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Safety-Oriented Modelling for Human-Robot Collaborative Assembly Line Balancing Problems (HRC-ALBPs)

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*

Génie industriel

Décembre 2025

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Cette thèse intitulée :

Safety-Oriented Modelling for Human-Robot Collaborative Assembly Line Balancing Problems (HRC-ALBPs)

présentée par **Mahboobe KHEIRABADI**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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DEDICATION

To the memory of my beloved father, whose love and perseverance *continue to inspire me.*

To my dear mother and sisters, for their endless support and encouragement.

And to my loving husband, for standing beside me through every step of this journey.

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I am deeply grateful to my husband, whose unwavering patience, understanding, and encouragement have carried me through the most demanding moments of this journey and helping as a constant source of strength and motivation.

RÉSUMÉ

La collaboration homme-robot (HRC) est devenue une caractéristique déterminante des systèmes de production modernes, apportant flexibilité et réactivité mais soulevant également des enjeux de sécurité et de fiabilité. Malgré les avancées rapides de la robotique collaborative, les problèmes d'équilibrage des lignes d'assemblage (Assembly Line Balancing Problems, ALBPs) demeurent centrés sur l'efficacité, en considérant souvent la sécurité comme une vérification externe plutôt que comme un facteur intrinsèque de décision. Cette recherche propose un cadre de modélisation orienté vers la sécurité pour les ALBPs collaboratifs homme–robot (HRC-ALBPs), en s'attaquant à une lacune critique au niveau tactique, là où l'allocation des tâches, le choix des modes d'exécution et l'affectation des ressources structurent les arbitrages entre productivité et risque.

L'étude s'est développée en trois étapes. Tout d'abord, une revue systématique de la littérature sur les HRC-ALBPs a permis de définir les contours du champ de recherche, en identifiant les niveaux décisionnels, les modes de collaboration et les méthodes de résolution existantes. Cette analyse a révélé que, tandis que la conformité stratégique et le suivi opérationnel avaient fait l'objet d'une attention considérable, le niveau tactique restait sous-développé en matière de modélisation des risques. En synthétisant les caractéristiques et les lacunes des travaux existants, la revue a mis en évidence l'optimisation tactique comme un domaine central, mais encore peu exploré, pour intégrer la sécurité dans les systèmes de production collaboratifs.

Ensuite, un modèle d'optimisation axé sur la sécurité a été développé à l'aide de la Programmation par Contraintes (CP), intégrant une politique de zonage qui restreint les parallélismes homme–robot jugés dangereux. Cette politique des zones de sécurité a traduit un principe de sécurité au travail en contraintes de faisabilité, éliminant les chevauchements de risque moyen ou élevé tout en préservant les parallélismes de faible risque. Les expérimentations numériques ont montré que l'intégration de telles règles ne se limite pas à filtrer les solutions dangereuses : elle reconfigure structurellement le paysage d'optimisation, contraignant le système à privilégier des modes plus sûrs ou des alternatives séquentielles lorsque cela est nécessaire. Le modèle devient ainsi un instrument conjoint de performance et de sécurité normative, et non un simple outil d'optimisation de l'efficacité.

Enfin, le cadre a été étendu par une approche inspirée de l'Analyse des Modes de Défaillance, de leurs Effets et de leur Criticité (AMDEC processuelle). Un Indice Alternatif de Priorité de Risque

(ARPN), agrégant les scores de sévérité, d'occurrence et de détection sur quatre dimensions (sécurité, temps, qualité, performance), a été introduit comme second objectif aux côtés du temps de cycle (CT). Le modèle bi-objectif résultant a produit un paysage de compromis CT–ARPN, révélant des enseignements structurels tels que l'impact supérieur de l'amélioration des compétences humaines par rapport à l'augmentation de la vitesse des cobots lorsque des contraintes de sécurité s'appliquent. Une contrainte additionnelle fondée sur la sévérité a en outre limité les parallélismes à haut risque, garantissant que les dangers graves ne puissent être compensés par d'autres facteurs. Ce double dispositif, alliant contrainte et objectif de risque, illustre la manière dont l'équilibrage tactique peut internaliser systématiquement la sécurité et le risque.

Les contributions de ce travail se situent à la fois sur le plan théorique et pratique. Sur le plan théorique, il redéfinit l'équilibrage de ligne en (i) considérant la sécurité comme une propriété de l'espace de solutions faisables, (ii) démontrant la pertinence de la CP pour traiter les interdépendances logiques et combinatoires des systèmes HRC, et (iii) introduisant l'ARPN comme une mesure de risque additive et interprétable. Sur le plan pratique, il fournit aux responsables industriels des outils d'aide à la décision qui ne se limitent pas à la minimisation du temps de cycle, mais permettent aussi de quantifier la redistribution des risques entre sécurité, temps, qualité et performance. Les modèles se présentent comme des bancs d'essai virtuels, capables de tester divers scénarios ("what-if") relatifs à la répartition des compétences, aux vitesses des cobots ou aux seuils de sécurité avant la mise en œuvre.

Dans leur ensemble, les résultats positionnent l'optimisation tactique comme un levier essentiel pour concrétiser les principes de l'Industrie 5.0, centrée sur l'humain, la résilience et la durabilité. En intégrant directement la sécurité dans les décisions d'allocation des tâches et des ressources, la recherche montre que productivité et protection ne sont pas des objectifs opposés, mais peuvent être harmonisés grâce à des modèles structurés générant des plans efficaces, explicables et conformes aux exigences de sécurité. Ce travail ouvre la voie à une nouvelle génération d'études sur les HRC-ALBPs sensibles aux risques, à l'interface entre la recherche opérationnelle et les impératifs pratiques de sécurité dans les environnements de production collaboratifs.

ABSTRACT

Human-robot collaboration (HRC) has become a defining feature of modern manufacturing systems, offering flexibility and responsiveness but also introducing safety and reliability concerns. Despite rapid advances in collaborative robotics, assembly line balancing problems (ALBPs) have remained largely focused on efficiency, often treating safety as an external check rather than an embedded decision factor. This thesis develops a safety-oriented framework for Human-Robot Collaborative Assembly Line Balancing Problems (HRC-ALBPs), addressing a critical gap at the tactical decision-making layer where task allocation, mode choice, and resource pairing shape the trade-offs between productivity and risk.

The research unfolds in three stages. First, a systematic review of HRC-ALBP literature established the field's outlines, identifying decision layers, collaboration modes, and existing solution methods. The review revealed that while strategic compliance and operational monitoring had received considerable attention, the tactical layer remained underdeveloped in terms of risk-aware modeling. By synthesizing problem features and gaps, the review highlighted tactical optimization as a central, though underdeveloped, domain for embedding safety into collaborative manufacturing systems.

Second, a safety-driven optimization model was developed using Constraint Programming (CP), introducing a zone-based policy that restricted unsafe human-cobot parallelism. This safe-zone policy formalized an occupational-safety principle as feasibility constraints, eliminating medium- and high-risk overlaps while preserving low-risk concurrency. Computational experiments showed that embedding such rules not only filters hazardous solutions but also structurally reshapes the optimization landscape. Under such circumstances, throughput gains cannot be pursued through unsafe overlaps and force the system toward safer modes and sequential alternatives when needed. The result represents the optimization model as a joint pursuit of efficiency and regulatory-grade safety, rather than an efficiency-only exercise.

Third, the framework was extended through a Process Failure Mode and Effects Analysis (PFMEA)-inspired approach, embedding failure risk into the optimization objective. An Alternative Risk Priority Number (ARPN), aggregating severity, occurrence, and detection scores across four effect categories (safety, time, quality, performance), was introduced as a second objective alongside cycle time (CT). The resulting bi-objective model produced a Pareto landscape

of CT–ARPN trade-offs, revealing structural insights such as the superior impact of human skill improvements over cobot speed increases when safety constraints are binding. A severity-based safety constraint further limited unsafe parallels, ensuring that high-severity hazards could not be compensated by other factors. Together, this dual-lever design, which constraint adds additional safety layer to the risk objective, demonstrated how tactical balancing can systematically internalize safety and risk.

The contributions of the thesis extend both theoretically and practically. Theoretically, it advances ALBP research by (i) reframing safety as a property of feasible solution spaces, (ii) demonstrating the suitability of CP for handling logical and combinatorial dependencies in HRC systems, and (iii) introducing ARPN as a continuous, interpretable risk measure for optimization. Practically, it provides managers with decision-support tools that not only minimize cycle time but also quantify the redistribution of risks across safety, time, quality, and performance. The models function as virtual testbeds, enabling "what-if" analyses of skill distributions, cobot speeds, and safety thresholds before implementation.

Taken together, the findings position tactical optimization as a critical lever for realizing Industry 5.0 principles of human-centricity, resilience, and sustainability. By embedding safety directly into task allocation and resource assignment decisions, the research demonstrates that productivity and protection need not be competing objectives. Instead, they can be harmonized through structured models that deliver plans that are efficient, explainable, and well-regulated. This work lays the foundation for a new generation of risk-aware HRC-ALBP studies that bridge rigorous operations research with practical safety-critical requirements in collaborative manufacturing.

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LISTE OF SYMBOLS AND ABBREVIATIONS

The list of acronyms and abbreviations presents, in alphabetical order, the acronyms and abbreviations used in the thesis and their meaning. Examples:

ABC	Artificial Bee Colony
ALBP	Assembly Line Balancing Problem
ARPN	Alternative Risk Priority Number
BA	Bee Algorithm
BD	Benders Decomposition
Config	Configuration
CP	Constraint Programming
CT	Cycle Time
Cobot	Collaborative Robot
EPN	Effect Priority Number
FMEA	Failure Mode and Effect Analysis
FTA	Fault Tree Analysis
GA	Genetic Algorithm
GALBP	General Assembly Line Balancing Problem
HAZOP	Hazard And Operability study
HG	Hand Guidance
HRC	Human-Robot Collaboration
HRCALBP	Human-Robot Collaborative Assembly Line Balancing Problem
JHA	Job Hazard Analysis
MOGA	Multi-Objective Genetic Algorithm
MBO	Migrating Bird Optimization

ML	Machine Learning
MILP	Mixed-Integer Linear Programming (MILP)
NLP	Non-linear programming
PAL	Parallel Assembly Line
PFL	Power and Force Limitation
PFMEA	Process Failure Mode and Effect Analysis
PHR	Pilz Hazard Rating
PSO	Particle Swarm Optimization
RPN	Risk Priority Number
SALBP	Simple Assembly Line Balancing Problem
SOD	Severity, Occurrence, Detection
SA	Simulated Annealing
SRMS	Safety-Rated Monitored Stop
SSM	Speed and Separation Monitoring
TS	Tabu Search
UAL	U-shaped Assembly Line
ZE	Zone Engagement

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CHAPTER 1 INTRODUCTION

The rapid evolution of manufacturing systems has been shaped by successive industrial revolutions, from mechanization and electrification to automation and digitalization. Industry 4.0, characterized by cyber-physical systems, the Internet of Things (IoT), and advanced analytics, has significantly transformed production environments by enabling flexible and interconnected assembly systems. While automation and digital integration remain central to efficiency, emerging industrial paradigms emphasize that productivity alone is insufficient to address future societal and technological challenges. In this context, Industry 5.0 has emerged as a complementary vision, prioritizing human-centricity, sustainability, and resilience alongside technological advancement. Unlike Industry 4.0's automation-driven orientation, Industry 5.0 explicitly recognizes the indispensable role of human workers and promotes collaboration between humans and intelligent machines, including collaborative robots (cobots), as a pathway to achieving more adaptive, safe, and resilient production systems. Integrating safety early in task and workforce planning not only protects workers but also enhances system robustness by reducing unexpected stoppages and operational failures.

