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Line balancing for energy efficiency in production: A qualitative and quantitative literature analysis

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A R T I C L E I N F O

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A B S T R A C T

In the rapidly evolving landscape of hyperconnected digital manufacturing, known as Industry 4.0, achieving energy efficiency has become a critical priority. As manufacturers worldwide strive to meet sustainable development goals, enhancing energy efficiency is essential for reducing operational costs and minimizing environmental impact. In this context, line balancing is a pivotal strategy for optimizing energy consumption within manufacturing processes. This study presents a comprehensive literature review on the Line Balancing Problems (LBPs) focused on enhancing energy efficiency. The review aims to provide a holistic understanding of this domain by examining past, present, and future trends. A systematic literature review is conducted using the PRISMA method, incorporating both qualitative and quantitative analyses. The quantitative analysis identifies prevalent patterns and emerging trends in energy efficiency optimization within the LBP domain. Concurrently, the qualitative analysis explores various aspects of existing studies, including configurations of lines, managerial considerations, objectives, solution methodologies, and real-world applications. This review synthesizes current knowledge and highlights potential avenues for future research, underlining the importance of energy efficiency in driving sustainable practices in Industry 4.0 and the emerging Industry 5.0 paradigm.

1. Introduction

Energy efficiency is a crucial aspect of modern manufacturing, driven by the need for economic viability and environmental sustainability (Batouta et al., 2023). Energy efficiency significantly enhances manufacturers' transition toward sustainable production within the Industry 4.0 framework (Ghobakhloo & Fathi, 2021), which relies on energy-intensive advanced technologies such as cyber-physical systems, IoT, big data analytics, and cloud computing (Chen et al., 2021). Energy-efficient manufacturing ensures regulatory compliance and provides a competitive edge by cutting production expenses and appealing to environmentally conscious consumers (Hao et al., 2022). As the industry evolves towards Industry 5.0, the focus shifts even more toward sustainable practices, prioritizing energy efficiency to achieve sustainability goals, optimize resource use, and build resilient manufacturing systems (Leng et al., 2023). Industry 5.0 relies on energy-efficient production systems to ensure adaptability to energy fluctuations and enhance overall operational resilience (Masoomi et al., 2023).

Production line balancing is critical in achieving energy efficiency within this advanced manufacturing landscape (Ramli & Ab Rashid, 2022). Efficiently balanced lines ensure that production processes are streamlined, minimizing idle times and reducing the energy consumption of machinery, equipment, and digital technologies (Tian et al., 2024). By aligning production rates and workloads across the production line, manufacturers can prevent bottlenecks and ensure continuous flow, thereby enhancing operational efficiency and reducing energy waste (Wang et al., 2021a). The role of line balancing-driven energy efficiency can be more salient within Industry 4.0 and 5.0 environments where integrating smart technologies can be a double-edged sword, ensuring optimal energy use at every stage or further skyrocketing the

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overall energy consumption (Ghobakhloo et al., 2021). Consequently, the strategic importance of energy efficiency in driving advancements in manufacturing, fostering sustainability, and achieving long-term economic and environmental viability is further underscored (Tian et al., 2024). This is why energy-efficient line balancing has become essential for the manufacturing sector to meet present and future challenges and contribute to a more efficient, resilient, and environmentally responsible industrial ecosystem (Dalle Mura & Dini, 2023).

In terms of production economics, to remain competitive in today's mass-customized production landscape, manufacturing systems must quickly adapt to rapid market and product changes (Schulz et al., 2023). Under such circumstances, the line balancing problem (LBP) is among the most important decision steps to smoothen the path from the product design to the final product delivery (Battaïa & Dolgui, 2022). The LBP primarily intends to divide tasks among the workstations to optimize one or more objectives, such as efficiency, cycle time (CT), etc., while satisfying some constraints (Nourmohammadi et al., 2019; Fathi et al., 2020; Boysen et al., 2022).

From the industrial environment perspective, the LBP can be considered for three line types: assembly, disassembly, and transfer/machining lines (Battaïa & Dolgui, 2022). The assembly lines traditionally add components to the final products, e.g., cars (Scholl, 1999). The disassembly lines recycle end-of-life products, e.g., hazardous parts (Bentaha et al., 2014). The transfer lines focus on the machining of the products, e.g., cylinder heads (Beldar et al., 2025; Delorme et al., 2009).

Since the first formulation of LBP by Salveson and Louisville (1955), the field has attracted much research by including additional real-world aspects. Considering the line layout, the main extensions to the traditional straight line are the U-shaped line (Fathi et al., 2016; Fathi et al., 2018; Işık & Yildiz, 2023; Li et al., 2023), two-sided line (Liang et al., 2022; Liao et al., 2023) and parallel line (Aguilar et al., 2023). From the number of models' perspectives, the main extensions are the mixed-model (Sawik, 2023; Sikora, 2024) and the multi-model (Jafari Asl et al., 2019; Pereira, 2018). Considering the level of automation, the main extensions are robotic (Albus et al., 2024; Aslan, 2023; Wu et al., 2024) and human-robot collaboration (Nourmohammadi et al., 2024; Nourmohammadi et al., 2022; Stecke & Mokhtarzadeh, 2022) following the Industry 4.0 and 5.0 concepts.

LBPs have been extensively studied for over 70 years, and several review studies have been published on the topic, synthesizing various aspects of LBPs. Recent contributions include reviews by Chutima (2022), Boysen et al. (2022), Battaïa and Dolgui (2022), Ramli and Ab Rashid (2022), Fathi et al. (2024) and Güler et al. (2024). While these studies have advanced the field, they exhibit limitations in systematically addressing energy efficiency in line balancing.

A major shortcoming of existing reviews is the lack of a structured categorization of energy efficiency efforts in LBPs. Most reviews do not comprehensively examine how energy efficiency is considered across different line configurations, layout designs, and production types. Additionally, the managerial aspects of energy efficiency, including macro and micro-level decision-making, remain underexplored. Furthermore, the relationship between energy efficiency and other key performance measures in production systems has not been sufficiently addressed, limiting the understanding of trade-offs and synergies between energy consumption and operational efficiency.

A closer examination of the literature reveals that while some reviews touch on energy efficiency, they do not provide a focused and systematic analysis. For instance, Güler et al. (2024) reviewed disassembly lines but did not consider energy efficiency a central theme. Similarly, Chutima (2022) and Fathi et al. (2024) examined robotics and semi-robotic assembly lines, which are highly relevant to energy optimization. However, their discussions are mainly limited to identifying energy-related objectives rather than exploring detailed methodologies for energy consumption calculations or analyzing the challenges of balancing energy efficiency with other performance metrics. Boysen et al. (2022) and Battaïa and Dolgui (2022) provided extensive overviews of decades of LBP research but primarily focused on defining the field and its scope, dedicating only minimal attention to opportunities for optimizing energy consumption. Among the existing reviews, the study by Ramli and Ab Rashid (2022) is the most closely related to the present work. However, it is narrowly focused on assembly lines and exclusively examines studies employing metaheuristic solution methods. While it offers insights into optimization approaches, it lacks a broader perspective on different LBP types, energy assessment techniques, and managerial implications.

Despite these relevant contributions, there is still no systematic review that categorizes energy efficiency efforts in LBP research from multiple perspectives. The existing literature does not sufficiently explore how different line types, layouts, and production settings influence energy efficiency, nor does it adequately address the role of managerial decision-making in achieving energy-efficient production systems. Additionally, limited research has been conducted on methods used to evaluate energy consumption and its relationship with other performance indicators such as cost, productivity, and sustainability. Furthermore, while various solution approaches in LBP studies incorporate energy efficiency considerations, a comparative analysis of these methodologies remains absent.

This review study addresses these gaps by systematically examining LBP literature with an explicit focus on energy efficiency. Unlike prior reviews, it categorizes energy efficiency research across various line configurations—including assembly, disassembly, and machining/transfer lines—and explores managerial drivers, real-world challenges, and the interplay between energy optimization and other production objectives. By adopting a comprehensive approach, this review contributes to understanding the fragmented and evolving research landscape in this critical area. Moreover, it aligns with the growing emphasis on operational efficiency and sustainability within the frameworks of Industry 4.0 and Industry 5.0. By explicitly positioning energy efficiency as a central theme, this study integrates perspectives on energy consumption, managerial considerations, and solution methodologies, providing both theoretical contributions and practical insights. It also lays the groundwork for advancing research into underexplored areas, such as machining and transfer lines, while equipping practitioners with actionable knowledge to address real-world constraints and trade-offs.

To achieve these objectives, this review aims to answer the following research questions:

RQ1: Which types of line configurations are considered for optimizing energy efficiency in line balancing problems?

RQ2: What managerial aspects and drivers necessitate energy optimization, and what direct benefits can companies achieve from it in line balancing? In which sectors is energy efficiency optimization applied, and to what extent has it been implemented in the real world?

RQ3: Which objectives are used to calculate energy consumption in production lines, and what is the relationship between energy and other production measures?

RQ4: What methods are used to optimize energy efficiency in line balancing, and which are most frequently employed?

The remainder of the manuscript is organized as follows. Section 2 describes the methodological approach to the literature review. Section 3 presents the quantitative analysis of the identified literature using a bibliometric method. Section 4 develops a classification scheme and provides a qualitative literature analysis. Section 5 discusses and summarizes the main findings of the review. Finally, Section 6 concludes the study by highlighting its contributions to practice and research, as well as its limitations and suggestions for future research.

2. Methodology

This study followed the Preferred Reporting Items for Systematic Reviews (PRISMA) guidelines (Page et al., 2021) to ensure the high quality and replicability of the review process. PRISMA provides a standardized, peer-accepted methodology using a flow chart diagram and guideline checklist. Considering the PRISMA guideline, the research process was divided into "Literature Search," "Literature Selection," and "Analysis Process." In the following subsections, the three process steps are described in detail.

2.1. Literature search

The literature search aims to identify a literature pool containing as many relevant publications as possible. Therefore, a literature search was conducted using the three scientific databases Science Direct, Scopus, and Web of Science. The applied search string is divided into three levels containing specific keywords. These parts are linked with the operator "AND" to search for the keywords simultaneously, as shown in Fig. 1. The first level limits the literature selection to "Balancing." Since the term "Balancing" can be found in several scientific disciplines, the second level narrows the search to the line types of "Assembly Line", "Disassembly Line," "Transfer Line," and "Machining Line". The third level relates to the objective of the balancing method considered in this study, namely "Energy Efficiency." Although this objective is usually pursued directly, energy consumption can also be reduced to achieve ecological goals such as reducing the carbon footprint. Considering this, the search string is differentiated into two branches in level 3. The left-hand branch focuses on the energy-specific keywords "Energy" and "Power Peak", while the right-hand branch considers environmental-specific keywords "Carbon" and "Eco". The literature search used title, abstract, and keywords for each level to achieve completeness. In conclusion, this process yielded a literature pool of 275 scientific publications.

2.2. Literature selection

The identified papers were analyzed in two steps in the literature selection process. Initially, the whole literature pool was screened for duplicates. Thereby, 83 duplicates have been identified and thus removed. Then, the remaining 192 papers were analyzed based on defined eligibility criteria. Table 1 outlines the utilized exclusion and inclusion criteria.

Since the research field is still developing and the available literature is limited, the literature selection includes all the peer-reviewed journal and conference papers to obtain a more comprehensive overview. Fig. 1 provides a detailed overview of the identification and selection process.

By applying exclusion criterion 1.1, 22 papers were removed according to the paper type, and 19 were removed due to the language. Then, the analysis of title, abstract, and keywords based on criterion 1.2 resulted in 47 publications being identified as unsuitable. Finally, the full texts of the remaining 104 papers were examined, resulting in 15

Table 1
Eligibility criteria.

Criteria	Description
Exclusion	The language of the paper is not English. The paper type is not "journal article" or "conference paper," or the paper is a review paper. The search string identifies the paper, but the paper hardly relates to the topic.
Inclusion	The focus is on production lines and line balancing. At least one objective function relates to improving energy efficiency.

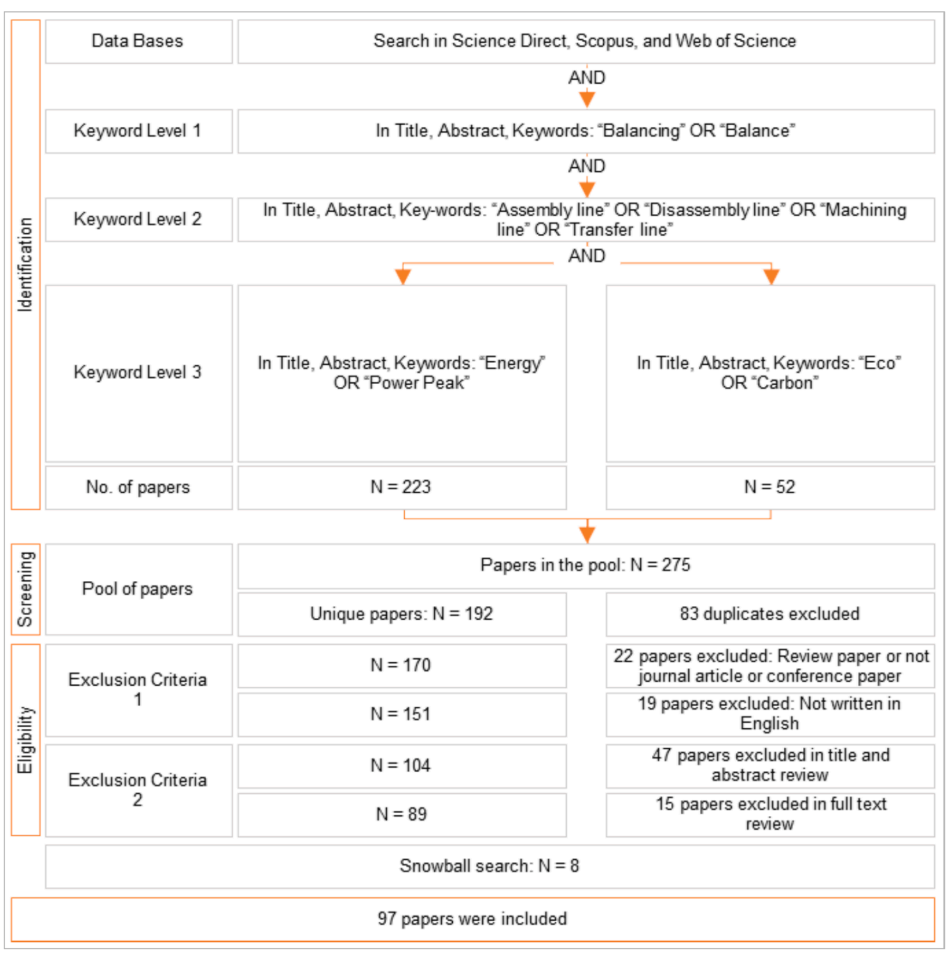

Fig. 1. PRISMA flow diagram.

papers not fulfilling the eligibility criteria. Hence, 89 publications have been selected from the initial literature pool.

