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The Effect of Learning on Assembly Line Balancing: A Review

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Abstract
Classical assembly line balancing (ALB) models assume constant cycle times during production. However, this assumption oversimplifies the actual situation, especially in small batch production of up to a few hundred units, since employees can significantly improve their performance thanks to the learning effect, causing task times to decrease. Several researchers have realised the importance of the effect of learning in ALB. However, only a limited number of papers have so far addressed this issue. This is problematic, since ignoring the learning effect in ALB may lead to inaccurate results and by extension misleading conclusions. This study summarises the main contributions in the field of ALB that focus on the learning effect. First, assembly lines (ALs) and ALB problems are characterised. Next, the importance of the learning effect in ALB is highlighted, and the main learning curve (LC) models are introduced. Finally, an exhaustive review of the main contributions in the field of ALB and learning effect is provided. The results highlight that many problems in this area need to be investigated further, in relation to both conceptual model building and the development of algorithms for solving practical size problems.

Keywords
assembly line balancing, learning effect, learning curve, operations management

1 Introduction

An *assembly line* is a well-known mass production method that consists of a series of workstations connected in a particular order by a conveyer belt or by other material handling equipment. In assembly lines, the entire work necessary to create one product is divided into simple, indivisible operations called tasks. Tasks are governed by precedence constraints, which may be related to cycle time, capacity, workers' skills, and zoning among other factors (Boysen et al., 2022; Özcan and Toklu, 2009). An operator (generally human) performs the same task repeatedly at the corresponding station. After passing through all the stations, finished units quit the assembly line at the last station. Assembly line balancing (ALB) is the problem of assigning tasks to workstations while satisfying certain constraints (e.g., precedence constraints) and optimising one or more performance measures.

Simple ALB models assume constant task times during production, an approach which implies that the time to finish a task remains unchanged no matter how often the task is repeated. Nonetheless, task times may decrease due to learning effects when a human operator repeats the task; as Andress (1954) puts it laconically, "A worker learns as he works; and the more often he repeats an operation". Wright (1936) was the first to demonstrate how repetition and learning affect aircraft production in assembly lines and other repetitive tasks. He discovered that as the cumulative output doubled, the average building costs per unit decreased by around 20%. This finding was formalised as the learning curve (LC), an inversely proportional connection between unit costs and cumulative output. Since then, the significant presence of learning effects in assembly lines has been reported in numerous industrial cases (see for example, Dutton and Thomas, 1984).

In assembly lines, learning effects are particularly significant during the launch of a new product, at the early stage of production (Baloff, 1971), or in case of small lot size production (Thongsanit et al., 2010). The period in which production time (or cost) decreases due to learning is called the learning stage. The length of the learning stage has now developed into a crucial performance metric for firms due to shorter product life cycles, increased innovation rates, and more frequent product introductions. Shorter learning stages enable greater profits if a new product enters the market faster as a result. Businesses therefore need to consider

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learning effects while planning, as this can substantially shorten their learning stage (Otto and Otto, 2014).

This paper sets out to review the relevant literature related to the application of the learning effect in ALB and to explore possible research directions in this area.

The rest of the paper is structured as follows. Section 2 describes the main characteristics of assembly lines and the different modelling concepts applied for the formulation of assembly line balancing problems (ALBPs). Section 3 highlights the importance of the learning effect in ALB and summarises the different concepts of LCs. Section 4 reviews the main contributions related to the consideration of learning effect in ALB. Section 5 discusses the gaps in literature and some future research possibilities. Finally, Section 6 draws some general conclusions.

2 Classification of assembly lines and ALBPs

In Section 2, we describe the main characteristics of assembly lines and the modelling concepts on which ALBPs are formulated and classified. Studies in the literature have classified ALBPs based on assembly line characteristics and several classification possibilities have been suggested (Baybars, 1986; Becker and Scholl, 2006; Boysen et al., 2008; Erel and Sarin, 1998; Ghosh and Gagnon, 1989).

2.1 Workflow characteristics

Assembly lines are divided into two major categories based on the workflow features: paced assembly lines and unpaced assembly lines. In paced assembly lines, the workstations are assumed to have equal cycle time (CT) (which is the longest operation time of any workstation). In this case, each station pushes the unit to the following station as the time equivalent to the cycle time passed. Some stations might finish their tasks earlier than the CT; however, parts still need to wait until the end of the CT.

Unpaced assembly lines are classified into two types based on the movement of finished parts: synchronous and asynchronous assembly lines. In synchronous assembly lines, all stations move their finished parts simultaneously after a fixed time, so there is no buffer between stations. While in asynchronous assembly lines, stations might have different station times, however, part at a station does not move to the next station unless the next station has finished its tasks.