Cobots are a class of industrial robots specifically designed to operate in shared workspaces with human operators, enabling direct physical proximity and interaction. Unlike conventional industrial robots that require physical separation, cobots are equipped with inherent or monitored safety functions such as power and force limiting, hand guiding, speed and separation monitoring, and safety-rated stops that allows human-robot collaboration in performing industrial tasks as a team in accordance with international standards (ISO 10218, ISO/TS 15066, Realyvásquez-Vargas et al. (2019)).

Assembly lines have been the backbone of mass production for a long time, enabling standardized, efficient, and scalable manufacturing processes. However, assembly lines face increasing pressure to accommodate high product variability, shorter product life cycles, and growing demand for mass customization. To remain competitive, firms must adopt novel assembly line configurations that balance efficiency, adaptability, and worker well-being. Cobots have been introduced into these settings to complement human flexibility and problem-solving capabilities with robotic precision, repeatability, and endurance.

Traditional assembly line balancing problems (ALBPs) focus on optimizing the allocation of tasks across workstations to maximize throughput, minimize idle time, and ensure efficient use of resources. With the advent of automation and robotics, particularly cobots, the classical ALBP framework has evolved into more complex variants that integrate both human and robotic agents. This shift reflects the growing importance of human-robot collaboration (HRC) as a keystone of modern manufacturing systems. Despite benefits of cobots utilization in complex and variable assembly operations, achieving effective and reliable collaboration requires moving beyond traditional automation strategies to embrace safety-oriented planning and optimization frameworks. The optimization of performance criteria in a classical Assembly Line Balancing Problem (ALBP) has gained new dimensions under HRC. Decisions must now account not only for cycle time and productivity but also for safety, workload distribution, and the dynamic interaction of human and robotic agents within shared workspaces. Consequently, the safety-aware Human-Robot Collaborative Assembly Line Balancing Problem (HRC-ALBP) emerges as a crucial research domain that bridges operational optimization with safety-critical requirements.

Safety becomes a vital prerequisite in this landscape. Unlike traditional robotized environments where physical barriers separate humans and machines, fenceless collaborative settings expose workers to new categories of risk. According to the standard ISO12100, the term hazard refers to the potential source of harm, while risk quantifies the combination of the probability of occurrence of harm and the severity of that harm. This distinction is crucial in collaborative assembly, where the same hazard, such as proximity to an active cobot, may lead to different risk levels depending on operational conditions including workspace overlap, cobot speed, exposure duration, and worker experience. Beyond physical risks such as collision or musculoskeletal strain, human-robot collaboration may also impose cognitive demands, including sustained vigilance and trust, mental workload, and stress associated with working close to autonomous systems, that need further attention during cobot integration procedures (Rahman & Wang (2018), Gualtieri et al. (2021)).

Process planning must therefore incorporate structured safety evaluation to ensure compliance with industrial standards and the well-being of human operators. Occupational health and safety remain a major global concern. According to the International Labour Organization (ILO), work-related accidents and diseases cause more than 2.7 million deaths annually worldwide with an additional 395 million non-fatal injuries, and manufacturing is among the most affected sectors. Lee et al. (2021) reports 369 robot-related accident cases in Korea from 2009 to 2019 with 95% related to manufacturing business which half of them happened while working and the rest related to maintenance and pre-settings. Severe Injury Reports (SIRs) of the U.S. Occupational Safety and Health Administration (OSHA) reports 77 accidents related to stationary and mobile robots from 2015-2022. Despite advancements in automation and safety standards and control measures, the persistence of high injury rates necessitates addressing safety proactively in production system design.

By embedding safety constraints into optimization models such as ALBPs, it becomes possible to bridge the gap between theoretical efficiency and practical feasibility. At the same time, global manufacturing is undergoing a transition from Industry 4.0 to Industry 5.0 in which HRC plays a fundamental role by supporting human well-being and taking over physically demanding, repetitive, or hazardous tasks besides productivity improvements. Human-centricity, sustainability, and resilience are the core concepts of Industry 5.0 paradigm. Developing safe human-robot collaboration models contribute to increasing the utilization of cobots as a more sustainable solution compared to industrial robots due to low power consumption and enhancing safety of the operations as the driver of decisions that prioritize human workers well-being. In this regard, the integration of safety-oriented modelling into ALBPs thus strongly aligns with the philosophy of Industry 5.0, where advanced technologies are employed to enhance both system performance and human value within production systems.

This thesis is therefore positioned at the intersection of emerging challenges and opportunities in HRC. It seeks to advance the modelling of HRC-ALBP by deep investigation and framing the engaged decisions, embedding safety concerns and their propagation effects into the mathematical structure of ALBPs, and drawing inspirations from assembly line aspects and established risk assessment techniques such as space zoning and Failure Mode and Effects Analysis (FMEA) to create the foundation of capturing the safety challenge of HRC and beyond. In doing so, the research contributes to both the theoretical development of HRC-ALBP models and the practical need for efficient, safe, and reliable human-robot collaboration in assembly lines.

1.1 HRC-ALBP context

Traditional ALBP models optimize system performance with respect to metrics such as cycle time, and number of stations or working resources, while assuming deterministic and risk-neutral task execution. In collaborative assembly environments, however, such assumptions are no longer adequate. When humans and cobots share tasks at a station, the potential for failures, hazards, or safety-critical incidents increases. For instance, a poorly sequenced task may expose the worker to musculoskeletal strain or increase collision risk, while delays in cobot operation may propagate through the line and undermine overall throughput. In this manner, recent extensions of ALBP problems in the context of HRC have begun integrating ergonomics while safety risks remain underexplored (Gualtieri et al. (2021), Hashemi-Petroodi et al. (2020), Papetti et al., (2022)).

In the context of HRC-ALBPs, one of the main objectives is minimizing cycle time, which makes task time variability a critical concern. As illustrated in Figure 1.1, factors such as interaction modes, required risk controls and safety constraints can propagate uncertainty upwards to the cycle time level. By addressing these root causes, particularly the safety dimension, we can reduce task time variability at its source rather than reacting to their consequences at the cycle time level. For example, while a cobot may execute a task with precision, when performed in parallel with a human operator, the same task could involve safety requirements such as reduced speed, enforced separation distances, or power-force limitations. These safety measures directly alter execution time and contribute to variability. Our approach in this thesis targets decreasing unpredictable slowdowns or interruptions by considering these root causes of uncertainty rather than only treating task time as a non-deterministic parameter. This approach ensures that improvements in lower-level causes cascade upward, leading to more stable task times, less fluctuation in line balancing, and ultimately more predictable and efficient assembly performance. In this way, safety is not treated just as an external constraint addressed through compliance with standards ISO 10218 and ISO/TS 15066 regulations but as an intrinsic factor shaping HRC system variability and a lever for strengthening assembly line resilience.

Existing research has investigated HRC in assembly primarily from two perspectives: (1) operational optimization, focusing on task allocation and scheduling to improve performance; and (2) safety engineering, focusing on design, standards, sensing technologies, and real-time control mechanisms to mitigate risks. However, there remains a gap in the integration of safety considerations into mid-level decision-making models such as ALBPs. Most line balancing formulations treat safety as an external constraint rather than as an inherent dimension of the

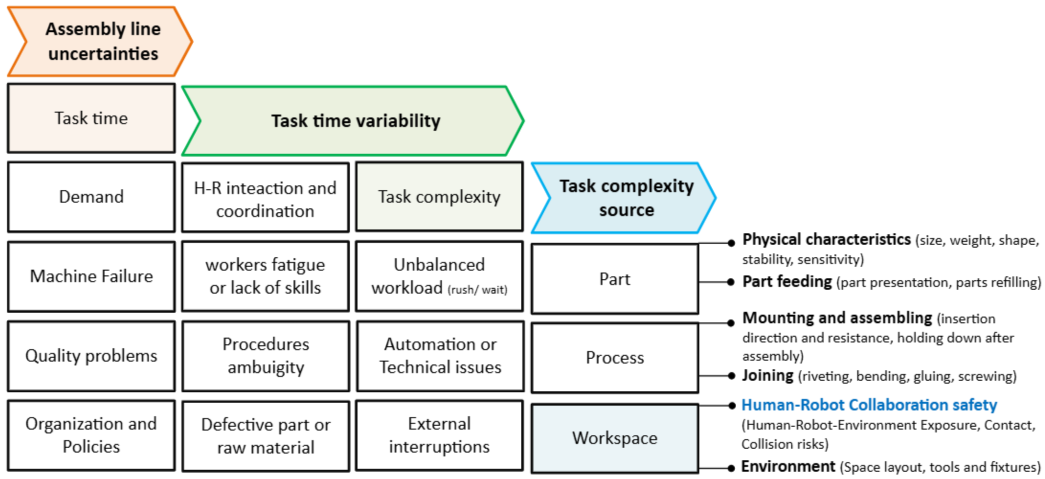

Figure 1.1. HRC Assembly line uncertainty map towards the safety role

optimization problem. The absence of safety integration into ALBP models is problematic for two reasons. First, cobots operate without physical barriers which create scenarios where task assignment decisions may directly expose human operators to hazards. Second, focusing solely on productivity disregards the trade-offs between efficiency and risk, potentially undermining both regulatory compliance and human well-being.

1.2 Problem Statement and Research Questions

Despite the growing adoption of human-robot collaboration in assembly systems, existing planning and optimization approaches remain largely productivity-driven. Classical assembly line balancing models are primarily designed to minimize cycle time, often assuming consistent processes where safety is ensured at design level or an external validation step rather than an integral planning dimension.

In collaborative assembly environments, however, humans and robots share workspaces, tasks, and temporal dependencies, leading to increased exposure to safety risks, time uncertainty propagation, and operational disruptions. Decisions made at the planning stage, particularly regarding task allocation, execution modes, and concurrency, can significantly influence both productivity and operator safety. Yet, current optimization frameworks provide limited mechanisms to explicitly account for these safety-related impacts within tactical decision-making.

As a result, there exists a critical gap between safety-oriented regulations and controls at workstation level decisions and the optimization models used to plan collaborative assembly lines containing multiple stations, cobots, and human operators. Addressing this gap requires decision-support approaches that integrate safety and risk considerations directly into assembly line balancing, enabling informed trade-offs between efficiency, worker protection, and system resilience in line with Industry 5.0 principles. Therefore, the thesis is shaped around addressing the following main question that will be further divided into multiple detailed research questions and objectives:

- How can safety be systematically incorporated into the mathematical modelling of Human-Robot Collaborative Assembly Line Balancing Problems to ensure both system efficiency and worker protection?

