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► To cite this version:

Pedram Beldar, Masood Fathi, Amir Nourmohammadi, Xavier Delorme, Olga Battaïa, et al.. Transfer line balancing problem: A comprehensive review, classification, and research avenues. *Computers & Industrial Engineering*, 2025, pp.110913. 10.1016/j.cie.2025.110913 . hal-04925450

HAL Id: hal-04925450

<https://hal.science/hal-04925450v1>

Submitted on 20 Feb 2025

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Transfer line balancing problem: A comprehensive review, classification, and research avenues[☆]

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ARTICLE INFO

Keywords:

Transfer line
Machining line
Line balancing
Line design
Systematic review

ABSTRACT

The Transfer Line Balancing Problem (TLBP) is characterized as the challenge of optimally distributing tasks across various workstations in an automated machining line to ensure its maximum efficiency. This problem holds pivotal importance for industries reliant on high-volume production, such as the automotive and aerospace sectors, where it directly influences the overall productivity and cost efficiency of the manufacturing process. TLBP has been studied for over two decades, and many problem variants and solution approaches have been devised to address real-world challenges. Despite the long history of the topic, no review study exists to shed light on its past, current, and future developments. This study conducted a systematic literature review on TLBP to identify and address the research gaps, focusing on classifying existing studies. A tuple notation classification framework has been introduced to organize TLBP research based on system configuration, problem characteristics, and optimization objectives. This framework offers a structured overview of the field, clarifying the current state of research and highlighting prospective research pathways. Consequently, this review study establishes itself as a foundational guide for academics and industry professionals interested in TLBP studies.

1. Introduction

In today's ever-changing industrial landscape, intensified by globalization, manufacturers are dealing with an environment filled with intense competition (Lahrichi, Grangeon et al., 2021). They are challenged by fluctuating consumer demands, frequent updates in product designs, and continuous shifts in manufacturing technologies. To effectively tackle these challenges, a thorough revision and enhancement of their production systems are essential. Machining is still a major technology in modern production systems. In this context, the optimal design of automatic machining lines, commonly known as transfer lines, becomes particularly significant (Lahrichi, Deroussi et al., 2021). These transfer lines are instrumental in ensuring high efficiency, substantial output, and economical production, thereby playing

a crucial role in maintaining manufacturers' competitive strength and their adaptability to market dynamics (Liu et al., 2016).

Transfer lines, entailing a sequence of workstations and an advanced transport mechanism, ensure a seamless flow of parts through various machining operations (Essafi, Delorme, Dolgui, Guschinskaya, 2010). Noted for their capacity to produce high volumes of identical or similar products (Borisovsky et al., 2012b), transfer lines are indispensable in high-demand sectors like automotive and aerospace manufacturing. The key advantages of transfer lines are their ability to guarantee high productivity, product quality, operational efficiency, and cost-effectiveness, achieved through consistent operations conducted at each workstation in every cycle (Osman & Baki, 2018). Despite the benefits of transfer lines, their efficiency significantly relies on successfully addressing several challenges at different decision levels that require

[☆] The first three authors would like to acknowledge funding from the Knowledge Foundation (KKS) and Sweden's Innovation Agency through the ACCURATE 4.0 (grant agreement No. 20200181) and PREFER projects, respectively.

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<https://doi.org/10.1016/j.cie.2025.110913>

careful optimization. One of these challenges is line balancing, which comprises assigning tasks to workstations while adhering to a range of constraints to optimize one or several criteria, such as the number of machines, cycle time, or/and the total cost of the line, to name a few (Battaia et al., 2024; Liu et al., 2021). While line balancing has been a common practice in manual assembly lines, its importance extends to transfer lines, with unique considerations due to specific features of machining technologies. The process of line balancing in transfer lines is complex and multifaceted, encompassing steps like selecting operations, creating a logical layout, and designing the necessary equipment for each station (Dolgui et al., 2006b) with the possibility of parallel processing of operations at stations. This led to the introduction of a specific problem known as the Transfer Line Balancing Problem (TLBP) in the literature (Dolgui et al., 1999).

Despite the multifaceted nature of TLBP, which has captured considerable attention for over two decades, no studies can be found providing a comprehensive classification of existing research based on varied criteria such as system configuration, problem specifications, and optimization objectives. Although there are recent review papers on line balancing, the majority of them focus on assembly lines (e.g., Battaia & Dolgui, 2022; Boysen et al., 2022) or disassembly lines (e.g., Deniz & Ozcelik, 2019; Eren Özceylan & Gupta, 2019). Some studies, such as Battaia and Dolgui (2022), review machining line balancing, but their purpose was to identify hybrid approaches to line balancing, integrating other optimization problems such as process planning, workforce planning, and/or resource scheduling. Therefore, they include only a few studies on TLBP, underscoring the need for a comprehensive classification that spans various aspects of TLBP research.

This gap is significant due to the complexity of TLBP, which is influenced by strategic, tactical, and operational decision-making, as well as by the diversity of transfer lines. Such a classification is not merely a matter of academic interest; it serves as a road map for manufacturers navigating the challenges of TLBP. A well-defined classification would provide clarity in problem formulation. Researchers would gain a structured understanding of the various aspects of TLBP, helping them in defining problems more precisely. Each category within the classification may necessitate specific optimization techniques. Researchers could adjust their approaches to address the unique challenges posed by different types of TLBPs. Professionals in the field would benefit from precise solutions designed to address the specific challenges within their industry. This would result in more efficient and cost-effective production systems. A comprehensive classification would encourage inclusive research, allowing for a deeper understanding of the correlations among strategic, tactical, and operational decisions. This could lead to innovative solutions that bridge the gaps between these levels.

Given the absence of thorough classification in TLBP literature, this study endeavors to bridge the aforementioned gaps by:

1. conducting a systematic literature review (SLR) on TLBP to provide a comprehensive knowledge of the subject.
2. introducing a tuple notation classification framework that considers different system configurations, problem characteristics, and optimization objectives, providing a structured procedure to classify various TLBP scenarios.
3. presenting the state-of-the-art literature using customized tuple notations to enhance the clarity and precision in the field of TLBP.
4. providing insights into future research directions for TLBP, paving the way for more exploration and development in this area.

The rest of this article is divided into the following sections: Section 2 will provide an overview of the TLBP definitions, forming the foundation for the classification scheme that is unveiled in Section 4. In Section 3, the research methodology employed for the literature review is discussed. Section 4 presents the proposed classification scheme.

Section 5 utilizes the classification approach to arrange the body of current literature. Section 6 analyzes the findings from the literature classifications. Section 7 outlines potential future research directions. Finally, Section 8 presents the conclusions drawn from this review.

2. Transfer line balancing problem

Line balancing has long been a fundamental problem in the operational management of manufacturing systems, particularly concerning the efficient allocation of tasks among workstations along a production line (Essafi, Delorme, Dolgui, Guschinskaya, 2010). Historically, the problem first received academic attention in the realm of assembly lines (Salveson, 1955). The primary goal of assembly line balancing (ALBP) is to assign tasks to stations such that one or more objectives (based on time, cost, and efficiency measures) are optimized. This problem has been thoroughly explored over the past decades, with numerous methodologies developed to address its inherent NP-hard complexity (see Boysen et al., 2022). Despite the extensive research on ALBP, the distinct nature of machining processes led to the emergence of the TLBP, which focuses on production lines that involve machining operations (Dolgui & Ihnatsenka, 2009b). The need to consider unique features of machining posed a new challenge that the solutions developed for ALBP could not directly address (Dolgui et al., 2010). The key differences are as follows (Dolgui et al., 2020; Essafi et al., 2009; Essafi, Delorme, Dolgui, Guschinskaya, 2010):

- **Automation:** TLBP are characterized by a high degree of automation involving sophisticated machinery and automated material handling systems, whereas ALBP typically includes more manual operations.
- **Parallel processing:** TLBP enables simultaneous operations through multi-spindle heads or parallel machines, enhancing productivity. In contrast, ALBP typically performs tasks sequentially.
- **Equipment design (selection):** In TLBP, equipment design (selection) is essential and must be addressed alongside line balancing, as machinery and tool choices directly influence line configuration and performance. Task times are often unknown prior to optimization, with only machining operation parameters known (such as working stroke and feed rate). In ALBP, equipment design (selection) is important but generally less central to the balancing process than in TLBP.
- **Specific constraints:** Numerous specific constraints are associated with the unique characteristics of machining processes. For instance, zoning constraints are more complex, concerning not only the stations but also the designed (selected) equipment. In TLBP, different machining centers have varying features that directly influence task grouping or separation, adding a layer of complexity that is not typically present in ALBP. Unlike ALBP, where tasks are typically performed sequentially, TLBP often involves parallel processing using multi-spindle heads or multiple machines at a single station. This capability introduces additional considerations for zoning constraints, as tasks assigned to the same station must be compatible for simultaneous execution without causing operational conflicts. The choice of machinery and tools directly influences the feasibility and efficiency of task groupings, as different equipment configurations may enable or restrict certain zoning options. For example, selecting a multi-spindle machine may allow for positive zoning of compatible tasks, while choosing specialized tools might necessitate negative zoning for certain operations.
- **Adjustability of cutting speed (feed rate):** In machining, cutting speed (feed rate) can be adjusted to modify task durations, allowing adjustments for specific equipment and tasks. Thus, transfer line balancing combines balancing, process, and equipment design optimization.

The TLBP concept was first introduced by Dolgui et al. (1999) for mass production of a single type of product (i.e., a product model), marking a shift in line balancing research from assembly to machining. In a typical TLBP, the line is paced and serial, consisting of stations connected by automated material handling systems (Dolgui et al., 2006d). Parts move automatically from one station to the next, maintaining an uninterrupted flow (Osman & Baki, 2014). Each station is equipped with specialized tools that perform machining operations using single or multiple spindle heads on the part.

In the literature, the emergence of various transfer lines has promoted the development of specialized TLBPs, each type of transfer line designed to address the changing demands of modern manufacturing sectors. Traditional Dedicated Transfer Lines (DTLs) are designed for high-volume production of a single model (Guschinskaya & Dolgui, 2008), optimizing productivity and minimizing cost per unit. However, as market demands shifted, more adaptable systems emerged. Flexible Transfer Lines (FTLs) were introduced to handle small sets of various models within a large product family. These systems employ flexible machines, typically machining centers with Computer Numerical Control (CNC), and advanced material handling systems (Essafi et al., 2010b). FTLs, however, are costly and less productive. Responding to the growing need for both large-volume production and market flexibility, Reconfigurable Transfer Lines (RTLs) have gained prominence (Borisovsky et al., 2014). RTLs offer a balanced solution between the high production rates of DTLs and the flexibility of FTLs. RTLs use modular components for quick reconfiguration, allowing for efficient handling of a single model or a small family of models (i.e., customized flexibility). RTLs are also characterized by their scalability, allowing for modification of the production volume.

