research on the objective function (OF), which is a calculated metric used to evaluate the efficiency of a production line (Abdullah-Make et al., 2017). It is widely used in decision analysis, operations research, and optimisation studies. The OF plays a central role in research, particularly in the area of optimisation.

In ALBPs, the OF is a fundamental element. It provides researchers with a clear direction, allowing them to focus their efforts on identifying the most effective solution to their problems. Two principal categories of ALBPs are distinguished: those that are optimised based on a single OF and those that are simultaneously optimised with multiple objectives (Battaïa & Dolgui, 2022).

Multi-Objective Optimisation Problems (MOPs) are a common method for tackling complex real-world engineering challenges, of which ALBP is a notable example. In MOPs, a set of competing objectives must be optimised simultaneously.

2.4. Multi-Objective Optimisation

Combining an ALBP with another optimisation problem often results in a modification of the OF considered for the combined problem. In the context of MOPs, the quality of feasible solutions is evaluated based on an OF, to identify the one that represents the best solution (Scholl & Becker, 2006). The following OFs are commonly used in SALBPs:

- Minimise M (SALBP-1);
- Minimise C_T (SALBP-2);
- Maximise E (SALBP-E). This is equivalent to minimising the product $M \times C_T$.
- Other commonly used OFs include the following:
- Minimise the Smoothness Index (SI), the objective is to reduce the workload differences between different workstations, where $SI = \sqrt{\sum_{i=1}^{m}(C_T - T_i)^2}$ and T_i represents the time spent working at workstation i, $i \in \{1, \ldots, m\}$;
- Minimise the idle time I_d;
- Minimise the cost of the line while ensuring that all line constraints are respected;
- Minimise energy consumption.

2.5. Solution Procedures

Once the problem has been presented and the objectives have been defined, the solution method must be specified. To address the issue of production line balancing, it is essential to use combinatorial optimisation techniques. The objective is to identify the best solution among the feasible solutions, based on the criteria outlined in the problem constraints. Two methods are described in the literature: the exact method and the approximate method (Scholl & Becker, 2006).

2.5.1. Exact Methods

Two methods can be used to solve LBPs optimally. The first method involves the use of a standard general solver, such as LINGO, ILOG Solver, or ILOG Cplex, among others. The second method is an original dedicated solution approach (Battaïa & Dolgui, 2013). The ALB process requires the application of mathematical procedures to ensure the accurate and optimal solution of LBPs. The primary objective of the first approach is to develop a suitable mathematical model (MM) for the issue and to optimise the solver parameters to obtain the fastest feasible solution. Various MMs have been mentioned in the research literature, including Mixed Integer Linear Programming (MILP) (Azizoğlu & İmat, 2018), Nonlinear Integer Programming (NIP) (Hamta, Fatemi-Ghomi, Jolai & Bahalke, 2011), and Constraint Programming (CP) (Bukchin & Raviv, 2018).

Due to their primary purpose of handling a wide range of optimisation problems, solvers may not be efficient enough when used for specific variations of LBPs or a specific input data structure. In such cases, it may be necessary to develop a novel and specialised exact approach, such as Branch-and-Bound (B&B) (Walter & Schulze, 2022) or Dynamic Programming (DP) (Walter, Schulze & Scholl, 2021).

The computational time required to solve a problem is a key determinant of the effectiveness of an exact approach. While these methods can provide optimal solutions, they are often computationally expensive and require significant computational resources (Li, Kucukkoc & Tang, 2020). However, it is important to note that these methods may be less effective when applied to real-world situations on a large scale, which may make the optimal solution less feasible.

As the SALBP is NP-hard, the use of approximation techniques is required for large-scale problems or when time constraints significantly influence the decision context.

2.5.2. Approximate Methods

The computational time required by exact methods can be unacceptably long due to the size and complexity of the problem under consideration. As a result, approximation methods are often preferred. These strategies seek high quality solutions that are not always optimal. Several approximation approaches for solving ALBPs have been presented in the literature (e.g., Amen, 2000; Scholl & Voß, 1997). There are two types of approaches: heuristic and metaheuristic.

2.5.2.1. Heuristic Methods

Heuristic approaches use intuitive criteria to select the best candidate (an intermediate solution) during the problem-solving process. While they facilitate rapid solution generation, the quality of the solution may not be optimal. Heuristics are often used to generate initial solutions that allow a more efficient search for an optimal solution. In addition, heuristics are often used to improve the solution process in other approaches (Jiao et al., 2021; Rekiek et al., 2002; Scholl & Becker, 2006). Constructive techniques are based on priority criteria, typically determined by the number of successors and predecessors, and the PT of the task. The Ranked Positional Weight (RPW) method is one of the earliest heuristics, described by Helgeson and Birnie (1961). This method ranks tasks in descending order by their positional weight, which is calculated as the sum of the task duration and the PTs of all its successors. Many alternative heuristic approaches can be used in SALBP, including Shortest PT (Pitakaso, Sethanan, Jirasirilerd & Golinska-Dawson, 2023), Precedence Diagramming (Pintzos, Triantafyllou, Papakostas, Mourtzis & Chryssolouris, 2016), and Largest Candidate (Make, Rashid, Razali & Perumal, 2017).

Despite their speed, heuristic methods have several inherent limitations that must be taken into account. These methods are unable to guarantee optimal solutions, are sensitive to initial inputs, and present difficulties in handling complex constraints and multiple objectives. In the context of ALB, it is typical to consider multiple objectives simultaneously (Ahmad, Osman, Osman, Mohd-Azhar, Jamaludin, Abu-Bakar et al., 2024; Battaïa & Dolgui, 2013). As a result, metaheuristic methods are often used to develop optimal solutions.

2.5.2.2. Metaheuristic Methods

Metaheuristics have demonstrated greater efficiency and effectiveness than heuristics in the context of ALB, primarily due to their more extensive search processes. Glover (1997) was the first to propose this concept, defining it as a method that uses constructive techniques to identify initial solutions and local search algorithms to facilitate progress towards better neighbouring solutions. Unlike local search techniques, metaheuristics do not terminate when no better neighbour solutions are found. Instead, they can even move to inferior solutions to avoid premature convergence to a local optimum.

The majority of metaheuristic algorithms are inspired by natural phenomena. The ability to effectively address the NP-hard optimisation problem is becoming increasingly crucial. As the complexity of SALBPs increases every day, it is clear that there is an increasing need for the development of advanced algorithms (El Machouti et al., 2024a). Commonly used metaheuristics for solving SALBPs include Genetic Algorithms (GA) (Álvarez-Miranda, Pereira, Torrez-Meruvia & Vilà, 2021; El Machouti et al., 2024a; Zhang, 2019), Ant Colony Optimisation (ACO) (Huo, Wang, Chan, Lee & Strandhagen, 2018; Yagmahan, 2011), Simulated Annealing (SA) (Li, Janardhanan, Nielsen & Tang, 2018), Tabu Search (TS) (Abdeljaouad & Klement, 2021; Arikan, 2021; Özcan & Toklu, 2009b), and Greedy

Randomised Adaptive Search Procedure (GRASP) (Abdeljaouad & Klement, 2021; Arikan, 2021; Özcan & Toklu, 2009b; Andrés, Miralles & Pastor, 2008; Bautista, Alfaro-Pozo & Batalla-García, 2016; Bautista Valhondo & Alfaro Pozo, 2017; Belkharroubi & Yahyaoui, 2021, 2022b; El Machouti, Hlyal, & El Alami, 2024b).

3. Existing Works

This section presents a review and classification of SALBPs based on an analysis of the existing research literature. Furthermore, it provides a perspective on the novel contributions and research objectives of the present study in comparison to previous studies in this area.

The introduction of the first analytical description of the ALBP by Salveson (1955) has led to a considerable increase in the number of published solution strategies. Since the SALBP is NP-hard, it is crucial to develop both exact and approximate techniques. Following the initial presentation of the heuristic method by Tonge (1960), several heuristic techniques have been proposed. For example, Baybars (1986b) proposed an efficient single heuristic solution that outperforms all others in solving the deterministic LBPs for a SiM. The solution is then obtained by combining several heuristic criteria. Another approach to solving SALBPs was proposed by Saltzman and Baybars (1987). They developed an implicit enumeration method for the SALBP-1 to reduce M along the line for a given C_T. Computational results for many well-known problems from the literature are discussed. Over the years, researchers have proposed a variety of methods for solving SALBPs.

3.1. Exact Solution Procedures

Since 1990, a number of exact methods have been developed for different types of SALBP, based on DP or B&B. Well-established exact solution strategies include a variety of complex enumeration systems, boundary processes and dominance rules. These strategies are effective for small to medium-sized problems, but their effectiveness is reduced when applied to extremely large examples.

However, the exact method that has received the most attention in recent years is the use of B&B techniques, as demonstrated by Klein and Scholl (1996) with their method for solving SALBP-2. This method uses an enumeration approach, namely the Local Lower Bound Method, which is further enhanced by a set of restrictive constraints. Computational studies have demonstrated that this method is highly efficient in terms of computational speed. Another notable contribution is the work of Sprecher (1999) on SALBP-1, which is based on a precedence tree-guided enumeration scheme developed to address a variety of resource-constrained project scheduling problems. In another paper, Liu, Ng and Ong (2008) proposed three novel B&B algorithms for solving SALBP-1. The Hoffmann heuristic solution (Hoffmann, 1963, 1992) is used as the upper bound (UB) solution for all three methods.