2.2 Product characteristics

Assembly lines are classified into three basic types based on product characteristics: single model, mixed model, and multi-mixed assembly lines (see Fig. 1). In single model assembly lines (Fig. 1(a)), only one product is assembled. Therefore, there is a higher possibility for learning effect due to the uninterrupted repetition of the same tasks. In a mixed-model assembly line (Fig. 1(b)), distinct models of the same product are assembled. Similar tasks of the different models are assigned to the same stations; hence, set-up time between models can be reduced significantly, and intermixed model sequences can be assembled on the same line. The third type, the multi-model assembly line (Fig. 1(c)), deals with assembling different products in batch form on an assembly line. Once a model's batch is produced, the stations are set up according to the requirements of the next batch.

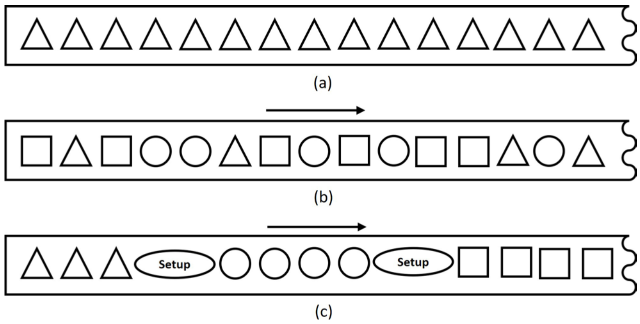

Fig. 1 Assembly lines for single and multiple models; (a) single model line; (b) mixed-model line; (c) multi-model line

2.3 Layout characteristic

Based on layout characteristics, assembly lines can be categorised into four types: Serial lines, parallel lines, U-shaped lines, and two-sided assembly lines (see Fig. 2). In serial assembly lines, also called straight lines (Fig. 2(a)), stations are organised serially along a conveyor belt. After finishing the processing at the first station, parts move down the line one by one to the next station, finally leaving the last station. The cycle time is determined based on the station with the maximum load in case of a paced line. In a U-shaped line (Fig. 2(b)), stations are arranged in a U-shaped layout (see Fig. 2). One of the benefits of this layout is that some tasks can revisit some stations during the assembly process; hence fewer stations are needed. Another advantage is that operators can move freely inside the U shape, and can serve several stations, unlike the straight-line layout where each operator manages one specific station. Parallel stations (Fig. 2(c)) are used to divide the workload between the stations. For instance, if the line's CT is more than desired, the station with the maximum workload is paralleled with another station to split the workload, thereby reducing the line CT. The same set of tasks are assigned to the parallel stations. The last type is the two-sided layout (Fig. 2(d)).

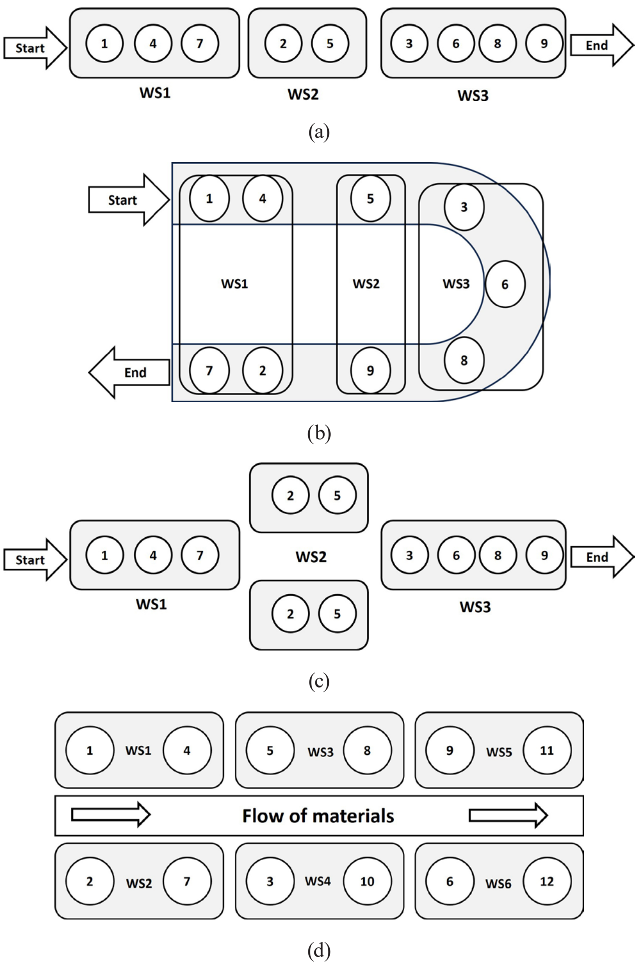

Fig. 2 Different types of assembly line layouts; (a) straight line; (b) U-shaped line; (c) line with parallel stations; (d) two-sided line

This layout is beneficial when assembling heavy and large-sized products such as automobiles, trucks, and large construction machinery. Parts are assembled from both sides of the line, and more than one operator or machine works simultaneously at a station.