Based on the literature selection, a snowball search was conducted. This method serves to identify further suitable papers based on the reference lists of a first starting set (Mahmoodi et al., 2022). Thus, the reference lists of the 89 identified papers were reviewed, and potentially suitable publications were analyzed according to the eligibility criteria. This procedure was repeated step by step for the newly identified papers. As a result, eight additional papers were included in the final literature selection. Thus, 97 eligible papers were identified for the literature review.

2.3. Analysis process

The required insights from the papers were extracted based on the grounded theory by Wolfswinkel et al. (2013). This method focuses on the three sequential process steps of "open coding," "axial coding," and "selective coding". Hence, it provides a structured approach to extracting and categorizing the information needed to answer the research questions.

First, each paper was read to conceptualize any relevant findings. For these findings, abstract codes were generated according to their content. Second, the codes across all papers were compared to identify connections. This approach allows codes to be grouped into categories. Hence, four categories were identified, namely "line types," "managerial aspects," "objective aspects," and "solution approach." Third, these categories were again compared and refined to elaborate high-level dimensions. The coding was documented in the software MAXQDA 2022 to keep track of these steps.

3. Quantitative analysis

This section provides an analysis of the bibliometric data from the identified literature. In this regard, the literature pool is examined from three interconnected perspectives, namely, the milestones of research, the temporal development of the research field, and the keyword analysis, as explained below:

- *Milestones of research:*

Milestones of research are papers cited particularly often in other publications. During the quantitative analysis, the reference lists of the selected papers were examined for links to one another. The analysis revealed that researchers most frequently referred Mukund Nilakantan et al. (2015a) (30 times) and Li et al. (2016) (27 times), both focusing on including the energy aspect in the simple assembly lines. Thus, these papers can be considered milestones in the research area of line balancing for energy efficiency. These papers were published at the beginning of research on line balancing for increasing energy efficiency.

- *Temporal development:*

Optimising Energy Efficiency through Line Balancing is a developing concept, with the first publication dating back to 2014. A general trend can be identified based on the distribution frequency of publications over time. The annual number of published papers is rising steadily, as shown in Fig. 2. Thus, the research area seems to have gained more relevance in recent years.

- *Keyword analysis:*

The keywords analysis identifies the keywords mentioned most frequently and the temporal development. The analysis was conducted using the Software VosViewer. In detail, it considers 63 keywords mentioned at least two times in the literature pool. Fig. 3 depicts that the keywords "energy consumption," "disassembly line balancing", "multi-objective optimization," and "assembly line balancing" are mentioned most often in the literature. Moreover, Fig. 5 reveals a temporal relationship and development. In this regard, robotic-related keywords mainly occurred around 2019. Thus, the application of robotic technology could have been a trigger for the considered research field.

Moreover, research seems to have focused initially on balancing on the assembly line and, later, on balancing on the disassembly line. Finally, environment-related keywords such as "green manufacturing" or "carbon emission" mainly appear after 2021. This development indicates a trend towards greater importance of environmental factors within production due to the recent sustainable and green manufacturing trends.

4. Qualitative analyses

To conduct a qualitative analysis of the literature, this study employs a categorization scheme to systematically classify the reviewed studies and address the research questions outlined in Section 1. The primary categories in this classification scheme include Line Configuration, Managerial Aspects, Objective Approaches, and Solution Approaches. These categories serve as a framework for analyzing LBP literature concerning energy efficiency. As discussed below, each primary category is further divided into subcategories to enhance analytical depth.

Line Configuration is categorized into Line Type, Layout, and Production Type. Line Type comprises three subcategories representing production environments: Assembly, Disassembly, and Machining. Layout is classified into four spatial configurations: Straight, U-shaped, Two-sided, and Parallel. Production Type is categorized into Single, Multi, and Mixed, indicating the number of product variants or models manufactured within the system.

Managerial Aspects are categorized into Drivers, Benefits, Specific Industries, and Real-world Cases. The Drivers include key factors influencing sustainable manufacturing, such as Climate Change,

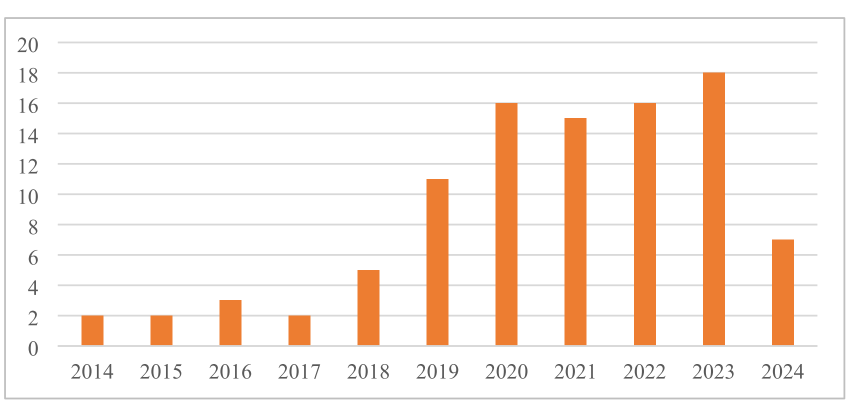

Fig. 2. Frequency distribution over time.

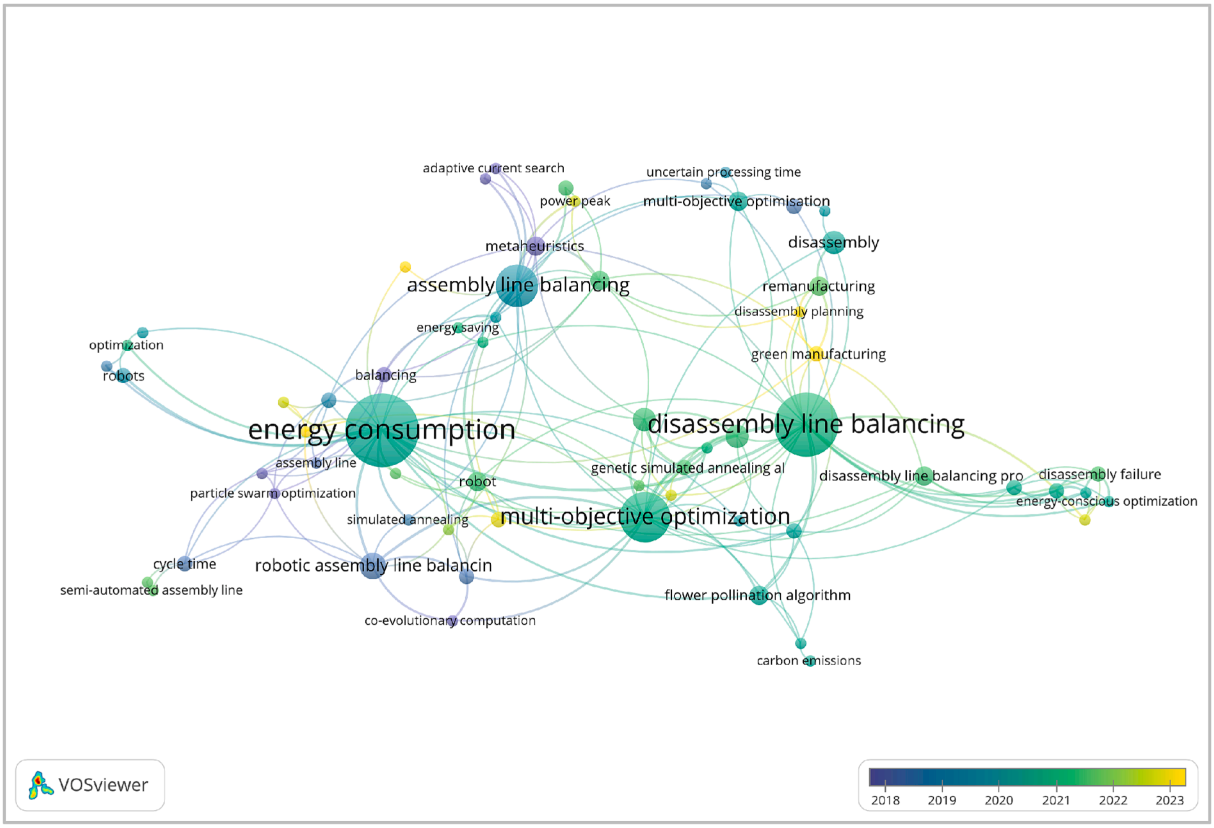

Fig. 3. Keyword development over time generated by VosViewer.

Industry 4.0, the Energy Market, and the Market Situation. Benefits highlight the advantages of energy-efficient practices, including Reduction of Energy Costs, Improvement of Image, and Compliance with Regulations. Specific Industries encompass sectors adopting these practices, including Automotive, Home Appliances, Shipbuilding, Apparel, and Furniture. Real-world Cases provide practical examples of energy-efficient implementations in manufacturing.

Objective Approaches are divided into Energy Consideration and Relations. Energy Consideration includes six key aspects defining different energy consumption types in production systems: Total, Fixed, Standby, Operation, Auxiliary, and Power Peak. Relations describe interactions between energy consumption patterns, which can be Complementary (mutually beneficial energy interactions) or Conflicting (where energy demands create inefficiencies).

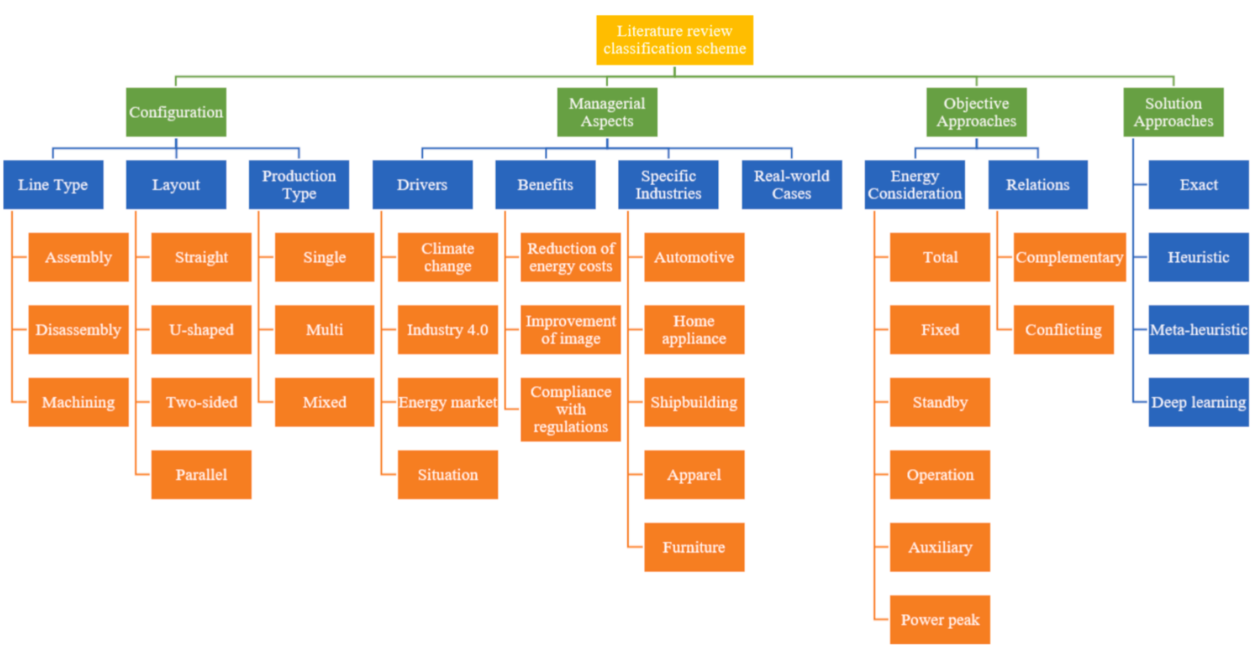

Fig. 4. Graphical representation of the classification scheme.

Solution Approaches are classified into Exact, Heuristic, Meta-heuristic, and Deep Learning. Exact methods provide optimal solutions through mathematical programming. Heuristic approaches offer efficient approximations for complex problems. Meta-heuristic techniques explore large solution spaces to identify near-optimal solutions. Deep Learning leverages AI-based models to optimize production planning and energy management decision-making.

Fig. 4 provides a visual representation of this classification scheme, which is elaborated in detail in subsequent sections. Following the provided classification, the relevant information from the reviewed papers is extracted and reported in Table A1 in the Appendix to facilitate the examination of LBP literature in the context of energy efficiency. Unlike existing LBP literature classifications, our approach introduces a more detailed examination of Managerial Aspects and Objective Approaches, incorporating lower-level subcategories that enhance the understanding of energy efficiency in production systems. This classification captures key drivers, benefits, and industry-specific insights and provides a structured breakdown of energy considerations and their interrelations, offering a more comprehensive framework for analyzing LBP with energy efficiency.

4.1. *Configuration*

This section aims to answer the RQ1. Therefore, it provides insights into the connection between the line configurations and the managerial aspects of energy efficiency in terms of different lines, layouts, and production types, as discussed below.

4.1.1. *Line type*

The line type comprises three main categories, namely assembly (43 times), disassembly (53 times), and machining/transfer lines (one time).

Assembly line: The managerial aspects of energy optimization in assembly line studies are considered in Fig. 5(a). On the macro level, climate change (45 %), Industry 4.0 (30 %), and the energy market situation (25 %) are key drivers, respectively. On the micro level, the benefits are the reduction of energy costs (68 %), compliance with regulations (21 %), and improvement of corporate image (11 %), respectively. The energy optimization efforts are most prevalent in the automotive (72 %) and home appliance (20 %) industries, with other sectors like shipbuilding (3 %), apparel (3 %), and furniture (2 %) also engaging to a lesser extent.

Disassembly line: In the context of disassembly line studies, the managerial aspects of energy optimization are shown in Fig. 5(b). At the macro level, the primary drivers are climate change (83 %), followed by Industry 4.0 (17 %). At the micro level, the most notable benefit is the reduction of energy costs (67 %), followed by compliance with regulations (19 %) and improvement of corporate image (14 %). From a specific industry perspective, the home appliance industry (62 %) leads in implementing energy-efficient practices, followed by the automation sector (38 %).