This question necessitates bridging the domains of operations research, robotics, and safety science to formulate a decision-support framework that balances productivity and safety in collaborative assembly lines. This research addresses this challenge by advancing from a conceptual mapping of HRC-ALBPs and their decision layers, toward a constraint programming model that introduces zoning-based safety constraints, and finally to a risk-conscious multi-objective optimization model that explicitly minimizes task failure risks alongside cycle time while reinforcing safety through additional constraints. Together, these steps build a safety-oriented modelling framework that bridges the gap between classical ALBPs and the demands of safe, efficient, and human-centered HRC assembly lines. This research will therefore be guided by the following questions:

1. Conceptual Foundation: What are the distinctive decision-making layers (strategic, tactical, operational) in HRC-ALBPs, and how does HRC reform the classical ALBPs? What gaps exist in the current literature concerning safety and risk integration?
2. Safety Integration: How can safety requirements, such as those in ISO/TS 15066 regarding spatial separation, be conceptualized as mathematical constraints within ALBP formulations?
3. Efficiency-Risk Trade-offs: How can optimization models simultaneously minimize cycle time and safety-related risks, and what trade-offs emerge between these objectives?
4. Managerial Implications: What actionable guidelines can be derived for managers to navigate the trade-offs between productivity and safety in Industry 5.0 contexts?

1.3 Objectives and Contributions

The overall objective of this thesis is to develop and validate a safety-oriented decision-making framework for HRC-ALBPs that integrates productivity and risk considerations into line balancing decisions. This framework bridges safety science and assembly optimization, offering a novel perspective for both researchers and practitioners in manufacturing. Accordingly, the thesis pursues the following specific objectives to address the research questions in previous sub-section respectively:

Objective 1: To characterize and synthesize the existing literature on HRC-ALBPs by identifying decision layers, consolidating early findings, and revealing research gaps, particularly with respect to safety and risk integration.

Objective 2: To establish a structured approach for integrating safety requirements into collaborative assembly line balancing decisions, with the aim of reducing workers' exposure to hazards in human-cobot task overlaps while maintaining productivity.

Objective 3: To address the HRC challenges beyond safety concerns and evaluate trade-offs between productivity and multi-dimensional task failure risks, including safety, time, quality, and performance impacts, within tactical assembly line balancing decisions

Objective 4: To derive managerial insights that support decisions on cobot deployment, worker expertise, and safety enforcement in alignment with the industry 5.0 principles of human-centricity, sustainability, and resilience.

The significance of this research lies in its theoretical advancements and practical relevance. Theoretically, it provides the first systematic review of HRC-ALBPs, categorizing decision levels and mapping future research directions, with particular emphasis on the underexplored role of safety in tactical planning. It further introduces a novel constraint programming (CP)-based model that operationalizes safety risk mitigation through zoning-based constraints, thereby integrating safety directly into assembly line balancing. The extended modeling framework incorporates PFMEA-inspired failure risk metrics into the optimization objectives, creating a risk-conscious, multi-objective decision-support structure that balances productivity with safety and other failure impacts. Together, these contributions advance the limited but growing body of literature on safety-aware combinatorial optimization in assembly systems.

From a practical standpoint, the proposed framework offers decision-support tools to help managers navigate the trade-offs between efficiency and safety in human–robot collaborative assembly. By incorporating risk mitigation into mid-term (tactical) planning rather than relying solely on reactive safety controls, the framework supports more proactive, stable, and efficient operations. Moreover, it provides insights into cobot deployment strategies, skill allocation, and constraint-based scheduling that reduce duration of human exposure to the source of harm which is the active cobot and its end effector while maintaining competitiveness.

In alignment with the principles of Industry 5.0, the proposed framework contributes to the development of resilient, sustainable, and human-centric manufacturing systems. By proactively integrating safety-related concepts into decision-making, it reduces the likelihood of risk-induced disruptions and strengthens operational continuity, key attributes of system resilience. Furthermore, by minimizing duration of exposure to potential source of harm for parallel tasks, improving workload distribution, and accounting for multi-dimensional impacts of task failures, the framework supports sustainable operations that prioritize worker well-being alongside resource efficiency. Potentially reduced process interruptions and error-related waste further reinforce the sustainability dimension. This dual emphasis on human safety and system stability reflects the essence of Industry 5.0, where technological intelligence and human values converge to create production systems that are not only productive but also adaptive, responsible, and enduring.

1.4 Thesis structure

The remainder of this thesis is organized as follows:

Chapter 2 provides a foundational literature review covering the broader domains of Human-Robot Collaboration, assembly line balancing, and safety engineering. This chapter sets the general context for the specific research presented in subsequent chapters. In Chapter 3, the research methodology is detailed, outlining the mathematical modeling techniques employed, including constraint programming (CP) and multi-objective optimization, and explaining the validation approach for the proposed models. Chapter 4 presents the published literature review focused on assembly line decision layers in the presence of cobots and the blended decisions in the tactical layer of line balancing due to HRC characteristics. The identified research gaps in this study include but are not limited to safety concerns and lay the groundwork for subsequent research and provide a much-needed roadmap for future HRC investigations. Chapter 5 includes the study of "Safety-driven optimization of human-robot collaborative assembly line balancing”. It introduced a safe zone policy to restrict potentially hazardous tasks concurrency due to overlooking spatial human-cobot separation necessity inspired by distance regulations in ISO/TS 15066. Chapter 6 relates to the proposed multi-objective HRC-ALBP model that seeks productivity (cycle time) and reliability (aggregated risk) with additional limitation on safety-related consequences of tasks failure. Throughout chapters 7 and 8, the thesis synthesizes key research findings, discusses their theoretical and practical implications, highlights limitations, and concludes by summarizing contributions and proposing avenues for expanding the research.

Appendix 1 includes a published conference paper that served as the foundation for the first journal article later published in CAIE journal. Following its presentation at the MIM2022 conference, the paper was selected and invited for journal publication due to the novelty of its literature review and its contribution in addressing a research gap; specifically, the lack of a comprehensive overview of HRC assembly line decisions with a particular emphasis on ALBPs. Appendix 2 contains an abstract presented at the IEOM2025 conference, which builds on the second journal article published in IJPR. This abstract reflects ongoing research aimed at extending the model to incorporate sustainability considerations and the principles of Industry 5.0.

CHAPTER 2 LITERATURE REVIEW

The purpose of this chapter is to provide a broad and integrative literature review that situates the Human-Robot Collaborative Assembly Line Balancing Problem (HRC-ALBP) at the intersection of manufacturing systems, safety science, and mathematical optimization (Figure 2.1). Adopting a scoping review approach, this chapter maps the existing domains, conceptual linkages, and research gaps across these disciplines to establish a coherent foundation for the thesis. Unlike the systematic review conducted in the first paper, which catalogued individual contributions in assembly line optimization, this chapter emphasizes conceptual synthesis and domain mapping to highlight underexplored intersections between safety, human-centric collaboration, and line balancing. It positions the safe HRC-ALBP not only as an operational research challenge but also as a socio-technical transformation aligned with Industry 5.0, where human centricity and safety are as crucial as productivity.

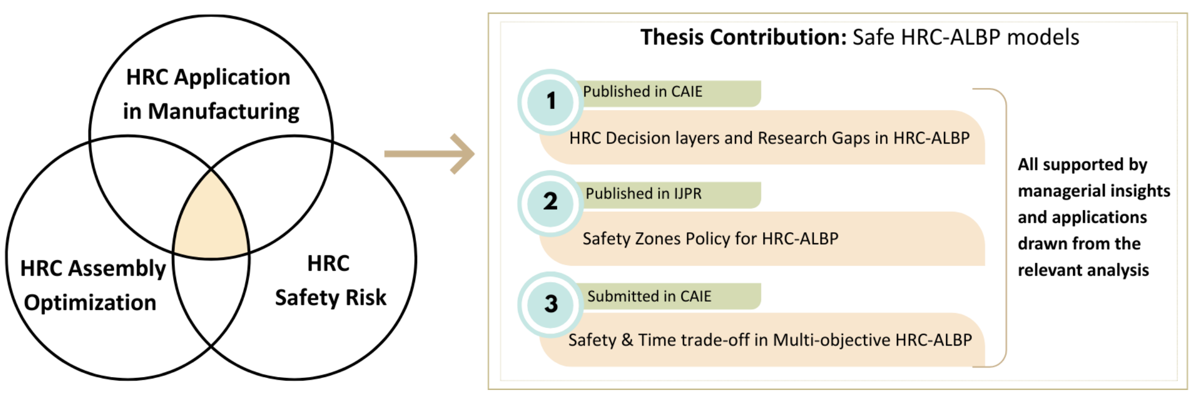

Figure 2.1. Intersection of research areas leading to thesis contributions in Safety and Optimality of HRC assembly

2.1 Human-Robot Collaboration in Manufacturing

Collaboration of humans and robots in performing manufacturing tasks is a recently developed technology that supports manual production systems. This technology provides the advantage of having both automated and manual processes in the manufacturing system (Weckenborg and Spengler, 2019). Generally, human-robot collaboration (HRC) refers to a sequence of shared actions actively performed by humans and collaborative robots toward a shared goal (Weiss et al., 2021). The technology of collaborative robotics is primarily utilized in the assembly processes due to its benefits in this labor-intensive part of the manufacturing systems (Malik and Bilberg, 2018). Although human workers are flexible resources, the cost of employing them is continuously growing. Cobots' utilization helps the companies manage the resources' cost while providing the required degree of flexibility and reconfigurability in production (Malik and Bilberg, 2018).

2.1.1 Evolution of HRC in industry

The evolution of Human–Robot Collaboration (HRC) in manufacturing reflects the broader path of industrial revolutions, each of which reshaped the relationship between humans and machines. In Industry 1.0 and Industry 2.0, manufacturing was first dominated by manual labor and later enhanced by mechanization and electrification. Human workers were the central agents of production, with machines serving as tools to increase strength and consistency rather than independent decision-making entities. The automation wave of Industry 3.0 introduced industrial robots to the shop floor starting 1961, particularly in automotive and heavy manufacturing. These robots were highly efficient but operated in complete isolation from humans, typically surrounded by safety cages to eliminate the risk of collisions (Bilberg & Malik, 2019). This "robotic isolation" maximized productivity in repetitive, hazardous, or precision-driven tasks, but it also introduced inflexibility and reduced adaptability in dynamic production environments essential to customization demand paradigm (Michalos et al., 2018).

The industry 4.0 paradigm brought the digitalization of manufacturing through cyber–physical systems, advanced sensors, connectivity, and artificial intelligence. Since 2010 robots began to interact more intelligently with their environment, enabling the first structured HRC attempts. Collaboration takes multiple forms: a) Sequential, where robots and humans performed tasks on the same product at different times; b) Parallel, where both operated simultaneously but independently in shared spaces; and c) Supportive, where humans and robots worked together on the same task in real time (Marvel et al., 2015; Ragaglia et al., 2018).