2.4 Task time characteristics

Assembly lines can be divided into two groups based on the nature of task time, i.e., deterministic, and stochastic task time (see for example Battaïa and Dolgui, 2013). When the expected variation in task times is negligible, e.g., in assembly lines with automated machines performing simple tasks, task times are assumed deterministic, rendering ALBPs easier to solve (Sivasankaran and Shahabudeen, 2014). In contrast, in labour-intensive assembly lines, task times vary due to the intrinsically human nature of the work, implying that probabilistic modelling may be more appropriate (Bentaha et al., 2015). However, regardless of whether task times have a deterministic or stochastic property, they usually decrease with repetition when a task is given to manual labour. This systematic decrease in task time arises due to the learning effect. In such a problem, task time is considered a variable that depends on the learning rate of the operator (Lolli et al., 2018).

3 Simple versus generalised ALBPs

Baybars (1986) divides ALBPs into two categories: simple assembly line balancing problems (SALBPs) and generalised assembly line balancing problems (GALBPs). SALBPs are the most known and best-studied problems. Despite being too constrained to reflect the complexity of real-world line balancing problems, simple assembly lines capture the main aspects of line balancing and are considered the core of any ALBP. SALBPs are based on the following nine assumptions:

- all input parameters are known with certainty (A-1),
- a task cannot be split among two or more stations (A-2),
- the processing of tasks is subject to precedence constraints (A-3),
- all tasks must be processed (A-4),
- all stations are equipped with machines and workers to perform any task (A-5),
- task times are deterministic and not sequence dependent (A-6),
- any task can be processed at any station (A-7),
- the line is considered as serial with no feeder or parallel subassembly lines (A-8),
- the line is designed for a unique model of a single product (A-9).

Depending on the objective function considered, SALBPs can be differentiated into four versions: SALBP-1, SALBP-2, SALBP-E, and SALBP-F. SALBP-1 aims to minimise the line's total idle time, which is equivalent to minimising the number of stations, assuming a given cycle time. SALBP-2 aims to minimise the cycle time for a given number of stations which is equivalent to maximising the output quantity. SALBP-E attempts to maximise line efficiency (E), where:

$$E = {T_{sum}} \big/ {m \times T_c} . \tag{1}$$

The total time of all tasks (T_{sum}) is divided by the number of workstations (m) multiplied by cycle time (T_c). As the total idle time is equal to:

$$T_{sum} - m \times T_c . \tag{2}$$

A maximisation of E leads to a minimisation of idle times. Finally, SALBP-F aims to find a feasible balance between a given number of stations and cycle time.

Any assumption characterising SALBPs or any combination thereof needs to be relaxed to account for the large variety of ALBPs. The line may be used to produce multi-models or mixed models. Zoning constraints may also restrict the grouping of specific tasks at the same station/area (Baybars, 1986). There might be tasks that have to be performed at a specific station. There may exist parallel lines, U-shape lines, or two-sided lines. There may be other forms of positional restrictions, buffer stocks, and other generalities such as feeder or parallel subassembly lines. Besides, task times may be either deterministic or stochastic. Whether the objective is to minimise the number of stations or cycle time, maximise the line efficiency, find a feasible balance, or optimise any other metric(s), these problems are referred to as GALBPs, which are a generalisation of SALBPs.

4 The effect of learning in quality management

Today's competitive environment requires organisational learning and quality improvement. Scholars have extensively studied the relationship between learning processes and product or service quality improvement. These studies have revealed the benefits of high-quality standards and their influence on cost reduction, the optimisation of staffing methods, and the interplay between learning in different production processes. These studies can help firms improve performance and sustain success by revealing the link between learning and quality.

Fine (1986) researched learning and quality enhancement, introducing the quality-based LC. He demonstrated that companies striving for high-quality levels learn faster than those producing low-quality products. Fine compared two quality-based LCs to a volume-based LC and found that manufacturing higher-quality products reduces costs quicker. In a subsequent article, Fine (1988) applied quality-based learning to machine maintenance, recommending intensive inspection to decrease failure costs and improve the production process. He emphasised the need for managers to conduct inspections when a machine's failure probability surpasses a predetermined threshold, highlighting the benefits of learning in this context.