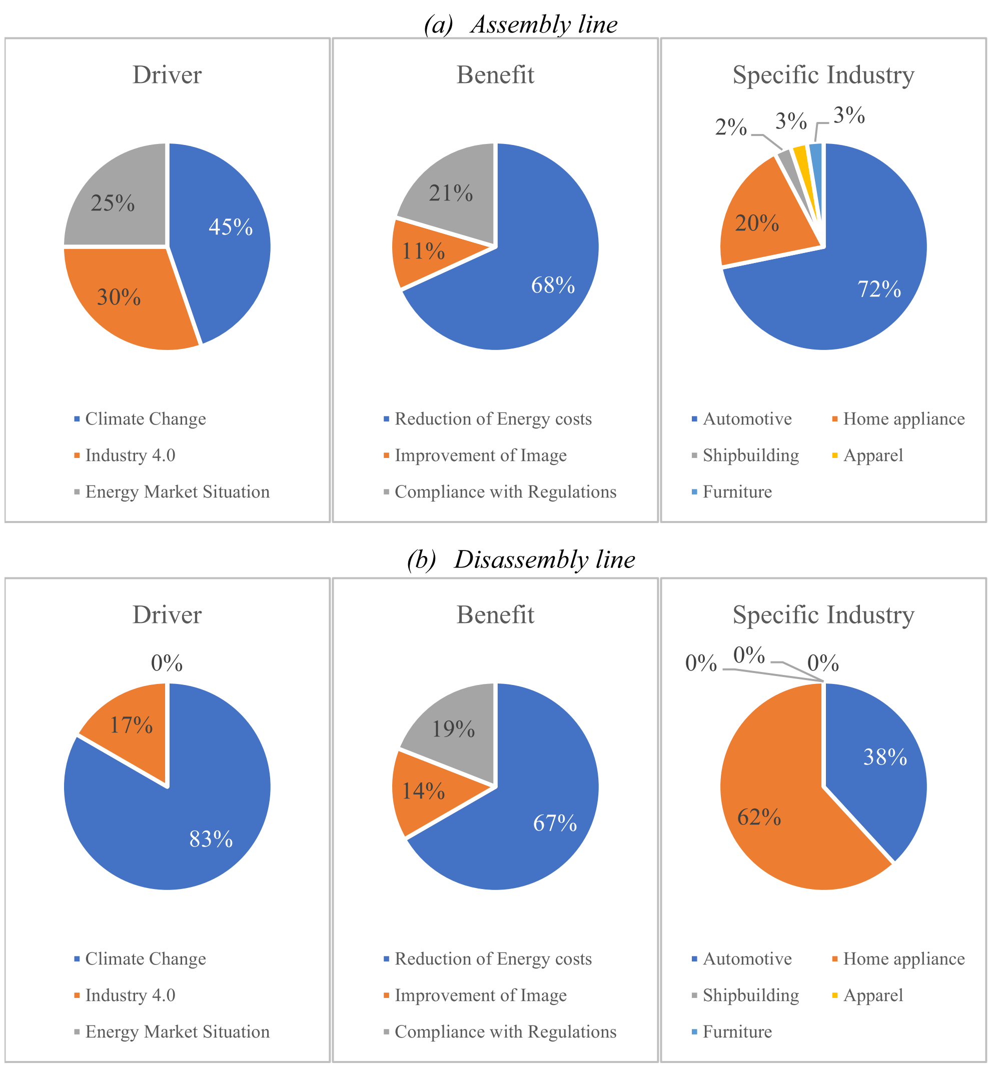

Fig. 5. Managerial aspects of energy efficiency in different line types.

Machining line: A few studies consider the machining transfer line balancing with energy efficiency, e.g., Cerqueus et al. (2020). The analysis of this study showed that climate change and Industry 4.0 were among the main drivers, while cost reduction and company image improvement were considered the main benefits.

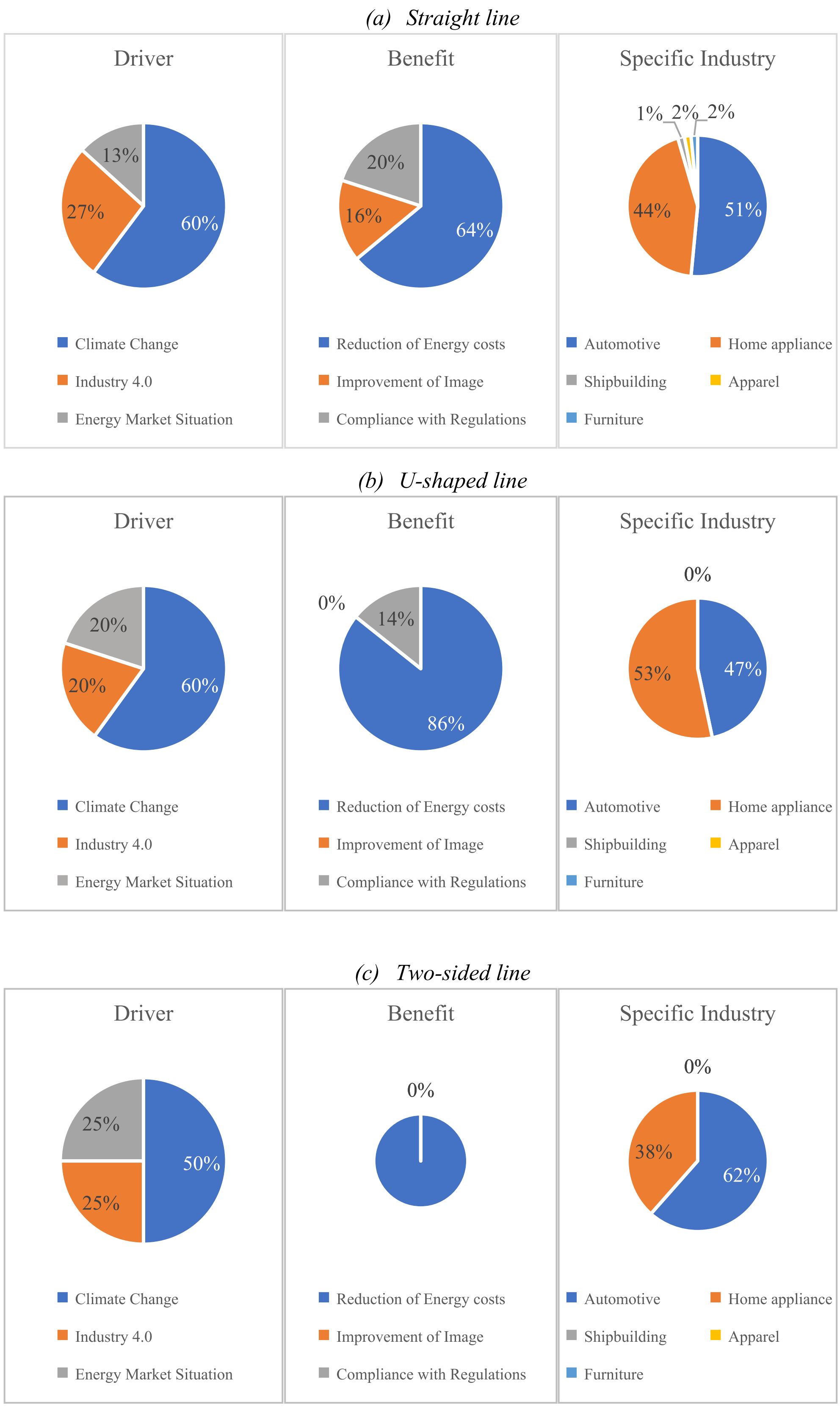

Fig. 6. Managerial aspects of energy efficiency in different line types.

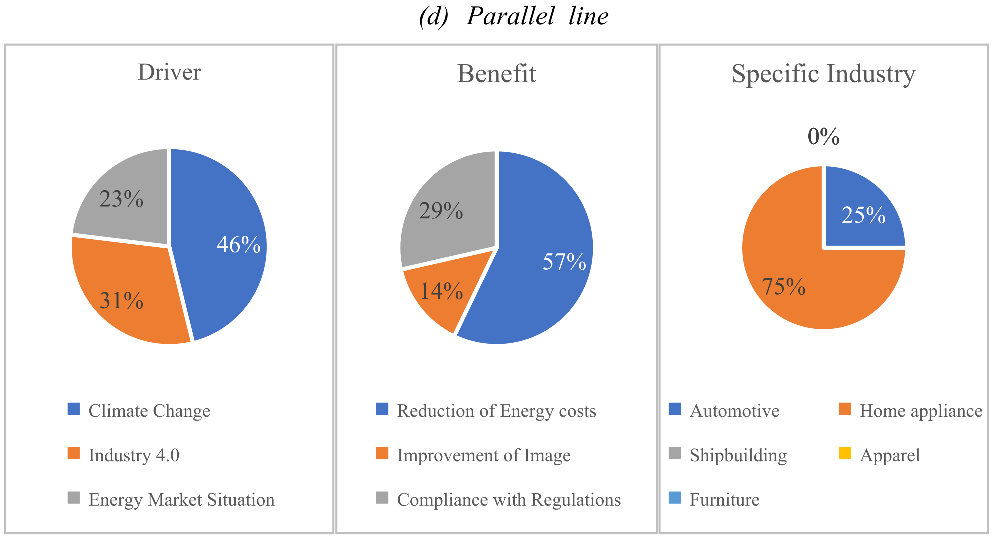

Fig. 6. (*continued*).

4.1.2. Layout type

The line layout comprises four main categories, namely Straight (72 times), U-shape (13 times), Two-sided (9 times), and Parallel (7 times) layouts, as discussed below. It is worth mentioning that Liang et al. (2023c) compared the four different layouts with each other. For this reason, the layout numbers do not correspond to the total number of reviewed studies.

Straight line: In the context of straight-line studies, the managerial aspects of energy optimization are shown in Fig. 6(a). At the macro level, the primary drivers are climate change (60 %), followed by Industry 4.0 (27 %) and the energy market situation (13 %). At the micro level, the most notable benefit is the reduction of energy costs (64 %), followed by compliance with regulations (20 %) and improvement of image (16 %). From a specific industry perspective, the automotive sector (52 %) leads in implementing energy-efficient practices, followed by the home appliance industry (44 %). Other sectors, such as furniture (2 %), shipbuilding (1 %), and apparel (1 %) show lower engagement.

U-shaped line: In the context of U-shaped line studies, the managerial aspects of energy optimization are shown in Fig. 6(b). At the macro level, the primary drivers are climate change (60 %), followed by Industry 4.0 (20 %) and energy market situation (20 %). At the micro level, the most notable benefit is the reduction of energy costs (86 %), followed by compliance with regulations (14 %). From a specific industry perspective, the home appliance sector (53 %) leads in implementing energy-efficient practices in U-shaped layouts, followed by the automotive industry (47 %). Other sectors, such as furniture (0 %), shipbuilding (0 %), and apparel (0 %), show no engagement.

Two-sided line: In the context of two-sided line studies, the managerial aspects of energy optimization are shown in Fig. 6(c). At the macro level, the primary drivers are climate change (50 %), followed by Industry 4.0 (25 %) and the energy market situation (25 %). At the micro level, the most notable benefit is the reduction of energy costs (100 %), with no emphasis on compliance with regulations (0 %) or improvement of image (0 %). From a specific industry perspective, the automotive sector (62 %) leads in implementing energy-efficient practices in two-sided layouts, followed by the home appliance sector (38 %).

Parallel line: In the context of parallel line studies, the managerial aspects of energy optimization are shown in Fig. 6(d). At the macro level, the primary drivers are climate change (46 %), followed by Industry 4.0 (31 %) and the energy market situation (23 %). At the micro level, the most notable benefit is the reduction of energy costs (57 %), followed by compliance with regulations (29 %) and improvement of image (14 %). From a specific industry perspective, the home appliance sector (75 %) leads in implementing energy-efficient practices in parallel layouts, followed by the automotive industry (25 %).

4.1.3. Product type

Regarding product variety, most authors focused on single-model production (76 papers), while mixed-model and multi-model were addressed by 9 and 12 papers, respectively.

Single-model: In the context of single-model studies, the managerial aspects of energy optimization are shown in Fig. 7(a). At the macro level, the primary drivers are climate change (60 %), followed by Industry 4.0 (23 %) and the energy market situation (17 %). At the micro level, the most notable benefit is the reduction of energy costs (69 %), followed by compliance with regulations (18 %) and improvement of image (13 %). From a specific industry perspective, the automotive sector (52 %) leads in implementing energy-efficient practices in single-model layouts, followed by the home appliance sector (45 %). Other sectors, such as shipbuilding (2 %), apparel (1 %), and furniture (0 %), show lower engagement.

Mixed-model: In mixed-model studies, the managerial aspects of energy optimization are shown in Fig. 7(b). At the macro level, the primary drivers are climate change (45 %), followed by Industry 4.0 (35 %) and the energy market situation (20 %). At the micro level, the most notable benefit is the reduction of energy costs (67 %), followed by compliance with regulations (22 %) and improvement of image (11 %). From a specific industry perspective, the automotive sector (67 %) leads in implementing energy-efficient practices in mixed-model layouts, followed by the home appliance sector (25 %) and furniture (8 %). Other sectors, such as shipbuilding (0 %) and apparel (0 %), show no engagement.

Multi-model: In the context of multi-model studies, the managerial aspects of energy optimization are shown in Fig. 7(c). At the macro level, the primary drivers are climate change (50 %) and Industry 4.0 (50 %), with no influence from the energy market situation (0 %). At the micro level, the benefits are balanced, with a reduction in energy costs (34 %), compliance with regulations (33 %), and improvement of image (33 %), each of which plays a significant role. From a specific industry perspective, the home appliance sector (67 %) leads in implementing energy-efficient practices in multi-model layouts, followed by the automotive industry (33 %). Other sectors, such as furniture (0 %), shipbuilding (0 %), and apparel (0 %), show no engagement.