To achieve a smoothed workload, it is necessary to minimise the sum of the squares of the workloads (SI). This is the same aim as that proposed by Azizoğlu and İmat (2018). In their paper, the authors address a SALBP with a given M and a given C_T. The results show that M and the work are the most important factors influencing the complexity of the solutions. Another important factor influencing the solution time is C_T. A B&B algorithm and a MILP formulation are proposed, as well as numerous optimality properties and bounds. The results show that the B&B technique can effectively solve medium-sized problems in real time. On the other hand, Walter (2020) shows that one of the LBs used in their algorithm is incorrect, and the author uses an example to show how the incorrect bound could prevent their B&B method from finding optimal solutions. As a result, the author corrects the bound argument and proposes a more rigorous formulation. Furthermore, Hazır, Agi and Guérin (2021) investigate the problem of reducing SI in the context of a fixed C_T and M. In this paper, the researchers develop a B&B solution technique to address the workload smoothing problem and evaluate it in comparison to the approach presented by Azizoğlu and İmat (2018).

The paper by Walter et al. (2021) considered a subset of the well-known SALBP with fixed M and C_T that seeks fully smoothed workloads across workstations along the assembly line (SALBP-SX: an optimised version of SALBP-F). The main objective is to achieve a balanced distribution of workloads rather than to minimise C_T. In this case, OF is the squared deviation of each workstation's workload from the ideal workload and is therefore closely related to variance. The researchers showed that their OF is equivalent to that optimised by Azizoğlu and

İmat (2018), who were the first to present an exact method for SALBP-SX. Walter et al. (2021) proposed a modified B&B method for the optimal solution of SALBP-SX. The experimental and computational results show that SALSA (SAL Smoothing Algorithm) is more effective than the task-oriented B&B technique proposed by Azizoğlu and İmat (2018). In a study by Walter and Schulze (2022), the effectiveness of two exact B&B algorithms in addressing the workload smoothing problem in SALs was presented and evaluated. The researchers found that the B&B technique proposed by Hazır et al. (2021) (BB-HAG) was not more effective than the algorithm proposed by Azizoğlu and İmat (2018) (BB-AI).

SALBP represents a fundamental integer programming (IP) problem in the field of operations research. Conversely, Ritt and Costa (2018) proposed an IP model for SALB and related issues, including USLs with priority constraints. In a notable contribution, Gökçen et al. (2005) presented the shortest route formulation of the U-shaped ALBP (SUALBP), which was originally proposed by Gutjahr and Nemhauser (1964). This formulation was developed to minimise M for a given C_T. The model presented in this article can be used as a basis for developing successful heuristic techniques for solving the SUALBP.

CP is a general technique for solving combinatorial optimisation problems. It combines the efficiency of linear programming with the ability to formulate mathematical equations characteristic of computer programming (Bukchin & Raviv, 2018). Several authors have proposed CP-based methods for solving certain types of SALBPs. Pastor, Ferrer and García (2007) conducted an analysis of the effectiveness of CP and IP formulations in addressing the SALBP. In this context, it is becoming increasingly important to determine the optimal technique for modelling and solving SALBPs. The aim of this research is to identify the most effective technique for modelling SALBP-1 and SALBP-2. According to Pastor and Ferrer (2009), the authors proposed an improved MM to solve these types. The main concept is to introduce supplementary constraints, given that the range of M is calculated based on the UB of M or the UB of C_T.

SALBP has been studied extensively. However, the E-type of the problem deserves further attention. This was identified by El Machouti et al. (2024a), who aimed to examine existing research on SALBP-E issues and predict future research directions by reviewing papers published between 1995 and 2023. The review demonstrated that the objective of this issue is to minimise the line capacity $M \times C_T$. Furthermore, the study demonstrated that the majority of SALBP-E problems are single-objective optimisation problems. In addition, researchers often analyse SALBP-E using SLs. With regard to methodology, the study identified a gap in the utilisation of exact methods to address SALBP-E.

3.2. Construction Heuristics

In the context of optimisation objectives, feasible SALB solutions are needed as starting points for local searches or to generate initial lower (upper) bounds for exact solution methods (Boysen et al., 2022). Traditionally, Priority Rule-Based methods (PRBMs) or partial enumeration methods have been used to determine such solutions. Another line of research aims at improving PRBMs, which are well suited for fast initial answers (even for extremely large cases) and can be easily extended to different types of problems (Otto & Otto, 2014).

Scholl and Voß (1997) present heuristic techniques for solving SALBP-1 and SALBP-2, with particular focus on PBMs for determining initial reasonable solutions and improvement procedures. As novel contributions to the field, they introduce new priority constraints, an extension of dynamic rules, and bidirectional planning. Furthermore, they describe a fundamental improvement process based on task repetition between workstations. This improvement process is linked to a static version of TS. On the other hand, Otto and Otto (2014) propose general design guidelines for the development of well-performing PRBMs through a thorough computational analysis. They also evaluate and demonstrate their effectiveness on the SALBPs. PRBMs are of great importance in solving NP-hard optimisation problems. For this problem, it has been shown that PRBMs can achieve superior results in a matter of seconds. In addition, another promising heuristic approach to solving SALBP-1 is the use of Petri nets (PNs), as described in the study by Kilincci and Bayhan (2006). The algorithm identifies tasks within the PNs model that can be assigned to the workstation with the shortest I_d. The algorithm is capable of producing a feasible solution in less than one minute.

All enumerative exact techniques can be constrained in terms of PT and/or search space to generate heuristics. Blum and Miralles (2011) and Li, Kucukkoc and Tang (2021), among others, present Beam Search (BS) strategies for various SALB problems. These strategies limit the size of the enumeration tree by setting a beam width, which is defined as the maximum number of transitions from one level of the tree to the next.

Sewell and Jacobson (2012) presented the Branch-Bound, and remember (BBR) algorithm, for addressing SALBP-1. Following the combined standards of Hoffmann, Talbot and Scholl, the algorithm finds and validates the optimal solution for each problem. BBR is a hybrid strategy that combines B&B with DP (Li et al., 2020). B&B uses bounds to reject subproblems that cannot reasonably provide a better solution than the best solution found. The method has been shown to find optimal solutions and verify their optimality for 269 known benchmark problems in a short time. Similarly, Morrison, Sewell and Jacobson (2014) discuss the computational results obtained by applying Sewell and Jacobson's (2012) BBR method with cyclic best-first search to Otto, Otto and Scholl (2013) database of SALBPs.

For SALBP-2, where it is necessary to minimise C_T, the researchers recommend the B&B method of Klein and Scholl (1996) and the iterative BBR method of Li et al. (2021). In their study, they presented an enhanced iterative BBR (IBBR) algorithm and an iterative BS (IBS) approach. IBBR uses additional LBs to provide more partial solutions and a different order of using LBs and dominance rules to speed up the search. Furthermore, additional LBs, supplementary dominance criteria, and a new workstation load selection criteria are used to improve the proposed IBS. The computational research showed that both proposed techniques, IBBR and IBS, outperformed the IBS-Blum method developed by Blum and Miralles (2011).

Furthermore, SALBP research has also focused on DP. Bautista and Pereira (2009) proposed a DP-based heuristic for ALBP. This paper presents a technique for solving SALBP-1, called "bounded DP (BDP)." The proposed method combines different heuristic criteria to minimise the search space within a DP framework, thereby improving the results of any previous solution to the issue. The results show that the implementation can find an optimal solution. Even when using shorter PTs, these results outperform any previous approach identified in the literature. In another paper, Bautista and Pereira (2011) presented TSALBP-1, a variant of SALBP with time and space constraints. Subsequent research presented different BDP bounds and solution methods tailored to the specific characteristics of the problem at hand, based on the methods in the literature for solving SALBP-1. In addition, the number of LBs for the simple issue was increased to account for the BDP method and to evaluate the quality of the exact solutions.

For a more comprehensive understanding of heuristic methods, readers are encouraged to consult the following reviews: (Abdullah-Make et al., 2017; Ahmad et al., 2024; Álvarez-Miranda, Pereira & Vilà, 2023; Battaïa & Dolgui, 2013; Boysen et al., 2022; Chetna, Ram-Chauhan & Chawla, 2019; Chutima, 2020; Eghtesadifard et al., 2020; El Machouti et al., 2024a; Fathi, Fontes, Urenda-Moris & Ghobakhloo, 2018; Jiao et al., 2021; Kharuddin & Ramli, 2020; Razali, Kamarudin, Ab. Rashid & Mohd-Rose, 2019). Constructive heuristics are widely used and important, but it is crucial to note that they do not guarantee an optimal solution. Instead, they generate feasible solutions that approach the true optimum. Therefore, it is important to study metaheuristic methods.

3.3. Metaheuristics Solution Procedures

Today, operations research has a variety of metaheuristics that are used to find near-optimal solutions wherever possible. In SALB research, different metaheuristics are applied to different categories of problems. Our comprehensive overview covers the many forms of metaheuristics that are most commonly used for SALB problems and can provide a number of references.