3. Research methodology

To present a systematic review of TLBP, this study followed the PRISMA protocol (Moher et al., 2009), comprising (i) establishing specific research questions, (ii) identifying reputable information sources, (iii) organizing the search approach, (iv) defining criteria for selecting relevant papers, (v) extracting important data methodically, and (vi) examining and discussing the findings thoroughly.

3.1. Research inquiries

The design and configuration of transfer lines exhibit different types, each characterized by distinct characteristics and objectives. This investigation delves into the landscape of TLBP, aiming to uncover the critical questions and insights that define their optimization. To guide this exploration, the following research questions (RQ) are proposed:

RQ1: How can a classification framework be developed to categorize TLBP literature effectively?

RQ2: What current trends and thematic focuses have shaped the TLBP field?

RQ3: What are the future research directions in TLBP?

3.2. Data sources and search approach

This study conducted an exhaustive exploration of prominent peer-reviewed scientific databases, Scopus, Web of Science, and Science Direct, to systematically identify and evaluate the most relevant research papers. The search stream was constructed by considering two components linked by the “AND” operator. The primary search component involved the consideration of three keywords, “manufacturing system”, “transfer line” and “machining line” with a specific focus on retrieving articles with these terms in their titles. Given these three keywords are broad terms that can span various fields, the inclusion of “line balancing” and “line design” keywords in the “title, abstract, and keywords” was employed as the second search component. This approach aimed to refine the search results, ensuring the retrieval of the most pertinent articles (see Fig. 1).

3.3. Inclusion and exclusion guidelines

Comprehensive inclusion and exclusion criteria were employed to either include or exclude a paper from the list. Concerning exclusion criteria, three distinct conditions were implemented: (a) papers not written in English, (b) the title and abstract review, and (c) a full-text review. No restrictions were placed on publication years, allowing for a comprehensive coverage of the field from its inception to the present. On the other hand, the inclusion criteria were established based on the exclusive consideration of journal and conference papers.

3.4. Paper extraction

As illustrated in Fig. 1, the initial search yielded a total of 250 research papers. Subsequently, 84 duplicate papers and book chapters were excluded from the list. Furthermore, 9 papers that were not written in English were eliminated. During the meticulous “title and abstract” review, 66 papers were also removed from the list since they addressed topics that lay outside the scope of manufacturing systems. Additionally, 25 papers were excluded upon conducting a full-text review of the remaining papers.

3.5. Snowball search

To ensure comprehensive coverage of the TLBP literature, a snowball search approach was employed to supplement the initial database search (Wohlin, 2014). This approach involved two complementary strategies. First, a “backward search” was conducted by examining the reference lists of key articles identified in the initial search. This allowed for tracing back to foundational studies and identifying seminal works frequently cited in the field. Second, a “forward search” was performed to identify articles that cited these key references, ensuring the inclusion of more recent studies building upon the foundational works. Notably, some relevant papers, including those containing terms such as “rotary” did not appear in the initial search results. The snowball search method effectively addressed this gap by identifying and incorporating these studies. The combined use of forward and backward search methods yielded 18 additional papers that met the inclusion criteria. These papers were subsequently incorporated into the review, bringing the total number of papers analyzed in this study to 84. By employing this rigorous and systematic approach, the review ensures comprehensive coverage of the literature in the field of TLBP, capturing both foundational works and recent advancements.

A comprehensive dataset of 84 papers was established through the systematic review process, forming the basis for a structured approach to analyzing and categorizing this literature. In the following section, a novel classification framework is introduced to organize and analyze the diverse body of TLBP research. This framework aids in understanding the current state of the field and provides a foundation for identifying research trends and potential gaps in the literature.

4. The classification framework

Drawing on the systematically collected literature, this section addresses the first research question by presenting a comprehensive classification framework for TLBP research. Numerous proficient and thoughtfully designed frameworks have been presented across diverse academic domains. These frameworks serve the purpose of addressing the inherent challenges within their respective fields of study and contribute to the clarity of problem formulation. Inspired by the renowned and effective classification frameworks pioneered by Graham et al. (1979) for machine scheduling, Brucker et al. (1999) for project scheduling, and Battaia and Dolgui (2013) and Boysen et al. (2007) for assembly line balancing problems, a novel classification approach is introduced for the TLBP based on tuple-notation. This approach seeks to provide a structured and systematic framework for categorizing

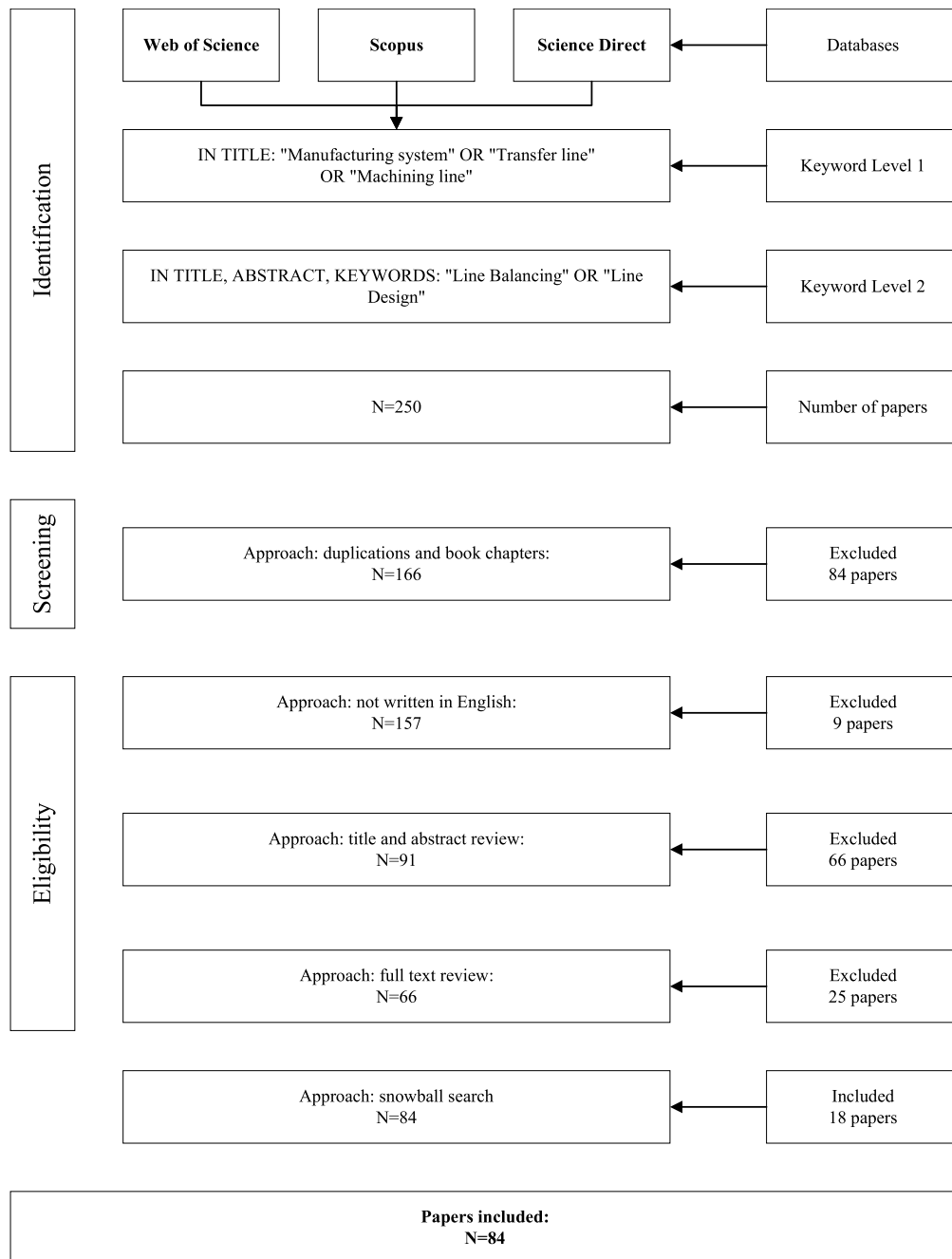


Fig. 1. PRISMA Method: the process of collecting papers.

TLBPs, drawing upon the successes observed in related fields. The framework aims to enhance the understanding of TLBPs and pave the way for more targeted research efforts in this critical domain of manufacturing optimization. Therefore, each TLBP is encapsulated by three fundamental components, symbolized as $\alpha | \beta | \gamma$. First, α serves as the identifier of the TLBP system configuration, helping to classify it within the broader landscape of manufacturing challenges. Second, β outlines the specific characteristics and attributes taken into account when formulating the problem, creating a detailed profile of the TLBP. Finally, γ signifies the objective function, clarifying the ultimate goal and optimization criterion guiding the problem-solving process.

In the following subsections, the details of this tuple-notation classification scheme are discussed, with its key components highlighted and its potential applications in the context of TLBPs illustrated.

4.1. Classification of TLBP according to line type (α)

In this section, the classification of TLBP is considered in order to distinguish between various systems using a three-part format: $\alpha_1 \alpha_2 (+\alpha_3)$. Here, α_1 represents the system configuration (S for serial, R for rotary, PS for parallel-serial, C for cellular), α_2 denotes the number of models considered during the design stage (0 for existing line, 1 for single model, n for mixed models, nb for multi-model), and the optional α_3 indicates reconfigurability, showing if additional models can be integrated later. For instance, a DTL could be S1 or R1, a FTL could be Sn or Cn, and a RTL could be PS1 + 0, PS1 + n, PSn + 0, or PSn + n. Also, a paper dealing with the reconfiguration of an existing line could be S0 + 1 or PS0 + 1. Therefore, a serial line for a single model is labeled as S1, while a rotary line for a family of models, considering several different models at the design stage, is

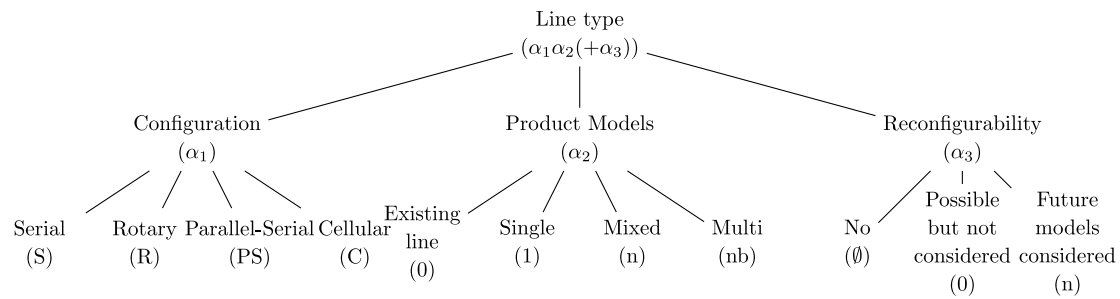


Fig. 2. Line type classification.