4.2. Managerial aspects

This section deals with the RQ2. Viewed from a managerial standpoint, managers depend on line balancing to decrease energy

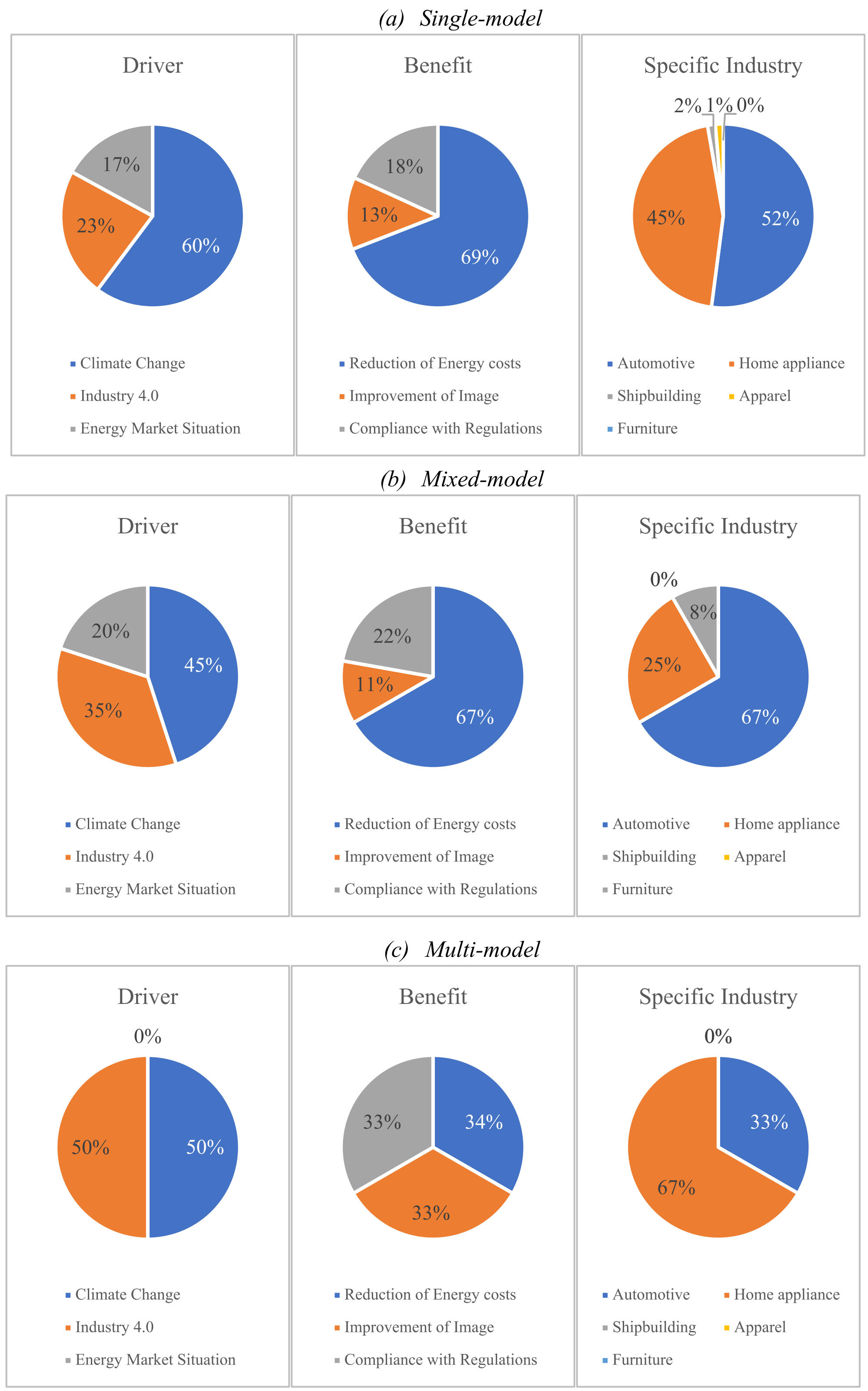

Fig. 7. Managerial aspects of energy efficiency in different production types.

consumption for several reasons. This section outlines the overarching factors (macro perspective) and the company's advantages (micro perspective). Furthermore, it explores the industries where this innovative approach holds particular relevance and previous real-world cases.

4.2.1. *Macro perspective*

The macro perspective examines the drivers for improving energy efficiency through line balancing. This section analyses today's relevance of the methodological approach. In the qualitative analysis, pivotal drivers, namely, climate change, Industry 4.0, and the dynamics within the energy market, were identified as influential factors in elevating awareness of energy efficiency in production.

- *Climate change*:

This driver and its repercussions are highlighted in most papers (57 %, s. Fig. 8). The term "green manufacturer" is frequently cited in this context, as exemplified by Zhang et al. (2019), Zhou and Wu (2020), and Wang et al. (2020a). The production of electrical energy from fossil fuels is identified as a significant source of high carbon dioxide emissions (Rashid et al., 2022), and the availability of emission-free energy capacities is reported to be insufficient (Rashid et al., 2022). Moreover, the manufacturing industry contributes significantly to global energy consumption, with varying estimates such as approximately 50 % according to Zhang et al. (2019) and 35 % according to Ramli and Ab Rashid (2022), citing the United Nations Environment Program. Given the ongoing rise in energy consumption (Lamy et al., 2020; Soysal-Kurt & İşleyen, 2022), several authors emphasize the need for improvements not only as a driver but also as a responsibility of the industry.

- *Industry 4.0*:

The driver of Industry 4.0 pertains to the growing production line automation involving using robots in manufacturing. It is mentioned in 26 % of the considered papers. To illustrate, global sales of industrial robots nearly doubled, reaching 435,000 units between 2015 and 2021 (ifr.org, 2021). Despite the advantages, such as high efficiency and no fatigue, the deployment of robots results in increased energy consumption in manufacturing, as demonstrated by studies like Li et al. (2016), Nilakantan et al. (2018), and Chi et al. (2022). Consequently, robotic technology is now recognized as one of the major energy consumers in the manufacturing process and, therefore, a significant cost factor, as highlighted in works by Zhang et al. (2019), Fang et al. (2020a), and Zhou and Wu (2020). Consequently, companies are compelled to devise strategies to optimize energy consumption, as proposed in studies like Gao et al. (2018), Nilakantan et al. (2018), and Sun et al. (2020).

- *Energy market*:

This driver corresponds to the escalation of energy prices. The driver of the energy market has a relatively low role within the literature selection (17 %) While some authors, like Haotian and Hongjun (2021), Rashid et al. (2022), and Soysal-Kurt and İşleyen (2022), do not explain this increase, Zhou and Wu (2020) attribute it to an energy crisis. Specifically, Zhang and Xu (2020) characterize this crisis as an energy shortage. Additionally, Zhou and Kang (2019) suggest that the augmented costs in the energy market are linked to the overall global surge in energy demand.

4.2.2. *Micro perspective*

The micro-perspective focuses on the concrete benefits that companies gain by improving energy efficiency through line balancing. This section enables researchers to understand practical demands and tailor their research accordingly. In terms of benefits, three categories have been identified: reduction of energy costs, improvement of the company's image, and compliance with regulations.

- *Energy cost reduction*:

The most frequently considered benefit is the reduction of energy costs, as indicated in (67 %, Fig. 9). The selected literature often references a 2012 study on energy consumption in automotive assembly (Zhou & Kang, 2019; Li et al., 2016; Chi et al., 2022). According to this review finings, energy costs in the manufacturing process of an automobile represent approximately 9–12 % of total manufacturing costs. Additionally, a 20 % reduction in energy consumption can result in a 2–2.4 % saving in final manufacturing costs (Fysikopoulos et al., 2012). Consequently, such a cost reduction can significantly enhance competitiveness (Nilakantan et al., 2016; Sariguzel et al., 2022; Chen & Jia, 2022). Moreover, Zhang et al. (2019) emphasize the significance of this benefit for robotic production lines, where energy consumption constitutes a significant expense.

- *Image improvement*:

Contemporary consumers increasingly consider whether products are produced sustainably (Jaca et al., 2018). As sustainability is highly valued today, companies can gain a competitive advantage by being known as sustainable companies. This benefit is rather marketing-related and only considered by 13 % of the identified papers. By reducing energy consumption, a company promotes sustainable development and meets customer demands. The enhanced sustainability can be leveraged for advertising purposes. This benefit is relatively marginal and indirect in the literature despite its importance.

- *Regulations compliance*:

The third considered benefit is associated with the driver of climate change and the corresponding government regulations. A share of 19 % mentions this benefit. To mitigate climate change, many governments enforce regulations on CO2 emissions (Kazancoglu & Ozturkoglu, 2018; Sun et al., 2020). Non-compliance with these restrictions may result in fines (Urban & Chiang, 2016). Improved energy efficiency can lead to reduced emissions of greenhouse gases such as CO2, facilitating companies' compliance with these regulations (Mukund Nilakantan et al., 2015a). An illustrative example of the advantage of adhering to regulations is the EU Emissions Trading Scheme (EU ETS) (European Commission, 2015). Specifically, the EU sets an upper limit on greenhouse gases for companies within their industry sector. Companies receive emission rights accordingly. If emissions are below the upper limit,

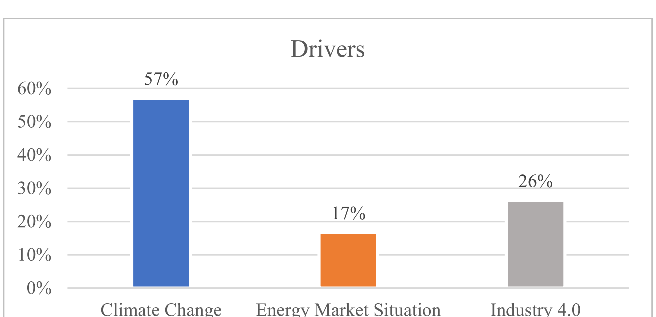

Fig. 8. Share of the considered drivers.

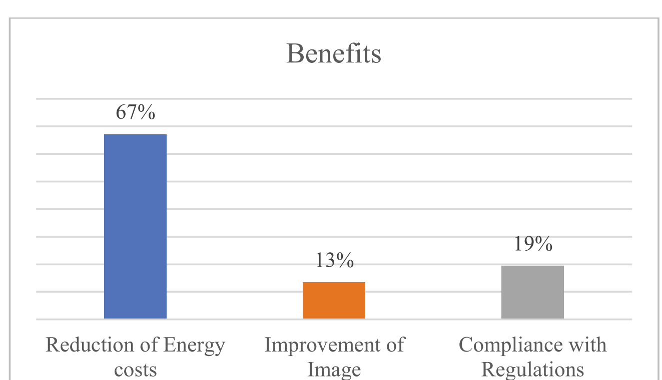

Fig. 9. Share of the considered benefits.

companies can sell the emission rights; if they exceed the limit, they must purchase additional rights. This trading mechanism benefits environmentally sustainable companies (European Commission, 2015).

4.2.3. Specific industry sectors

Considering this study mainly targets energy efficiency in production, all the reviewed studies focus on the manufacturing industry. This section examines the specific sectors that received attention in the reviewed studies.

The reviewed studies frequently reference the vehicle manufacturing industry (52 %, Fig. 10), and two main factors contribute to this focus. First, vehicle manufacturers often employ mass production techniques, using assembly lines to achieve high efficiency (Li et al., 2022). This approach results in a significant quantity of end-of-life goods, which justifies investments in disassembly lines (Ming et al., 2019; Zeng et al., 2022). Secondly, the vehicle manufacturing industry increasingly utilizes robots to enhance productivity in the assembly process (Sun et al., 2020). Consequently, the high energy consumption in this industry necessitates energy optimization.

The second most frequently mentioned industry is household appliances (45 %), highlighted for reasons similar to those of the automotive industry. This sector includes home electronics and white goods (Zhang et al., 2020b). Publications on disassembly line balancing within this industry often focus on electronic goods. Specifically, radios (Wang et al., 2021b), washing machines (Dong et al., 2021), printers (Wang et al., 2019b), and TVs (Wang et al., 2022) are each discussed four times.

One publication addressed assembly in the apparel industry, discussing specific devices like sewing and stitching machines (Zhang & Chen, 2019). Zhang et al. (2020b) also mention the shipbuilding industry as an application area for the semi-automatic assembly line. Lastly, Belkharroubi and Yahyaoui (2022) illustrate the diversity of production lines by referencing the furniture industry.

4.2.4. Real-world cases

Overall, 22 papers presented a case study in which the developed method is applied to a real-life problem. The real-world studies are carried out primarily on the disassembly lines (15), followed by the assembly lines (7). The authors hardly consider the drivers and benefits of energy efficiency through line balancing (see section 4.2). In some cases, concrete information is provided on how high the maximum and minimum energy consumption could be (Pareto solution); however, this is not converted into monetary savings (Liang et al., 2021b; Zhang et al., 2020b). Accordingly, it can be concluded that the case studies focus on demonstrating the applicability of the developed optimization methodology in practice from a research perspective. There is no information about the company’s benefits or further application. Thus, the considered case studies do not offer insights for practitioners in the industry.

Regarding the industry sector, most of the papers obtain data from companies that assemble or disassemble cars. Some exceptions include the study by Wang et al. (2020b), which examined the disassembly line of a company that disassembles refrigerators, and another case study by Wang et al. (2021a), which involved a company that disassembles televisions.

4.3. Objective aspects

This section relates to the RQ3. In this section, the discussion revolves around how existing studies approached the topic of energy efficiency. It delves into various methods of calculating Total Energy Consumption (TEC). Additionally, the analysis explores the interrelationships between energy efficiency and other objectives, highlighting instances where these objectives can complement or conflict.

4.3.1. Consideration of energy

Within the literature, the TEC calculation takes various forms, often following similar patterns and incorporating common components. These components typically encompass $e^{powerpeak}$, $e^{overall}$, $e^{operation}$, $e^{standby}$, e^{fixed}, and $e^{auxiliary}$. The following analysis first provides a detailed description of these six components and then shows how these components can be related to each other.

- *Power peak energy*:

The power peak consumption represents the highest power usage level in the overall system (Delorme et al., 2023) and is considered by 5 % of the paper pool (Fig. 11). Systematically organizing tasks across workstations helps smooth out peak power consumption profile, reducing overall power consumption (Delorme et al., 2023). This reduction in power consumption contributes to a decrease in energy consumption, as the latter is determined by the power consumption p of each workstation multiplied by the time consumed t across all workstations (Grafman, 2022). Equation (1) is commonly used to calculate the energy (e^{total}) consumed by workstation *j* during power peaks ($e^{powerpeak}$) (Ming, 2019).

$$e^{powerpeak} = \left\{ max\left(e_j^{total}\right), \forall j \in J \right\} \quad (1)$$

- *Overall energy:*

The concept of $e^{overall}$ is also explored in the literature (4 %). This approach involves examining the energy consumption of workstations at a highly aggregated level without distinguishing between operating and non-operating energy consumption. In this regard, Wang et al. (2021c) considered the overall energy consumption per task without providing a detailed calculation. An interesting observation is that Sariguzel et al. (2022) derived $e^{overall}$ based on the acceleration profiles of the machines.

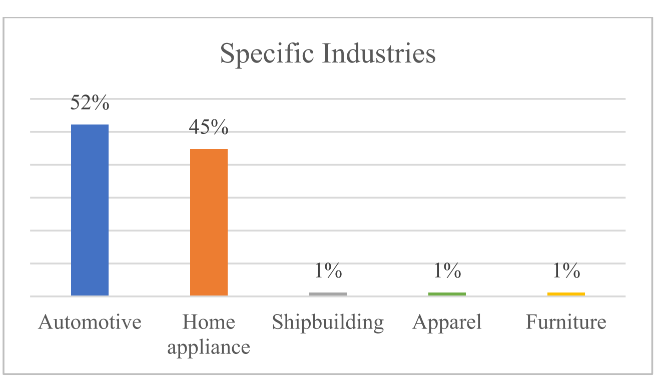

Fig. 10. Share of the considered industries.

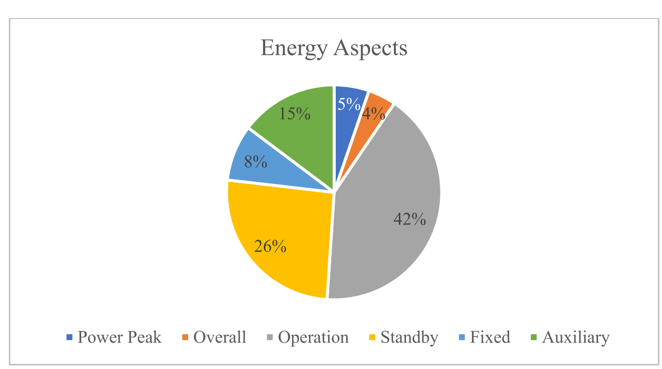

Fig. 11. Share of the energy aspects.