3.3.1. TS Method

Although the application of TS to SALBPs is challenging (Scholl & Voß, 1997), there are several TS approaches available for both basic and extended versions, such as SALBP-1. Lapierre, Ruiz and Soriano (2006) proposed a TS algorithm for SALBP-1, which they tested on real industrial data. Their findings showed that the algorithm performed well on real cases and produced better results. However, a thorough statistical study is needed to determine the effectiveness of the method. On the other hand, Özcan, Çerçđoğlu, Gökçen and Toklu (2009) investigated parallel lines with deterministic task times and developed a TS method that aims to minimise *M* while minimising *SI*. They compared the theoretical minimum *M* with the results of the research problems using the TS method.

It may be impossible to achieve effective learning through metaheuristics for this problem. This conclusion is based on the findings of Pape (2015), who conducted a thorough study of several heuristics and metaheuristics for SALBP-1. Pape (2015) found that the results of the most effective metaheuristic (TS) were inferior to other approaches, and not comparable to exact methods. On the other hand, Abdeljaouad and Klement (2021) used a generalised TS algorithm to solve the MiM case, focusing on minimising C_T, similar to the approach used for SiM lines (SALBP). The existing MM and a proposed LB inspired by the fundamental SALBP bound were compared with the solutions of their algorithm, which showed strong performance.

3.3.2. SA Method

The SA algorithm is presented as one of the most common metaheuristic approaches for addressing a range of SALB problems. A review of this study was provided by numerous articles, including (Li et al., 2018; Özcan & Toklu, 2009a).

The SA algorithm is a simple strategy that can quickly find the best solutions to problems of any size. Notably, Özcan and Toklu (2009a) had a similar goal in their study of SALBP-1. They aimed to minimise *M* while minimising *SI* and maximising *E*. Based on the concepts of adaptive learning and SA, this paper proposes a hybrid improvement heuristic solution for SLs and USLs. A series of comparative tests are performed on the benchmark problems presented by Scholl (1995). With the exception of one difficult case, the proposed approach identified the best solution. In contrast, Li et al. (2018) developed MMs and SA algorithms with the objective of minimising C_T and addressing the robotic ALBP-2 (RALBP-2). To address problems of a large scale, two SA algorithms are proposed, and four MILPs have been developed with the objective of identifying optimal solutions for small-scale problem instances. The efficacy of the proposed methods is confirmed by a comparative study of the tested algorithms and other adapted methods.

3.3.3. GA Method

GA is one of the well-known techniques in Artificial Intelligence (AI) and is commonly applied to solve SALB problems. Studies have shown that GA outperforms other algorithms in terms of solution quality and convergence speed, especially for challenging combinatorial problems (Abdullah-Make et al., 2017; Hlyal, Ait-Bassou, Soulhi, El Alami & El Alami, 2015). This metaheuristic begins by generating an initial population of chromosomes, which represent initial solutions. A fitness function is then applied to assess the quality of each solution, guiding the stopping criteria. The best individuals are selected for crossover and mutation, producing new offspring chromosomes. These new individuals are evaluated, and the process continues iteratively until the specified conditions are met (El Machouti et al., 2024a).

In addressing SALB problems, a significant number of researchers have used the GA approach. Tasan and Tunali (2006) present a hybrid GA strategy that combines GA and TS to solve a SALBP-1. Furthermore, the control parameters including population size, crossover and mutation were optimised to improve the performance of the hybrid GA. The results of the parameter optimisation showed that changes in the parameters had a significant impact on the issue solution. In addition, to understand the implementation of the hybrid GA, the researchers applied it to a number of benchmark problems. The results of this comparative study confirm that the integration of the GA with the TS can lead to a significant improvement in its performance. Moreover, Zamzam and Elakkad (2021) address the bi-objective Time and Space ALBP (TSALBP) in their paper, with a particular focus on time and space constraints, which are critical for reducing wasted time and unplanned travel. A hybrid GA is used to reduce *M* and the number of workers. The study illustrates a significant advance in addressing a real-world issue and indicates that a SALB can outperform a multi-manned AL under specific conditions. This study makes a significant contribution to the field as it is the first to implement a GA under these constraints. For further articles, refer to (Álvarez-Miranda et al., 2021; Triki, Mellouli, Hachicha & Masmoudi, 2016).

3.3.4. GRASP Method

The GRASP technique consists of two key stages: the construction stage (CS), which generates a feasible solution, and the improvement stage, which uses local search (LS) to explore the neighbourhood of the generated solution and further improve it (Essafi, Delorme & Dolgui, 2012).

Belkharroubi and Yahyaoui (2021) introduced a hybrid approach that combines GRASP and GA techniques to address the MiMALBP-2, which aims to find the best C_T for a given M. The GRASP method uses an RPW heuristic during the CS to generate the GA's initial population, while a neighbourhood search procedure is employed to enhance solution quality. The approach was tested on a numerical example, demonstrating the improved solution efficiency from the GRASP method when combined with GA. In a subsequent study (Belkharroubi & Yahyaoui, 2022b), the authors addressed MiMALBP-1, focusing on minimising M for a given C_T, and proposed a hybrid reactive GRASP (HRGRASP) algorithm, which they evaluated across seven problem sets of varying sizes.

A recent study by El Machouti et al. (2024b) focused on worker allocation in MiMALBP-E, aiming to identify the best combination of C_T and the number of workers to achieve maximum E. To tackle this, the researchers developed an HRGRASP method. The goal of this approach was to minimise the time required to complete tasks at each workstation by assigning tasks to the worker with the shortest PT. To evaluate the effectiveness of the algorithm, an illustrative problem was used in which eight workers had to be allocated between two models. The results of this problem were compared with a GA that includes three key operations: scramble mutation, cyclic crossover and roulette wheel selection. The study found that the proposed HRGRASP algorithm is generally more efficient and robust than the GA.

3.3.5. ACO Method

ACO is an AI method inspired by the foraging behaviour of ants. In this algorithm, ants release pheromones along the paths they visit, and more pheromones are produced on the better paths, attracting more ants to follow those paths in the next iteration. Over time, most ants will gravitate towards the shortest path. ACO has been effectively applied to a wide range of classical NP-hard problems and has been extensively studied for its application in solving different types of SALBPs (Zheng, Li, Li & Tang, 2012).

Yagmahan (2011) discusses the MiMALBP-1 and addresses concerns related to capacity utilisation and discrepancies between workstation times due to variations in operating times, M, E and smooth production. The author proposes a multi-objective ACO (MOACO) algorithm to solve these problems. To demonstrate the efficiency of the algorithm, several test problems are solved and the results show that the MOACO algorithm outperforms other methods. As well as this, Huo et al. (2018) used a hybrid approach that combined the ACO algorithm with BS (ACO-BS) to solve SALBP-1. The aim was to improve the solution quality and speed up the search process. However, when the results were compared with those obtained using the priority rule; it was found that ACO-BS significantly improved the quality of the best solutions.

3.4. AI-Based Approaches

The ALBP represents a significant challenge in optimising production systems. This issue has been addressed using a variety of methods, including exact, heuristic, and metaheuristic approaches. While these methods have considerably enhanced production system performance, it is important not to underestimate the increasing role of AI techniques (Aferhane, Bouallal, Douzi, Harba, Vilcahuaman & Arbanil, 2024; Atwani, Hlyal & El Alami, 2020). The application of AI methods, including artificial neural networks (ANN) and reinforcement learning (RL) algorithms, introduces a novel approach to the resolution of ALBP. The integration of learning and adaptation capabilities enables these approaches to address complex and dynamic problems more effectively than traditional methods (Aferhane, Bouallal, Douzi & Harba, 2024; Ibáñez, Cordón, Damas & Magdalena, 2009). The use of these advanced techniques allows AI to model and analyse operator performance in real time. Furthermore, AI can adapt to fluctuating production conditions, enabling dynamic reallocation of tasks according to changing performance and constraints (Polo-Triana, Gutierrez & Leon-Becerra, 2024). By incorporating these adaptive and learning capabilities, AI adds significant value to traditional ALB methods, transforming production systems into more responsive and optimised environments (Nagy, Ruppert & Abonyi, 2020).

By exploring these techniques, Ali and Tirel (2023) have investigated the application of AI techniques, specifically RL, to address the challenges of ALB. They focus on the use of deep RL (DRL) to control industrial assembly lines. This approach aims to optimise task assignment and resource allocation while respecting priority constraints, using an action masking method to reduce the action space to feasible actions. Recently, Mumcu (2024) proposed a combined approach of heuristic methods and ANN to optimise assembly lines in the lighting industry. Four heuristic methods achieved a maximum efficiency of 93.955%. In addition, a neural network model was trained and achieved 99.940% accuracy in predicting the operations of another line. This study illustrates the effectiveness of ANN as a complement to heuristic methods. In a separate study, Chourabi, Khedher, Babay and Cheikhrouhou (2023) proposed an approach to solve the ALBP in the garment industry using ACO and a worker performance index. Their method includes a global competence index based on measurable criteria such as quality, activity and attendance. The purpose is to maximise this competence index for optimal worker and task allocation, thus demonstrating the effectiveness of their model in a real production environment. Further studies can be found in the works of (Khalid, Yusof & Iida, 2020; Woo, Cho, Nam & Nam, 2021).