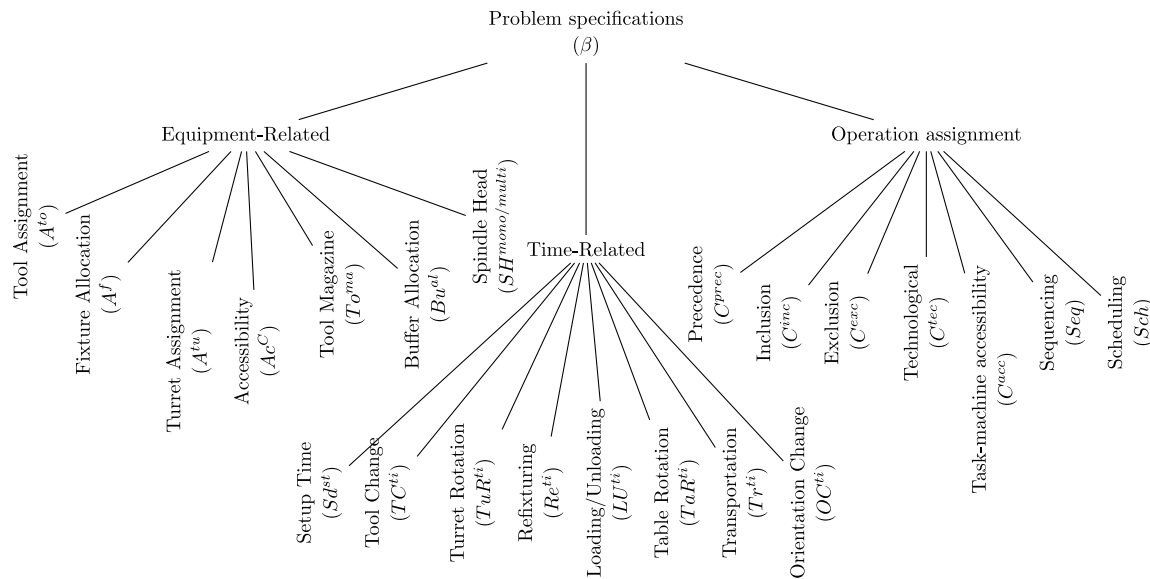


Fig. 3. Classification of problem specifications.

Rn. A parallel–serial line initially designed for one model but allowing future unknown reconfiguration is PS1+0, and one considering multiple future models is PS1+n. Additionally, a line initially designed for a single model, now being reconfigured to integrate one additional model is denoted S0+1 or PS0+1. Fig. 2 illustrates the classification for line types considered in TLBP, showing how configurations, number of models, and reconfigurability are represented in the notation $\alpha_1\alpha_2(+\alpha_3)$.

4.2. The problem specifications (β)

In this section, key attributes of TLBP are systematically organized into three primary categories: equipment-related characteristics, time-related characteristics, and operation assignment characteristics. This organizational approach establishes a solid base for a detailed understanding of TLBP, making the investigation of its complex elements more straightforward. The specifics of this β classification will be discussed in the subsequent sections. Fig. 3 provides an overview of the problem specifications, illustrating the classification of key attributes into equipment-related, time-related, and operation assignment categories.

4.2.1. Equipment-related characteristics

In the existing body of literature, considerable attention has been devoted to incorporating various equipment-related properties associated with machines in workstations. By incorporating these equipment-related elements, researchers aim to create TLBP scenarios that closely reflect practical industrial settings.

$\beta = A^{to}$. In machining operations, the precise tool-task relationship is critically essential. For example, using a specific tool for a designated

task reflects the careful selection and sequencing of operations. This precise assignment of tools to their respective tasks is a key element in modern machining. It ensures that each operation is performed with the most suitable tool, underscoring the detailed planning and efficiency necessary in these processes.

$\beta = A^f$. Allocation of specific sides of a workpiece to dedicated fixtures is also a crucial aspect considered in machining operations. This process ensures that operations are accurately performed on the specified surfaces and features of the workpiece, highlighting the importance of precision in fixture allocation for successful machining outcomes.

$\beta = A^{tu}$. Turret assignment involves the allocation of individual tasks or operations to specific turrets. This assignment process plays a pivotal role in optimizing the machining operations across various workstations, ensuring efficiency, precision, and effective task management. Turrets in the machining process serve as a vital component for accessing different sides of workpieces at various working positions. These turrets facilitate both sequential and parallel activation of spindle heads or machining modules to carry out operations on the parts. They enable the machinery to work efficiently on the components by allowing horizontal and vertical spindle heads, whether separate or mounted in turrets, to access different sides of the workpiece. These turrets, which can hold multiple machining tools, are instrumental in executing operations in a specific sequence.

$\beta = Ac^c$. Accessibility constraints in the context of part positioning are crucial considerations. In specific orientations, certain sides of a part may become inaccessible, necessitating repositioning to facilitate the required operations (Essafi et al., 2009).

$\beta = To^{ma}$. A tool magazine is a storage system predominantly associated with CNC machining centers, containing various types of

cutting tools needed for different machining operations. These tools are loaded onto the CNC machine while adhering to the magazine's capacity constraint (Osman & Baki, 2014). In a CNC machining center, when one operation is completed with a specific cutting tool, and the next operation requires a different tool, the machine's spindle returns to the tool magazine to retrieve and load the required tool for the next step in the machining process (Bhale et al., 2014). Essentially, a tool magazine in a CNC machining center ensures that the right tools are readily available for efficient and seamless machining operations.

$\beta = Bu^{ol}$. Buffer allocation between stations is a key factor in improving the independence of sequential workstations within a process under random disturbances (Shao et al., 2020). This strategy primarily aims to allow these workstations to function more independently from each other, thereby streamlining the overall workflow and improving operational efficiency.

$\beta = SH^{mono}$: A mono-spindle head machine can sequentially use different tools and rotate the part to perform various operations, moving to each position one at a time in a machining operation (Essafi et al., 2010a).

$\beta = SH^{multi}$: A multi-spindle head machine can simultaneously use multiple tools to perform various operations in parallel (Dolgui & Ihnatsenka, 2009c).

4.2.2. Time-related characteristics

$\beta = Sd^{st}$. The focus on sequence-dependent setup times highlights that the time needed for two consecutive operations in a manufacturing process is affected by the particular sequence in which they are performed. This is because factors such as tool changes and table or part rotation introduce variability in setup times (Essafi et al., 2010a).

$\beta = TC^{ti}$. The consideration of tool change time is essential, especially when a different tool is required to perform another operation (Osman & Baki, 2014).

$\beta = TuR^{ti}$. The time taken for the turret to rotate affects the overall efficiency and flow of operations within the machining cycle (Afrin et al., 2016).

$\beta = Re^{ti}$. Considering the time needed for refixturing or reloading is a vital part of the process.

$\beta = LU^{ti}$. Addressing the loading and unloading time of a part on a machine is a crucial aspect of the process.

$\beta = TaR^{ti}$. The consideration of table rotation time is crucial in the machining process. As the table rotates, it relocates the workpiece to various working positions, each designated for specific operations (Afrin et al., 2016).

$\beta = Tr^{ti}$. Addressing the transportation time between stations is a key aspect of the process. It involves the time taken to move materials or parts from one station to another.

$\beta = OC^{ti}$. The time required for an orientation change is an essential aspect of the process. This occurs when an operation needs to be performed on a different surface of the workpiece (Osman & Baki, 2014).

4.2.3. Operation assignment characteristics

$\beta = C^{prec}$. Precedence constraints refer to the established order of tasks or operations. This order dictates a partial sequence for all tasks and operations to be executed (Dolgui et al., 2006a). These constraints define a set of feasible task/operation sequences (Essafi, Delorme, Dolgui, Guschinskaya, 2010), ensuring that certain tasks/operations must be completed before others can begin, thereby dictating the acceptable order in which tasks/operations are executed. For systems such as multi-spindle heads with parallel execution of operations, an extended definition of precedence constraints is applied. Specifically, if task a precedes task b , this means that task a should be executed before task b or simultaneously with task b , i.e., in parallel. This flexibility accommodates scenarios where parallelism is inherent to the operational process.

$\beta = C^{inc}$. Inclusion constraints, which specify the grouping of tasks/operations that must share a workstation or executed with the same equipment (e.g., multi-spindle head), are often driven by essential machining tolerance considerations (Guschinskaya & Dolgui, 2009).

$\beta = C^{exc}$. Exclusion constraints are rules preventing particular sets of operations from being allocated to the same workstation or piece of equipment due to technological incompatibility (Guschinskaya & Dolgui, 2009).

$\beta = C^{tec}$. Technological constraints dictate that certain task can only be executed on specific machine due to compatibility requirements (Nourmohammadi et al., 2024).

$\beta = C^{acc}$. Task-machine accessibility constraints specify which tasks are feasible on particular machines. This constraint ensures that a task can only be assigned to machines that are capable of performing it based on compatibility and accessibility requirements (Nourmohammadi et al., 2024).

$\beta = Seq$. Sequencing addresses the tasks/operations sequences, which refer to determining the order in which tasks or operations should be performed at various workstations or positions within the line (Lahrichi, Grangeon et al., 2021).

$\beta = Sch$. Scheduling refers to determining the specific start and finish times for each task to be performed at various workstations.

4.3. Objectives (γ)

The optimization of TLBP is motivated by the aim of achieving specific objectives that act as metrics for assessing solutions. These objectives can be grouped into three primary categories: time-related objectives (operational level), cost-related objectives (tactical or strategic level), and efficiency-related objectives (tactical level). In some cases, a research paper can often include multiple objectives. Fig. 4 categorizes the objectives for optimizing TLBP into time-related, cost-related, and efficiency-related metrics, highlighting the main objectives used to evaluate solutions.

4.3.1. Time-related objectives

$\gamma = NonP^{ti}$. The concept of non-productive time (NPT), encompasses various activities such as tool change time, reloading time, transportation time, reposition time, refixturing time, and any other tasks that do not directly contribute to the actual production of a workpiece. Minimizing NPT enhances transfer line productivity by shortening the production lead time (Osman & Baki, 2018).

$\gamma = Cyc^{ti}$. The cycle time is determined by the load on the bottleneck workstation, which represents the longest time required among all workstations (Telemeci & Azizoğlu, 2024). For manufacturers heavily invested in transfer lines, reducing the cycle time is crucial for maximizing production rates. Since the transfers are automated and synchronized, minimizing cycle time also reduces the flow time, which is the duration each product unit spends in the system.