- *Operational energy:*

With 42 %, many papers delved into a more detailed examination of energy consumption, with $e^{operation}$ characterizing the energy consumption of a workstation during the execution of a task (Li et al., 2016). This consumption is determined by the time of task *i* at workstations *j* ($t_{i,j}^{operation}$) and the power consumption ($p_{i,j}^{operation}$) per time unit (Li et al., 2016; Zhang et al., 2019; Wang et al., 2020a). Publications on the disassembly line, in particular, provide further specifications of this energy component. For instance, hazardous tasks in the disassembly process consume more energy, leading to the introduction of $e^{operation,\ hazardous}$ (Wang et al., 2019b). Additionally, in multi-model production, Wang et al. (2021c) considered that different products require different amounts of $e^{operation}$. The energy consumption during operation can be calculated using Equation (2).

$$e^{operation} = \sum_i \sum_j t_{i,j}^{operation} \bullet p_{i,j}^{operation} \tag{2}$$

- *Standby energy:*

Energy consumption during standby refers to the energy consumed when a machine or workstation is at a standstill. In this context, the reviewed studies (26 %) used the terms standby, idle, and waiting mode interchangeably. Some papers assume that $p^{standby}$ is approximately 10 % of $e^{operation}$ (Li et al., 2016; Mukund Nilakantan et al., 2015a; Zhang et al., 2021a). With $p^{standby}$ and CT, the amount of $e^{standby}$ can be calculated using Equation (3) (Li et al., 2016).

$$e^{standby} = \sum_i \sum_j \left(CT - t_{i,j}^{operation}\right) \bullet p_j^{standby} \tag{3}$$

- *Fixed energy:*

Instead of standby energy, some authors consider fixed energy consumption (8 %). This consumption is a continuous amount of energy a workstation consumes as soon as it is switched on (Qin et al., 2020). Interestingly, the literature calculates it as a time function (Wang et al., 2019a) as well as a fixed amount per machine (Qin et al., 2020; Zhang et al., 2020c). Furthermore, Wang et al. (2019a) distinguished between the fixed energy consumption of single and mated stations in a two-sided assembly line.

- *Auxiliary energy:*

Finally, the category $e^{auxiliary}$ covers all energy consumed apart from the operating and non-operating energy of the workstations. Those additional consumers were elaborated in 15 % of the publications. The energy processes can be divided into setup, transport, and others. The consumption e^{others} includes energy generated by lighting and ventilation (Liang et al., 2023a; Suwannarongsri et al., 2014b). The $e^{transport}$ considers the energy consumed by moving the workpiece along two adjacent workstations. This consumption depends on the energy the conveyor belts consume and the number of workstations (Zhou & Wu, 2020). The setup energy is mentioned by several authors and comprises two subcategories:

- *Tools and fixtures:* The consumption category includes the energy required to change tools or fixtures (Gao et al., 2018; Liang et al., 2021a; Zhou & Wu, 2020). The calculation can be based on the time consumed and the number of changes. Furthermore, Liang et al. (2023a) introduced an energy consumption matrix for tool switching, stating that switching tools leads to varying energy consumption. In some cases, upstream and downstream processes must be considered to determine the proper energy consumption (Lu et al., 2021; Qin et al., 2020).
- *Direction changing:* The second consumption category includes energy consumed during a change of direction (Gao et al., 2018; Wang et al., 2022). The calculation is based on time consumed, the number of direction changes, and the direction change (in degree).

Nine patterns are identified for calculating energy consumption based on the described components. First, power peak consumption can be optimized as a single objective function (pattern 1) or combined with minimizing total energy consumption (TEC) (pattern 2). While some authors explicitly consider the $e^{overall}$ (pattern 3), others add the auxiliary energy (pattern 4). Furthermore, few papers focus on $e^{operation}$ exclusively (pattern 5). This approach is appropriate if, e.g., the production line produces continuously without standby times. In addition, $e^{auxiliary}$ can be added to $e^{operation}$ (pattern 6). Other authors consider $e^{operation}$ exclusively in the objective function but add $e^{standby}$ afterward. Moreover, if $e^{operation}$ is the same for all configurations, the optimization can be limited to $e^{standby}$ (pattern 7). This situation occurs when the energy consumed is the same for all configurations (Rashid et al., 2022). However, several selected publications optimize the sum of $e^{operation}$ and $e^{standby}$ or e^{fixed} as TEC (pattern 8). Finally, eleven authors attempt to include the entire production environment and calculate the sum of operation energy, fixed/standby energy, and auxiliary energy consumption (pattern 9).

Fig. 12 provides an overview of the nine patterns for the calculation of the energy consumption of a production line.

4.3.2. Interrelations of objectives

A reduction in energy efficiency can impact various production objectives. For instance, while modern machines are designed to consume less energy, they often come with high investment costs. Similarly, using an eco-mode can lower energy consumption but typically results in longer cycle times, thereby reducing overall production efficiency. On the other hand, decreasing energy consumption can also lead to lower CO_2 emissions, which benefits the manufacturing company by improving its environmental footprint. When optimizing energy efficiency, it is essential to consider these interrelations to maximize positive outcomes while minimizing negative trade-offs.

This section provides an overview of the objectives optimized simultaneously with energy efficiency in the multi-objective approach. Furthermore, it examines the intercalations between those objectives. It is important to note that the considered interrelations pertain to simultaneous optimization. Some authors optimize a primary objective first and then perform energy optimization based on the result or vice versa (Chi et al., 2022; Nilakantan et al., 2018; Nilakantan et al., 2016). For instance, Nilakantan et al. (2018) sought to maximize line efficiency by minimizing energy utilization but enhancing energy efficiency initially and subsequently improving line efficiency based on the corresponding outcomes. This approach is not considered, as there is no direct correlation.

With 90 % of the reviewed papers adopting a multi-objective optimization approach, energy efficiency was not the sole focus. Instead, most studies optimized energy efficiency alongside one or more additional production-related objectives. Following the classification by Güler et al. (2024), these objectives can be categorized into three main groups—economic, social, and environmental. Fig. 13 illustrates these categories and their associated objectives, which are further explained below.

The category of Economic Objectives comprises objectives in relation to economic factors:

- **E1 (Cost and profit):** The aim is to minimize the costs, e.g., comprising capital investment, labor, material, and energy costs. This objective aims to minimize the profit, which refers to the

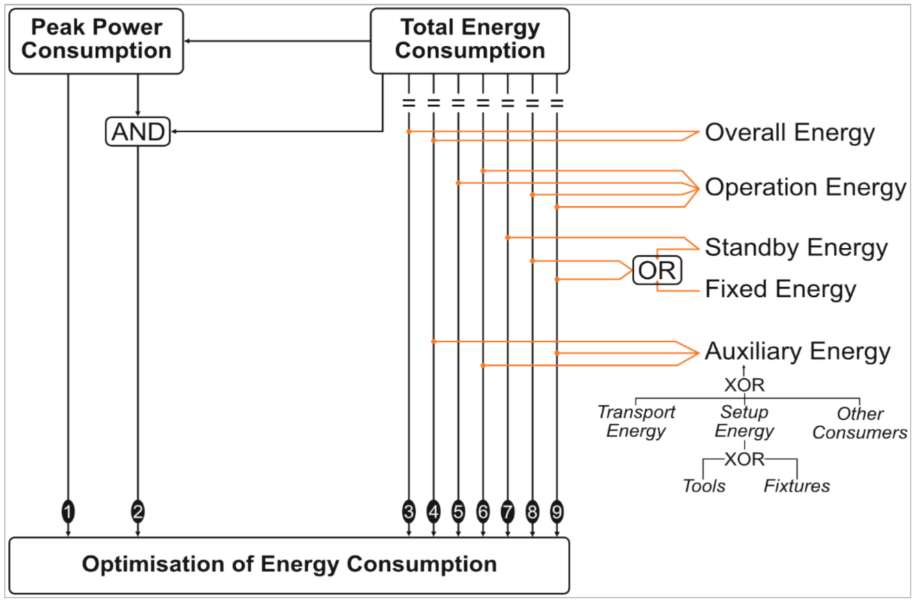

Fig. 12. Combination of energy components.

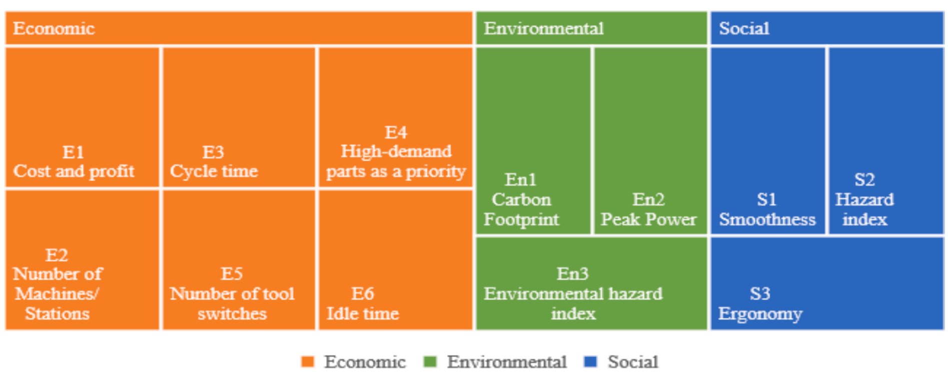

Fig. 13. Categorization of the objectives considered in the literature selection.

revenue generated by the production activities after deducting the costs (Wang et al., 2021).

- **E2 (Number of machines, robots, and stations):** This objective aims to minimize the total number of machines, robots, and stations utilized for the production process, thereby reducing the investment costs of the production line (Zeng et al., 2023).
- **E3 (Cycle time):** The aim is to minimize the time between two consecutive products exiting from the production line (Sariguzel et al., 2022).
- **E4 (High-demand parts):** This measure aims to increase profit by acquiring the necessary components to achieve higher returns and reducing the amount of waste to lower environmentally-related costs (Liu & Wang, 2017).
- **E5 (Number of tool switches):** This objective aims to decrease the number of tool changes to minimize downtime and increase production speed (Liang et al., 2023a).
- **E6 (Idle times):** Aims towards minimizing idle times in the production process to increase line efficiency (Tian et al., 2023).

The category of Environmental Objectives focuses on:

- **En1 (Carbon emissions):** Various sources, such as machine energy consumption or the utilization of cutting fluids, contribute to CO2 emissions in a production plant. The objective is to reduce these emissions across the facility (Nilakantan et al., 2017).
- **En2 (Power peaks):** Power Peaks can lead to high energy consumption and stress on the power grid. This objective aims to minimize power peak demands to improve energy efficiency and reduce stress on the power grid (Gianessi et al., 2019).
- **En3 (Environmental hazard index):** This objective focuses on preventing processes with high environmental hazard indices (Yuan et al., 2020).

The category of Social Objectives considers:

- **S1 (Smoothness):** The aim is to maximize the line smoothness, create a seamless production flow, minimize disruptions, and ensure consistent operations with equal workloads among the workstations (Zeng et al., 2023; Liang et al., 2021b).
- **S2 (Disassembly hazard):** This objective aims to decrease hazards especially associated with disassembly processes, ensuring a safer working environment (Wang et al., 2021a).
- **S3 (Ergonomic aspects):** The aim is to enhance workplace ergonomics to promote worker health and comfort, thereby improving overall job satisfaction and productivity (Nourmohammadi et al., 2024).

When comparing line types (see Section 4.1.1) for the most commonly mentioned objectives—Cycle Time and Profit—a clear pattern emerges. As shown in Fig. 14, studies on disassembly lines tend

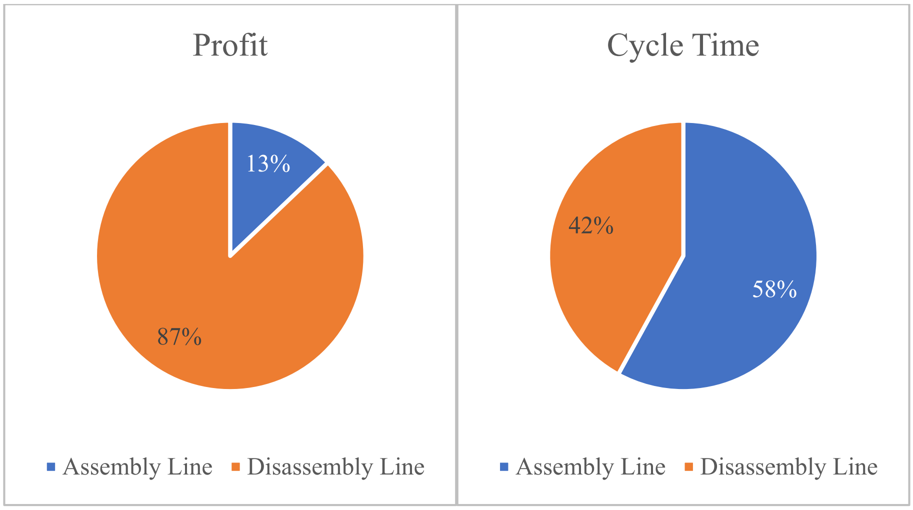

Fig. 14. Considered objectives in different line types.

to focus more on Profit, while those on assembly line balancing primarily consider Cycle Time.

After examining the objectives in general, the following section discusses their interrelations with energy efficiency. In detail, complementary objectives are improved by enhancing energy efficiency, while conflicting objectives are exacerbated.

- *Complementary objectives:*

As shown in Fig. 15, the primary focus of the complementary objectives is on environmental factors, particularly improving the carbon footprint and reducing peak power, both of which positively correlate with optimizing energy efficiency.

In detail, the authors incorporate the factor of CO2 emissions (En1) per unit of energy consumed into their objective functions (Nilakantan et al., 2017; Zhang et al., 2019). Similarly, the reduction of energy costs, including the power peak energy (En2), exhibits a positive linear association with energy consumption (Cerqueus et al., 2020; Rashid et al., 2022; Wang et al., 2021a). According to the formula for calculating energy consumption, which is power consumption (*p*) multiplied by time consumption (*t*), a decrease in power consumption also optimizes energy efficiency (Gianessi et al., 2019; Lamy et al., 2020). Furthermore, assigning tasks based on an environmental hazard index (En3) appears to align with the energy-optimal assignment.

While a few papers suggest that some objectives (i.e., E1, E2, S1) have a complementary relationship with energy efficiency, the majority identify them as conflicting. This aspect, along with conflicting objectives in general, is discussed in the following section.

- *Conflicting objectives:*

The analysis of conflicting objectives presented in Fig. 16 shows that several objectives within the Economic and Social categories conflict with increasing energy efficiency. Among these, the most frequently mentioned objective is cost and profit (E1), which appears in 38 studies. Energy-efficient machines generally have higher upfront costs compared to conventional machines, leading to increased investment costs (E1). Although these machines contribute to improved energy efficiency, the higher costs often result in reduced overall profits (Chen & Jia, 2022). Additionally, Zhang et al. (2020b) highlighted that a high level of automation increases energy consumption, which subsequently raises production and energy costs. Similarly, Fan et al. (2022) also identify profit and energy efficiency as conflicting targets.