Foster and Adam (1996) improved the quality-based learning curve model by considering the quality improvement rate. Using case study data from an automotive parts manufacturer, they found that rapid quality enhancements hinder learning, while gradual improvements reduce costs and enhance competitiveness. Lapré et al. (2000) derived a learning curve for quality enhancement, focusing on reducing waste from defects. They analysed longitudinal data from a manufacturing plant to study learning in total quality management (TQM) initiatives. The authors showed how different forms of learning contribute to organisational learning and the success of TQM projects.

Pinker and Shumsky (2000) created a learning model to optimise staffing for service quality. They compared the cost-efficiency and quality of cross-trained or generalist workers with specialist workers with experience-based learning. Their findings recommended a combination of experienced workers for quality assurance and flexible workers to benefit from economies of scale. In a related study, Jaber and Bonney (2003) developed a learning curve for product quality improvement in lot sizing. They considered learning in setups and product quality, with lot-size quantity as the decision variable. The model included a cycle length where forgetting occurs and hampers performance (total cost). Testing the model with data from a problematic electronics manufacturing line, they discovered a conflict between learning in quality and learning in setups. Learning in quality favoured larger lot sizes while learning in setups favoured smaller ones.

5 LC models

The effect of learning is generally illustrated by an exponential LC. For a comprehensive literature review, see for instance (Anzanello and Fogliatto, 2011). The exponential learning curve is defined as follows:

$$Y(Q) = aQ^b, \tag{3}$$

where:

- $Y(Q)$ = time required to produce the Q^{th} unit,
- a = time required to produce the first unit,
- Q = cumulative units number,
- b = learning coefficient.

It can be demonstrated that a doubling in the cumulative production, yields a constant percentage of reduction of the unit production time. This percentage is called learning rate (L). For instance, $L = 0.8$ means that the time required to produce the $2Q^{\text{th}}$ unit is merely 80% of the time required to produce the Q^{th} unit.

The following equation shows the relationship between the learning rate L and the learning coefficient b.

$$L = \frac{Y(2Q)}{Y(Q)} = \frac{a(2Q)^b}{aQ^b} = 2^b. \tag{4}$$

The nature of the LC is that the highest decrease in production time per unit occurs during the beginning of production and then decreases with time as Fig. 3 shows. Several LC models have been suggested since the initial discovery by Wright (1936). The widely known models are:

1. the log-linear model,
2. the plateau model,
3. the Stanford-B model,
4. the DeJong model,
5. the S-model.

The listed models are well explored by Carlson (1961). A graphical representation of these models based on Yelle (1979) are depicted in Fig. 4.

Although the log-linear model remains by far the most adopted model, some manufacturers have discovered that other models better capture their learning experience. For example, Garg and Milliman (1961) presented the case

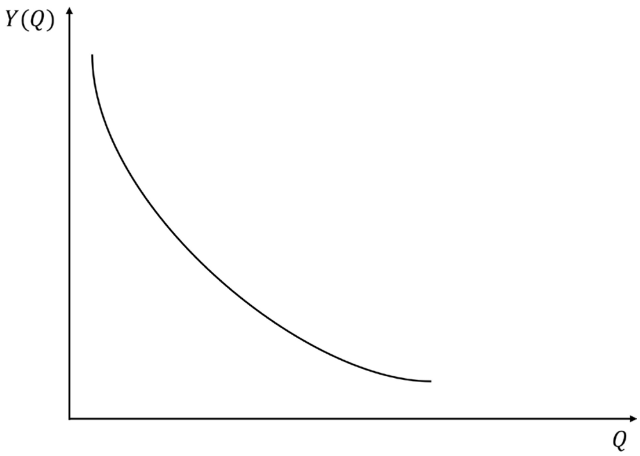

Fig. 3 The relationship between the cumulative output and the unit time

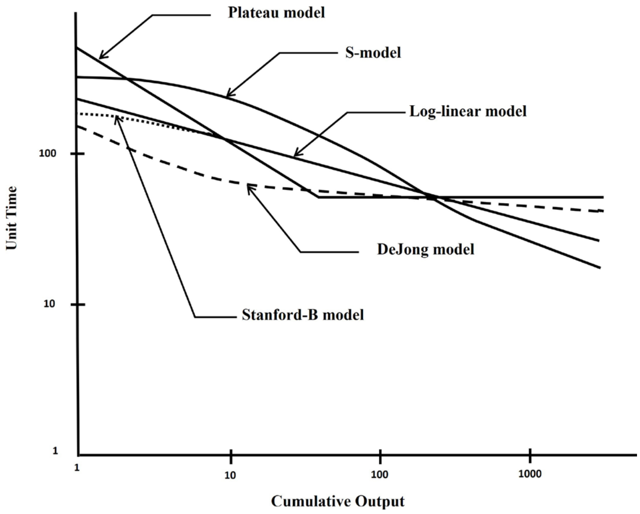

Fig. 4 Different models all having the same value of Unit time (Yelle, 1979)

of the Boeing company which show that the Stanford-B model describes best their operators' accumulated experience for the assembly of the Boeing 707 aircrafts.