$\gamma = SI$. The goal is to minimize the smoothness index by evenly distributing processing time and keeping cycle time variations at each workstation as close to the line cycle time as possible, thus promoting a uniform workload distribution throughout all workstations (He et al., 2020).

$\gamma = Pro$. The goal is to minimize the probability of workstation cycle time exceeding the line cycle time (He et al., 2020).

4.3.2. Cost-related objectives

$\gamma = Li^{co}$. Consideration is given to the comprehensive cost of designing and equipping the production line. This includes the strategic minimization of investment required by reducing the total number of stations as well as evaluating expenses associated with installing various types of equipment such as turrets, machining modules, and spindle heads (Battaia et al., 2020; Guschinskaya & Dolgui, 2006).

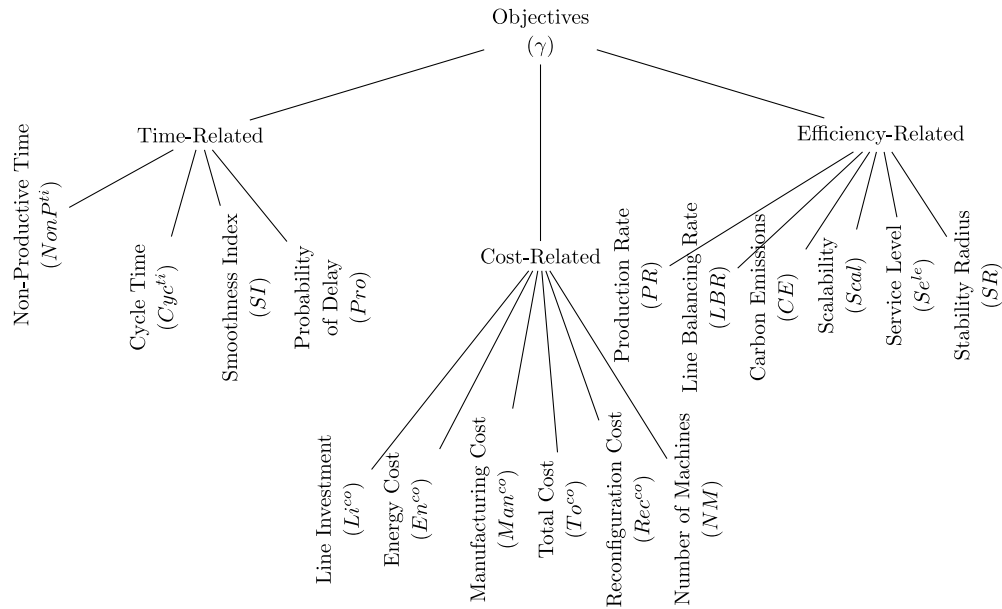


Fig. 4. Classification of objectives for TLBP.

$\gamma = En^{co}$. Energy related cost is considered. This can include Time-Of-Use energy prices, power peak or total energy consumption minimization (Delorme & Gianessi, 2024).

$\gamma = Man^{co}$. Manufacturing cost optimization is targeted, with a focus on minimizing the annual costs of machinery and tooling (Osman & Baki, 2018).

$\gamma = To^{co}$. All costs are considered, including design and manufacturing costs. Machines and buffers are taken into account within the concept of total cost.

$\gamma = Rec^{co}$. Reconfiguration costs are taken into account, which include costs related to equipment, labor, and order loss (Liu et al., 2021).

$\gamma = NM$. The aim is to minimize the total number of machines installed on the workstations.

4.3.3. Efficiency-related objectives

$\gamma = PR$. The focus is placed on maximizing the production rate, which serves as a measure of the throughput of the production line (Shao et al., 2020).

$\gamma = LBR$. The objective includes maximizing the line balancing rate (Liu et al., 2016). It is a critical parameter that is maximized when the total workload is equitably allocated across all workstations in proportion to the number of machines and the overall number of workstations within the system.

$\gamma = CE$. The study considers the minimization of the carbon emissions (Afrin et al., 2016).

$\gamma = Scal$. The objective is to maximize the scalability of the production line, i.e., its ability to adjust production capacity (Cerqueus & Delorme, 2023).

$\gamma = Se^{le}$. It refers to maximizing the service level (Delorme et al., 2023).

$\gamma = SR$. The objective is to maximize the stability radius (Pirogov et al., 2021). The stability radius measures the robustness of a feasible solution in the face of uncertainty. It is defined as the maximum amount of processing time increase that a solution can withstand while remaining feasible, regardless of how this extra processing time is distributed among uncertain tasks. The stability radius is computed by determining the radius of the largest closed ball, called the stability ball, that contains all feasible solutions within a certain distance from the nominal solution.

4.4. Examples of TLBP classification

This section provides examples of how the proposed framework can be applied to classify TLBP across a range of industrial scenarios. The framework's versatility is demonstrated through three representative cases, each highlighting a unique production configuration and optimization objective.

In the first scenario, a manufacturer aims to design a reconfigurable transfer line for a single product model, with the flexibility to accommodate new models in the future. This problem can be expressed as $PS1 + 0 \mid C^{prec}, Ac^C, SH^{mono} \mid NM$ where the classification captures the essential features of the system. Specifically, the designation $PS1 + 0$ refers to a parallel-serial line configured for single-model production with provisions for future reconfigurability. Constraints related to precedence (C^{prec}) and accessibility (Ac^C) are incorporated into the design. The use of mono-spindle heads (SH^{mono}) ensures efficient machining processes, while the primary objective of the optimization (NM) is to minimize the number of machines required.

A second scenario involves a flexible transfer line intended for mixed-model production. This system is represented as $Sn \mid A^{to}, To^{ma}, Sd^{st}, SH^{mono} \mid NonP^{ti}$ indicating a serial line (Sn) capable of handling mixed models. The classification accounts for tool assignment (A^{to}), tool magazine capacity (To^{ma}), and sequence-dependent setup times (Sd^{st}). The production setup employs mono-spindle heads (SH^{mono}), while the optimization goal ($NonP^{ti}$) focuses on minimizing non-productive time, thereby enhancing the system's operational efficiency.

The final example considers a rotary transfer line designed for single-model production, which can be characterized as $R1 \mid A^{tu}, TaR^{ti}, TuR^{ti}, SH^{multi} \mid Li^{co}, CE$. Here, $R1$ signifies a rotary line configuration tailored to single-model manufacturing. The framework incorporates critical factors such as turret assignment (A^{tu}), table rotation time (TaR^{ti}), and turret rotation time (TuR^{ti}), reflecting the complexity of rotary systems. Multi-spindle heads (SH^{multi}) are employed to maximize productivity, while the optimization objectives include minimizing both line cost (Li^{co}) and carbon emissions (CE).

These examples underscore the flexibility and comprehensiveness of the TLBP classification framework, demonstrating its ability to represent diverse production scenarios systematically and to support targeted optimization strategies.

Table 1
Abbreviations for the approaches and decision-making levels.

Exact methods	Decomposition approach (D), Graph approach (G), Branch and Bound (B&B), Branch and Cut (B&C), Polynomial algorithm (PA), Dynamic programming (DP), Set partitioning (SP), Reduction method (RM), Constraint generation (CG)
Metaheuristics	Greedy randomized adaptive search procedure (GRASP), Non-Dominated Sorting Genetic Algorithm II (NSGA-II), Genetic Algorithm (GA), Ant colony optimization (ACO), Cuckoo search (CS), Multi-Objective Particle Swarm Optimization (MOPSO), Artificial Bee Colony (ABC), Tabu search (TS)
Other approaches	Mathematical model (MM), Heuristic (H), Simulation (Sim), Matheuristic (MH), Combinatorial approach (CA)
Decision-making level	Strategic (ST), Tactical (TA), Operational (OP)

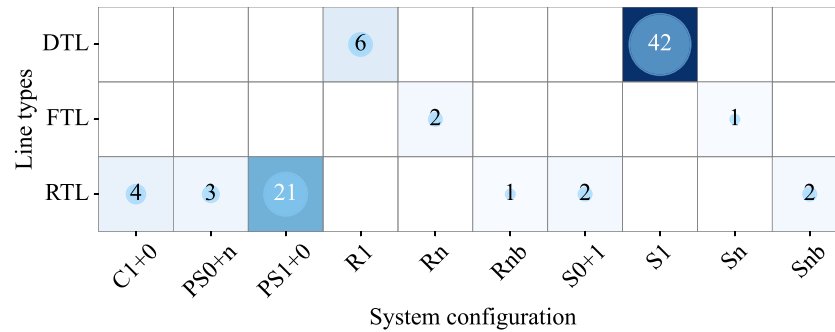


Fig. 5. Frequency of different system configurations for three types of transfer lines.

5. The literature classification

This section also contributes to addressing the first research question by systematically classifying the TLBP studies following the framework detailed in Section 4. For the sake of completeness, the solution approach used and the targeted decision-making level are also reported for each study. In general, the TLBPs encompass strategic, tactical, and operational decision-making levels, each critical to the production line’s performance. Strategically, decisions dictate the line’s overall configuration, impacting long-term efficiency and adaptability. Tactically, the focus shifts to the assignment of tools and equipment, which is crucial for optimizing throughput and flexibility. Operationally, tasks are allocated to workstations, directly influencing day-to-day efficiency and productivity. These intertwined layers of decision-making shape the line’s ability to meet current production demands while retaining the agility to adjust to future changes, underlining the multifaceted nature of TLBP.

For clarity and brevity, abbreviations are proposed for the distinct solution approaches and decision-making levels, as shown in Table 1. Following this, Table 2 presents a comprehensive chronological analysis of each publication, incorporating notations, decision-making levels, and solution approaches employed. The papers are arranged in ascending order by publication year to illustrate the evolution of TLBP research over time.

6. Analysis of classification findings

This section contributes to addressing the second research question. It provides an overview of the main findings according to the literature classification. Fig. 5 shows the frequency of different system configurations for three types of transfer lines: DTL, FTL, and RTL. This distribution indicates that the DTL configuration ‘S1’ is the most discussed in the literature, suggesting that it may be the most common or established type of system configuration. The RTL configuration ‘PS1+0’ is also frequently mentioned, which may indicate a growing preference due to their efficiency and flexibility balance. Other configurations like ‘R1’, ‘C1+0’ and ‘PS0+n’ are less commonly discussed. FTL configurations, although essential for flexibility in production, are less frequently mentioned than DTLs and RTLs. Similarly, we found no paper considering configuration ‘Cn’, which could mean that authors

focus on other problems than line balancing when they study such systems.