Literature	Type of SALBP	Solution method			Optimisation objective					Type of production line			Line layout		
		Exact method	Approximate method												
			Heuristic	Metaheuristic	1	2	3	4	5	SiM	MiM	MuM	SLs	TSLs	USLs
Nearchou, 2005	SALBP-1			Differential Evolution algorithm (DEA)	✓					✓			✓		
Gökçen et al., 2005	SUALBP	Shortest route formulation			✓					✓					✓
Tasan & Tunali, 2006	SALBP-1			Hybrid GA and TS	✓					✓			✓		
Kilinci & Bayhan, 2006	SALBP-1		Petri nets (PNs)		✓		✓		✓	✓			✓		
Lapierre et al., 2006	SALBP-1			TS	✓			✓		✓			✓		
Ze-Qiang, Wen-Ming, Lian-Sheng & Bin, 2007	SALBP-1			ACO	✓					✓			✓		
Kilinci & Bayhan, 2008	SALBP-1		P-invariants of PNs		✓					✓			✓		
Andrés et al., 2008	GSALBP-1			GRASP	✓					✓			✓		
Blum, 2008	SALBP-1			ACO-BS	✓					✓			✓		
Liu et al., 2008	SALBP-1	B&B			✓					✓			✓		
Özcan & Toklu, 2009b	SALBP			SA, adaptive learning			✓	✓		✓			✓		✓
Pastor & Ferrer, 2009	SALBP-1 SALBP-2	MILP			✓	✓				✓			✓		

Literature	Type of SALBP	Solution method			Optimisation objective					Type of production line			Line layout		
		Exact method	Approximate method												
			Heuristic	Metaheuristic	1	2	3	4	5	SiM	MiM	MuM	SLs	TSLs	USLs
Bautista & Pereira, 2009	SALBP-1		BDP		✓					✓			✓		
Kilincci, 2010	SALBP-2		PNs-based heuristic			✓			✓	✓			✓		
Jonnalagedda & Dabade, 2010	SALBP-2		Priority rule, Station-oriented heuristic			✓					✓		✓		
Blum & Miralles, 2011	SALWABP -2		BS			✓				✓			✓		
Petropoulos & Nearchou, 2011	SALBP-2			PSO				✓	✓	✓			✓		
Kilincci, 2011	SALBP-1		PNs-based heuristic		✓					✓			✓		
Yagmahan, 2011	SALBP-1			ACO	✓		✓	✓			✓		✓		
Emrani-Noushabadi, Bahalke, Dolatkhahi, Dolatkhahi & Makui, 2011	SALBP-1			GA	✓					✓			✓		
Bautista & Pereira, 2011	TSALBP-1		BDP		✓					✓			✓		
Zheng et al., 2012	SALBP-1			ACO	✓					✓			✓		
Dou, Li & Su, 2013	SALBP-1			Particle Swarm Optimisation (PSO)	✓					✓			✓		
Yu & Shi, 2013	SALBP-1			GA	✓							✓	✓		
Su, Wu & Yu, 2014	SALBP-E		PNs based heuristic		✓	✓					✓		✓		
Esmaeilbeigi, Naderi & Charkhgard, 2015	SALBP-E	MILP			✓	✓	✓	✓		✓			✓		
Kucukkoc & Zhang, 2015b	PTALBP-E			ACO			✓			✓				✓	
Pitakaso & Sethanan, 2016	SALBP-1 SALBP-1M			A modified DEA	✓					✓			✓		

Literature	Type of SALBP	Solution method			Optimisation objective					Type of production line			Line layout		
		Exact method	Approximate method												
			Heuristic	Metaheuristic	1	2	3	4	5	SiM	MiM	MuM	SLs	TSLs	USLs
Corominas, Garcıa-Villoria & Pastor, 2016	SALBP-E	MILP	OH				✓			✓			✓		
Zhang, Yan, Liu & Jiang, 2016	SALBP-2			Integer Coded DEA		✓				✓			✓		
Nearchou & Omirou, 2017	SALBP-1 SALBP-2			DEA			✓			✓			✓		
Kammer-Christensen, Janardhanan & Nielsen, 2017	MuRALBP -2		OH			✓						✓	✓		
Zhang, 2017	SALBP-1			Improved Immune Algorithm	✓			✓		✓			✓		
Belassiria, Mazouzi, El Fezazi & El Maskaoui, 2017	SALBP-E			Hybrid GA			✓	✓		✓			✓		
Azizoğlu & İmat, 2018	SALBP-3	B&B						✓		✓			✓		
Huo et al., 2018	SALBP-1			ACO-BS	✓					✓			✓		
Zhang, 2019	SALBP-1			Immune GA (IGA)	✓			✓		✓			✓		
Hazır et al., 2021	SALBP-3	B&B						✓		✓			✓		
Li et al., 2021	SALBP-2	Enhanced IBBR	Enhanced IBS			✓				✓			✓		
Arikan, 2021	SALBP-2			Reactive TS		✓		✓		✓			✓		
Álvarez-Miranda et al., 2021	SALBP-2			GA-BDP		✓				✓			✓		
Walter et al., 2021	SALBP-F (SALBP-SX)	B&B						✓		✓			✓		
Abdeljaouad & Klement, 2021	SALBP-2		OH	TS		✓				✓		✓	✓		
Belkharroubi & Yahyaoui, 2021	SALBP-2			GA-GRASP		✓						✓	✓		
Walter & Schulze, 2022	SALBP-3	Task-oriented B&B algorithms						✓		✓			✓		

Literature	Type of SALBP	Solution method			Optimisation objective					Type of production line			Line layout		
		Exact method	Approximate method												
			Heuristic	Metaheuristic	1	2	3	4	5	SiM	MiM	MuM	SLs	TSLs	USLs
Belkharroubi & Yahyaoui, 2022a	SALBP-E			GA			✓			✓			✓		
Belkharroubi & Yahyaoui, 2022b	SALBP-1			HRGRASP	✓						✓		✓		
El Machouti et al., 2024b	SALBP-E			HRGRASP			✓				✓		✓		

SALWABP: SAL worker assignment and BP, SALBP-1M: SALBP-1 with the maximum number of machine types considered in a workstation, SALBP-3: to minimise *SI*, MuRALBP-2: Type two MuM Robotic ALBP, OH: Other heuristics, 1: Minimise *M*, 2: Minimise C_T, 3: Maximise *E*, 4: Minimise *SI*, 5: Minimise I_d.

Table 1. An overview of some SALBP research using exact and approximate approaches

4. Results and Discussion

A review of the literature (Table 1) leads to the following conclusions.

Researchers have identified a number of different types of SALBPs, with SALBP-1 and SALBP-2 problems representing the primary focus of their investigations, as shown in Figure 4. This trend can be attributed to the fundamental importance of these two problems in the field of ALB theory. Several algorithms, optimisation techniques, and heuristics have been developed with a specific focus on SALBP-1 and SALBP-2, contributing significantly to the extensive existing literature on this topic. The study of SALBP-1 is often motivated by its relevance to the initial design of assembly lines, while the study of SALBP-2 is attracting attention due to its importance in improving the efficiency of existing lines.

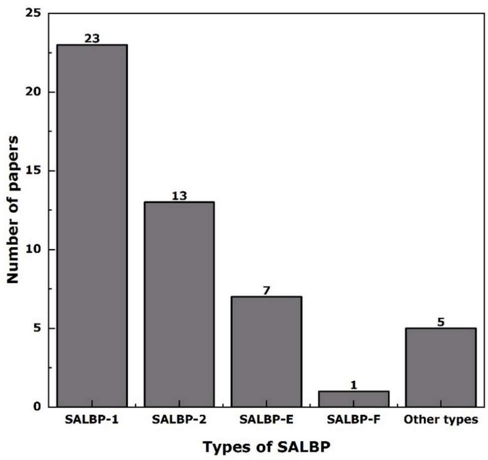

Figure 4. Frequency of SALBP types in selected articles

The study of SALBP-1 is often motivated by its relevance to the initial design of ALs. Similarly, SALBP-2 has attracted considerable interest for its potential to improve the efficiency of existing lines. However, these two variants do not fully address the complex and evolving needs of modern industry. There is a clear opportunity to explore more complex variants, such as SALBP-E, which incorporates environmental efficiency criteria, or multi-objective variants that optimise multiple aspects simultaneously. It is important to note that this problem is more complex than SALBP-1 and SALBP-2 due to its non-linear form. This is the reason why only a few researchers have focused on SALBP-E. Furthermore, additional studies are required to gain a greater understanding of the complexity of SALBP-E.

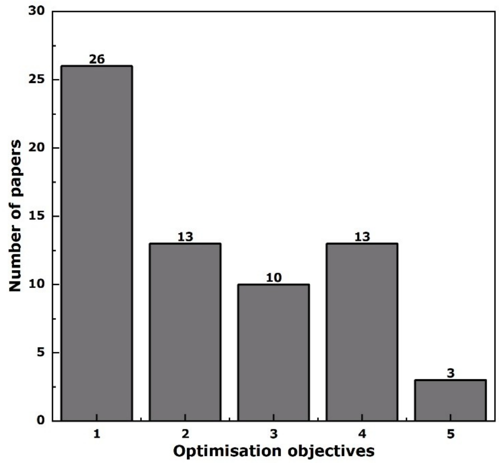

Figure 5. Frequency of SALBP objectives in selected articles

In the context of SALBPs, the most commonly addressed objectives are the minimisation of *M*, C_T and *SI*, as illustrated in Figure 5. By reducing the *M* required to perform a set of tasks, companies can limit infrastructure expenditure and improve the overall efficiency of the AL. This minimisation is a fundamental aspect of SALBP-1. Secondly, C_T minimisation is a key objective of SALBP-2, particularly in situations where production times are critical. The focus on C_T minimisation reflects the importance for companies to respond rapidly to market demands while maintaining high productivity. Furthermore, the minimisation of *SI* is also widely studied. The aim of this indicator is to ensure a better distribution of tasks and greater homogeneity in the production flow, which is often prioritised in environments where the stability and fluidity of the production process are essential.