The current Industry 5.0 vision reframes the robot's integration track by recognizing human's central role, sustainability and resilience as equal priorities to productivity. In this setting, collaborative robots (cobots) are not only tools but partners in value creation, designed to complement human cognitive and problem-solving abilities with robotic strength, repeatability, and endurance. Enhanced with safety-rated monitored stops, force/torque sensors, and speed/distance compliance mechanisms, cobots can operate more securely in shared workspaces without cages (ISO/TS 15066; Murino et al., 2023). Their role has expanded across multiple manufacturing domains, from palletizing and pick and place tasks to assembly/disassembly, machining, welding, injection molding, and quality inspection, illustrating the versatility of collaborative paradigms (Li et al., 2024; Gao et al., 2025).

The progression from manual systems to isolated robots and ultimately to collaborative, human-centered production illustrates how HRC contributes to establishing flexible and adaptive manufacturing ecosystems which are vital for SMEs dealing with customized products market as a competitive advantage strategy. Industry 5.0 supports this path by emphasizing that technological sophistication must serve both operational efficiency and human well-being, positioning HRC as a basis for future industrial competitiveness.

2.1.2 Core enabling technologies

The expansion of HRC in manufacturing has been made possible by a set of enabling technologies that allow robots to sense, adapt, and interact safely with their environment. Advanced sensors and machine vision systems provide cobots with the ability to perceive human presence and product states, making it possible to share workspace without physical barriers (Alenjareghi et al., 2024). Artificial Intelligence (AI) algorithms for motion planning, trajectory optimization, and task allocation further improve adaptability, enabling robots to dynamically adjust their actions in response to human movements or production variability (Cimino et al., 2024). These technologies transform robots from rigidly programmed machines into responsive collaborators that can support flexibility, customization, and error reduction in assembly and other manufacturing processes.

Beyond sensing and AI, the emergence of digital twin technologies has redefined how collaboration is designed and managed. By creating real-time virtual representations of manufacturing systems, digital twins simulate human–robot interactions to test task sequences, identify potential hazards, and evaluate system performance before actual deployment (Gao et al., 2025). This virtual experimentation reduces uncertainty and supports safer integration of cobots on the shop floor. Complementing these advances, global safety standards such as ISO/TS 15066, ANSI/RIA R15.606, and ISO 10218 have set clear technical requirements for collaborative operations, emphasizing layout features, power and force limitation, speed and separation monitoring, and protective stop mechanisms in cobots to physically safeguard human operators and enable HRC in fenceless environments (Gualtieri et al., 2022; Lacevic et al., 2023).

2.1.3 HRC decision domains

Decision-making in Human–Robot Collaboration (HRC) spans a broad range of domains, from design-phase programming choices to real-time scheduling targeting process continuity and operators' safety and ergonomics as the explicit goals which are beyond throughput maximization. At the design stage, decisions include the selection of parameters like robot speed, separation zones, and force limitations, which are often justified by international standards such as ISO/TS 15066 (Gualtieri et al., 2022; Lacevic et al., 2023). Programming and trajectory planning decisions further involve minimizing unnecessary movements, tool changes, and position shifts to maintain the production flow (Ragaglia et al., 2018; Michalos et al., 2018). Motion planning is not limited to geometric efficiency; it also considers collision avoidance, ergonomic postures, and operator visibility that reflect the dual objective of avoiding hazardous conditions while sustaining production quality. From the cobot integration perspective, strategic decisions at the design level are responsible for configuring workspace layout and evaluating the suitability of operations with cobot capabilities and collaborative execution requirements to determine incompatible operations. This information will be used along with the data from online monitoring system to rescheduling the operations based on the situation in rea-time (online scheduling) for time saving and safety purposes. However, the static/offline scheduling approaches determines a fixed sequence of operations and responsible agents without adapting to system changes (Pupa et al., 2021).

Beyond design and programming, tactical and operational domains shape daily task execution. Tactical planning covers workforce allocation, task-to-workstation assignments, and mode selection (e.g., human-only, robot-only, or collaborative execution), which directly influence cycle time (CT), ergonomic and safety risks, and costs (Bogner et al., 2018; Cai et al., 2025). Operational decisions mostly include scheduling and sequencing of sub-tasks under real-time conditions, accounting for workforce variability, cobot availability, and unexpected disruptions (Yu et al., 2021). These operational adjustments often rely on advanced monitoring systems and adaptive algorithms that redistribute tasks dynamically to preserve safety and productivity in response to deviations from expected conditions. Across all domains, the underlying challenge is balancing efficiency and safety in a shared workspace, with each decision layer (design and programming, tactical, and operational) contributing to how effectively humans and cobots complement one another.

2.1.4 HRC benefits and challenges manufacturing context

The integration of Human-Robot Collaboration (HRC) into manufacturing has unlocked significant opportunities for efficiency, flexibility, and mass customization. By combining the precision and endurance of robots with the cognitive adaptability and dexterity of humans, collaborative assembly systems can respond more effectively to product variability and shortened life cycles (Boschetti et al., 2021; Stecke & Mokhtarzadeh, 2022). Cobots are particularly valuable in scenarios requiring frequent changeovers or small-batch production, where fully automated lines would lack adaptability. In addition, HRC can relieve operators from repetitive, ergonomically demanding, or hazardous tasks, thereby reducing musculoskeletal strain and improving long-term workforce well-being (Michalos et al., 2018; Gualtieri et al., 2021a-b). These benefits align closely with the principles of Industry 5.0, where human-centeredness and resilience are emphasized alongside productivity.

At the same time, the adoption of HRC introduces distinct challenges. Sharing workspaces with cobots exposes human operators to collision risks and unanticipated contact, making safety management a critical concern (Huck et al., 2021). Unlike traditional industrial robots that operated behind barriers, cobots require sophisticated monitoring systems, force-limiting controls, and risk assessment frameworks to ensure compliance with safety standards (Li et al., 2024; Lacevic et al., 2023). Beyond physical risks, HRC can also create mental workload pressures, as workers must remain constantly vigilant when collaborating with autonomous agents. Moreover, variability in human skill levels complicates task allocation: assigning the wrong task to a novice worker in a cobot-assisted station may jeopardize both productivity and safety (Berx et al., 2022). Finally, integrating these human and robotic elements into cohesive assembly systems remains a technical and managerial challenge, demanding careful planning at the design, tactical, and operational levels. Thus, while HRC offers pathways toward safer and more flexible manufacturing, realizing these benefits requires deliberate strategies to mitigate safety risks, accommodate workforce diversity, and manage the complexity of human–machine interactions.

2.2 Safety and Risk in HRC

Working with robots requires some safety considerations, which are not considered when multiple operators work together in the same station. Safety of Collaborative robots is mainly achieved through standard risk assessment (ISO 12100) procedures and implementing protective measures or safety functions (ISO 10218 and ISO/TS 15066) to allow working in a fenceless environment with humans. However, production processes are usually dangerous by nature because of using sharp tools, performing actions such as drilling, punching and pressing. Moreover, there is wide category of mechanical, electrical, thermal, ergonomics, substance, radiation, vibration, and noise hazards in the manufacturing or assembly environment that could affect operators' safety (Chinniah, 2016; Chemweno et al., 2020).

Sanders et al. (2024) analyze 77-robot related accidents from 2015 to 2022 by OSHA Severe Injury Reports (SIRs) in which 54 accidents relate to stationary robots 23 relate to mobile robots. They discuss accidents and injuries still happen given the existing regulations, standards, protective and control measures and explain existing shortages and required modifications in pre-contact (design, collision avoidance system, administrative controls) and post-contact hazard (robot-specific injury indices and injury tolerances) controls. Non-standard work arrangements, temporary workers with insufficient expertise, and production pressure are among the factors in the category of administrative pre-contact hazard controls that affect individual safety behavior and cause human errors leading to accidents or injuries (Sanders et al., 2024). Malm et al. (2010) studied 25 sever robotic accidents in Finland and attributed 60% of accidents to inadequate instructions, training or supervision and highlights that the close proximity of the human and robots means that there is very little time to escape from crushing hazard. The study of 369 operator-injured robot accidents in Korea from 2009 to 2019 by Lee et al. (2021) revealed that two-thirds of injuries occurring from robot accidents mostly caused by psychological and personal traits of robot operators. They categorize the direct source of these accidents into two types of unsafe behavior (64%) and unsafe conditions (36%). "Access to dangerous places or parts" and "Excessive action or movement" in the category of unsafe behavior caused by psychological pressures and stress, inappropriate work order, and a tight delivery deadline, lack of workforce, night shifts and fatigue. "Maloperation" and "faulty correction and breakdown/failure" in the category of unsafe condition may occur due to narrow workspace, disobediences of accurate operation time, forced circumstances of complying with tight deadlines.

The worldwide pattern in safety challenge of robotic environments is the complex human behavior which is the inseparable element of human-robot collaborative environments. Productivity-focused assembly line balancing plans with cycle time minimization goal may impose time pressures and change human behavior due to stress and fatigue and consequently affect the overall safety culture of the system. As a result, considering safety and productivity goals together is crucial to the systems where human and cobot work side by side in a fenceless environment and perform operations on product parts in various forms of individually, simultaneously, or jointly. This ensures a reliable and productive line with fewer process interruptions and failures due to any errors or human-cobot contacts/collisions.

National Institute for Occupational Safety and Health (NIOSH) proposes a hierarchy of risk controls starting with the most effective ones as elimination and substitution of hazard, then engineering and administrative controls, and finally to the least effective one which is the personal protective equipment (PPE). In this hierarchy, constant monitoring of the collaborative environment, using the safety zones to isolate operators from hazards, modifying task procedures or task planning and human operators training falls within the engineering and administrative controls for managing the potential safety risks.

2.2.1 Fundamental safety in HRC

Safety is a non-negotiable prerequisite in Human–Robot Collaboration (HRC), where humans and robots share workspaces without protective barriers (Chinniah, 2016). Unlike traditional industrial robots that were segregated to prevent accidents, collaborative robots (cobots) are designed to physically interact with operators. ISO/TS 15066 formalizes this paradigm by outlining four collaborative operation modes: (i) safety-rated monitored stop, (ii) hand guiding, (iii) power and force limiting, and (iv) speed and separation monitoring. Each of these modes represents a mechanism to control risks by either limiting the cobot's physical behavior or actively monitoring its proximity to human operators. Their application is task-dependent: power and force limiting is more suitable for lightweight assembly, whereas speed and separation monitoring is critical in tasks involving faster or heavier motions. Safety in HRC, however, extends beyond physical protection; cognitive strain, stress from continuous vigilance, and musculoskeletal workload can also threaten worker well-being and compromise system reliability (Gualtieri et al., 2021a,b).

2.2.2 Standards, frameworks, and risk assessment methodologies

To address the multifaceted risks of Human–Robot Collaboration (HRC), industries rely on structured risk assessment methodologies that provide both systematic evaluation and actionable prioritization. Techniques such as Failure Modes and Effects Analysis (FMEA) and its process-oriented extension, PFMEA, remain among the most widely applied tools. These methods identify potential failure modes, assess their severity, occurrence, and detectability, and assign priority scores to guide mitigation strategies (Carlson, 2012). PFMEA, in particular, is well-suited for collaborative assembly contexts because it explicitly evaluates risks at the task level, thereby accounting for how specific process characteristics influence both the likelihood and the consequences of failure. Other methods, such as fault tree analysis (FTA), hazard and operability studies (HAZOP), and job hazard analysis (JHA), complement this approach by mapping causal pathways, examining system-level vulnerabilities, and structuring preventive actions (Guiochet, 2016). This should be noted that accuracy of FMEA/PFMEA method depends on the quality of available data in the specific context and experts' judgments in assigning the scores and criticality.