Fig. 6 presents a heatmap showcasing the frequency of various objectives concerning different line types considered in TLBP, with a striking predominance of cost-related objectives. This focus on cost is significant, constituting 78.49% of the literature, which underscores its critical role in shaping TLBP strategies, particularly within DTL and RTL, where it is most pronounced. The ‘Line cost’ objective, as shown in Fig. 7, is particularly notable, appearing 53 times, underscoring its significance in the context of TLBP considerations. The emphasis on ‘Number of machines’ with frequencies of 13, further reinforces the priority given to cost optimization in equipment and resource allocation. The lower frequency of time-related objectives such as ‘Cycle time’ (with a frequency of 8) and ‘Non-productive time’ (with a frequency of 3), in conjunction with their smaller representation in the heatmap (13.98%), suggests that these factors are less prioritized. However, they are still important as they directly impact throughput and efficiency. In the data depicted by the provided plots, the ‘Production rate’ and ‘Line balancing rate’ objectives appear 3 and 1 times, respectively, suggesting their relevance to enhancing operational efficiency within TLBP strategies, albeit less emphasized compared to cost-related considerations.

There is limited literature focusing on sustainability aspects such as energy efficiency, emissions reduction, and overall eco-performance in the context of TLBP. The predominant focus of the existing studies is on cost and time optimization, with minimal direct attention given to the environmental impact of TLBP strategies. This gap in the literature highlights a crucial area for future research, underscoring the need to integrate sustainability considerations into TLBP analysis and decision-making.

According to Fig. 8, most research in the field of TLBP focuses on single-objective (SO) optimization. Based on the chart, it can be observed that 45 studies for the DTL are centered around SO, whereas just three studies address multi-objective (MO) problems. Other line types also exhibit this tendency, with RTL displaying a lower percentage of studies (26 SO and seven MO studies, respectively). FTL has the fewest studies, with three papers focusing on SO and no paper on MO optimization. The strong tendency towards SO studies suggests that most research simplifies the problem to a single dimension. A very small fraction of the studies are MO, which implies considering two or more objectives simultaneously. This is the most complex approach

Table 2
The literature classification.

Authors	Line type	Notation	Decision-making level	Approach
Dolgui et al. (1999)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM, G
Dolgui, Guschinsky, Levin (2000)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM, D
Dolgui, Guschinsky, Levin et al. (2000)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM, G
Bratcu et al. (2003)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, A^{to}, SH^{multi} Li^{co}$	ST, OP	MM, B&B
Dolgui et al. (2003)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM, H
Dolgui et al. (2004)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM, H
Bratcu et al. (2005)	FTL	$Sn C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM
Dolgui, Finel et al. (2005)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	H
Dolgui, Guschinsky et al. (2005)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	H
Dolgui and Ihnatsenka (2005)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	B&B
Battaia et al. (2005)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	H
Belmokhtar et al. (2006)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM
Masood (2006)	RTL	$PS1 + 0 C^{prec}, SH^{mono} C_{yc}^{ti}$	ST, OP	Sim
Dolgui et al. (2006b)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM, H
Dolgui et al. (2006c)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM, D
Guschinskaya and Dolgui (2006)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM, H
Dolgui et al. (2006d)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	G
Dolgui et al. (2006a)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	D
Guschinskaya et al. (2007)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	RM
Guschinskaya and Dolgui (2007)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	GRASP
Dolgui, Guschinsky, Levin et al. (2008)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	G, MM, H
Dolgui, Guschinsky, Levin et al. (2008)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	G
Finel et al. (2008)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	H
Guschinskaya et al. (2008)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, LU^{ti}, SH^{multi} Li^{co}$	ST, OP	H
Dolgui, Guschinskaya, Guschinsky et al. (2009)	DTL	$R1 C^{prec}, C^{inc}, C^{exc}, LU^{ti}, SH^{multi} Li^{co}$	ST, OP	MM
Dolgui and Ihnatsenka (2009a)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	SP
Dolgui and Ihnatsenka (2009b)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	B&B
Dolgui and Ihnatsenka (2009c)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	B&B
Essafi et al. (2009)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, SH^{mono} Li^{co}$	ST, OP	GRASP
Gurevsky et al. (2009)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	GA
Dolgui, Guschinsky, Levin (2009)	DTL	$R1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM, G
Essafi, Delorme, Dolgui, Guschinskaya (2010)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, SH^{mono} NM$	ST, OP	MM
Essafi et al. (2010a)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, SH^{mono} Li^{co}$	ST, OP	ACO
Borisovsky et al. (2011)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	RM
Guschinskaya et al. (2011)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, LU^{ti}, SH^{multi} Li^{co}$	ST, OP	GRASP, GA
Borisovsky et al. (2012b)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	SP
Borisovsky et al. (2012c)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	SP
Borisovsky, Delorme et al. (2012)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, Seq, SH^{mono} NM$	ST, OP	DP
Dolgui et al. (2012)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	MM
Essafi et al. (2012)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, SH^{mono} Li^{co}$	ST, OP	GRASP
Makssoud et al. (2012)	RTL	$S0 + 1 C^{prec}, C^{inc}, C^{exc}, LU^{ti}, SH^{multi} Li^{co}$	ST, OP	MM
Delorme et al. (2012)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	CA
Battaia and Dolgui (2012)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, SH^{multi} Li^{co}$	ST, OP	RM
Wang and Koren (2012)	RTL	$PS0 + n C^{prec} NM$	ST, OP	GA
Battaia et al. (2013)	DTL	$R1 C^{prec}, C^{inc}, C^{exc}, A^{tu}, TaR^{ti}, TuR^{ti}, SH^{multi} Li^{co}$	ST, OP	MM, D
Borisovsky et al. (2013)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, SH^{mono} NM$	ST, OP	GA
Bhale et al. (2014)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, A^{to}, T_o^{ma}, Seq, TC^{ti}, Re^{ti}, T_r^{ti}, OC^{ti}, SH^{mono} NonP^{ti}$	ST, TA, OP	MM
Dolgui et al. (2014)	RTL	$Snb C^{prec}, T_o^{ma}, SH^{multi} Li^{co}$	ST, OP	MM, H
Borisovsky et al. (2014)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, SH^{mono} NM$	ST, OP	CG, B&C, parallel B&C
Makssoud et al. (2014)	RTL	$S0 + 1 C^{prec}, C^{inc}, C^{exc}, LU^{ti}, SH^{multi} Li^{co}$	ST, OP	MM
Osman and Baki (2014)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, A^{to}, T_o^{ma}, Seq, TC^{ti}, Re^{ti}, T_r^{ti}, OC^{ti}, SH^{mono} NonP^{ti}$	ST, TA, OP	MM, D, D+ACO, ACO
Battaia et al. (2014a)	DTL	$R1 C^{prec}, C^{inc}, C^{exc}, TaR^{ti}, TuR^{ti}, SH^{multi} Li^{co}$	ST, OP	MM, G
Battaia et al. (2014b)	DTL	$R1 C^{prec}, C^{inc}, C^{exc}, LU^{ti}, SH^{multi} Li^{co}$	ST, OP	MM, G, H
Delorme et al. (2016)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, SH^{mono} Li^{co}, PR$	ST, OP	MM, GRASP
Liu et al. (2016)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, T_o^{ma}, T_c^{ti}, OC^{ti}, Sd^{st}, SH^{mono} NM, C_{yc}^{ti}, LBR$	ST, OP	MM, H
Afrin et al. (2016)	DTL	$R1 C^{prec}, C^{inc}, C^{exc}, TC^{ti}, TaR^{ti}, TuR^{ti}, SH^{mono} Li^{co}, CE$	ST, OP	MM, TS

(continued on next page)

Table 2 (continued).

Koren et al. (2017)	RTL	$PS0 + n C^{prec} NM$	ST, OP	MM, GA
Battaia et al. (2017a)	FTL	$Rn C^{prec}, C^{inc}, C^{exc}, A^{tu}, TC^{ti}, TaR^{ti}, TuR^{ti}, SH^{mono} Li^{co}$	ST, TA, OP	MM, H
Battaia et al. (2017b)	FTL	$Rn C^{prec}, C^{inc}, C^{exc}, A^{tu}, TC^{ti}, TaR^{ti}, TuR^{ti}, SH^{multi} Li^{co}$	ST, TA, OP	MM
Xuemei et al. (2017)	DTL	$S1 Bu^{dl}, A^f Li^{co}, PR$	ST, OP	Sim, GA-PSO
He et al. (2018)	RTL	$C1 + 0 C^{prec}, SH^{mono} C^{yc}^{ti}$	ST, OP	MM, H
Osman and Baki (2018)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, A^{to}, Ac^C, T\alpha^{na}, Seq, TC^{ti}, LU^{ti}, OC^{ti}, SH^{mono} NonP^{ti}, Man^{co}$	ST, TA, OP	MM, CS
Shao et al. (2019)	RTL	$PS0 + n C^{prec} NM$	ST, OP	MM, GA
He, Guan, Gong et al. (2019)	RTL	$C1 + 0 C^{prec}, C^{inc}, C^{exc}, SH^{mono} Li^{co}$	ST, OP	MM, B&B, DB&B
He, Guan, Luo et al. (2019)	RTL	$C1 + 0 C^{prec}, SH^{mono} NM$	ST	MM, D
Lahrichi et al. (2019)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, SH^{mono} NM$	ST, OP	PA
Borisovsky (2020)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, SH^{mono} NM$	ST, OP	GA
He et al. (2020)	RTL	$C1 + 0 SH^{mono} C^{yc}^{ti}, SI, Pro$	ST	HB&B, HABC
Shao et al. (2020)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, A^{to}, A^f, Bu^{dl}, SH^{mono} T\alpha^{co}, PR$	ST, OP	MM, MOPSO, NSGA-II, Sim
Battaia et al. (2020)	RTL	$Snb C^{prec}, C^{inc}, C^{exc}, A^{tu}, TC^{ti}, TuR^{ti}, T_p^{ti}, SH^{multi} Li^{co}$	ST, TA, OP	MM
Liu et al. (2021)	RTL	$PS1 + 0 C^{prec}, Ac^C, SH^{mono} Man^{co}, Rec^{co}$	ST, OP	MM, GRASP
Pirogov et al. (2021)	DTL	$S1 C^{prec}, SH^{multi} SR$	ST, OP	MM, H
Lahrichi, Deroussi et al. (2021)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, Seq, SH^{mono} NM$	ST, OP	MH
Lahrichi, Grangeon et al. (2021)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, Ac^C, Sd^{st}, Seq, SH^{mono} NM$	ST, OP	PA
Telemeci and glu (2022)	DTL	$S1 C^{prec}, C^{exc}, SH^{multi} C^{yc}^{ti}$	OP	MM, B&B
Battaia et al. (2023)	RTL	$Rnb C^{prec}, C^{inc}, C^{exc}, A^{tu}, TC^{ti}, TaR^{ti}, TuR^{ti}, SH^{multi} Li^{co}$	ST, TA, OP	MM, H
Carqueus and Delorme (2023)	RTL	$PS1 + 0 C^{prec} Scal$	ST, OP	CA
Delorme et al. (2023)	RTL	$PS1 + 0 C^{prec} Li^{co}, En^{co}, S_e^{le}$	ST, OP	MH
Borisovsky (2023)	RTL	$PS1 + 0 C^{prec}, C^{inc}, C^{exc}, SH^{mono}, Sd^{st} NM$	ST, OP	GA
Battaia et al. (2024)	DTL	$S1 C^{prec}, C^{inc}, C^{exc}, TaR^{ti}, TuR^{ti}, SH^{mono}, A^{tu} Li^{co}$	ST, TA, OP	MM, H
Delorme and Gianessi (2024)	RTL	$PS1 + 0 C^{prec}, Sch En^{co}$	ST, OP	MM, MH
Telemeci and Azizoglu (2024)	DTL	$S1 C^{prec}, C^{exc}, SH^{multi} C^{yc}^{ti}$	OP	MM, B&B
Nourmohammadi et al. (2024)	DTL	$S1 C^{prec}, C^{exc}, C^{tec}, C^{inc}, C^{acc}, SH^{mono}, TC^{ti}, TaR^{ti}, Sch C^{yc}^{ti}, En^{co}$	OP	MM
Beldar et al. (2024)	DTL	$S1 C^{prec}, C^{exc}, C^{inc}, C^{acc}, SH^{mono}, TC^{ti}, TaR^{ti} C^{yc}^{ti}$	OP	H