It is important to note that the majority of SALBPs are formulated as single-objective optimisation problems. Consequently, they do not always reflect the complexity of real production systems, which often require the simultaneous optimisation of multiple criteria. Table 1 presents an overview of the limited number of papers that have studied MOPs.

A significant number of articles in the field of production and manufacturing process optimisation have focused on SiM lines, as shown in Table 1, which are designed to produce a specific type of product. This approach is widely used in the academic literature because SiM lines have distinctive characteristics and present particular challenges that are of interest to researchers. By focusing on these lines, studies can investigate in detail the optimal planning and scheduling strategies for a specific production task. They can also analyse in great detail the impact of changes in demand, capacity constraints and cycle times on the overall performance of the production system (Battaïa & Dolgui, 2013). The production of personalised products, on the other hand, requires the use of different products on the same line. To address this issue, a MiMAL and a MuMAL have been developed for the production of a range of products.

A recurring observation in the literature is the predominance of studies on SLs to the detriment of more complex configurations such as TSLs and USLs. The principal reasons for this trend are the simplicity of SL models, which facilitate the analysis and modelling of SALBPs, and their linear design, which is particularly well suited to conventional production lines. However, TSLs and USLs offer significant potential advantages. The introduction of TSLs increases workstation density and reduces unnecessary travel for operators (Abdullah-Make et al., 2017). Similarly, USLs allow operators to work at multiple workstations simultaneously, thereby encouraging collaboration between workers in different sections of the line (Chutima & Khotsaenlee, 2022; Kucukkoc & Zhang, 2015a).

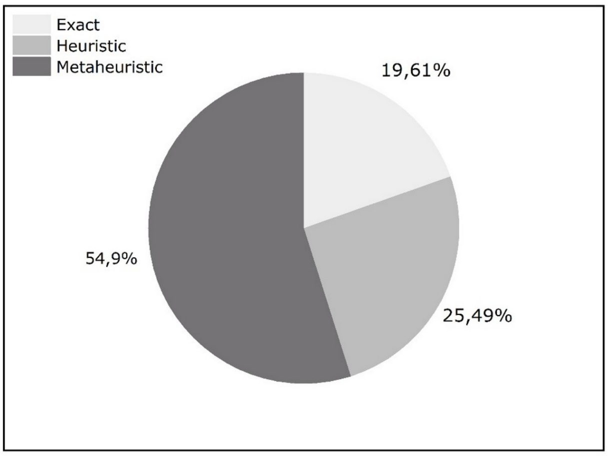

Figure 6. Distribution of articles based on the methods used

The results presented in Table 1 clearly show a growing trend in the use of hybrid methods for solving SALBPs. Hybrid methods allow higher-quality solutions to be obtained in reasonable computational times. Hybridisation could potentially solve the SALBP by synthesising several algorithms into a single one. This would allow the system to benefit from the strengths of each algorithm, so hybridisation could potentially reduce the complexity of SALBP systems. Based on our observations, metaheuristic algorithms were found to be remarkably effective in exploring spaces, avoiding local optima, and identifying near-optimal solutions. Our results show that metaheuristic algorithms have considerable potential for solving SALBPs (see Figure 6). The analysis of Table 1 also shows a notable adoption of two particular artificial intelligence methods, GA and ACO.

Recent publications on SALBPs are numerous and diverse, indicating that the topic continues to be of interest to both academics and practitioners. To build on this momentum, it is recommended that the following suggestions for future SALB research be considered.

- SALBP-E and SALBP-F are advanced versions of SALBP that present additional challenges. Finding a balanced solution in a given configuration while respecting these specific constraints is a critical aspect of these problems. Despite their complexity, understanding and solving these variants is essential to simulate realistic production line conditions and to develop optimisation strategies capable of meeting practical manufacturing challenges.
- To accurately and comprehensively reflect operational requirements in SALBPs, it is essential to use multi-objective functions rather than just one. By considering multiple objectives, decision-makers can conduct a thorough evaluation of the production system, taking into account different performance metrics. This approach enables decision-makers to make well-informed and balanced decisions that are consistent with the overall objectives of the production process.
- The advent of rapid advances in computer technology and AI has resulted in an increased reliance on hybrid methods combining various intelligent approaches for SALBP resolution. These methods integrate the efficacy of conventional metaheuristics with the efficiency of AI techniques, thereby providing more robust and efficient solutions. The advent of these AI techniques has facilitated the exploration of novel avenues for SALBP resolution, enabling the tackling of more complex and realistic problems with optimised solutions.
- It is important to note that more research is needed to address issues related to production lines that include MiM and MuM lines. These production lines represent a superior means of production and are well placed to adapt successfully to the present diversity of consumer demands and short product life cycles.
- To improve production systems, future studies should investigate different configurations of SALBPs, including USLs and TSLs, taking into account additional constraints such as zoning. It would be beneficial to conduct a study to demonstrate the practicality of implementing such layouts in real industries.

5. Conclusion

This paper provides an overview and analysis of SALBP. A large number of academic papers have studied this topic using various exact, heuristic and metaheuristic methods. The choice of the most appropriate approach is crucial and depends on the specific requirements, constraints and objectives of the SALBP. While the exact method is the best option, it is also the most time consuming. Therefore, a comprehensive review of recent research on SALBPs is needed to identify trends in the problems and appropriate solution methods. Although SALBPs are a class of NP-hard optimisation problems, efficient methods and techniques are available to solve large instances with good quality for practical use. Based on a survey of the types of problems and production lines, as well as the research objectives in SALBP and the methods used to solve these problems, the results indicate that SALBP-1 and SALBP-2 are the most commonly used. Our research shows that the majority of SALBPs have been classified as single objective optimisation problems. However, there is a significant gap in the existing literature with implications for MiM and MuM lines with USLs or TSLs. Furthermore, a hybrid metaheuristic can be investigated to exploit the advantages of these techniques. The integration of new AI techniques, such as ANN and RL algorithms, can be explored to improve the effectiveness of SALB approaches and to address new manufacturing challenges.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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References

Abdeljaouad, M.A., & Klement, N. (2021). Tabu search algorithm for single and multi-model line Balancing problems. *Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems (APMS 2021) IFIP Advances in Information and Communication Technology* (630, 409-415). Springer, Cham. https://doi.org/10.1007/978-3-030-85874-2_43

Abdullah-Make, M.R., Ab. Rashid, M.F.F., & Razali, M.M. (2017). A review of two-sided assembly line balancing problem. *The International Journal of Advanced Manufacturing Technology,* 89(5-8), 1743-1763. https://doi.org/10.1007/s00170-016-9158-3

Aferhane, A., Bouallal, D., Douzi, H., & Harba, R. (2024). Affine Registration of Plantar Foot Thermal Images with Deep Learning: Application to Diabetic Foot Diagnosis. In Gherabi, N., Awad, A. I., Nayyar, A., & Bahaj, M. (Eds.), *Advances in Intelligent System and Smart Technologies* (826, 387-397). Springer International Publishing. https://doi.org/10.1007/978-3-031-47672-3_37

Aferhane, A., Bouallal, D., Douzi, H., Harba, R., Vilcahuaman, L., & Arbanil, H. (2024). Affine registration of thermal images of plantar feet using convolutional neural networks. *Biomedical Signal Processing and Control,* 95, 106407. https://doi.org/10.1016/j.bspc.2024.106407

Ahmad, A.H., Osman, S.A., Osman, S.A., Mohd-Azhar, M.F.A., Jamaludin, M.H., Abu-Bakar, H.A. et al. (2024). A Comprehensive Review: Analysing the Pros and Cons of Assembly Line Balancing Methods. *Journal of Advanced Research in Applied Sciences and Engineering Technology,* 44(2), 72-88. https://doi.org/10.37934/araset.44.2.7288

Ali, A.M., & Tirel, L. (2023). Action masked deep reinforcement learning for controlling industrial assembly lines. *IEEE World AI IoT Congress (AIIoT)* (0797-0803). https://doi.org/10.1109/AIIoT58121.2023.10174426

Álvarez-Miranda, E., Pereira, J., Torrez-Meruvia, H., & Vilà, M. (2021). A Hybrid Genetic Algorithm for the Simple Assembly Line Balancing Problem with a Fixed Number of Workstations. *Mathematics,* 9(17), 2157. https://doi.org/10.3390/math9172157

Álvarez-Miranda, E., Pereira, J., & Vilà, M. (2023). Analysis of the simple assembly line balancing problem complexity. *Computers & Operations Research,* 159, 106323. https://doi.org/10.1016/j.cor.2023.106323

Amen, M. (2000). Heuristic methods for cost-oriented assembly line balancing: A survey. *International Journal of Production Economics,* 68(1), 1-14. https://doi.org/10.1016/S0925-5273(99)00095-X

Andrés, C., Miralles, C., & Pastor, R. (2008). Balancing and scheduling tasks in assembly lines with sequence-dependent setup times. *European Journal of Operational Research,* 187(3), 1212-1223. https://doi.org/10.1016/j.ejor.2006.07.044

Arikan, M. (2021). Type-2 Assembly Line Balancing Using Reactive Tabu Search. *Gazi University Journal of Science,* 34(1), 162-178. https://doi.org/10.35378/gujs.690131

Atwani, M., Hlyal, M., & El Alami, J. (2020). AI in Supply chain performance and resilience: A literature review. *13ème Conference Internationale de Modelisation, Optimisation et Simulation (MOSIM2020).* Agadir, Maroc.