Alongside these methodological approaches, international standards play a pivotal role in translating risk assessment into compliance frameworks. Standards such as ISO 10218 and ISO/TS 15066 define technical and organizational requirements for safe collaborative operations, including emergency stop protocols, hand-guiding methods, force thresholds, permissible contact limits and speed and separation monitoring procedures (Murino et al., 2023). These standards not only prescribe safety limits but also encourage a proactive approach to integrating protective measures into system design and operation. Together, risk assessment methodologies and international standards form the backbone of modern HRC safety management: methodologies help to quantify and prioritize risks, while standards ensure that these efforts are aligned with globally recognized safety expectations. This dual foundation provides manufacturers with both the analytical tools and regulatory guidance needed to sustain safe, reliable, and efficient collaborative environments.

2.2.3 Risk quantification challenge in collaborative environments

Despite available methods, quantifying risk in dynamic, fenceless collaborative environments remain highly challenging. Human behavior is inherently variable, robots can operate under multiple speed or force modes, and tasks differ in both duration and interaction intensity. This complexity makes it difficult to accurately capture risk with traditional static metrics (Liu et al., 2020). For example, a cobot operating under reduced speed might be safe in isolation but hazardous if paired with a beginner worker in a parallel task execution. Furthermore, conventional safety indices often overlook the temporal and contextual dimension of collaboration, where risk levels change dynamically during task execution and it increases by longer human proximity to cobot.

These limitations motivate the development of risk-aware optimization approaches that integrate discrete decision variables such as task allocation and mode selection with explicit safety constraints (Weckenborg et al., 2022; Nourmohammadi et al., 2025). Embedding quantifiable risk into mathematical models bridges the gap between theoretical optimization and the real-world variability of collaborative production, laying the groundwork for safer and more resilient HRC systems. This must be noted that risks may have compounding influence, adding an additional complexity layer to the risk assessment methods in general which is rarely addressed in literature, and we approach it through parallel task execution restrictions.

2.2.4 Safety-Productivity trade-off

A recurring theme in HRC is the tension between maximizing productivity and safeguarding workers. Measures that reduce risk such as limiting cobot speed, capping applied forces, or increasing monitoring sensitivity; almost inevitably result in longer cycle times or reduced throughput (Scalera et al., 2022). Conversely, strategies that push for efficiency, like high-speed parallel task execution, can elevate the likelihood of collisions, errors, or musculoskeletal strain (Zhao et al., 2025). This interplay highlights that safety and productivity are rarely independent; rather, they form two ends of a spectrum that managers and engineers must continuously balance. Similarly, ergonomically optimized workstations contribute to both workers' well-being and time efficiency goals (Abdous et al., 2022)

The challenge is not to eliminate this trade-off, an impossible task in dynamic manufacturing systems, but to manage it intelligently. Emerging research argues for embedding safety considerations directly into tactical and strategic decision-making frameworks, such as assembly line balancing and scheduling models. By doing so, safety is no longer treated as an external constraint to be checked after optimization but as an integrated objective alongside productivity. This approach not only ensures regulatory compliance but also helps organizations build resilience against disruptions and costly accidents. In the broader context of Industry 5.0, this balance is especially critical: factories are expected to be not only fast and efficient but also human-centric, where safety and well-being are elevated to strategic priorities equal to economic performance.

2.3 Assembly Line Balancing Problems (ALBPs)

Assembly Line Balancing Problems (ALBPs) are at the core of production planning, aiming to assign tasks to workstations in a way that meets precedence constraints and achieves system-level objectives. In the context of Human-Robot Collaboration (HRC), these classical problems evolve into richer formulations that must integrate safety, skill variability, and the various task modes in shared human-robot environments. This subsection reviews the classical foundation of ALBPs and their extensions with automation and robotic integration to situate the ground for HRC-ALBPs.

2.3.1 Classical ALBP

The classical ALBP is defined as the problem of distributing tasks among a sequence of workstations to optimize performance criteria while respecting task precedence constraints (Otto, Otto, & Scholl, 2013). Traditionally, the objectives include minimizing cycle time (CT), maximizing line efficiency, and balancing workload across stations. Two well-known variants dominate literature are as follow:

SALBP-I: minimizing the number of workstations given a fixed CT.

SALBP-II: minimizing the CT given a fixed number of workstations.

Over time, these variants have been extended to account for multiple objectives such as costs minimization, equipment utilization, and human fatigue/energy consumption controls. Solution approaches include exact mathematical programming formulations for small-to-medium instances, as well as heuristics and metaheuristics (e.g., genetic algorithms, simulated annealing, Benders' decomposition) for large-scale industrial problems (Michels, Lopes, Sikora, & Magatão, 2019). Despite these advances, classical ALBPs treat human operators as predictable resources, largely ignoring their behavior and performance variability or safety-critical constraints when working with another human or robot at a different pace and some creative changes based on training or experience are probable.

2.3.2 Automation and robot integration into ALBPs

The integration of automation and robotics into ALBPs has significantly reshaped the problem structure. Robots introduce new decision variables such as robot type, operation speed levels, setup times, and integration levels, which alter both the feasible task assignments and the line performance (Çil, Li, Mete, & Özceylan, 2020). These additions complicate the balancing problem, often requiring hybrid models that blend precedence, resource, and synchronization constraints.

With the expansion of human-robot interactions to fenceless simultaneous task execution at the same workspace, the complexity increases further. Collaborative robots (cobots) introduce heterogeneous resources, where task execution times, failure probabilities, and risk exposures depend not only on the infrastructures, environment, and task characteristics but also on, decision policies, responsible agents (human or cobot), and execution mode (e.g., sequential, parallel, collaborative). Studies highlight that such integration requires multi-mode ALBP formulations where human proficiency, robot speed flexibility, and safety considerations are explicitly modeled (Boschetti, Faccio, Milanese, & Minto, 2021; Mao, Zhang, Sun, Fang, & Huang, 2025).

These developments illustrate a clear progression: from classical ALBPs focused solely on efficiency, toward automation-augmented ALBPs where robotics and collaboration necessitate balancing not only time and resources but also safety, reliability, and human-centered constraints. This transition sets the stage for the next step, safety-oriented HRC-ALBPs, the focus of this thesis.

2.3.3 Assembly decision layers and the balancing problem

Assembly line decisions unfold across three interconnected levels of strategic, tactical, and operational, each with its own scope, time horizon, and implications for safety and efficiency. Recognizing these layers helps situate the Human-Robot Collaborative Assembly Line Balancing Problem (HRC-ALBP) within the broader decision-making ecosystem of manufacturing.

Strategic decisions shape the long-term structure of the system, including line configuration, workstation layout, and automation levels reflecting as cobot acquisition policies (Dolgui et al., 2022). At this level, organizations decide how much automation to invest in, how arrange collaborative workstations, and which safety devices and regulations or ergonomic principles influence layout design. Safety and ergonomics thus become embedded into capital investment choices, determining the potential of a line to support sustainable and human-centric collaboration over its lifecycle.

Tactical decisions concern line balancing, task assignment, and cobot allocation; the core focus of this thesis. These mid-level decisions link design to day-to-day operations, directly affecting cycle time, workload distribution, and operator exposure to risks (Nourmohammadi, Fathi, & Ng, 2024).

The tactical layer is unique because it is where efficiency targets and safety requirements intersect most strongly: assigning tasks to workers and cobots requires balancing execution times with proper execution mode selection based on human and cobot capability and availability that directly impact operational risks and probability of creating hazardous situations. In collaborative contexts, tactical decisions become especially complex due to heterogeneous resources (human and cobot) and the need to manage shared workspace interactions.

Operational decisions address scheduling, sequencing, and real-time monitoring (Dimény & Koltai, 2023). Here, safety is enforced dynamically through online adjustments, such as slowing cobots, reassigning tasks when unexpected risks arise, or using real-time monitoring systems for collision avoidance trajectory. This layer relies heavily on sensor technologies, adaptive control, and human oversight to prevent hazards as they emerge during production.

Framing ALBP decisions within this layered perspective emphasizes that while safety and risk are relevant at all levels, the tactical layer provides a pivotal entry point for embedding structured, safety-oriented modeling. Strategic planning defines the system's safety potential, and operational systems enforce compliance in real time, but tactical optimization directly determines how tasks are distributed between humans and cobots complying with strategic decisions yet reducing operational adjustments. This makes it the most influential layer for balancing productivity with risk-conscious decision-making; a perspective that underpins the contributions of this thesis.

2.3.4 Emerging HRC-ALBPs

Recent developments in Human–Robot Collaborative Assembly Line Balancing Problems (HRC-ALBPs) reflect a shift toward addressing uncertainty, variability, and intensifying collaboration requirements. Unlike classical ALBP formulations with deterministic task times and fixed resource behavior, newer models incorporate stochastic task durations, variable human performance states, and probabilistic failure risks (Yin et al., 2025; Ren et al., 2023). These approaches acknowledge that in real assembly environments, task execution is rarely constant mainly due to operator fatigue, cobot speed adaptation, and unexpected disruptions. As such, optimization models increasingly rely on stochastic or robust frameworks that can handle randomness and provide decision-makers with resilient solutions under uncertainty.

At the same time, the Industry 5.0 paradigm reshapes how these problems are framed. Industry 5.0 emphasizes human-centricity, resilience, and sustainability, positioning HRC not simply as a productivity enhancer but to redefine work around human well-being and system adaptability (Malik & Brem, 2021; Yang et al., 2025). Within this vision, HRC-ALBPs must balance operational efficiency with worker protection, sustainability goals, and the long-term resilience of production systems. This human-centered framing motivates the integration of safety- and risk-aware optimization models that go beyond throughput maximization, ensuring that decision-making remains aligned with regulatory compliance and social responsibility.

Finally, the adoption of digital twins and simulation-based optimization has become a central trend in emerging HRC-ALBPs. Digital twins enable the creation of virtual replicas of assembly systems where task assignments, resource allocations, and safety constraints can be tested in silico before implementation (Cimino et al., 2024). This allows managers to anticipate risks, evaluate different collaboration strategies, and optimize system behavior without disrupting production. Combined with advanced simulation and AI-driven analytics, digital twins support the integration of safety awareness into tactical and operational decisions, bridging the gap between theoretical optimization frameworks and practical deployment.

2.4 Safe Assembly Line Balancing decisions

The intersection of Human–Robot Collaboration (HRC) safety risks and Assembly Line Balancing Problem (ALBP) modeling represents one of the most underexplored yet critical areas of modern manufacturing research. While HRC brings opportunities for flexibility and productivity, it simultaneously introduces uncertainty in task execution and exposure to safety hazards. These factors call for decision-making models that not only balance workloads and minimize cycle time but also embed risk-awareness into task allocation, workstation design, and sequencing strategies. Despite growing recognition of these issues, most ALBP formulations still treat safety and risk as external factors, managed through standards or online monitoring devices, rather than as integral elements influencing by mid-term decisions as well (Berx et al., 2022; Murino et al., 2023).