6 Learning effect and ALB

6.1 The effect of learning on ALB

Since assembly line tasks are intrinsically repetitive, task times decrease with repetition because of learning. Commonly available ALB methods tend to ignore the learning effect and assume that average task times remain constant during production, while others allow some possible deviations around the average task time. These assumptions oversimplify the actual situation since operators can significantly improve their performance thanks to the learning effect, particularly in small batch production of up to a few hundred units where the relative change of execution time between one unit to the next can be substantial (Globerson and Shtub, 1984). To illustrate this, suppose the stations are balanced according to the task time of the first unit. As the learning effect sets in, the time required at a station will decrease for the subsequent units. This decrease of task times, however, will not be uniform across all stations, because the degree of learning may vary based on task complexity and operators' learning capacity (see e.g., Argote et al., 1995; Nembhard and Uzumeri, 2000). If the cycle time reduces over time, the line will soon lose its balance leading to inefficiencies. Bukchin and Wexler (2016) claim that small lot size production is gaining more importance compared to mass production due to the increasing interest in product customisation. This claim further emphasises the importance of considering the effect of learning in ALB as small batches are becoming more common.

6.2 Review methodology

Given the vast amount of literature on ALB and learning effect (the keyword "assembly line balancing" leads to more than 2,527 hits in Scopus, and the keyword "learning effect" produces more than 341,808 hits in the same database), we limited our literature search to a set of articles that explore both topics jointly, excluding articles that merely deal with one or the other.

We used Scopus and Web of Science comprehensive databases comprising the leading operations and production management journals- to explore the relevant literature. Researchers have used them in previous reviews (e.g., Felsberger and Reiner, 2020; Glock et al., 2019). For searching the databases, a list of terms related to the topic of this study- ALB and learning effect- was defined, including the following synonyms:

- ALB,
- assembly line balancing,
- experience curve,
- forgetting curve,
- forgetting function,
- LC,
- learning curve,
- learning effect,
- learning function.

The keywords of this study can be found in articles addressing the notions of ALB and/or learning effect.

Despite the significant importance of the effect of learning in ALB, the related literature is not extended, and many topics remain unexplored (Eghtesadifard et al., 2020; Tamás and Koltai, 2020). The filtering of papers based on their relevance to the reviewed topic- The effect of learning in ALB- resulted in 29 papers we included in this review. Here we present an exhaustive review of the existing literature about incorporating the effect of learning into ALB models. For the sake of coherence, the literature review is divided into three sub-topics: Deterministic learning in ALB, stochastic learning in ALB, and the effect of learning and other effects in ALB. A classification of the literature based on the ALBPs and ALs' characteristics is also provided (see Table 1).

6.3 The effect of deterministic learning in ALB

6.3.1 The effect of deterministic learning on utilisation and efficiency in ALB

Globerson and Shtub (1984) were among the first to emphasise the importance of learning in ALB. For a simplified case where the infinite divisibility of tasks and the absence of precedence relations between tasks were assumed, they have shown that adopting a line design strategy by considering the operator's learning effect may increase the assembly line's utilisation by up to 20%. Chakravarty (1988) completed the research by using dynamic recursive optimisation to minimise the line's total idle time. By comparing the line’s idle time with and without the learning effects, the author demonstrated that ignoring learning may lead to severe line inefficiencies causing assembly line imbalance and total cost increase.

Chakravarty and Shtub (1986) used iterative linear programming to minimise the total cost, e.g., labour cost, hiring, and layoff in a long cycle time assembly line by periodically varying the line's cycle time due to the learning effect. They concluded that a more efficient line design could be achieved by implementing varying cycle times. Chakravarty and Shtub (1992) later extended their previous publication by integrating mixed-model LCs with aggregate planning. They proposed a non-linear integer optimisation model that adjusts the capacity to varying demand while minimising the production and buffer stock costs. The proposed model can be used for the evaluation of line design alternatives and for choosing the most efficient line configuration during the start-up phase.