Azizoğlu, M., & İmat, S. (2018). Workload smoothing in simple assembly line balancing. *Computers & Operations Research,* 89, 51-57. https://doi.org/10.1016/j.cor.2017.08.006

Battaïa, O., & Dolgui, A. (2013). A taxonomy of line balancing problems and their solutionapproaches. *International Journal of Production Economics,* 142(2), 259-277. https://doi.org/10.1016/j.ijpe.2012.10.020

Battaïa, O., & Dolgui, A. (2022). Hybridizations in line balancing problems: A comprehensive review on new trends and formulations. *International Journal of Production Economics,* 250, 108673. https://doi.org/10.1016/j.ijpe.2022.108673

Bautista, J., Alfaro-Pozo, R., & Batalla-García, C. (2016). GRASP for sequencing mixed models in an assembly line with work overload, useless time and production regularity. *Progress in Artificial Intelligence,* 5(1), 27-33. https://doi.org/10.1007/s13748-015-0071-z

Bautista, J., & Pereira, J. (2009). A dynamic programming based heuristic for the assembly line balancing problem. *European Journal of Operational Research,* 194(3), 787-794. https://doi.org/10.1016/j.ejor.2008.01.016

Bautista, J., & Pereira, J. (2011). Procedures for the Time and Space constrained Assembly Line Balancing Problem. *European Journal of Operational Research,* 212(3), 473-481. https://doi.org/10.1016/j.ejor.2011.01.052

Bautista-Valhondo, J., & Alfaro-Pozo, R. (2017). *Minimizing the ergonomic risk and its dispersion in a mixed model assembly line using GRASP.*

Baybars, I. (1986a). *A Survey of Exact Algorithms for the Simple Assembly Line Balancing Problem.* Management Science, 32(8), 909-932. https://doi.org/10.1287/mnsc.32.8.909

Baybars, I. (1986b). An efficient heuristic method for the simple assembly line balancing problem. *International Journal of Production Research,* 24(1), 149-166. https://doi.org/10.1080/00207548608919719

Belassiria, I., Mazouzi, M., El Fezazi, S., & El Maskaoui, Z. (2017). An efficient approach for workload balancing of assembly line systems with assignment restrictions. *2017 International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA)* (7-12). https://doi.org/10.1109/LOGISTIQUA.2017.7962865

Belkharroubi, L., & Yahyaoui, K. (2021). A Hybrid Grasp-genetic Algorithm for Mixed-model Assembly Line Balancing Problem Type 2. *International Journal of Computing,* 424-432. https://doi.org/10.47839/ijc.20.3.2289

Belkharroubi, L., & Yahyaoui, K. (2022a). Maximization of the assembly line efficiency using an approach based on Genetic Algorithm. *2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)* (1-6). https://doi.org/10.1109/IRASET52964.2022.9737934

Belkharroubi, L., & Yahyaoui, K. (2022b). Solving the mixed-model assembly line balancing problem type-I using a Hybrid Reactive GRASP. *Production & Manufacturing Research,* 10(1), 108-131. https://doi.org/10.1080/21693277.2022.2065380

Blum, C. (2008). Beam-ACO for Simple Assembly Line Balancing. *INFORMS Journal on Computing,* 20(4), 618-627. https://doi.org/10.1287/ijoc.1080.0271

Blum, C., & Miralles, C. (2011). On solving the assembly line worker assignment and balancing problem via beam search. *Computers & Operations Research,* 38(1), 328-339. https://doi.org/10.1016/j.cor.2010.05.008

Boysen, N., Schulze, P., & Scholl, A. (2022). Assembly line balancing: What happened in the last fifteen years? *European Journal of Operational Research,* 301(3), 797-814. https://doi.org/10.1016/j.ejor.2021.11.043

Bukchin, Y., & Raviv, T. (2018). Constraint programming for solving various assembly line balancing problems. *Omega,* 78, 57-68. https://doi.org/10.1016/j.omega.2017.06.008

Chetna, Ram-Chauhan, N., & Chawla, V. (2019). A review on mixed assembly line balancing, sequencing and scheduling in an industry. *IOP Conference Series: Materials Science and Engineering,* 691(1), 012060. https://doi.org/10.1088/1757-899X/691/1/012060

Chourabi, Z., Khedher, F., Babay, A., & Cheikhrouhou, M. (2023). Developing a metaheuristic model for the general assembly line balancing optimization based on a new workforce performance index: A case study in the garment industry. *The Journal of The Textile Institute,* 1-12. https://doi.org/10.1080/00405000.2023.2288364

Chutima, P. (2020). Research trends and outlooks in assembly line balancing problems. *Engineering Journal,* 24(5), 93-134.

Chutima, P., & Khotsaenlee, A. (2022). Multi-objective parallel adjacent U-shaped assembly line balancing collaborated by robots and normal and disabled workers. *Computers & Operations Research,* 143, 105775. https://doi.org/10.1016/j.cor.2022.105775

Corominas, A., Garcıa-Villoria, A., & Pastor, R. (2016). Improving the resolution of the simple assembly line balancing problem type E. *SORT-Statistics and Operations Research Transactions*, 40(2), 227-242.

Dou, J., Li, J., & Su, C. (2013). A novel feasible task sequence-oriented discrete particle swarm algorithm for simple assembly line balancing problem of type 1. *The International Journal of Advanced Manufacturing Technology,* 69(9-12), 2445-2457. https://doi.org/10.1007/s00170-013-5216-2

Eghtesadifard, M., Khalifeh, M., & Khorram, M. (2020). A systematic review of research themes and hot topics in assembly line balancing through the web of science within 1990-2017. *Computers & Industrial Engineering,* 139, 106182. https://doi.org/10.1016/j.cie.2019.106182

El Machouti, S., Hlyal, M., Babay, A., & El Alami, J. (2024a). Optimisation of Simple Assembly Line Balancing Problem Type E: A Systematic Literature Review. *Management Systems in Production Engineering,* 32(2), 162-173. https://doi.org/10.2478/mspe-2024-0016

El Machouti, S., Hlyal, M., & El Alami, J. (2024b). A Hybrid Reactive GRASP approach for the balancing of a mixed-model assembly line of type E with worker allocation. *Scientific African,* 26, e02378. https://doi.org/10.1016/j.sciaf.2024.e02378

Emrani Noushabadi, Bahalke, Dolatkhahi, Dolatkhahi, & Makui. (2011). Simple assembly line balancing problem under task deterioration. *International Journal of Industrial Engineering Computations,* 2, 583-592. https://doi.org/10.5267/j.ijiec.2011.02.003

Esmaeilbeigi, R., Naderi, B., & Charkhgard, P. (2015). The type E simple assembly line balancing problem: A mixed integer linear programming formulation. *Computers & Operations Research,* 64, 168-177. https://doi.org/10.1016/j.cor.2015.05.017

Essafi, M., Delorme, X., & Dolgui, A. (2012). A reactive GRASP and Path Relinking for balancing reconfigurable transfer lines. *International Journal of Production Research,* 50(18), 5213-5238. https://doi.org/10.1080/00207543.2012.677864

Fathi, M., Fontes, D.B.M.M., Urenda-Moris, M., & Ghobakhloo, M. (2018). Assembly line balancing problem: A comparative evaluation of heuristics and a computational assessment of objectives. *Journal of Modelling in Management,* 13(2), 455-474. https://doi.org/10.1108/JM2-03-2017-0027

Glover, F. (1997). Tabu Search and Adaptive Memory Programming–Advances, Applications and Challenges. In Barr, R.S., Helgason, R.V., & Kennington, J.L. (Eds.), *Interfaces in Computer Science and Operations Research* (7, 1-75). Springer US. https://doi.org/10.1007/978-1-4615-4102-8_1

Gökçen, H., Ağpak, K., Gencer, C., & Kizilkaya, E. (2005). A shortest route formulation of simple U-type assembly line balancing problem. *Applied Mathematical Modelling,* 29(4), 373-380. https://doi.org/10.1016/j.apm.2004.10.003

Gutjahr, A.L., & Nemhauser, G.L. (1964). An algorithm for the line balancing problem. *Management Science,* 11(2), 308-315.

Hackman, S.T., Magazine, M.J., & Wee, T.S. (1989). Fast, Effective Algorithms for Simple Assembly Line Balancing Problems. *Operations Research,* 37(6), 916-924. https://doi.org/10.1287/opre.37.6.916

Hager, T., Wafik, H., & Faouzi, M. (2017). Manufacturing system design based on axiomatic design: Case of assembly line. *Journal of Industrial Engineering and Management,* 10(1), 111-139.

Hamta, N., Fatemi-Ghomi, S.M.T., Jolai, F., & Bahalke, U. (2011). Bi-criteria assembly line balancing by considering flexible operation times. *Applied Mathematical Modelling,* 35(12), 5592-5608. https://doi.org/10.1016/j.apm.2011.05.016

Hazır, Ö., Agi, M.A.N., & Guérin, J. (2021). An efficient branch and bound algorithm for smoothing the workloads on simple assembly lines. *International Journal of Production Research,* 59(2), 617-634. https://doi.org/10.1080/00207543.2019.1701208

Helgeson, W.B., & Birnie, D.P. (1961). Assembly line balancing using the ranked positional weight technique. *Journal of Industrial Engineering,* 12(6), 394-398.