2.4.1 HRC uncertainties in ALBP models

Uncertainty in HRC stems from diverse sources, including variable task durations (Figure 1.1), fluctuating worker performance, and the probabilistic nature of failure risks. Yet, ALBP models have traditionally assumed deterministic task times and simplified resource capabilities, thereby overlooking how risks propagate in collaborative environments. This simplification limits their applicability in dynamic shop-floor conditions where even small deviations can cascade into delays or safety incidents (Berx et al., 2022). As Murino et al. (2023) argue, the absence of risk parameters in current balancing models restricts their ability to capture the complexity of real-world HRC systems. Addressing this gap requires models that incorporate discrete uncertainty elements, explicitly quantifying how task assignments influence not only productivity but also cumulative exposure to risk.

2.4.2 Safety-aware decision-making

Examples of safety-aware decision-making in assembly systems are limited but gradually emerging. Some efforts extend ALBP formulations by incorporating ergonomic principles, ensuring that task allocation avoids excessive physical strain (Stecke & Mokhtarzadeh, 2022). Others adapt Failure Mode and Effects Analysis (FMEA) and its process-oriented variant (PFMEA) to structure risk assessment at the task level, integrating severity, occurrence, and detection parameters into balancing formulations (Murino et al., 2023). However, comprehensive frameworks that account for multiple categories of risk—including safety, quality, time, and performance—at the tactical level of task-to-workstation assignment remain scarce. This gap motivates the present thesis, which explicitly positions safety as a co-equal consideration to productivity, thereby aligning tactical ALBP decision-making with the broader principles of Industry 5.0.

2.4.3 Structured framework for risk-conscious HRC-ALBP

Despite the progress, there is still no established structured framework for risk-conscious ALBP decision-making. Current research tends to focus on risk management at either the design level (e.g., implementing safety-rated monitored stop or separation devices) or the operational level (e.g., real-time monitoring of cobot proximity and speed). Tactical task allocation—the layer where decisions about which tasks should be assigned to which human–robot pairs are made—remains underexplored in terms of structured safety integration (Nourmohammadi et al., 2025). This omission is critical, as tactical decisions directly influence both cycle time and the likelihood of hazardous task overlaps. Therefore, the central contribution of this thesis is to introduce a safety-oriented optimization framework for HRC-ALBP at the tactical level, embedding risk-awareness directly into balancing decisions. By doing so, it provides a structured pathway for reconciling productivity goals with worker protection, bridging a gap that has long persisted in both ALBP and HRC literature.

2.5 Towards Safe HRC Optimization in ALBPs (HRC-ALBPs)

This section situates the present thesis within the broader academic and industrial discourse. While prior work has advanced HRC, risk assessment, and ALBP modeling individually, their integration into a unified framework remains underdeveloped. The aim here is to highlight how cross-disciplinary advances can converge, identify the gaps preventing this convergence, and argue for the necessity of a safety-oriented optimization framework at the tactical decision-making level.

2.5.1 Combined HRC safety and HRC assembly optimization

Cross-disciplinary research has begun to bridge robotics, safety science, and optimization, but progress has been fragmented. Studies on collaborative assembly scheduling demonstrate the feasibility of allocating shared tasks with respect to time efficiency and resource availability (Bogner et al., 2018). Similarly, safety-oriented approaches have integrated safe robot trajectory algorithms and risk assessment methodologies, such as FMEA, JHA, and FTA to evaluate hazards and failure likelihood in collaborative assembly (Gualtieri et al., 2023). Research into cobot allocation within assembly line contexts has also shown the potential of optimization models to adapt resources to varying task complexities and worker capabilities (Sikora & Weckenborg, 2022). However, these contributions tend to remain isolated without joining with mid-level optimization policies that simultaneously address productivity and multi-category risk.

2.5.2 Research gaps

Despite promising advances, several research gaps remain evident that we address three of them. At the beginning of this thesis, literature lacked a comprehensive framework that presents various decisions associated with collaborative robots' integration into assembly systems as the co-workers of human operators. Although an inclusive review of studies focusing on HRC-ALBPs could brighten the path for joint optimization and safety community of researchers, the emphasis was placed on eighter design or operational stage practices. Thus, there is a need to investigate the mid-level decisions impacts where long-term strategies and short-term approaches meet and blend from both collaboration efficiency and safety/reliability perspectives.

There are insufficient safety factors integration into ALBPs as well as discussion on how mid-term task-workstation-workforce decisions may affect the safety of human operators. Existing HRC-ALBP formulations emphasize productivity and workload balance as well as solution methodology superiority but rarely embed structured safety constraints or risk propagation into tactical decision-making or even disclose safety concerns in their discussions (Table 2.1). Moreover, most safety-aware approaches concentrate on design-phase compliance or operational monitoring, leaving the tactical task-to-workstation layer underexplored despite its critical impact on both cycle time and risks. Additionally, the absence of models handling multiple risk categories is also unexplored in HRC-ALBP context. Research has often restricted its focus to safety hazards, neglecting broader consequences such as time loss, quality issues, and overall performance degradation. A multi-dimensional risk representation is necessary to reflect the complexity of collaborative environments and capture the HRC variation origins for creating a more resilient collaborative assembly system.

At the early stages of cobot integration into manufacturing systems, careful assessment of existing assembly tasks is essential to determine whether they can be executed by a cobot alone or collaboratively with a human, based on criteria such as safety and ergonomics. However, many studies stop at this evaluation and implicitly assume that simultaneous execution of separate tasks by a human and a cobot within the same workstation is inherently safe. Even when individual tasks are considered low risk in the given mode, their concurrent execution can compound risks and generate hazardous situations, a factor largely neglected in literature. Classical optimization objectives such as minimizing cycle time or reducing the number of stations tend to encourage parallel task assignments wherever possible. Ignoring the safety consequences of cobots task on the other ongoing task by human in the same workstation may lead to unsafe assignment outcomes and process interruptions underscoring the necessity of risk-informed parallelization in human-robot collaborative environments.

In today's manufacturing landscape, the alignment of optimization objectives with the human-centered values of Industry 5.0 remains largely overlooked. While recent studies develop advanced algorithms for HRC-ALBPs, with time and cost efficiency focus, few have explicitly connected these models to principles such as human-centricity and resilience despite their central role in shaping the future of industrial systems. Moreover, comparatively little attention is paid to providing actionable insights for managers and practitioners using these models. This leaves a gap in addressing the conceptual and practical challenges that arise when safety, task failure risk, and human variability are integrated into tactical assembly planning. Addressing this gap requires more than methodological refinement; it calls for integrative approaches that merge safety science with operations research to produce frameworks that are both mathematically rigorous and practically meaningful for modern collaborative assembly systems.

Table 2.1. Collaborative assembly line decisions layers with safety integration approach

Decision layers	Key decisions	How safety is integrated	Gap highlight
Strategic	Automation level by Cobot type selection and task modes availability based on skills Line layout design	Compliance based: standards and preventive risk assessments	Safety is considered, but mainly as compliance; not linked to task balancing decisions.
Tactical	Workforce (Cobots and humans) planning Assembly line balancing	Indirect: model assumptions and integrated ergonomics	No structured framework for safety-aware tactical balancing existed before this thesis.
Operational	Task flow control and re-sequencing human-robot interaction monitoring	Explicit reactive/adaptive: Dynamic monitoring through sensors, laser scanners, cameras, and wearable devices	Focus on real-time adjustment or emergency stops to ensure safety, not proactive planning.

2.5.3 Necessity of Safe HRC-ALBP optimization

Systematic reviews of HRC-ALBPs, such as Kheirabadi et al. (2023), have already highlighted the infancy of this research field and the absence of structured frameworks that bridge ALBP optimization with safety risk management. Building on this foundation, the present thesis responds by embedding Safe Zone Policy, PFMEA-inspired risk parameters, and safety-severity constraint directly into the tactical ALBP optimization layer. This integration advances the field in two ways: first, by broadening the optimization objective to jointly minimize cycle time and multi-category risks, and second, by explicitly safeguarding parallel human–robot task execution through safe zone regulations and severity thresholds.

By applying these safety-oriented models to task-to-workforce-to-workstation, decision-makers are no longer restricted to assigning only light tasks to cobots to ensure operator safety, nor to reducing their speed to a minimum level that hinders production efficiency. This represents a shift away from productivity-only formulations toward safety-integrated tactical decision-making. Such an approach is essential for both theory and practice: academically, it expands the modeling frontier of ALBPs; industrially, it equips managers with decision-support tools that align with Industry 5.0 priorities by enhancing productivity while ensuring human well-being and system resilience.

CHAPTER 3 METHODOLOGY

The methodological framework of this thesis builds on three interrelated studies that progressively deepen the understanding and modelling of Human–Robot Collaborative Assembly Line Balancing Problems (HRC-ALBP) with a safety orientation. Unlike classical ALBP research, where the focus has predominantly been on productivity metrics such as cycle time and line efficiency, this work systematically embeds safety considerations into tactical decision-making. The methodology follows a layered approach: it begins with a comprehensive review of existing literature to identify conceptual and practical gaps in the integration of safety into ALBP models; advances with the development of a constraint-based optimization model incorporating a safety-zone policy; and culminates with the design of a tactical framework that integrates risk assessment parameters inspired by Failure Mode and Effects Analysis (FMEA). This staged methodology as presented in Figure 3.1 ensures that the thesis not only contributes to new models but also provides a holistic, interdisciplinary foundation where optimization techniques are tightly coupled with safety science and human-centric principles of Industry 5.0.

3.1 Literature review on HRC-ALBP

The first step in the methodology was to establish a clear research foundation through a systematic literature review, conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure methodological transparency and reproducibility (Kheirabadi, Keivanpour, Chinniah, & Frayret, 2023). At the time of its execution (January to February 2023), no review study had specifically examined assembly line balancing in the context of human–robot collaboration from 2012 to 2023, a field then at its infancy. The review mapped existing decision layers (strategic, tactical, and operational) and highlighted the absence of structured approaches for embedding safety risks into balancing models' insights on safety consequences of mid-term balancing approaches. It also revealed that while ergonomics had been increasingly integrated into ALBP formulations, safety considerations had been treated superficially, primarily as compliance issues at the design phase or as reactive controls at the operational level. By identifying these gaps, the review laid the groundwork for positioning safety as a tactical-level concern in assembly planning. This paper served as both a reference point for subsequent research and a unique contribution to a emerging research area.