Bruno et al. (2021) analysed the effect of learning on task assignment to operators and on-line balancing. The authors did not aim to find an optimal solution but compared different real-time task allocation strategies. They recommended larger batch size to maximise the operator's and stations' efficiency during the learning phase.

6.3.2 The effect of deterministic learning in SALBPs

Despite their limitations in reflecting the complexity of real-world ALBPs, several research papers have addressed SALBPs by considering the effect of learning in a deterministic context.

Cohen and Dar-El (1998) were the firsts to consider incorporating learning effect in SALBP-1. They solved SALBP-1 by considering the effect of learning through two different approaches: cost minimisation and profit maximisation. In each approach, the optimal number of workstations was analytically derived via makespan (also referred to as throughput time) formulation with deterministic task times. The major simplification in their paper is the possibility of splitting task times and station times freely.

Toksarı et al. (2008) developed an algorithm that aims to minimise the number of stations in simple (SALBP-1) and U-shaped assembly lines (UALBP-1) by adopting the position-dependent LC proposed by Biskup (1999). Applying the algorithm for the widely known Jackson 11 problem (Jackson, 1956), they demonstrated that SALBP-1 and UALBP-1 with homogeneous learning are polynomially solvable and that the inclusion of learning effects leads to fewer stations than intuitively predicted.

Otto and Otto (2014) addressed SALBP-1 with learning effect during the production ramp-up phase and proposed a heuristic method to minimise the number of stations and shorten the learning stage. Several realistic assumptions were considered to account for the model's applicability, e.g., the integrity of tasks and individual LCs for each task. The authors showed that the duration of the learning stage can be shortened by 10% if the recommended approach is adopted.

Table 1 Classification of the literature based on ALBPs and ALs' characteristics

Authors	ALBP type		Task time type		Layout type			Product type		Workflow type	
	SALBP	GALBP	Deterministic	Stochastic	Straight	U-shaped	Parallel	Single model	Mixed-model	Paced	Un-paced
Globerson and Shtub (1984)		Others (Line utilisation maximisation)	X		X			X		X	
Chakravarty and Shtub (1986)		Others (Labor cost minimisation)	X		X			X			X
Chakravarty (1988)		Others (Total idle time minimisation)	X		X			X		X	
Chakravarty and Shtub (1992)		Others (production and buffer cost minimisation)	X		X				X		X
Karni and Herer (1995)		Others (Throughput time minimisation)	X		X			X			X
Cohen and Dar-El (1998)	SALPB-1		X		X			X			X
Cohen et al. (2006)		Others (Throughput time minimisation)	X		X			X			X
Cohen et al. (2008)		Others (Throughput time minimisation)	X		X			X			X
Toksarı et al. (2008)	SALPB-1	UALBP-1	X		X	X		X		X	
Toksarı et al. (2010a)	SALPB-1		X		X			X		X	
Toksarı et al. (2010b)	SALPB-1		X		X			X		X	
Hamta et al. (2011)		Others (Cycle time, total equipment cost and smoothness index minimisation)		X	X			X		X	
Hamta et al. (2013)		Others (Cycle time, total equipment cost, and smoothness index minimisation)		X	X			X		X	
Otto and Otto (2014)	SALPB-1		X		X			X		X	

Table 1 Classification of the literature based on ALBPs and ALs' characteristics (continued)

Authors	ALBP type		Task time type		Layout type			Product type		Workflow type	
	SALBP	GALBP	Deterministic	Stochastic	Straight	U-shaped	Parallel	Single model	Mixed-model	Paced	Un-paced
Koltai et al. (2015)			X		X			X			X
Rabbani et al. (2016)		UALBP-1,2,3 +Others (Line cost minimisation)	X			X			X		X
Li and Boucher (2017)	SALPB-1		X			X		X		X	
Li (2017)		ALBP-2		X	X			X		X	
Koltai and Kalló (2017)			X		X			X			X
Lolli et al. (2017)		ALBP-1		X	X			X		X	
Lolli et al. (2018)		ALBP-1		X	X			X		X	
Wang et al. (2019)		UALBP-1,2	X			X			X		X
Butturi et al. (2020)		Others (Total cost minimisation)		X	X			X		X	
Asadi-Zonouz et al. (2020)		MMALBP-1	X				X		X	X	
Bruno et al. (2021)		Others (Workers and line utilisation maximisation)	X		X			X		X	
Eslamipoor and Nobari (2021)		MMALBP-3	X		X				X	X	
Perez-Wheelock et al. (2022)		Others (Demand-driven rebalancing)	X		X			X			X
El Abidine et al. (2022)	SALPB-1		X		X			X			X

Li and Boucher (2017) presented a procedure to solve the SALBP-1 dynamically when learning occurs in an automated simple assembly line. The authors introduced backward induction rules to assist the procedure in solving the problem backward. They demonstrated that due to the introduction of the recommended procedure line efficiency increases, and the idle time of stations decreases.