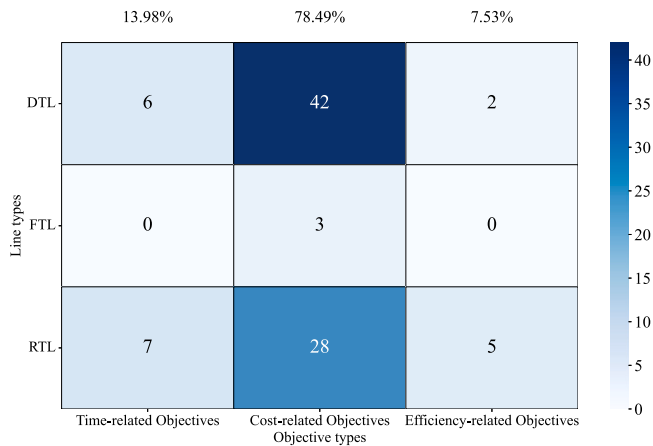


Fig. 6. Proportion of the type of objective functions in the literature.

as it requires the optimization of several conflicting objectives, and the solutions are typically represented as a set of trade-offs known as Pareto-optimal solutions. The low percentage of MO studies might reflect the increased complexity and computational effort required for such analyses, which can be challenging with current methodologies or computational resources. As a result, the chart highlights a notable research gap in MO optimization within TLBP and suggests possible directions for future studies to investigate more intricate, but maybe more thorough, solutions to TLBP.

Several approaches to tackling the TLBP have been suggested in the literature. To evaluate these methods, they are categorized into six groups: heuristic, metaheuristic, hybrid approach, mathematical models, exact algorithm, and simulation. From Fig. 9, it can be inferred that exact methods and mathematical models are the most frequently

used approaches in TLBP literature, especially prominent in addressing DTL.

Exact methods and mathematical models offer the advantage of finding optimal solutions for small to medium-sized problems and provide valuable benchmarks for evaluating other approaches. They excel in providing insights into problem structure and properties, which can be crucial for understanding the underlying complexities of TLBP. However, these methods face significant limitations in computational tractability for large-scale problems, often becoming impractical as problem size increases. They also struggle to incorporate complex real-world constraints and have limited applicability in dynamic or uncertain environments, which are increasingly common in modern manufacturing settings.

Metaheuristic and heuristic methods are also well-represented, suggesting their utility in tackling the complex and multifaceted challenges inherent in TLBP. These approaches excel in finding good solutions quickly for large-scale problems and offer flexibility in incorporating various constraints and objectives. Their adaptability to different problem variants makes them particularly valuable in real-world applications. However, they do not guarantee optimality, which can be a significant drawback in scenarios where finding the absolute best solution is critical. Additionally, their performance can be sensitive to parameter tuning, requiring expertise to achieve optimal results.

Hybrid approaches, while less common, offer potential advantages by combining strengths of different methods. These approaches aim to leverage the benefits of multiple techniques, potentially overcoming the limitations of individual methods. However, their relative scarcity in the literature may indicate challenges in effectively integrating different methodologies or a lack of exploration in this area. The development of more sophisticated hybrid approaches could be a promising avenue for future research.

Simulation techniques show fewer connections to the various line types considered in TLBP. While they excel in modeling complex system dynamics and incorporating stochastic elements, their limited use

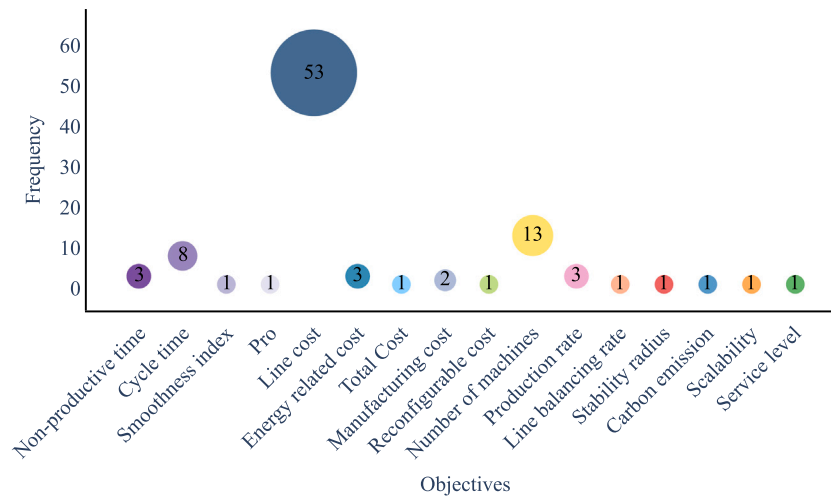


Fig. 7. Frequency of different objective functions in the literature.

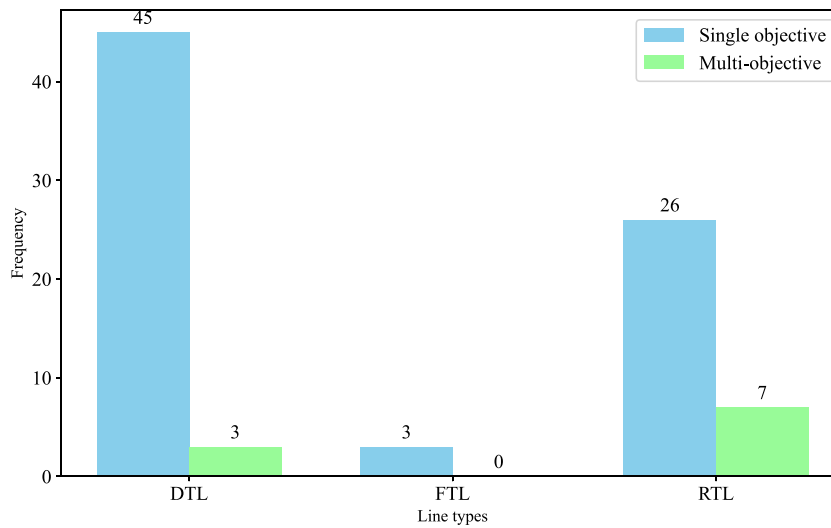


Fig. 8. Number of objective functions in the literature of TLBP.

may indicate challenges in effectively integrating simulation with optimization approaches. Simulation methods are particularly useful for evaluating system performance under uncertainty and can incorporate complex real-world dynamics. However, they are computationally intensive and may not provide direct optimization capabilities. The results from simulation studies can also be sensitive to model assumptions and input data quality.

Fig. 10 shows the distribution of TLBP articles with an emphasis on ‘Certainty’ and ‘Uncertainty’. Notably, the ‘Certainty’ portion significantly outweighs the ‘Uncertainty’ one, indicating that a majority of TLBP articles are based on certain or deterministic parameters. In such studies, all necessary information is assumed to be known and static, which simplifies both the modeling of problems and the development of solutions. On the other hand, the smaller but significant research component on “Uncertainty” acknowledges the complexity present in real-world production settings where variables are not always predictable. The chart shows a significant concentration of deterministic studies in the DTL category, with 47 papers compared to just one for uncertainty. To some extent, even if RTLs are supposed to provide systems able to deal with an uncertain future, the RTL category has 29 papers about certainty compared to just four for uncertainty, indicating a strong bias in favor of certainty. In the FTL category, there are three papers classified as certain and no papers as uncertain. This distribution

suggests a potential gap in the literature for developing more sophisticated models capable of managing uncertainty, which could be more relevant for dynamic and real-world manufacturing systems.

Fig. 11 indicates a clear predominance of articles focusing on strategic and operational levels of decision-making. Out of the 84 articles represented across all categories, 70 of them concern themselves with levels that are strategic and operational. This suggests that a significant majority of research in this field is dedicated to understanding and optimizing decision-making processes that are influenced by long-term strategic planning and the immediate considerations of operational management. In DTL, most articles (41 out of 48) discuss strategic and operational decision-making. RTL follows this trend, with 28 out of 33 articles also focusing on strategic and operational aspects, indicating these two levels are considered crucial in dynamic settings. FTL, although a smaller category with 3 articles, shows a pattern where strategic, tactical, and operational considerations are central in the majority of its articles (2 out of 3). Given the concentration on strategic and operational decision-making in the literature, future research could benefit from investigating the integration and impact of tactical decision-making processes, which act as a bridge between strategy and operations.

The heatmap, shown in Fig. 12, presents data for various equipment-related characteristics across different line types: DTL, FTL, and RTL.