Hlyal, M., Ait-Bassou, A., Soulhi, A., El Alami, J., & El Alami, N. (2015). Designing A Distribution Network Using A Two Level Capacity Location Allocation Problem: Formulation and Efficient Genetic Algorithm Resolution with an Application to A Moroccan Retail Company. *Journal of Theoretical & Applied Information Technology,* 72(2).

Hoffmann, T.R. (1963). Assembly Line Balancing with a Precedence Matrix. *Management Science,* 9(4), 551-562. https://doi.org/10.1287/mnsc.9.4.551

Hoffmann, T.R. (1992). Eureka: A Hybrid System for Assembly Line Balancing. *Management Science,* 38(1), 39-47. https://doi.org/10.1287/mnsc.38.1.39

Huo, J., Wang, Z., Chan, F.T.S., Lee, C.K.M., & Strandhagen, J.O. (2018). Assembly Line Balancing Based on Beam Ant Colony Optimisation. *Mathematical Problems in Engineering,* 2018, 1-17. https://doi.org/10.1155/2018/2481435

Ibáñez, O., Cordón, O., Damas, S., & Magdalena, L. (2009). A Review on the Application of Hybrid Artificial Intelligence Systems to Optimization Problems in Operations Management. In Corchado, E. Wu, X., Oja, E., Herrero, Á., & Baruque, B. (Eds.), *Hybrid Artificial Intelligence Systems* (5572, 360-367). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-02319-4_43

Jiao, Y., Jin, H., Xing, X., Li, M., & Liu, X. (2021). Assembly line balance research methods, literature and development review. *Concurrent Engineering,* 29(2), 183-194. https://doi.org/10.1177/1063293X20987910

Jonnalagedda, V.L.V., & Dabade, B.M. (2010). Heuristic procedure for Mixed Model Assembly Line Balancing Problem. *2010 IEEE International Conference on Industrial Engineering and Engineering Management* (552-556). https://doi.org/10.1109/IEEM.2010.5674505

Kammer-Christensen, M., Janardhanan, M.N., & Nielsen, P. (2017). Heuristics for solving a multi-model robotic assembly line balancing problem. *Production & Manufacturing Research,* 5(1), 410-424. https://doi.org/10.1080/21693277.2017.1403977

Khalid, M.N.A., Yusof, U.K., & Iida, H. (2020). An Artificial Immune System Approach for Solving Type-E Assembly Line Balancing Problem with Problem-Specific Information. *2020 IEEE 16th International Conference on Control & Automation (ICCA)* (1590-1595). https://doi.org/10.1109/ICCA51439.2020.9264382

Kharuddin, M.H., & Ramli, M.F. (2020). A Review on Methods to Improve and Balance the Assembly Line. *IOP Conference Series: Materials Science and Engineering,* 767(1), 012022. https://doi.org/10.1088/1757-899X/767/1/012022

Kilincci, O. (2010). A Petri net-based heuristic for simple assembly line balancing problem of type 2. *The International Journal of Advanced Manufacturing Technology,* 46(1-4), 329-338. https://doi.org/10.1007/s00170-009-2082-z

Kilincci, O. (2011). Firing sequences backward algorithm for simple assembly line balancing problem of type 1. *Computers & Industrial Engineering,* 60(4), 830-839. https://doi.org/10.1016/j.cie.2011.02.001

Kilincci, O., & Bayhan, G.M. (2006). A Petri net approach for simple assembly line balancing problems. *The International Journal of Advanced Manufacturing Technology,* 30(11-12), 1165-1173. https://doi.org/10.1007/s00170-005-0154-2

Kilincci, O., & Bayhan, G.M. (2008). A P-invariant-based algorithm for simple assembly line balancing problem of type-1. *The International Journal of Advanced Manufacturing Technology,* 37(3-4), 400-409. https://doi.org/10.1007/s00170-007-0975-2

Klein, R., & Scholl, A. (1996). Maximizing the production rate in simple assembly line balancing–A branch and bound procedure. *European Journal of Operational Research,* 91(2), 367-385. https://doi.org/10.1016/0377-2217(95)00047-X

Kucukkoc, I., & Zhang, D.Z. (2015a). Balancing of parallel U-shaped assembly lines. *Computers & Operations Research,* 64, 233-244. https://doi.org/10.1016/j.cor.2015.05.014

Kucukkoc, I., & Zhang, D.Z. (2015b). Type-E parallel two-sided assembly line balancing problem: Mathematical model and ant colony optimisation based approach with optimised parameters. *Computers & Industrial Engineering,* 84, 56-69. https://doi.org/10.1016/j.cie.2014.12.037

Lapierre, S.D., Ruiz, A., & Soriano, P. (2006). Balancing assembly lines with tabu search. *European Journal of Operational Research,* 168(3), 826-837. https://doi.org/10.1016/j.ejor.2004.07.031

Li, Z., Janardhanan, M.N., Nielsen, P., & Tang, Q. (2018). Mathematical models and simulated annealing algorithms for the robotic assembly line balancing problem. *Assembly Automation,* 38(4), 420-436. https://doi.org/10.1108/AA-09-2017-115

Li, Z., Kucukkoc, I., & Tang, Q. (2020). A comparative study of exact methods for the simple assembly line balancing problem. *Soft Computing,* 24(15), 11459-11475. https://doi.org/10.1007/s00500-019-04609-9

Li, Z., Kucukkoc, I., & Tang, Q. (2021). Enhanced branch-bound-remember and iterative beam search algorithms for type II assembly line balancing problem. *Computers & Operations Research,* 131, 105235. https://doi.org/10.1016/j.cor.2021.105235

Liu, S.B., Ng, K.M., & Ong, H.L. (2008). Branch-and-bound algorithms for simple assembly line balancing problem. *The International Journal of Advanced Manufacturing Technology,* 36(1-2), 169-177. https://doi.org/10.1007/s00170-006-0821-y

Make, M.R.A., Rashid, M., Razali, M.M., & Perumal, M. (2017). Assembly line balancing using heuristic approaches in manufacturing industry. *Journal of Mechanical Engineering,* 5514, 14.

Morrison, D.R., Sewell, E.C., & Jacobson, S.H. (2014). An application of the branch, bound, and remember algorithm to a new simple assembly line balancing dataset. *European Journal of Operational Research,* 236(2), 403-409. https://doi.org/10.1016/j.ejor.2013.11.033

Mumcu, Y.K. (2024). Solution approach using heuristic and artificial neural networks methods in assembly line balancing problems: A case study in the lighting industry. *Heliyon,* 10(5). https://doi.org/10.1016/j.heliyon.2024.e26950

Nagy, L., Ruppert, T., & Abonyi, J. (2020). Analytic hierarchy process and multilayer network-based method for assembly line balancing. *Applied Sciences,* 10(11), 3932. https://doi.org/10.3390/app10113932

Nearchou, A.C. (2005). A Differential Evolution Algorithm for Simple Assembly Line Balancing. *IFAC Proceedings Volumes,* 38(1), 247-252. https://doi.org/10.3182/20050703-6-CZ-1902.01463

Nearchou, A.C., & Omirou, S.L. (2017). Assembly Line Balancing Using Differential Evolution Models. *Cybernetics and Systems,* 48(5), 436-458. https://doi.org/10.1080/01969722.2017.1319238

Otto, A., & Otto, C. (2014). How to design effective priority rules: Example of simple assembly line balancing. *Computers & Industrial Engineering,* 69, 43-52. https://doi.org/10.1016/j.cie.2013.12.013

Otto, A., Otto, C., & Scholl, A. (2013). Systematic data generation and test design for solution algorithms on the example of SALBPGen for assembly line balancing. *European Journal of Operational Research,* 228(1), 33-45. https://doi.org/10.1016/j.ejor.2012.12.029

Özcan, U., Çerçđoğlu, H., Gökçen, H., & Toklu, B. (2009). *A Tabu Search Algorithm for the Parallel Assembly Line Balancing Problem.*

Özcan, U., & Toklu, B. (2009a). A new hybrid improvement heuristic approach to simple straight and U-type assembly line balancing problems. *Journal of Intelligent Manufacturing,* 20(1), 123-136. https://doi.org/10.1007/s10845-008-0108-2

Özcan, U., & Toklu, B. (2009b). A tabu search algorithm for two-sided assembly line balancing. *The International Journal of Advanced Manufacturing Technology,* 43(7-8), 822-829. https://doi.org/10.1007/s00170-008-1753-5

Pape, T. (2015). Heuristics and lower bounds for the simple assembly line balancing problem type 1: Overview, computational tests and improvements. *European Journal of Operational Research,* 240(1), 32-42. https://doi.org/10.1016/j.ejor.2014.06.023

Pastor, R., & Ferrer, L. (2009). An improved mathematical program to solve the simple assembly line balancing problem. *International Journal of Production Research,* 47(11), 2943-2959. https://doi.org/10.1080/00207540701713832

Pastor, R., Ferrer, L., & García, A. (2007). Evaluating Optimization Models to Solve SALBP. In Gervasi, O., & Gavrilova, M.L. (Eds.), *Computational Science and Its Applications (ICCSA)* (4705, 791-803). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-74472-6_65