El Abidine et al. (2022) formulated a modified mixed linear programming model that solves the SALBP-1 dynamically to find the optimal number of stations when operators' learning prevails. The authors applied Wright's LC (Wright, 1936) with and without plateau assuming homogeneous learning for all the stations. Through practical examples, they have demonstrated that the optimal number of stations decreases during production because of learning and that the speed of decrease slows as the learning rate increases.

6.3.3 The effect of deterministic learning in some GALBPs

The assumptions underlying SALBPs are very restrictive when the operation of real-world assembly line must be studied. Therefore, researchers have intensified their efforts to identify, formulate and solve more realistic ALBPs including the effects of learning.

Rabbani et al. (2016) developed a bi-objective optimisation model for a mixed-model UALBP by considering operator's learning. The model's objective function consists of two parts. The first part is related to type 1, 2, and 3 ALBPs, while the second is related to ALB considering human related parameters, i.e., salary, hiring and firing costs, training costs.

Li and Boucher (2017) presented a procedure to solve the SALBP-1 dynamically when learning occurs in an automated single-model straight assembly line. The authors introduced backward induction rules. They demonstrated the capability of the procedure to increase line efficiency by minimising the number of stations and decreasing idle time.

Wang et al. (2019) established a non-linear integer programming model coupled with a genetic algorithm to balance mixed-model UALBPs by incorporating the learning effect. Several constraints were considered, e.g., opening order of multiple products, workspace limitation and assembly technique restriction. The results showed the model's validity when reducing cycle time, increasing the balance ratio of the assembly line, and decreasing the standard deviations of task times. Asadi-Zonouz et al. (2020) used a hybrid unconscious search algorithm to solve a mixed-model type-1 ALB (MMALBP-1) in a parallel assembly line where the learning effect is present. They considered several realistic constraints, e.g., zoning constraints, sequence-dependent set ups, and operators' learning effects. Compared with other algorithms, they showed that the applied algorithm outperforms other procedures in terms of efficiency, especially when solving large-size problems.

6.3.4 The effect of deterministic learning on assembly line's throughput time

Besides the previously mentioned ALBPs, a handful of research papers touched upon the effect of learning on throughput time as a crucial metric which determines the production output.

One of the first papers related to throughput was published by Karni and Herer (1995) where they developed two heuristics: a linear programming model and a geometric mean ratio of successive task times model. The models determined the optimal task assignment to workstations when minimising the throughput times in a small-batch production environment. The authors demonstrated that optimal solutions are based on allocating work to stations in decreasing proportions, thus more work is assigned to the first station than to later stations. Cohen et al. (2006) addressed the same problem by developing a non-linear algorithm that minimises throughput time of low-demand products. The authors simplified the problem by making several assumptions, e.g., homogeneous learning for all the stations, no buffer between stations, and infinite divisibility of tasks between stations. They have shown that the optimal Throughput time requires an imbalanced allocation of work to stations in the presence of learning. Later, Cohen et al. (2008) revised their work by assuming different learning rates for workstations and showed that their previous conclusion concerning imbalanced allocation of work to stations in the presence of learning remains valid.

Koltai et al. (2015) developed an algorithm to calculate the throughput time of a production run in the presence of learning characterised by exponential LC and with homogeneous learning. The authors derived many theorems that serve to track the bottleneck shifts during learning and estimate the throughput time. Koltai and Kalló (2017) extended their work by analysing the sensitivity of throughput time with respect to the learning rate in a simple assembly line. They proved that the number of bottleneck shifts increases as the learning rate decreases. Furthermore, they underscored the importance of estimating the learning rate correctly, as the throughput time is very sensitive to changes in the learning rates, especially at small production quantities.

6.4 The effect of stochastic learning in ALB

Labor-intensive assembly lines intrinsically exhibit high variability in task times due to the human nature of the work.

Hamta et al. (2011) addressed a multi-objective single model stochastic ALBP by developing a multi-objective mixed non-linear programming model. Their approach was based on three objectives simultaneously: cycle time, total equipment cost, and smoothness index minimisation where task times are forced to vary between a lower and an upper bound and are updated depending on the operator's LC and setup sequence. Hamta et al. (2013) dealt again with the same multi-objective ALBP by introducing a hybrid meta-heuristic approach with Biskup (1999) LC. Through practical examples, the authors showed that the developed algorithm outperforms other existing algorithms in terms of execution speed.