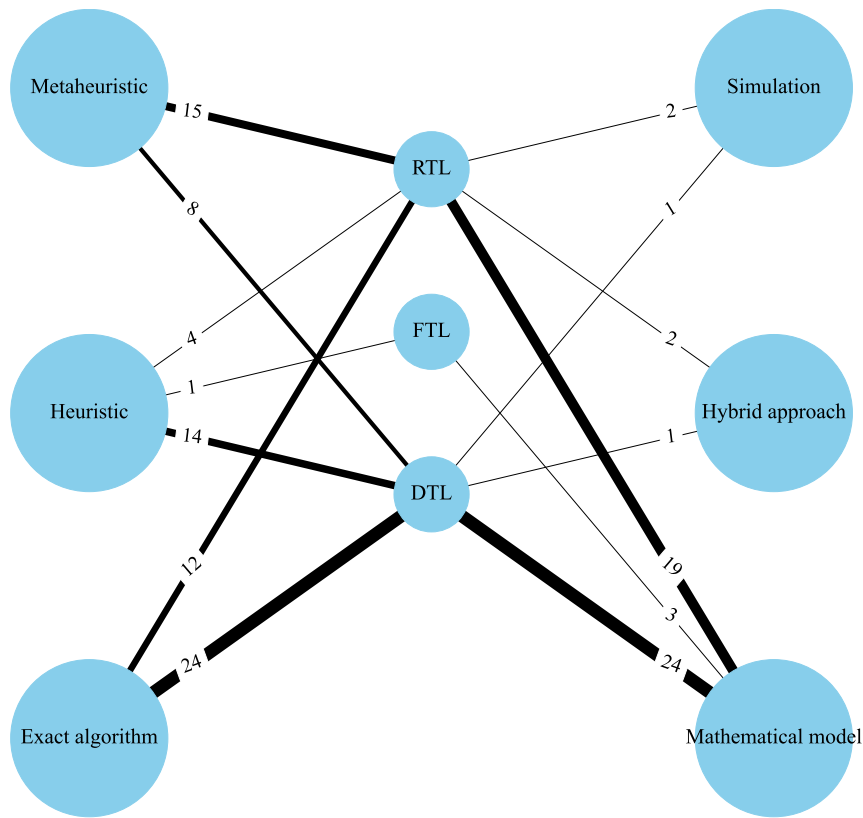


Fig. 9. Frequency of the solution methods in the literature of TLBP.

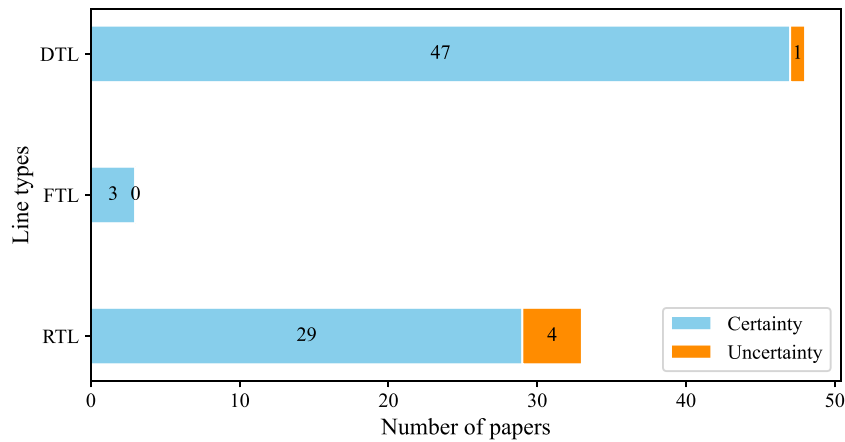


Fig. 10. Distribution of TLBP articles according to parameter types.

Each cell represents the frequency of a particular characteristic within each line type. The heatmap indicates that Ac^C is a common characteristic across RTL, with a frequency of 15. SH^{mono} shows a high frequency in RTL, with a value of 22 and SH^{multi} shows a high frequency in DTL, with a value of 41. The analysis also reveals that Bu^{al} , Af^t , and To^{ma} are areas that have not been extensively investigated. The lack of emphasis on FTL indicates a significant research opportunity, as these parameters are critical for the optimization and flexibility of manufacturing systems.

The heatmap presented in Fig. 13 provides an insightful view of the distribution of time-related characteristics within various line types. DTL and RTL are associated with a greater diversity of these characteristics. On the other hand, FTL shows a minimal presence in the research, as indicated by the sparse frequency of articles, which may imply that time-related issues in FTL have not been extensively investigated.

From Fig. 14, the heatmap highlights a predominant focus on the parameters C^{pres} , C^{inc} , and C^{exe} , especially within DTL. DTL shows the highest frequency for these parameters, suggesting precedence, inclusion, and execution relations. In contrast, the RTL exhibits a moderate emphasis on these parameters, while the FTL presents minimal occurrences. Given this distribution, the relatively lower emphasis on sequencing and scheduling problems, denoted by Seq and Sch , may suggest a potential gap in the literature.

7. Future directions

This section focuses on responding to the third research question. The proposed classification of the available literature brings many important research paths that necessitate careful exploration and consideration. These paths are crucial in bridging the gap between research

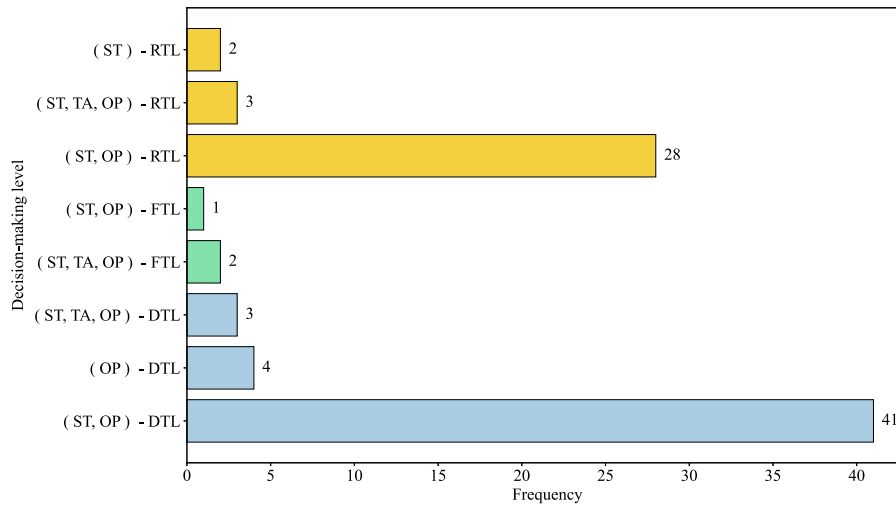


Fig. 11. Distribution of decision-making levels across line types considered in TLBP.

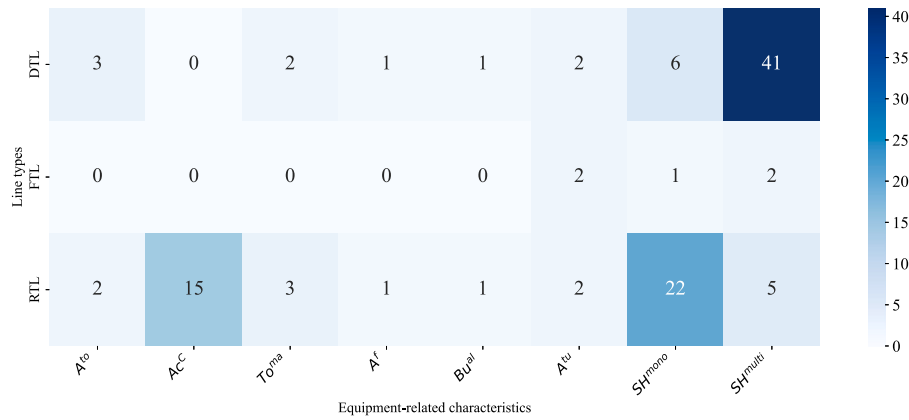


Fig. 12. Distribution of equipment-related parameters across line types considered in TLBP.

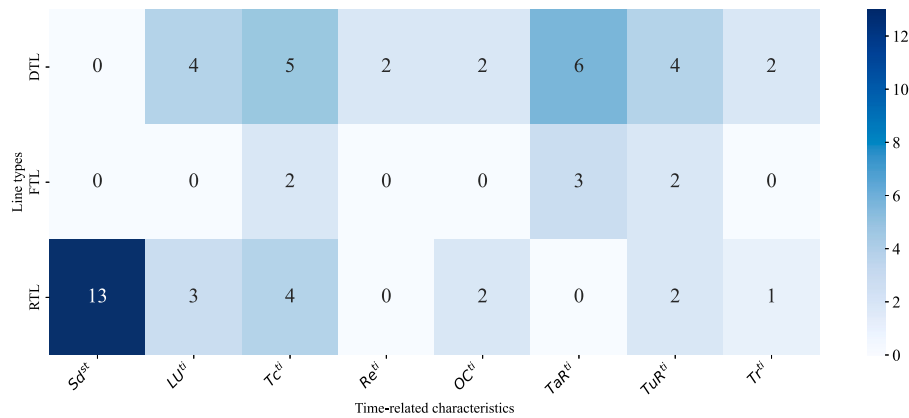


Fig. 13. Distribution of time-related parameters across line types considered in TLBP.

and its practical application, improving how scholarly work affects the real world. This review study also revealed that some dimensions of TLBPs have not been extensively explored in the current body of research. In this section, the crucial importance of these often-overlooked factors is highlighted, emphasizing their pivotal role in improving the understanding and strategies for addressing TLBPs. For a methodical presentation, the insights will be divided into two distinct categories: Problem-Related Insights and Solution-Related Insights.

7.1. Problem-related insights

7.1.1. Transfer line type

Given the predominance of DTLs in the literature and the less frequent mention of FTLs and RTLs, future research should delve deeper into these less common line types. FTLs, offering more flexibility, warrant thorough exploration to understand their benefits and challenges in modern manufacturing settings. Research could focus on the

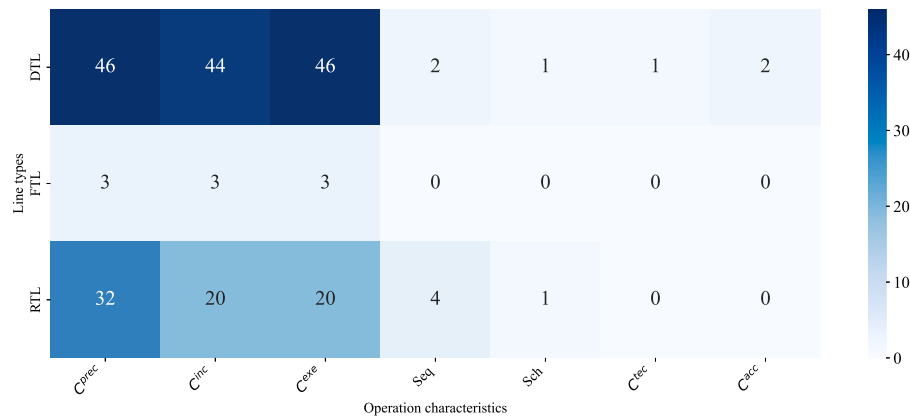


Fig. 14. Distribution of operation assignment parameters across line types considered in TLBP.

development and optimization of FTLs, assessing their applicability and efficiency across various manufacturing scenarios. A promising research avenue, driven by industrial demand, is the comparison of the efficiency of an FTL (or RTL) with several DTLs working in parallel, each dedicated to a specific product (Dolgui et al., 2021). Another potential area of study is the investigation of mixed lines, where one part functions as an FTL and another as an RTL or DTL.