Beyond cost and profit, CT (E3) is another objective that frequently conflicts with energy efficiency. In 24 studies, it has been argued that achieving an optimal balance between energy efficiency and CT is often

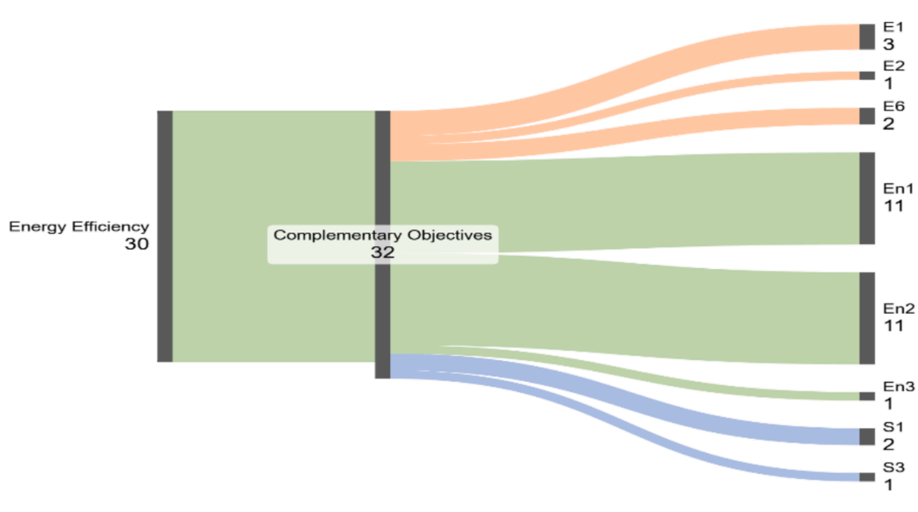

Fig. 15. Complementary relations.

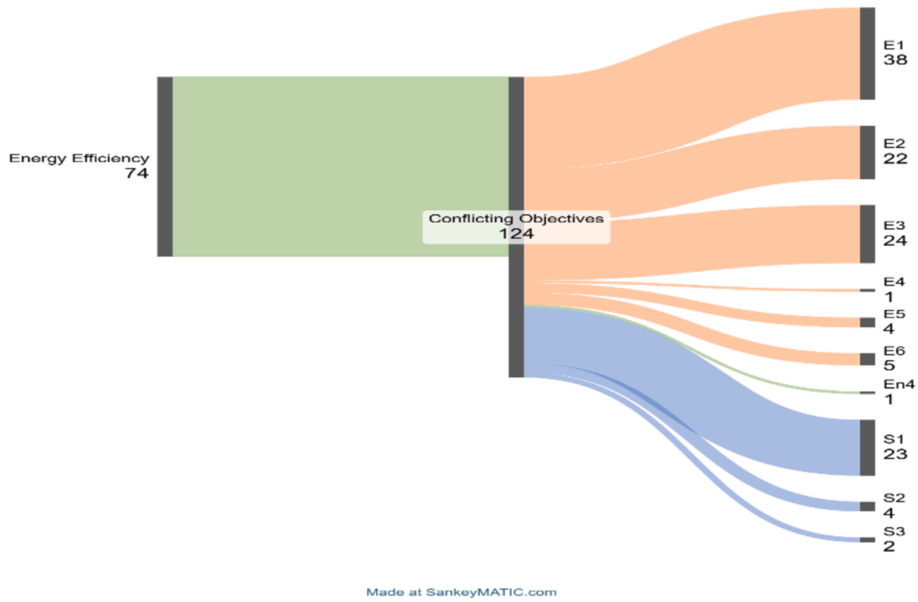

Fig. 16. Conflicting relations.

unattainable (see Fig. 16), as machines with lower energy consumption typically operate at slower speeds. On the other hand, Li et al. (2022) argue that a longer CT provides greater flexibility in task assignment, potentially leading to lower overall energy consumption. However, an extended CT negatively impacts production efficiency, which in turn affects profit (E1) due to its dependency on production output (Zhang & Xu, 2020). Optimizing the idle time index (E6)—which represents the sum of all idle times during production (Liang et al., 2023c)—also tends to conflict with the goal of reducing energy consumption.

Furthermore, as the smoothing index (S1) may also be influenced by cycle time (CT), there could be a conflict between optimizing this indicator and achieving higher energy efficiency. Since machines with lower energy consumption often operate at slower speeds, maintaining a balanced and efficient production process becomes more challenging. Additionally, other CT-related goals, such as reducing noise pollution of production lines (Zhang et al., 2019) and minimizing the entire makespan (Zhang et al., 2021a), conflict with the objective of reducing energy consumption (Liang et al., 2023c).

Overall, while energy efficiency is a critical goal, its relationship with economic and social objectives is complex, often requiring manufacturers to navigate trade-offs between cost, production efficiency, and sustainability.

Moreover, enhancing energy efficiency may adversely impact productivity. This finding arises from a computational experiment by Zhou and Wu (2020), aiming to optimize energy consumption and reduce the number of workstations (E2) with a given CT as a productivity-related objective. The result indicates that decreasing the number of machines leads to higher energy consumption and vice versa (Zhou & Wu, 2020). Interestingly, Liang et al. (2023d) and Wang et al. (2022) observe a positive relationship between these two goals. One possible explanation could be the insight by Li et al. (2022) that more machines allow for more diverse machine assignments but, at the same time, lead to increased idle time and, consequently, more standby energy consumption. Accordingly, the correlation between objectives depends on the extent to which high allocation freedom impacts each respective case.

4.4. Solution method

This section deals with the RQ4, namely, what methods have been used in the LBP to optimize energy efficiency. The literature review suggests four primary methods are used: exact, heuristic, metaheuristic, and deep learning. Fig. 17 visually shows the frequency of these methods applied to the LBP literature while considering energy efficiency. Among these methods, metaheuristics, with a 75 % usage rate, are mainly used,

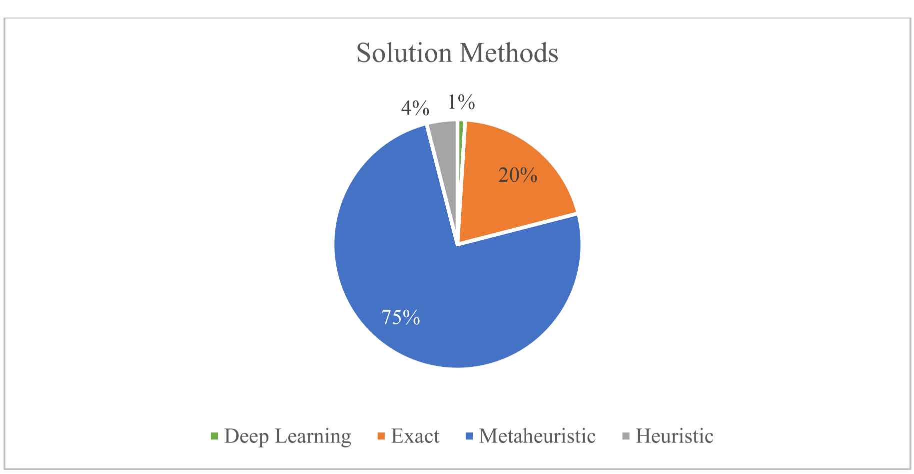

Fig. 17. Frequency of solution methods in LBP literature with energy efficiency.

followed by exact (20 %), heuristic (4 %), and deep learning (1 %). The details of each solution method are reviewed as follows. In addition, the advantages and disadvantages of each method are mentioned while considering their specific applications to the LBP literature with energy efficiency.

4.4.1. Exact methods

The exact methods are known for their ability to provide exact solutions. Their main advantage relies on guaranteeing the optimality of their solutions. On the contrary, they cannot ensure feasible or optimal solutions while solving large problems (Güler et al., 2024). The exact methods used in LBP studies with energy efficiency can be categorized as follows: mixed integer linear programming (MILP), mixed integer non-linear programming (MINLP), and integer linear programming (ILP). The ILP and MILP are exact solution methods to address optimization problems containing integer or mixed integer variables with linear equations. At the same time, MINLP is employed in the presence of non-linear equations (Edis et al., 2022).

The exact methods have been used in 22 studies to solve the LBP with energy efficiency. As Fig. 18 shows, the authors most frequently used mixed integer linear programming (MILP), followed by mixed integer non-linear programming (MINLP) and Integer Linear Programming (ILP). The MILP has been used in different LBP studies such as Nourmohammadi et al. (2024), Sun et al. (2020), and Urban and Chiang (2016) in the assembly line and K. Wang et al. (2023) in disassembly line. The MINLP was used in a few studies (Liang et al., 2023b; Liang et al., 2023a; Sariguzel et al., 2022), while ILP e. g. was used in Delorme et al. (2023) and Gianessi et al. (2019). In most studies where a mathematical model was presented, it was subsequently solved using commercial solvers such as CPLEX or GUROBI. As mentioned above, the exact methods might not be able to solve large and complex problems, justifying developing heuristic or metaheuristic methods.

Moreover, multi-objective optimization is crucial in solving LBP with an energy efficiency context. The methods of Weighted Sum and Epsilon Constraint are used in dealing with multi-objective optimization. The Epsilon Constraint generally converts all but one objective function into constraints to allow trade-offs between multiple objectives (Liu et al., 2021; Zhou & Bian, 2022). On the other hand, the Weighted Sum approach assigns importance to objectives for optimization (Liu et al., 2021; Zhang et al., 2019).

4.4.2. Heuristic methods

The heuristic methods have been developed in general to find near-optimal solutions. These methods are useful for handling large problems within a reasonable computational time. The heuristic methods rely on priority rules that allow the generation of a feasible solution while satisfying the problem constraints (e.g., precedence relationships). The heuristic methods are beneficial in finding a feasible solution or warm-starting another technique, such as a mathematical model or metaheuristic. On the contrary, the heuristic algorithms depend on the applied priority rules and are limited to only a specific solution (Bautista & Pereira, 2009).

Considering the complexity of the LBP, some authors have relied on heuristic algorithms to solve LBP, specifically with energy efficiency. The literature review shows that only some heuristic approaches have been identified. A constructive heuristic was proposed for an energy-efficient, unpaced synchronous assembly line balancing problem (Urban & Chiang, 2016). A constructive heuristic was developed to solve the large-sized test problem in a multi-products assembly line balancing problem while considering the total cost and energy consumption as conflicting objectives (R. Liu et al., 2021). An ILP and a permutation-based heuristic were developed to minimize power peaks in assembly line balancing (Kazancoglu & Ozturkoglu, 2018).

4.4.3. Metaheuristic method

Metaheuristic methods refer to iterative solutions that integrate heuristic and/or nature-inspired methods to one or a set of temporary solutions at each iteration to find one or a set of new solutions. The initial solutions can be randomly generated or inspired by other heuristic methods (Nesmachnow, 2014). Due to their advantage of yielding near-optimal solutions within a reasonable time compared to exact methods, metaheuristics have been frequently applied to large-sized optimization problems. Metaheuristics tend to be more effective at discovering superior solutions compared to heuristics, although they typically take longer to find a solution (Wang et al., 2021a). The performance of metaheuristics relies on finding a good balance between exploration (exploring the entire feasible solution space) and exploitation (exploring the surrounding areas of promising solutions) mechanisms. The metaheuristics can be categorized into evolutionary, physics-based, swarm-based, anduman-based categories (Tomar et al., 2023). The Evolutionary algorithms, inspired by Darwin's theory of evolution, employ mechanisms such as parent selection, recombination, mutation, and survivor selection across generations to explore and exploit the search space, with popular variants including genetic algorithms (GA) and differential evolution (DE). Physics-based metaheuristic algorithms replicate natural physical rules to find optimal solutions. These algorithms balance exploration and exploitation by leveraging physical principles to navigate complex search spaces and avoid local optima. Notable examples include Simulated Annealing (SA). Swarm intelligence algorithms, inspired by the collective behavior of social animals and insects, leverage information sharing within the swarm to balance exploration and exploitation of the search space, with notable examples including the Artificial Bee Colony (ABC) algorithm and the Particle Swarm Optimization (PSO) algorithm. Human-based metaheuristic algorithms draw inspiration from social interactions and behavioral patterns in people to solve optimization problems. These algorithms utilize collaborative search processes, knowledge exchange, and iterative refinement of potential solutions to explore the search space effectively and converge on optimal or near-optimal solutions. Notable examples include the Group Teaching Optimization (GTO) algorithm.

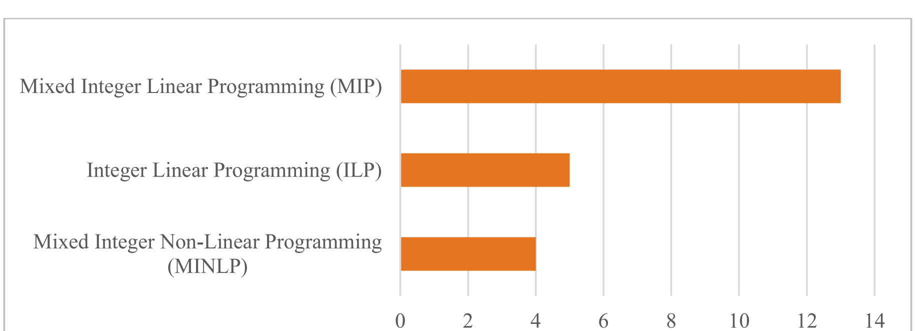

Fig. 18. Exact solution methods applied in the reviewed literature.

Considering the complexity of the LBP, many authors have also relied on metaheuristic algorithms to solve LBP with energy efficiency. In general, the metaheuristics have been used 84 times. It is worth noting that the total number of identified algorithms exceeds the number of reviewed papers because some papers have developed more than one algorithm (see Table A1 in the appendix for details). The studied literature includes a variety of different metaheuristics. Moreover, most authors propose to adjust the standard metaheuristic algorithm to enhance its performance or deal with multi-objectives. Given the abundant use of metaheuristics in this context, the literature selection has been analyzed further and classified into "Evolutionary," "Swarm-based," "Physics-based," "Human-based," and "Others" categories, following the characterization of Rajabi Moshtaghi et al. (2021). It should be emphasized that adaptations or combinations of algorithms were traced back to their origin to enable comparability (e.g., a Memory-Based Cuckoo Search Algorithm is referred to as Cuckoo Search Algorithm). Fig. 19 displays the result of this analysis and reveals that Simulated Annealing (SA) was applied most frequently (8 studies). Furthermore, the Artificial Bee Colony Algorithm (ABCA) and the Evolutionary Strategy Algorithm (ESA) (7 studies each) were also frequently applied. It is noticeable that the swarm-based category, in particular, offers various algorithms (14 studies) that can be used to optimize energy efficiency in production lines.