Pereira, J. (2018). Modelling and solving a cost-oriented resource-constrained multi-model assembly line balancing problem. *International Journal of Production Research,* 56(11), 3994-4016. https://doi.org/10.1080/00207543.2018.1427899

Petropoulos, D.I., & Nearchou, A.C. (2011). A particle swarm optimization algorithm for balancing assembly lines. *Assembly Automation,* 31(2), 118-129. https://doi.org/10.1108/01445151111117700

Pintzos, G., Triantafyllou, C., Papakostas, N., Mourtzis, D., & Chryssolouris, G. (2016). Assembly precedence diagram generation through assembly tiers determination. *International Journal of Computer Integrated Manufacturing,* 29(10), 1045-1057. https://doi.org/10.1080/0951192X.2015.1130260

Pitakaso, R., & Sethanan, K. (2016). Modified differential evolution algorithm for simple assembly line balancing with a limit on the number of machine types. *Engineering Optimization,* 48(2), 253-271. https://doi.org/10.1080/0305215X.2015.1005082

Pitakaso, R., Sethanan, K., Jirasirilerd, G., & Golinska-Dawson, P. (2023). A novel variable neighborhood strategy adaptive search for SALBP-2 problem with a limit on the number of machine's types. *Annals of Operations Research,* 324(1-2), 1501-1525. https://doi.org/10.1007/s10479-021-04015-1

Polo-Triana, S., Gutierrez, J.C., & Leon-Becerra, J. (2024). Integration of machine learning in the supply chain for decision making: A systematic literature review. *Journal of Industrial Engineering and Management,* 17(2), 344-372. https://doi.org/10.3926/jiem.6403

Priyono, A., Ijomah, W., & Bititci, U. (2016). Disassembly for remanufacturing: A systematic literature review, new model development and future research needs. *Journal of Industrial Engineering and Management,* 9(4), 899. https://doi.org/10.3926/jiem.2053

Rashid, M.F.F., Hutabarat, W., & Tiwari, A. (2012). A review on assembly sequence planning and assembly line balancing optimisation using soft computing approaches. *The International Journal of Advanced Manufacturing Technology,* 59(1-4), 335-349. https://doi.org/10.1007/s00170-011-3499-8

Razali, M.M., Kamarudin, N.H., Ab. Rashid, M.F.F., & Mohd-Rose, A.N. (2019). Recent trend in mixed-model assembly line balancing optimization using soft computing approaches. *Engineering Computations,* 36(2), 622-645. https://doi.org/10.1108/EC-05-2018-0205

Rekiek, B., Dolgui, A., Delchambre, A., & Bratcu, A. (2002). State of art of optimization methods for assembly line design. *Annual Reviews in Control,* 26(2), 163-174. https://doi.org/10.1016/S1367-5788(02)00027-5

Ritt, M., & Costa, A.M. (2018). Improved integer programming models for simple assembly line balancing and related problems. *International Transactions in Operational Research,* 25(4), 1345-1359. https://doi.org/10.1111/itor.12206

Saif, U., Guan, Z., Wang, B., Mirza, J., & Huang, S. (2014). A survey on assembly lines and its types. *Frontiers of Mechanical Engineering,* 9(2), 95-105. https://doi.org/10.1007/s11465-014-0302-1

Saltzman, M.J., & Baybars, I. (1987). A two-process implicit enumeration algorithm for the simple assembly line balancing problem. *European Journal of Operational Research,* 32(1), 118-129. https://doi.org/10.1016/0377-2217(87)90276-1

Salveson, M.E. (1955). The Assembly-Line Balancing Problem. *Transactions of the American Society of Mechanical Engineers,* 77(6), 939-947. https://doi.org/10.1115/1.4014559

Scholl, A. (1995). Data of assembly line balancing problems. Techn. Hochsch., Inst. für Betriebswirtschaftslehre.

Scholl, A., & Becker, C. (2006). State-of-the-art exact and heuristic solution procedures for simple assembly line balancing. *European Journal of Operational Research,* 168(3), 666-693. https://doi.org/10.1016/j.ejor.2004.07.022

Scholl, A., & Voß, S. (1997). Simple assembly line balancing? Heuristic approaches. *Journal of Heuristics,* 2(3), 217-244. https://doi.org/10.1007/BF00127358

Sewell, E.C., & Jacobson, S.H. (2012). A Branch, Bound, and Remember Algorithm for the Simple Assembly Line Balancing Problem. *INFORMS Journal on Computing,* 24(3), 433-442. https://doi.org/10.1287/ijoc.1110.0462

Sivasankaran, P., & Shahabudeen, P. (2014). Literature review of assembly line balancing problems. *The International Journal of Advanced Manufacturing Technology,* 73(9-12), 1665-1694. https://doi.org/10.1007/s00170-014-5944-y

Sprecher, A. (1999). A competitive branch-and-bound algorithm for the simple assembly line balancing problem. *International Journal of Production Research,* 37(8), 1787-1816. https://doi.org/10.1080/002075499191003

Su, P., Wu, N., & Yu, Z. (2014). A Petri net-based heuristic for mixed-model assembly line balancing problem of Type-E. *International Journal of Production Research,* 52(5), 1542-1556. https://doi.org/10.1080/00207543.2013.849010

Tasan, S.Ö., & Tunali, S. (2006). Improving the Genetic Algorithms Performance in Simple Assembly Line Balancing. In Gavrilova, M.L., Gervasi, O., Kumar, V., Tan, C.J.K., Taniar, D., Laganá, A. et al. (Eds.), *Computational Science and Its Applications (ICCSA)* (3984, 78-87). Springer Berlin Heidelberg. https://doi.org/10.1007/11751649_9

Tonge, F.M. (1960). Summary of a Heuristic Line Balancing Procedure. *Management Science,* 7(1), 21-42. https://doi.org/10.1287/mnsc.7.1.21

Triki, H., Mellouli, A., Hachicha, W., & Masmoudi, F. (2016). A hybrid genetic algorithm approach for solving an extension of assembly line balancing problem. *International Journal of Computer Integrated Manufacturing,* 29(5), 504-519. https://doi.org/10.1080/0951192X.2015.1067914

Van Zante-de-Fokkert, J.I., & De Kok, T.G. (1997). The mixed and multi model line balancing problem: A comparison. *European Journal of Operational Research,* 100(3), 399-412. https://doi.org/10.1016/S0377-2217(96)00162-2

Walter, R. (2020). A note on "Workload smoothing in simple assembly line balancing". *Computers & Operations Research,* 113, 104803. https://doi.org/10.1016/j.cor.2019.104803

Walter, R., & Schulze, P. (2022). On the performance of task-oriented branch-and-bound algorithms for workload smoothing in simple assembly line balancing. *International Journal of Production Research,* 60(15), 4654-4667. https://doi.org/10.1080/00207543.2021.1934589

Walter, R., Schulze, P., & Scholl, A. (2021). SALSA: Combining branch-and-bound with dynamic programming to smoothen workloads in simple assembly line balancing. *European Journal of Operational Research,* 295(3), 857-873. https://doi.org/10.1016/j.ejor.2021.03.021

Woo, J.H., Cho, Y.I., Nam, S.H., & Nam, J.H. (2021). Development of a reinforcement learning-based adaptive scheduling algorithm for block assembly production line. *2021 Winter Simulation Conference (WSC),* 1-12. https://doi.org/10.1109/WSC52266.2021.9715509

Yagmahan, B. (2011). Mixed-model assembly line balancing using a multi-objective ant colony optimization approach. *Expert Systems with Applications,* 38(10), 12453-12461. https://doi.org/10.1016/j.eswa.2011.04.026

Yu, H., & Shi, W. (2013). A genetic algorithm for Multi-Model Assembly Line Balancing Problem. *2013 IEEE International Symposium on Assembly and Manufacturing (ISAM)* (369-371). https://doi.org/10.1109/ISAM.2013.6643482

Zamzam, N., & Elakkad, A. (2021). Time and space multi-manned assembly line balancing problem using genetic algorithm. *Journal of Industrial Engineering and Management,* 14(4), 733. https://doi.org/10.3926/jiem.3542

Ze-Qiang, Z., Wen-Ming, C., Lian-Sheng, T., & Bin, Z. (2007). Ant Algorithm with Summation Rules for Assembly Line Balancing Problem. *2007 International Conference on Management Science and Engineering,* 369-374. https://doi.org/10.1109/ICMSE.2007.4421875

Zhang, H. (2017). An improved immune algorithm for simple assembly line balancing problem of type 1. *Journal of Algorithms & Computational Technology,* 11(4), 317-326. https://doi.org/10.1177/1748301817710924

Zhang, H. (2019). An immune genetic algorithm for simple assembly line balancing problem of type 1. *Assembly Automation,* 39(1), 113-123. https://doi.org/10.1108/AA-08-2017-101

Zhang, H., Yan, Q., Liu, Y., & Jiang, Z. (2016). An integer-coded differential evolution algorithm for simple assembly line balancing problem of type 2. *Assembly Automation,* 36(3), 246-261. https://doi.org/10.1108/AA-11-2015-089

Zheng, Q.X., Li, Y.X., Li, M., & Tang, Q.H. (2012). An Improved Ant Colony Optimization for Large-Scale Simple Assembly Line Balancing Problem of Type-1. *Applied Mechanics and Materials,* 159, 51-55. https://doi.org/10.4028/www.scientific.net/AMM.159.51