7.1.2. Sustainability

Due to the recent incorporation of sustainability elements in various manufacturing environments (see Renna & Materi, 2021), integrating sustainability criteria such as energy consumption and emissions into the decision-making processes of TLBPs is crucial, particularly as industries shift towards environmentally responsible practices. The high-volume production of transfer lines significantly impacts energy use and emissions, and thus, reorienting TLBP optimization to include environmental concerns alongside traditional time and cost objectives is imperative. To the best of our knowledge, there has been limited research published in the literature that takes sustainability factors into account in TLBPs. Future research should focus on developing models prioritizing energy efficiency, emissions reduction, and overall eco-performance, balancing these with economic goals. This includes exploring trade-offs between production and sustainability objectives and employing life cycle assessments to fully understand the environmental impact of transfer line designs over their lifespan. This approach not only improves the environmental footprint but also aligns with increasing regulatory and consumer demands for greener manufacturing.

7.1.3. Uncertainty

In the domain of TLBPs, an essential direction for future research lies in exploring the uncertainties associated with cycle and completion times that go beyond conventional factors like machine breakdowns and maintenance requirements. Despite the high level of automation in manufacturing processes, operational unpredictabilities such as material quality variability, environmental conditions, intermittent tool wear, and human factors introduce significant variances in cycle and completion times. Remarkably, only 6.3% of the literature (five papers) addresses the topic of uncertainty, specifically targeting “task processing time”, “processing time on machines”, “demand”, and “machine failures”. This underscores a significant gap in the literature and a great chance for further research in this area. To address this gap, future investigations must broaden the scope of uncertainties considered in TLBP models to include those affecting cycle and completion times in more subtle yet impactful ways. This expansion necessitates a revision of traditional TLBP frameworks to integrate probabilistic or stochastic elements that capture the wider spectrum of variability in operational timings. Embracing this broader perspective on uncertainty enables the

creation of manufacturing lines that are not just efficient under ideal conditions but are also robust and flexible in the face of the varied and unpredictable challenges characteristic of real-world manufacturing environments. Stochastic programming, robust optimization, and stability radius approaches are potential decision-aid tools for generating new insights in this research direction.

7.1.4. Multi-objective optimization

Future research in TLBPs should address the current focus on single-objective optimization, particularly the heavy emphasis on cost-related factors such as line cost, equipment cost, and the number of machines, and expand its scope to include multi-objective optimization strategies (Liu et al., 2021; Osman & Baki, 2018). This involves not only balancing cost with time-related objectives, like cycle time and non-productive time, which are crucial for throughput and overall efficiency, but also exploring the less emphasized efficiency and performance metrics like sustainability, smoothness index, and stability radius. These metrics can indirectly enhance both cost and time efficiencies and contribute to overall operational excellence. By integrating these aspects, research should aim to develop models that simultaneously address cost reduction, time management, and efficiency improvements. This multi-dimensional approach, while more complex and computationally demanding, is fundamental for achieving a balanced perspective in TLBP solutions. It requires optimizing a combination of different objectives and finding Pareto-optimal solutions that effectively balance trade-offs among these varying goals. Addressing these gaps by developing advanced methodologies and computational resources capable of handling the intricacies of multi-objective optimization, with an increased focus on efficiency and performance metrics, will significantly enhance the field, leading to more holistic and effective solutions in transfer line balancing.

7.1.5. Equipment-related consideration

The review of the existing literature reveals a notable gap at the tactical decision-making level, where intricate aspects such as A^f , A^{to} , To^{ma} , and Bu^{dl} have rarely been explored. The dynamic allocation of buffers (Bu^{dl}) is not only about ensuring workflow fluidity but also about maximizing the effective use of workspace and resources. The correct assignment of fixtures (A^f) is crucial for maintaining product quality and reducing cycle times by enabling quick changes between production processes. Similarly, tool assignment (A^{to}) is fundamental for operational efficiency and the minimization of machine downtime. Furthermore, the capacity of tool magazines (To^{ma}) is instrumental in ensuring that the right tools are available when needed, preventing delays, and maintaining the pace of production, which is especially crucial in FTL. Future research should pivot towards these overlooked characteristics, given their critical impact on the precision, flexibility, and uninterrupted operation of production systems at a tactical level.

7.1.6. Time-related consideration

Building upon the existing literature, it is clear that the completion time of tasks on machines in real-world settings is heavily influenced by critical time-related characteristics. Despite this, the current body of research within TLBP significantly overlooks these aspects, especially in the context of FTL. Although some time-related characteristics such as (Sd^{st}) and (OC^{ti}) have been acknowledged in specific line types, their study within FTL is markedly lacking. Parameters such as (Re^{ti}), (LU^{ti}), and (Tr^{ti}) are essential to accurately measure the task completion times and, thus, the overall efficiency of production systems. These elements contribute significantly to creating a realistic and holistic model of production processes, which is crucial for the optimization and enhancement of TLBPs. Future research should prioritize these overlooked influential characteristics.

7.1.7. Operation assignment consideration

The body of the TLBP literature indicates a significant research gap in the area of sequencing and scheduling problems (Seq and Sch) within the domain of TLBP across various types of lines. This gap is particularly concerning given the complexity of real-world manufacturing environments, where both the order of tasks (sequencing) and the allocation of tasks over time (scheduling) can dramatically impact the efficiency and performance of transfer lines. The scarcity of research in this area highlights a compelling opportunity for future investigation. Addressing both sequencing and scheduling challenges in TLBP could provide valuable insights into optimizing task arrangements and timing, ultimately enhancing the throughput and adaptability of these systems.

7.1.8. Industry 4.0

Due to the recent developments in Industry 4.0 emerging in various manufacturing settings (Facchini et al., 2023; Hosseinzadeh et al., 2023; Mahmoodi et al., 2024; Vlachos et al., 2022), incorporating Industry 4.0 technologies, such as digital twin, Artificial Intelligence (AI), and the Internet of Things (IoT), into TLBPs presents significant research opportunities.

Industry 4.0 technologies, particularly IoT sensors, offer unprecedented capabilities for collecting accurate data from machines within transfer lines. These sensors continuously monitor various parameters, including machine performance, downtime events, and energy usage across different operational modes. This granular data collection enables the creation of highly accurate digital twins (virtual replicas of the physical transfer line). Digital twins provide new possibilities for TLBP simulation and optimization. These virtual models allow rapid testing of various line balancing strategies without disrupting actual production. By incorporating real-time data on machine downtimes and energy consumption, digital twins can simulate more realistic scenarios, enabling manufacturers to evaluate multiple configurations and select the most efficient and energy-optimized transfer line setup.

With leveraging historical data from IoT sensors and applying machine learning algorithms, it becomes possible to accurately forecast potential equipment failures across workstations. This capability is especially valuable in transfer lines, where the malfunction of a single station can disrupt the entire production flow. Additionally, with the use of AI techniques it becomes possible to evaluate energy usage patterns of machines in various operational modes, providing valuable insights for optimizing energy consumption. These insights enable the development of TLBP solutions that integrate energy efficiency with traditional production metrics. The incorporation of AI-driven predictive maintenance and energy optimization ensures a holistic approach to line balancing, improving production efficiency, maintenance scheduling, and energy management across the entire transfer line.

Finally, as stated by Cerqueus and Delorme (2023) there is a clear relationship between Industry 4.0 and RTL since several technologies (e.g. cyber-physical systems, collaborative robots, additive manufacturing) can act as enablers for the development of RTL, and should be increasingly considered in research works.

7.2. Solution-related insights

Hybrid approaches, which combine elements from different methods such as heuristics, exact algorithms, metaheuristics, and simulations, could offer a more comprehensive and effective way of addressing the complexities of TLBPs (He et al., 2020; Osman & Baki, 2014). They might be particularly suited to scenarios that involve a high degree of uncertainty or where the balancing problem presents unique challenges that cannot be adequately addressed by a single method. Two of the promising solution approaches that future research could focus on developing and testing their applicability and effectiveness in various TLBP scenarios are simulation-based optimization and the integration of machine learning into meta-heuristics.

Despite the advantages of simulation models in capturing real-world scenarios and uncertainties, they have rarely been used in the context of TLBP. Simulation offers a unique perspective, particularly for large-scale systems, which often pose challenges for purely mathematical models. By simulating the dynamics of transfer line operations, researchers can gain valuable insights into how these systems perform in actual scenarios and under various conditions. This approach allows for a more comprehensive understanding of the intricate interactions between machines, workstations, and the production environment (Shao et al., 2020, 2022). Future research in TLBPs can focus on the development of efficient integration schemes that combine optimization and simulation techniques, forming a simulation-based optimization approach. This integration is crucial for streamlining the design process of transfer lines. Through a seamless integration of optimization algorithms with simulation models, researchers can create a closed-loop design framework. This framework enables the optimization algorithms to make decisions based on the feedback from the simulation while taking the production and equipment uncertainty into consideration.

In recent years, there has also been a growing interest in integrating machine learning techniques into meta-heuristics to solve combinatorial optimization problems (Karimi-Mamaghan et al., 2022). However, this has not yet been applied to the TLBP. This integration could guide meta-heuristics towards more efficient, effective, and robust searches, improving their performance in terms of solution quality, convergence rate, and robustness. Machine learning can help in understanding the search space better, predicting the performance of solutions, or even guiding the search process based on historical data. Such an approach could significantly enhance the capabilities of meta-heuristics in handling the complexity and dynamic nature of TLBPs.

8. Conclusion

This systematic review study examines TLBP literature, proposing a tuple notation classification framework that includes system configuration, specific problem characteristics, and objective functions. It draws attention to the complexities of the TLBP, revealing a prominent focus on DTLs while identifying significant gaps in the study of FTLs. The study emphasizes the importance of incorporating sustainability into TLBP techniques, which has been largely disregarded in the previous literature. It also highlights the scarcity of multi-objective optimization methods in TLBP investigations, suggesting this is an important field for future research. Furthermore, the study of hybrid techniques, the management of uncertainty, and the equipment-related, time-related, operation assignment considerations are highlighted, emphasizing their significance in improving the adaptability and efficiency of manufacturing lines. This study represents a critical turning point in TLBP research by emphasizing the necessity for thorough, long-lasting, and effective manufacturing solutions.

CRediT authorship contribution statement

Pedram Beldar: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Masood Fathi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Amir Nourmohammadi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Xavier Delorme:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Olga Battaia:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Alexandre Dolgui:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization.

Acknowledgments

This study is partly supported by the Knowledge Foundation (KKS) and Sweden's Innovation Agency through the ACCURATE 4.0 project (Grant No. 20200181) and the PREFER project, respectively. It is also partly supported by the project ANR-21-CE10-0019 "RECON-FIDURABLE" and by the project Carnot M.I.N.E.S. "Industrie responsable".

Data availability

Data will be made available on request.

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