3.2 Safe zone policy in HRC-ALBP

The second study addressed one of the key gaps identified in the review: the lack of mechanisms to manage safety risks in task concurrency at collaborative workstations of an assembly line. To tackle this, a Constraint Programming (CP) model was developed (Kheirabadi, Keivanpour, Frayret, & Chinniah, 2025). Constraint Programming was selected for its effectiveness in handling complex logical relationships and combinatorial decision structures inherent in scheduling and resource allocation problems, making it well-suited for modeling tasks sequencing constraints and task-mode-zone relations in collaborative assembly. The model introduced a safety-zone policy that regulated parallel task execution by restricting medium and high-risk human cobot task overlaps based on human-cobot proximity during parallel tasks. Given three defined workstation zones, performing parallel tasks by human and cobot without accessing common space is recognized low risk and assignment decision is feasible. However, if the human operator, cobot, or both uses the common space for completing their own tasks, the risk was ranked as medium and high respectively and parallelization was not permitted. This approach transferred safe human-robot distance necessity inspired by ISO/TS 15066 standard into optimization constraints, ensuring that task allocations adhered not only to productivity goals but also to predefined safety thresholds. Computational experiments across multiple line configurations demonstrated that enforcing the safety constraint led to measurable reductions in hazardous parallelisms at the cost of slightly longer cycle times.

This study established the feasibility of embedding safety logic directly into tactical assembly planning, as an engineering control within the hierarchy of risk controls, marking a shift from compliance and monitoring toward proactive safety-driven cycle time optimization. Note that the uncertainty of human behavior is excluded from the framework of this model, and it is assumed that the human operators always follow the rules of workspace utilization over the course of each task execution. Thus, considering unexpected human presence or extended task times due to reasons such as physical fatigue will be future research directions. The full list of problem assumptions, mathematical formulations, results and model limitations are available in chapter 5.

3.3 Time and Risk optimization in HRC-ALBP

Building on the safety-zone policy of the second paper, the third study expanded the scope of safety integration by introducing a PFMEA-inspired risk framework. Here, the classical Risk Priority

Number (RPN) was replaced with the Alternative Risk Priority Number (ARPN), which provides a more stable and continuous representation of risk by summing severity (S), occurrence (O), and detection (D) parameters instead of their multiplication. Moreover, the summation of SOD parameters resolves the issues of sparse solution space with the multiplication form where the algorithms face constant leaps in the feasible solution area with small change in each SOD parameter and couldn't correctly find the direction toward the optimal point. More details of this model are further provided in chapter 6.

The CP-based model was extended into a bi-objective optimization framework to minimize both cycle time and failure risk simultaneously. The weighted sum method was adopted for this purpose due to its simplicity, interpretability, and ease of integration with decision-support systems, allowing both objectives to be represented within a single scalar function that preserves compatibility with the CP framework. This approach enables decision-makers to directly interpret the weights as the relative importance of objectives, giving managers the flexibility to prioritize safety in high-risk operational contexts or efficiency during periods of high demand. Furthermore, it allows the exploration of trade-offs along the Pareto front without increasing model complexity or computational burden. During the sensitivity analysis of this model, which is provided in chapter 6, three different scenarios are explored for weights: balanced cycle time and risk weights, double and half cycle time weights. These weights can be further adjusted by the authorities' preferences or experts' opinion regarding the importance of objectives.

In addition, a safety constraint was retained to limit the severity of safety-related failures in parallel task executions. Unlike the second study, which was focused on binary safe/unsafe task allocations, this framework considered multi-dimensional risks (safety, time, quality, and performance) and allowed for a nuanced balancing of productivity and reliability. Numerical experiments confirmed that the model could guide managers in selecting task allocations that achieve safer and more resilient production outcomes. This final step advanced the methodology from a reactive paradigm which mitigates risks after they arise to a proactive one, where risks are anticipated and integrated directly into tactical line balancing decision-making.

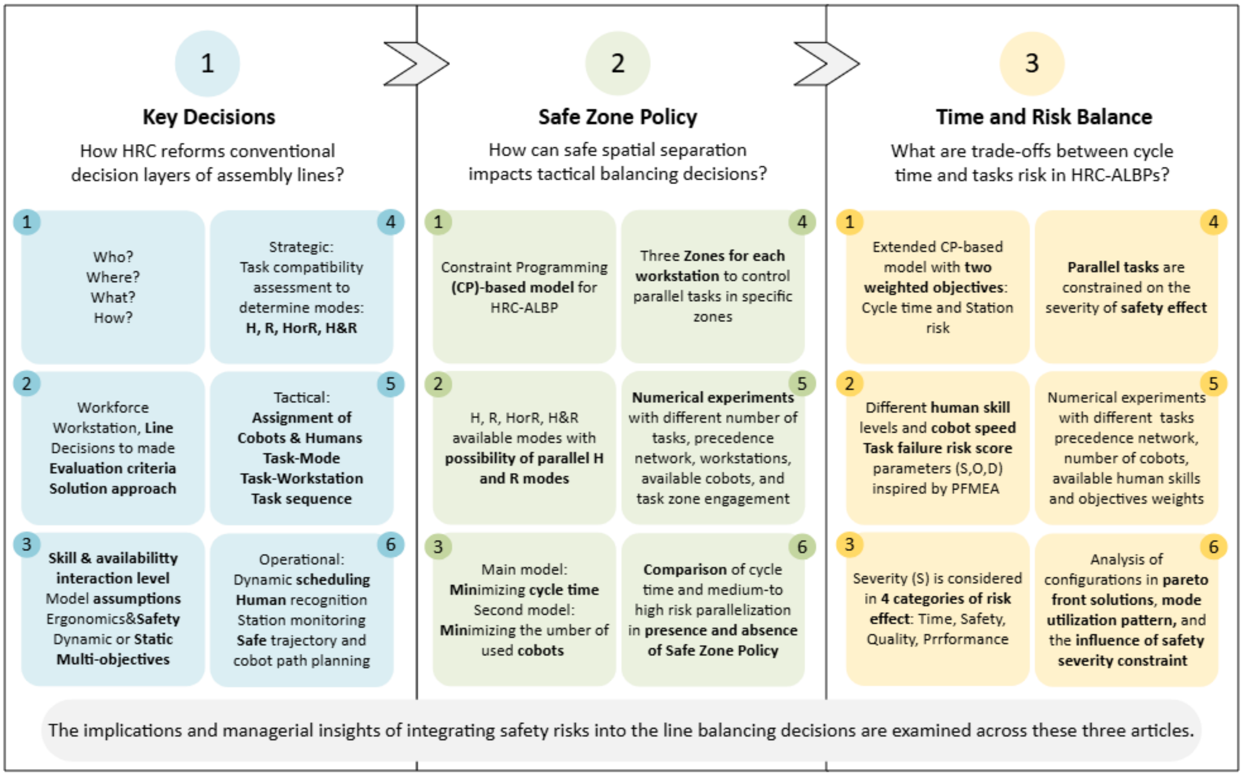

Figure 3.1. The backbone concepts of objectives in articles

CHAPTER 4 ARTICLE 1: HUMAN-ROBOT COLLABORATION IN ASSEMBLY LINE BALANCING PROBLEMS: REVIEW AND RESEARCH GAPS

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Résumé

Depuis des décennies, les chercheurs s’intéressent aux problèmes d’optimisation des chaînes de montage, en particulier à l’équilibrage des lignes d’assemblage. L’intégration des technologies de l’Industrie 4.0 dans les chaînes de montage engendre de nouveaux défis, notamment en matière de sélection optimale des ressources, d’affectation des tâches, d’équilibrage de la ligne et de planification. Au cours de la dernière décennie, de nouveaux cadres ont été proposés pour adapter les modèles d’optimisation classiques aux évolutions de la révolution industrielle et aux technologies émergentes. Dans ce contexte, les problèmes d’équilibrage de pointe dans les chaînes de montage intégrant des robots collaboratifs constituent le cœur de cette étude, en tant que décision clé dans l’Assembly 4.0. La collaboration entre humains et robots dans un environnement sans barrières exige une approche plus globale que l’affectation traditionnelle des tâches aux postes dans les modèles d’équilibrage. La sélection/allocation des ressources et la planification figurent parmi les décisions les plus fréquemment combinées aux modèles d’équilibrage. Ainsi, la présente revue synthétise les travaux publiés au cours des dix dernières années, identifiés via Web of Science et Engineering Village, portant sur ces défis d’optimisation. Nous analysons à la fois les caractéristiques bibliométriques des articles (p. ex., années de publication, revues) et leur contenu afin d’identifier les tendances et les lacunes de recherche, et de proposer des orientations pour de futures études sur l’optimisation des chaînes de montage collaboratives intégrant la santé et la sécurité au travail.

Abstract

Researchers have been working on assembly line optimization problems, especially assembly line balancing, for decades. Integration of Industry 4.0 technologies into assembly lines creates new challenges in optimal resource selection, task allocation, line balance, and scheduling decisions, to name a few. Over the last decade, researchers have developed novel frameworks for conventional assembly line optimization problems that comply with the recent industrial revolution and leading technologies. State-of-the-art Balancing problems in assembly lines with collaborative robots are the core of this study as a key decision in Assembly 4.0. The collaboration of humans and robots in a fenceless environment requires a more comprehensive approach than the traditional task-station assignment in a balancing model. Resource selection/allocation and scheduling are the most common decisions that researchers combine with balancing models. Thus, the studies on all these optimization challenges in the last ten years through the Web of Science and Engineering Village are present in the current review. We analyze the articles' statistics (e.g., year and journals) and contents to find the research trends and gaps for future research direction in collaborative robotic assembly line optimization which incorporates occupational health and safety.

Keywords: Human-Robot Collaboration, Assembly line balancing, Task assignment, Cobot, Industry 4.0, Occupational health and safety

4.1 Introduction

Because of the growing fluctuation and unpredictability of market demand, production strategies moved from mass production to small batches over the years. Variability and a short lifecycle are two characteristics of today's market demand. The manufacturing paradigm in Industry 4.0 (I4.0) is shifting toward mass customization to satisfy customer expectations, and consequently, production facilities require highly flexible processes. (Malik and Brem, 2021). This market evolution presents manufacturers with new challenges in managing the expenses associated with offering a flexible system capable of producing customized products (Wojtynek et al., 2017). However, the recent Integration of I4.0 technologies into processes such as assembly (Assembly 4.0 or A4.0) makes them more flexible, reliable, and efficient for achieving mass customization goals. Dolgui et al. (2022), and Cohen et al. (2019) investigate the implications of I4.0 technologies for strategic, tactical, and operational decisions in assembly lines, as well as the real-world application difficulties. From another perspective, Upadhyay et al. (2023) review studies that consider the social aspects of I4.0 implementation like required human skills, job security, organizational goals, and management support. Integration of human factors and ergonomics in Industry 4.0 publications is the topic of the Kadir et al. (2019) review.

One of the most current I4.0 technologies is the collaborative robot (cobot), which enables both manual and automated processes while maintaining low production costs (Weckenborg and Spengler, 2019). This new generation of industrial robots collaborates with humans in a shared fenceless workspace to merge the robot's speed and accuracy with human intelligence, creativity, and flexibility (Hashemi-Petroodi et al., 2020). Robots' lack of cognitive capabilities makes a fully automated system challenging. (Johannsmeier and Haddadin, 2017). However, cobots offer a desired level of flexibility and automation in assembly lines (Lv et al. (2022); Weckenborg and Spengler (2019)), decrease human workforce expenses, and perform repetitive or boring tasks instead of humans (Cohen et al. (2019); Çil et al. (2020); Chen et al. (2014)). Human-robot collaboration is also advantageous in disassembly operations for dealing with the consequences of uncertainty in frequency, quantity, and quality of End-of-Life (EOL) products (Huang et al., 2021). Even though some researchers refer to "Cooperation" and "Collaboration" interchangeably, these terms pertain to different human-robot interaction (HRI) types during assembly. Collaboration occurs when both collaborators actively participate in a series of activities that lead to a shared goal, whereas in cooperation humans and robots perform different subtasks for a common outcome (Weiss et al., 2021). Simões et al. (2022) investigate the research works on workspace design for establishing a sustainable and healthy human-robot collaboration.