Lolli et al. (2017) were the first to investigate a stochastic SALBP-1 with a learning effect. Using the Kottas-Lau (1973) heuristic coupled with the well-known Wright's curve (Wright, 1936) with a plateau, they showed that the optimal solution is affected by learning over time.

To include the human-machine collaboration, Lolli et al. (2018) addressed the stochastic SALBP-1 again by adopting a new LC where subtasks are performed partly manually and partly automatically, and task times are updated accordingly. The results showed the significant effect of learning on the optimal balancing solution.

Li (2017) extended their previous work by considering stochastic task times in an automatic assembly line where the agent's performance improves due to learning. They developed an optimisation model that aims to minimise the cycle time (SALPB-2) via dynamic line rebalancing.

6.5 The effect of learning and other effects in ALB

Some research papers considered simultaneously learning effect with other effects in ALB. Toksarı et al. (2010a) addressed SALBP-1 by formulating a mixed non-linear programming model that considers simultaneously learning effects with task deterioration, i.e., an increase in task times due to repeating the same or similar tasks. They concluded that the problem is polynomially solvable. Toksarı et al. (2010b) published another paper addressing SALBP-1, but this time, under four joint combinations of two learning effects.

7 Discussion

Most research papers on ALBPs and learning effects focus on GALBPs (20 papers). The explanation is straightforward, GALBPs provide more flexibility to formulate the different practical conditions of assembly lines. Furthermore, most research papers assume deterministic, straight, single-model, and paced assembly lines. Among the reviewed 29 papers, 23 papers assumed deterministic learning against only 6 papers for stochastic learning, 26 papers assumed straight lines against 4 papers for U-shaped lines, and only 1 for parallel lines, while none dealt with two-sided lines. Regarding the product type, 24 papers assumed single-model against 5 for Mixed-model, while multi-model has been ignored. Seventeen papers assumed a paced line, while only 12 addressed an un-paced line. Therefore, future research work needs to correct the underlying assumptions and account for real-world ALBPs in all their diversity.

Despite growing efforts to bridge theory and practice, the practical relevance of research results about ALB with learning remains limited. One of the limitations concerns the underlying assumptions that tend to oversimplify the real complexity of problems. For instance, most research studies addressing workforce allocation assume the same LC model for all workers. We understand, however, that a single LC model may not be able to capture the worker's personal learning experience. A promising course of action for future research is the application of different LC models based on the worker's individual characteristics (e.g., age, gender, prior experience, and level of education, among others) to better account for the workers' learning process.

The incapacity of current procedures to solve medium to large-size problems (30+ tasks) remains a challenge to solving practical ALB problems with learning. The ALBP is NP-hard since a simplified version of the problem, i.e., the one with no precedence constraints between tasks, is a bin-packing problem that is NP-hard in the strong sense. The existing optimum-seeking algorithms can merely be used to evaluate the performance of heuristic procedures by finding the optimal solutions to small-size problems. Hence, developing algorithms to solve realistic-size ALB problems with learning within acceptable computation time is another issue for future research.

In the presence of learning, the optimal solution is highly sensitive to the worker's learning rate, as a slight change in the learning rate may affect the solution's optimality. In practice, though, it is difficult to determine the worker's learning rate accurately. Analysing the shift of the optimal solution according to the change in the learning rate is essential in such cases. As most studies on ALB with learning lack such an analysis, we recommend that future studies conduct a sensitivity analysis to investigate the robustness of their solutions.

8 Conclusions

In this paper, the relevant literature on ALB with the learning effect has been explored. First, assembly lines based on their features have been characterised and ALBPs based on their underlying assumptions have been classified. Then, the importance of learning effect in ALB has has been discussed and the most relevant LCs has been explained. Finally, we have reviewed and classified the existing literature on ALB with leaning effect.

The review shows the growing interest in considering the effect of learning in ALB, although the literature is not very extended yet, and many research topics remain unexplored. We have also observed a tendency to address more generalised problems (GALBPs) rather than simple problems (SALBPs), presumably as they offer more flexibility with regard to modelling the different ALBPs. The review has also revealed that certain assembly line characteristics are more explored than others, e.g., deterministic, straight, single-model, paced assembly lines. Therefore, we recommend that future researchers diversify their model assumptions in a way that accounts for the large variety of real-world ALBPs.

It is hoped that this review can be a valuable reference for those who wish to undertake new research relating to ALB with a learning effect.

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