Furthermore, most authors have used specific adaptations of the metaheuristic algorithms to optimize multiple objectives. For example, Qin et al. (2020) use the Multi-Objective Discrete Migratory Bird Optimizer. Other examples are the Multi-Objective Multi-Verse Optimization Algorithm used by Zhang et al. (2022a) and the Multi-Objective Discrete Chemical Reaction Optimization Algorithm (Wang et al., 2021c). These and further multi-objective approaches are designed to determine Pareto solutions.

4.4.4. Deep learning

Recent advancements in artificial intelligence have led to the application of machine learning techniques, such as reinforcement learning and neural networks, to address challenges in LBP (Gao et al., 2020). This approach, which relies on the dynamic interaction between agents and their environment, has gained popularity across various fields of study (Guo et al., 2023). While these approaches are relatively new in this domain, they show significant promise for future development. However, their limited application thus far may be seen as a potential drawback due to uncertainties surrounding their effectiveness (Güler et al., 2024).

Mei and Fang (2021) presented a deep-reinforcement learning technique to balance the multi-robotic disassembly line balancing problem in the context of LBP with energy efficiency. By doing so, they aimed to provide efficient solutions for minimizing workstation non-productive time and energy consumption.

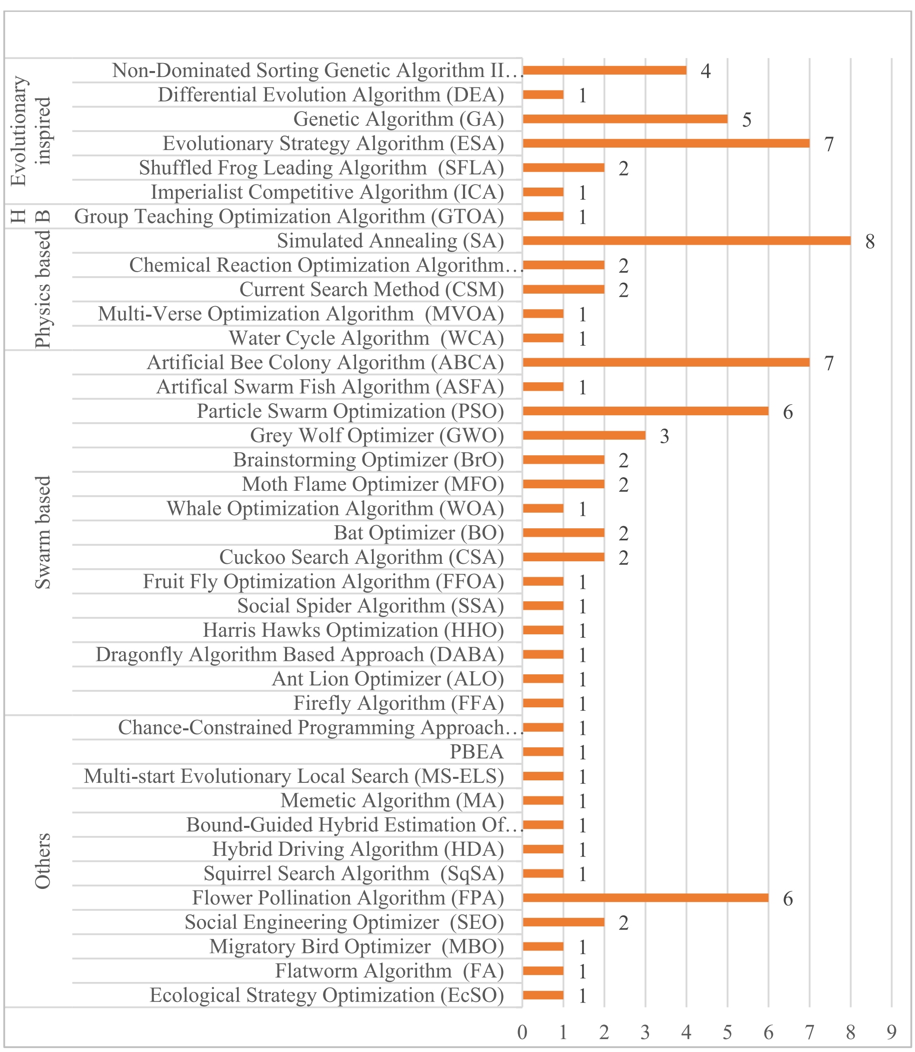

Fig. 19. Metaheuristics applied in reviewed literature (*HB = Human based).

5. Discussion

The recognition of the paramount significance of integrating energy efficiency into manufacturing lines has been the driving force behind this literature review, specifically focusing on enhancing energy efficiency in line balancing problems. According to four key research questions, a systematic literature review was conducted using the PRISMA method to pursue a comprehensive understanding of the field. The investigation explored various aspects, including line type, managerial considerations (macro and micro perspectives and industry sectors), objectives, solution methods, and real-world cases. This structured review aimed to unravel insights into the current state of knowledge and identify patterns, trends, and gaps in optimizing energy efficiency in line balancing scenarios.

Regarding RQ1, the existing literature focuses on assembly lines and disassembly lines. Transfer line balancing has only been studied to reduce energy consumption in one study focusing on power peak consumption. A chronological development within the research is notable, with earlier work focussing primarily on assembly lines and then moving on to consider disassembly lines. This observation is consistent with the results of the quantitative analysis (see Fig. 5). This thematic development seems to be a recurring pattern in the literature. While research on balancing assembly lines dates back to Salveson and Louisville (1955), it took about 50 more years for a similar focus on disassembly lines to emerge in early 2000 (Duta et al., 2005; Güngör & Gupta, 2001; Lambert & Gupta, 2005). Then, only a short time later, researchers turned their attention to transfer lines (Essafi et al., 2009; Guschinskaya et al., 2007; Guschinskaya & Dolgui, 2006). This chronological sequence indicates that, following the investigation of the energy efficiency of assembly and disassembly lines, the importance of transfer lines in this area of research will increase in the future.

Considering RQ2, from a macro perspective, climate change and the increasing use of robots are primary drivers of energy consumption reduction in manufacturing. The recent energy crisis in Europe has further elevated the importance of energy market conditions. From a micro perspective, companies mainly benefit from energy cost savings, while secondary benefits, such as an improved image (green branding) and regulatory compliance, receive less attention. Line balancing is particularly recommended for industries with high automation to reduce energy costs, with the automotive sector frequently cited in this context. However, a notable research gap remains in understanding how these benefits are achieved in the long term. Companies aiming to reduce energy consumption through line balancing must accept potential productivity declines, which means the perceived benefits must be substantial enough to justify these trade-offs.

Despite the growing focus on energy efficiency, most case studies remain theoretical, with limited practical implementation. One of the key challenges in translating theoretical models into industrial practice is the lack of detailed and standardized energy consumption data. Many companies do not systematically track energy usage at the workstation or production line level, making it difficult to validate optimization models with real-world inputs. Additionally, implementing energy-efficient line balancing in a real-world setting requires significant customization, as existing optimization frameworks are often tailored to specific assumptions that do not fully account for industrial constraints. The inherent complexity of integrating energy optimization into dynamic production environments further limits adoption, particularly in high-automation industries where disruptions in production flow could have costly consequences.

Another challenge is the conflict between energy efficiency and other production objectives, such as cycle time minimization and cost efficiency. While reducing energy consumption is desirable, companies may prioritize production speed and cost reduction over sustainability. The few real-world case studies available demonstrate this tension, as they often reveal that increasing energy efficiency negatively impacts other key performance indicators. Furthermore, the low number of practical implementations suggests that industries require more adaptable, scalable, and easily integrable optimization models to bridge the gap between theoretical advancements and real-world applications.

Regarding RQ3, there are different approaches and levels of aggregation on which the energy consumption can be calculated. In particular, studies often consider energy consumption to be the sum of operation and standby energy of the workstations. Additional energy consumers, such as the conveyor belt or the lighting, are usually neglected, probably due to the high overall complexity. Nevertheless, a few authors consider energy consumption in more detail, where additional energy consumers are identified, and the energy consumption is determined over time. It has also been shown that optimizing energy efficiency conflicts with other production targets. So far, little attention has been paid to recording and analyzing energy consumption data. This research gap should be closed to increase the validity of the LBP results.

Through RQ4, it was identified that authors often apply multi-objective optimization approaches to optimize energy efficiency with line balancing. Metaheuristics are mainly used and developed as promising solutions for addressing large real-world problems. However, small problems are solved in some cases using exact methods. This provides the authors with reference solutions to test the quality of their metaheuristics. Examples of developed, multi-objective metaheuristics are the NSGA-II, the Multi-Objective Multi-Verse Optimization Algorithm, and a new methodological approach that has emerged in deep learning.

6. Concluding remarks

This study systematically reviewed the literature on energy-efficient line balancing, synthesizing existing knowledge and identifying gaps to guide future research. It examined diverse line configurations, managerial drivers, and optimization methodologies, shedding light on the relationship between energy consumption and production efficiency in this research context. The findings can extend the theoretical understanding and suggest potential pathways for future research and practical innovations in energy-efficient manufacturing systems.

6.1. Contribution to practice and research

The findings of this systematic literature review illuminate several actionable pathways for integrating energy efficiency into line balancing strategies, providing valuable insights for practitioners across various industrial contexts. A key conclusion is the necessity of tailoring energy-efficient practices to the specific characteristics of production configurations, such as assembly, disassembly, and machining transfer lines.

For assembly and disassembly lines, characterized by manual or semi-automated production, workload balancing, minimizing idle times, and improving human–machine collaboration emerge as effective strategies for reducing unnecessary energy consumption. In industries such as automotive and home appliances, mixed-model or U-shaped layouts can significantly reduce peak energy loads and ensure a smoother energy flow, highlighting the importance of flexibility in line configuration. On the other hand, fully automated machining and transfer lines offer substantial opportunities for energy optimization due to their reliance on advanced digital technologies.

To bridge the gap between theoretical advancements and practical implementation, future research should focus on establishing industry-academic collaborations to improve access to real-world energy consumption data. Stronger partnerships with manufacturing companies could enable researchers to develop more data-driven energy optimization models that reflect actual industry constraints. Additionally, future studies should focus on developing adaptable and scalable optimization frameworks that can be easily integrated into existing production systems without extensive modifications.

Another critical area for improvement is the integration of real-time energy monitoring and dynamic scheduling algorithms. The use of IoT-enabled energy dashboards and AI-driven decision-support systems can enable continuous optimization of energy efficiency, allowing manufacturers to adjust energy consumption based on production demands dynamically. Expanding energy models to include auxiliary components such as lighting, ventilation, and material handling systems can also enhance the accuracy of energy efficiency assessments, ensuring that all energy-consuming elements are accounted for.

The review also emphasizes the broader operational and strategic implications of energy efficiency. Regulatory compliance, cost-reduction imperatives, and sustainability goals drive the adoption of energy-efficient practices, placing energy consumption at the center of managerial decision-making. For instance, regulatory frameworks like the EU Emissions Trading Scheme (ETS) offer both a compliance requirement and a financial incentive for companies to optimize their energy use. Line balancing strategies can reduce operational costs while minimizing carbon emissions, enabling firms to trade surplus emission rights and gain financial advantages.

Furthermore, the review highlights the importance of industry-specific barriers that affect energy-efficient line balancing adoption. In high-automation industries (e.g., automotive, electronics), real-time scheduling solutions and predictive energy management systems are essential for integrating energy efficiency without disrupting productivity. In contrast, lower-automation industries (e.g., apparel, furniture) may face higher adoption barriers due to limited digital infrastructure and the need for initial investments in energy monitoring technologies. Future research should explore sector-specific implementation challenges and develop tailored optimization models that address these varying constraints.

Additionally, this review study identified a significant oversight in current energy-efficient line balancing practices: the exclusion of auxiliary components such as lighting, ventilation, and transport systems in energy models. Addressing these gaps through comprehensive audits and system-wide energy monitoring can ensure that all energy-consuming components are accounted for, significantly enhancing the precision and impact of energy-efficient interventions. High-automation industries, such as those in electronics or automotive, can further integrate auxiliary system optimization with primary line balancing efforts to reduce standby energy consumption and smooth power peaks. Meanwhile, less automated sectors like apparel or furniture manufacturing can achieve incremental but meaningful improvements by optimizing workflows and refining task scheduling, achieving energy savings without requiring substantial capital investment. At the same time, the barrier to implementing the proposed optimization is higher for less automated companies, as they often first need to establish sufficient data quality.

Finally, the systematic literature review underscores the importance of balancing energy efficiency with other critical operational objectives, such as productivity, cycle time, and cost, using advanced optimization methods. Multi-objective optimization techniques, particularly Pareto-based approaches, provide practitioners with tools to navigate these trade-offs effectively. For instance, in high-speed production environments, where faster cycle times often increase energy use, simulation-based models can help identify configurations that maintain throughput while optimizing energy consumption. Furthermore, the review highlights the extensive use of metaheuristic algorithms, such as Genetic Algorithms (GA) and Simulated Annealing (SA), for solving complex line balancing problems. These techniques are particularly effective in addressing the scale and complexity of real-world applications, offering adaptable solutions for a variety of production scenarios. However, successful implementation of these methods depends heavily on the availability and quality of data. Establishing robust data pipelines using IoT-enabled sensors and energy dashboards can provide real-time insights into energy consumption, enabling practitioners to refine optimization models continuously. This data-driven approach not only enhances decision-making but also fosters a culture of continuous improvement, positioning companies to adapt to evolving energy demands and sustainability expectations.

The study also contributed to research by systematically synthesizing the comprehensive yet fragmented literature on energy-efficient line balancing, providing a detailed overview of the state of the art while identifying critical gaps that warrant further exploration. One significant contribution lies in its comprehensive coverage of diverse line configurations, including assembly, disassembly, and the underexplored machining transfer lines, where research remains sparse despite their high potential for energy optimization. The review also advanced academic understanding by analyzing how energy efficiency interacts with other production objectives, such as cycle time, productivity, and cost, highlighting the need for multi-objective optimization frameworks to address these trade-offs.

Another key contribution is the detailed evaluation of the methodologies used in energy-efficient line balancing. The study categorized and assessed optimization techniques, such as exact methods, metaheuristic approaches, and hybrid solutions, identifying trends in their application and gaps in their scalability and adaptability to real-world scenarios. Furthermore, the review expanded the scope of energy efficiency research by emphasizing overlooked areas, such as the role of auxiliary components like lighting, ventilation, and material handling systems, and advocating for their integration into energy consumption models. These contributions provide a structured foundation for further expanding the knowledge-base, encouraging scholars to address these gaps and develop innovative solutions to advance the field of energy-efficient manufacturing.

6.2. Limitations and future research

The findings of this review highlight critical gaps in the intersection of energy efficiency and line balancing, revealing opportunities for future research to contribute transformative insights and solutions. However, addressing these gaps requires not only identifying underexplored areas but also questioning the root causes and proposing robust approaches to overcome them. This section reflects on these challenges, offering directions for advancing the field.

Despite the methodological approach, the review has certain limitations that need to be acknowledged. The limitations are due to limited information available in some sources and categories. Firstly, the literature search is limited to three databases and English-language publications. Thus, the literature search lacks papers not published in the selected databases or English. Secondly, exclusion criteria based on paper quality are not introduced. Therefore, all peer-reviewed papers are included in the literature review. While this approach enlarges the database of this nascent research field, it could limit the quality of the results. Moreover, some studies lack clear and thorough expressions of problem assumptions, challenging further analysis.

Regardless of the limitations of the present work, this study identified several critical gaps in the literature on energy-efficient line balancing, providing a notable agenda for future research. A critical gap in the existing literature is the limited focus on machining transfer lines, despite their fully automated nature offering more significant opportunities for energy optimization compared to the predominantly manual or semi-automated assembly lines. Machining lines are inherently distinct due to their reliance on precise synchronization of operations and the integration of advanced technologies that enable high levels of manufacturing flexibility. While these characteristics present significant potential for optimizing energy efficiency, they also introduce complexities that have made the study of machining lines less prevalent. The long-standing focus on assembly line problems, coupled with the novelty of exploring energy efficiency within fully automated systems, has meant that scholars have yet to investigate machining lines extensively. Future research must prioritize these underexplored systems, delving into their unique energy consumption dynamics and addressing the intricate interplay of automation, flexibility, and operational precision. Leveraging advanced modeling techniques such as constraint programming or hybridized simulation approaches could be instrumental in reconciling energy efficiency with the operational demands of machining lines.

Furthermore, the organizational and managerial dimensions of energy efficiency in line balancing remain underexplored. Existing studies prioritize technical or algorithmic solutions without adequately considering the human and institutional factors that determine their adoption. Managers face significant trade-offs between short-term productivity and long-term energy savings, often in the absence of clear incentives or frameworks to guide decision-making. Understanding these dynamics through empirical studies could provide actionable insights, particularly regarding the role of economic instruments such as carbon pricing, subsidies for energy-efficient technologies, or performance-based tax incentives. Such research could also explore how cultural and regulatory differences across industries and regions influence the prioritization of energy efficiency. Addressing these gaps requires interdisciplinary approaches that integrate engineering, economics, and policy studies to develop decision-support tools tailored to industry needs.

Another fundamental gap lies in treating energy consumption as a static and oversimplified variable. Most models emphasize operational and standby energy while neglecting auxiliary components like lighting, conveyor systems, and ventilation, often due to the difficulty of acquiring granular data. Additionally, energy consumption is predominantly treated as deterministic, overlooking real-world variability caused by factors such as fluctuating production volumes or machine wear. Future studies should adopt a more holistic and probabilistic perspective, incorporating auxiliary components and stochastic modeling to reflect the variability inherent in real-world settings. This approach is essential and urgent to improve model fidelity and address the complexity of real-world energy consumption. Developing digital twin-based frameworks and real-time energy monitoring systems could enable a more precise and dynamic representation of energy usage in manufacturing environments.

The dominance of metaheuristic optimization methods in the literature reflects their practicality in tackling complex, multi-objective problems. However, the lack of hybrid approaches that integrate metaheuristics with exact methods represents a missed opportunity. Such hybrid approaches could capitalize on the strengths of different techniques, combining the global search capabilities of metaheuristics with the precision of exact algorithms. Developing these integrated methods will require addressing computational challenges, particularly in large-scale applications. Advances in computational infrastructure and parallel processing algorithms could make such approaches feasible, providing optimal and practically implementable solutions.

Despite the theoretical richness of the literature, the practical applicability of proposed methodologies remains underexamined. Many studies fall short in transitioning from theoretical modeling to real-world validation, which limits their impact on industry practices. Longitudinal case studies that assess the implementation of energy-efficient line-balancing strategies over time are urgently needed. Such studies should not only evaluate the technical feasibility of these methods but also explore their organizational, financial, and environmental impacts. Engaging with industry stakeholders to co-develop and validate these solutions would bridge the gap between research and practice, ensuring that academic advancements translate into tangible benefits. Collaborations between academia and industry should be strengthened through research consortia, pilot studies, and testbed environments where energy-efficient line balancing solutions can be implemented, monitored, and refined based on real-world constraints.

Lastly, the paradigm shifts in the industrial environment, such as the transition from Industry 4.0 to Industry 5.0, introduce a compelling context for future research. In particular, while Industry 4.0 emphasizes automation and connectivity, its reliance on energy-intensive technologies poses challenges for sustainability. Industry 5.0, focusing on human-centric and environmentally adaptive manufacturing, offers a framework within which line balancing can play a transformative role. Research should investigate how line balancing can counteract the rebound effects of advanced technologies by optimizing their energy use without compromising productivity. This line of inquiry aligns with global sustainability goals and positions line balancing as a cornerstone of the smart, resilient, and adaptive manufacturing systems envisioned for the future. Exploring the potential of AI-driven adaptive control systems and energy-aware scheduling algorithms could provide the necessary intelligence to optimize energy consumption dynamically.

Overall, addressing these research gaps requires a concerted effort to integrate technical, managerial, and societal dimensions into the study of energy-efficient line balancing. Future research can drive meaningful progress in both academic understanding and industrial application by critically engaging with the underlying reasons for these gaps and pursuing interdisciplinary and collaborative approaches.

CRediT authorship contribution statement

Julian Petersen: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Amir Nourmohammadi:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Masood Fathi:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Morteza Ghobakhloo:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Madjid Tavana:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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Appendix

Table A1
Extracted information from the reviewed papers. (See the below-mentioned references for further information.)

Source	Configuration										Managerial Aspects												Objective Aspects								Solution Approaches			
	Line Type			Layout				Production Type			Driver			Benefits			Specific industries						Energy Consideration						Rela-tions					
	Assembly Line	Disassembly Line	Machining/ Transfer Line	Straight	U-shape	Two-sided	Parallel	Single	Multi	Mixed	Climate Change	Industry 4.0	Energy Market Situation	Reduction of Energy costs	Improvement of Image	Compliance with Regulations	Automotive	Home appliance	Shipbuilding	Apparel	Furniture	Real World Cases	Total	Fixed	Standby	Operation	Auxiliary	Power Peak	Complementary	Conflicting	Exact	Heuristic	Metaheuristic	Deep Learning
Belkharroubi & Yahyaoui (2022)	x			x						x	x	x					x	x			x				x	x							CSA	
Cao et al. (2019)		x		x				x						x								x				x				x			ABCA	
Cerqueus et al. (2020)			x	x				x			x	x		x	x										x	x			x		LP		SA	
Chen & Jia (2022)	x			x				x			x			x		x									x	x	x			x			GA	
Chi et al. (2022)	x			x				x			x	x		x			x	x							x	x							SA	
Delorme & Gianessi (2022)	x						x	x			x	x		x														x	x		ILP			
Delorme et al. (2023)	x			x				x			x		x	x														x	x		ILP			
Delorme & Gianessi (2023)	x						x	x			x	x	x	x														x	x		ILP	x		
Dong et al. (2021)		x		x				x										x				x		x		x	x						ALO	
Fan et al. (2022)		x		x				x																x		x							SFLA	
Fang et al. (2018)		x		x						x	x														x	x		x	x	x			PBEA	
Fang et al. (2019)		x		x						x		x		x			x								x	x				x			NSGA-II	
Fang et al. (2020a)		x		x						x	x	x		x			x								x	x		x		x			SA	
Fang et al. (2020b)		x		x				x						x			x								x	x				x			NSGA-II	
Gao et al. (2018)		x		x				x			x	x		x			x					x			x	x	x			x			ABCA	
Gianessi et al. (2019)	x			x				x			x	x																x	x		ILP			
Guo et al. (2021)		x		x					x									x						x		x	x		x	x			GWO	
Guo et al. (2023)		x		x				x			x							x						x		x	x			x			SFLA	

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Table A1 (*continued*)

Haotian & Hongjun (2021)	x		x				x			x	x	x	x		x	x					x	x				x			GA	
Hartono et al. (2023)		x	x				x			x						x					x	x	x		x	x			ABCA	
Huang et al. (2021)		x		x			x						x				x					x	x			x			BO	
Huang et al. (2022)		x	x				x										x				x	x	x			x			BO	
Huang et al. (2024a)	x				x				x			x	x			x					x	x				x			SA	
Huang et al. (2024b)	x				x				x			x	x			x		x			x	x	x			x	MIP		ABCA	
Huang & Gu (2023)		x	x				x										x	x	x					x	x	x		x		
Janardhanan et al. (2018)	x		x				x				x		x			x						x			x				DEA	
Kazancoglu & Ozturkoglu (2018)		x	x				x			x				x	x				x						x	x		x		
Lamy et al. (2020)	x		x				x			x	x		x											x	x				MS-ELS	
Li et al. (2016)	x		x				x			x	x	x	x			x					x	x				x			SA	
Li et al. (2022)	x				x		x			x	x					x	x				x	x			x		MIP			
Liang et al. (2021a)		x			x		x									x	x	x				x	x			x			SA	
Liang et al. (2021b)		x			x		x			x						x	x	x			x	x				x			FA	
Liang et al. (2024)		x	x					x		x				x		x		x				x	x			x			GTOA	
Liang et al. (2023a)		x				x	x			x						x	x	x				x	x			x	MINLP		SSA	
Liang et al. (2023b)		x				x	x										x					x	x			x	MINLP		GATS	
Liang et al. (2023c)		x	x	x	x	x	x			x							x					x	x			x	MINLP		NSGA-II, ASFA, PSO	
Liang et al. (2023d)		x	x				x												x				x			x	MIP			
Liu & Wang (2017)		x	x				x			x			x				x				x				x	x			ABCA	
Liu et al. (2021)	x		x					x		x	x											x				x	MILP	x	NSGA-II, PSO	
Lu et al. (2021)		x		x				x									x					x	x			x			ESA	
Mei & Fang (2021)		x	x				x														x	x				x				x
Ming et al. (2019)		x	x						x	x	x		x			x	x				x	x		x	x	x	MIP			
Nilakantan et al. (2015a)	x		x				x			x		x	x	x	x	x					x	x				x			PSO	
Nilakantan et al. (2015b)	x			x			x			x		x	x			x					x	x							PSO	
Nilakantan et al. (2016)	x			x			x			x		x	x			x						x							ESA	
Nilakantan et al. (2017)	x		x				x			x			x			x	x				x	x			x	x			ESA	
Nilakantan et al. (2018)	x		x				x			x	x	x	x			x						x							PSO, ESA	

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Table A1 (*continued*)

Nourmohammadi et al. (2024)	x			x	x			x			x	x		x			x							x		x					MI LP			
Qin et al. (2020)		x		x				x									x					x		x		x	x			x			MBO	
Rahman et al. (2023)	x			x				x			x	x	x	x			x	x							x	x	x			x			CCPA, MA	
Ramli & Rashid (2023)	x			x				x			x															x	x		x	x	MI LP		PSO	
Rashid et al. (2020)	x					x		x						x			x								x	x			x	x			MFO	
Rashid et al. (2022)	x			x				x			x		x				x					x			x								MFO	
Sariguzel et al. (2022)	x			x				x						x			x						x						x		MIN LP			
Soysal-Kurt & İşleyen (2022)	x						x	x			x	x	x	x	x	x									x	x				x			FFA	
Soysal-Kurt et al. (2024)	x						x			x	x	x	x	x		x									x	x				x			NSGA -II	
Sun et al. (2020)	x			x				x			x	x	x	x		x	x	x							x	x				x	MI LP		BHED A	
Suwannarongsri et al. (2014a)	x			x				x																					x				CSM	
Suwannarongsri et al. (2014b)	x			x				x									x						x				x		x				CSM	
Tian et al. (2023a)		x		x				x										x							x	x				x			SEO	
Tian et al. (2023b)		x		x				x										x							x	x				x			ESA	
Tian et al. (2024)		x		x				x			x						x	x				x			x	x				x			SA	
Urban & Chiang (2016)	x			x				x			x			x		x	x					x							x		MI LP	x		
Wang et al. (2019a)		x				x		x			x			x			x							x		x				x			FPA	
Wang et al. (2019b)		x		x				x			x							x						x		x				x			FPA	
Wang et al. (2020a)		x			x			x			x							x						x		x				x			FPA	
Wang et al. (2020b)		x		x				x			x							x						x		x				x			FPA	
Wang et al. (2021a)		x		x				x			x							x				x		x		x			x	x			SA	
Wang et al. (2022)		x		x				x			x					x		x				x				x	x			x			ABCA	
Wang et al. (2023)		x		x				x			x							x				x		x		x			x	x	MI LP		GA	
Wang et al. (2020c)		x		x				x														x				x				x			CS	
Wang et al. (2021b)		x		x				x										x					x				x			x			CROA	
Wang et al. (2021c)		x			x				x									x							x	x				x			CROA	
Wu et al. (2021)		x			x				x									x					x				x			x			BrO	
Wu et al. (2023)		x				x			x			x					x	x							x	x				x	MIP		SqSA	
Xu et al. (2023)		x		x					x													x		x		x	x			x			BrO	
Yang et al. (2019)		x		x				x			x			x			x												x	x			FFOA	
Yin et al. (2022)		x		x					x		x	x		x		x	x	x							x	x		x		x			HDA	
Yuan et al. (2020)		x		x				x			x						x									x			x	x			NSGA -II	
Zeng et al. (2022)		x		x				x			x					x	x	x							x	x	x			x			FPA	
Zeng et al. (2023)		x		x						x	x				x			x						x		x				x			GSA	
Zhang & Xu (2020)	x				x			x			x		x				x					x			x	x				x			FPA	
Zhang et al. (2020a)	x			x						x	x		x				x								x	x				x			GA	
Zhang et al. (2020b)	x			x				x			x	x					x	x	x						x	x				x			WOA	
Zhang et al. (2021a)	x				x					x	x	x				x	x					x			x	x				x			DABA	
Zhang et al. (2021b)		x		x				x			x			x			x								x	x			x	x			GA	
Zhang et al. (2022a)		x		x				x			x							x						x		x			x	x			MVO A	
Zhang & Chen (2019)	x			x				x			x			x	x					x					x	x			x	x			NSGA -II	
Zhang et al. (2022b)		x		x				x			x			x				x							x	x							WCA	
Zhang et al. (2023)		x		x				x			x						x	x							x	x							SEO	
Zhang et al. (2019a)	x				x			x			x	x		x			x	x				x			x	x				x	MIP		ABCA	
Zhang et al. (2019b)		x			x			x			x			x			x	x				x			x	x			x	x			GWO	
Zhang et al. (2024)	x			x						x	x	x											x							x			ESA	
Zhang et al. (2020c)	x			x				x						x										x		x	x		x	x			GWO	
Zhou & Bian (2022)	x			x				x				x		x		x									x	x	x			x	MI LP		HHO	
Zhou & Kang (2019)	x			x				x			x		x	x	x		x								x	x				x			ICA	
Zhou & Wu (2020)	x			x				x			x	x	x	x	x		x								x	x	x			x			ESA	
Sum	43	53	1	72	13	9	7	76	9	12	65	30	19	45	9	13	49	42	1	1	1	22	8	16	49	79	28	10	30	74	22	5	84	1

Data availability

Data will be made available on request.

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