Manufacturing companies are increasingly investing in Cobots, and it is necessary to investigate the contributions, requirements, and guidelines of a collaborative workspace where humans and robots closely interact with each other (Simões et al., 2022). As we move from automation to real collaboration with robots, new issues emerge in industrial settings, necessitating the study of new practices to address them (Weiss et al., 2021). The speed of industrial robots is a serious source of threat to human workers' safety in collaborative environments and necessitates a continuous safety risk assessment (Liu et al., 2020). Finding the appropriate work balance is a way to achieve Human-Robot Collaboration (HRC) goals regarding worker well-being improvement (e.g., collaboration respecting ergonomics and safety principles) (Stecke and Mokhtarzadeh, 2021). Although numerous studies have been working on Assembly line Balancing Problems (ALBP) for decades, cobot presence in an assembly line brings new challenges and increases the complexity of problems (Chutima, 2020). For example, task execution time varies depending on the type of robot which remarks the importance of robot selection in a line balancing problem (Boysen et al., 2022). Therefore, our research highlights the critical aspects of literature coping with ALBP with cobots and potentials in a new research direction known as Collaborative Robotic Assembly Line Balancing Problems (CRALBP). An ALBP handles the task-to-station assignment considering sequential relations in assembly lines (Li et al., 2021). Besides this decision, CRALBP determine the task executer agent (human/robot) in multi-resource stations (Weckenborg et al., 2020).

Chutima (2020) reviews robotic assembly line balancing problems in detail. He categorizes the papers based on the assembly layout and the concept of 4M (Man, Machine, Material, Method). On the other hand, Battaïa & Dolgui (2022) review the assembly line balancing problem trends and their combination with other decisions in production lines over the last decade. They argue that assembly lines' cobotization deals with handling different types of resources (cobot and human operator) and scheduling their tasks. The review of Simões et al. (2022) concerns the design aspects of a human-robot collaborative workspace and Dolgui et al. (2022) develop a research agenda for the assembly systems of Industry 4.0 in which collaborative robot is one of the enabling technologies. Although there are few CRALBPs in the review papers mentioned above, none of them analyze these problems in depth. Thus, we expand the study of Kheirabadi et al. (2022) on the collaborative robotic assembly line balancing problem by reviewing the most recent relevant research works and providing detailed features of CRALBPs in literature over the last decade. The current review also includes studies on task mode selection and scheduling, as these topics appear to be related to CRALBPs. In this way, we target three basic questions in the context of the collaborative assembly line optimization problem:

1. Who (human/robot) can perform each assembly task?

2. Which station is suitable for executing each task?

3. When is the optimal starting/finishing time of assigned tasks inside a station?

In section 4.3, we address these questions with task mode selection and task allocation studies, CRALBPs, and scheduling papers, respectively. Following an elaborative analysis of the literature, we discuss research trends in section 4.4 and future research directions in section 4.5, which set this study apart from Kheirabadi et al. (2022). Besides being novel for conducting a review focused on collaborative robot assembly line balancing problems, our work contributes to the existing literature with the following features:

- Presenting the literature as three main groups according to the decision levels in assembly lines: Strategic task mode selection (determine the automation level), Tactical line balancing, and Operational scheduling.

- Analyzing the criteria for deciding the assembly automation level, configurations of CRALBPs and the developed solution methodologies, as well as scheduling approaches for human-robot collaboration.

-Statistical data of the papers to find information like active researchers and top journals/conferences related to human-robot collaborative assembly lines.

- Identifying the trends in literature over the past decade and the future research directions with the emergence of Industry 5.0.

4.2 Research Methodology

With a systematic approach inspired by the studies of Acerbi et al. (2021) and Dolgui et al. (2021), we searched the papers through the Web of Science (WOS) without a time limit and then selected the most relevant documents for the final literature review. This review primarily tends to investigate CRALBPs and then explore other decisions that researchers typically combine with ALBP in collaborative assembly settings. The list of words in Table 4.1 is suitable for examining the literature after multiple attempts with various keyword combinations over the Web of Science and Engineering Village (EV). These keywords are in three categories regarding the literature review targets. HRC workspace design is out of the scope of our study, and we refer the researchers to Simões et al. (2022) for a comprehensive review of this subject.

Table 4.1. Keywords of the search strategy in the Web of Science

Category	**Cobot**	**Industry**	**Decision**
Keywords	-Collaborative robot -Human-robot collaboration - Cobot - Cobotics	- Assembly	- Balancing - Planning - Task allocation - Scheduling

This search strategy in the title, keywords, and abstract of papers leads to 201 documents spanning 2003 to 2023 in the WOS. Since the papers from 2003 to 2009 were irrelevant to the context, we excluded them immediately from the list of papers and started the papers' examination with 198 articles since 2010. The procedure for selecting records is shown in Figure 4.1. Review papers as well as studies on robotic programming or technology development including human recognition and trajectory planning are excluded from the review list. Investigating the human-cobot interaction challenges in assembly work is a key concept in this study. So, the studies on collaborative robot teams or fully automated systems without human engagement are not considered in the review, leaving us with 66 documents. To ensure that all CRALBPs are covered, we implemented the designed search strategy on EV as a complementary source of articles. Comparing the search results with the collected papers through the WOS, we found 25 more records. We found 6 new articles among the papers' references in the full content analysis phase. So, the final review list contains 97 documents, 68% from WOS, 26% from EV, and 6% from indirect sources (Figure 4.1). After the revision process of the paper, four conference papers found from the WOS are replaced by a journal paper or a book chapter that is published in a similar research area.

Integrating cobots into ALBPs brings task allocation (robot/human) and sequencing challenges to the conventional balancing problem (Weckenborg et al., 2019). Furthermore, ALBPs merged with other assembly line optimization decisions are a major trend over the last decade and provide a higher line performance (Battaïa & Dolgui, 2022). For these reasons, the studies on task allocation and scheduling in the context of human-robot collaborative assembly are included in the review. Also, these papers enrich the discussion on existing research gaps, and finding future research potentials in the field of CRALBP. All 97 studies are inside the three strategic, tactical, and operational categories addressing decisions related to automation level, workload balance, and task management.

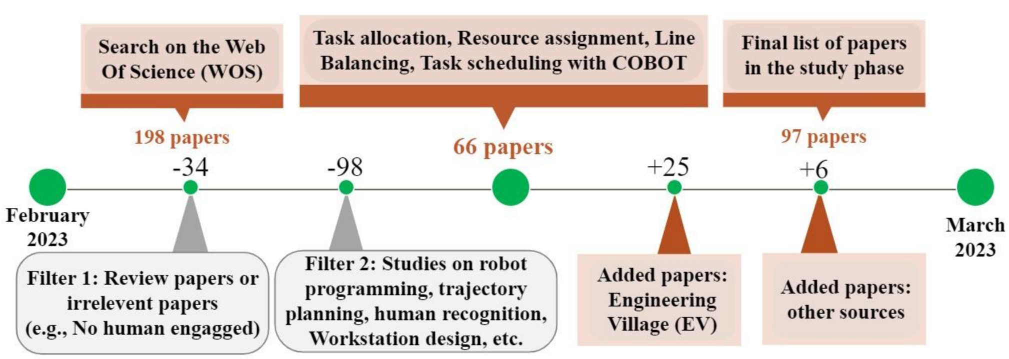

Figure 4.1. Papers selection procedure

4.3 Content analysis

4.3.1 Literature's statistical data

Despite the matured research area of ALB, the collaborative robotic assembly line balancing is still under development. As evidence, only 30 out of 97 (31%) papers directly address the CRALBP (Table 4.4). The rest of the documents in the review list relate to task mode selection, task allocation, and scheduling decisions linked with balancing problems in a human-robot collaborative assembly line. However, the interest in exploring collaborative assembly line optimization decisions has increased (Figure 4.3) over the last five years. This trend will expand the research area and methodologies to cope with various collaborative assembly problems in the future. Researchers greatly participate in conferences to introduce their latest findings and novel ideas. About 33% of the reviewed papers are presented at conferences all over the world, and 67% are published in scientific journals. Most of the conference papers (24 out of 32) in our review relate to 2020 and later, which reveal the interest of researchers in the topic in recent years and the potential for future studies. "The International Journal of Advanced Manufacturing Technology", "International Journal of Production Research", and "International Journal of Computer-Integrated Manufacturing" are the top three journals due to their higher number of papers in our review (Figure 4.2). Figure 4.2 contains 64% (62 records) of the review list and the rest of the papers (36%) are from other journals/conferences.

Figure 4.2. Journals/Conferences with a minimum of two papers in the review list

Figures 4.3 to 5 provide data regarding the publication years, authors, and their countries. Christian Weckenborg, Edoardo Lamon, Paolo Rocco, Andrea Maria Zanchettin, Arash Ajoudani, Ali

Ahmad Malik, and Fabio Fusaro are the top three prolific authors in the context of human-robot collaboration assembly optimization with more than three research works per author among 97 reviewed papers (Figure 4.4). The majority of records in our review belong to the years 2019 to 2022 and the number of papers in 2023 promises upcoming studies in the collaborative assembly line optimization research (Figure 4.3). Italy, China, and the United States of America (USA) are the top three countries with 54% of the articles in total (Figure 4.5).

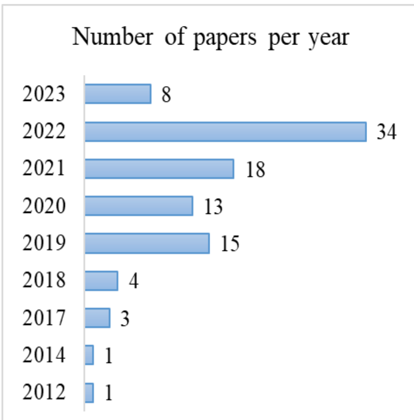

Figure 4.3. Publishing year of documents

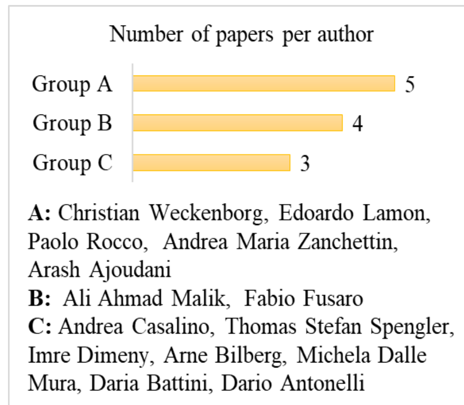

Figure 4.4. The most prolific authors of literature

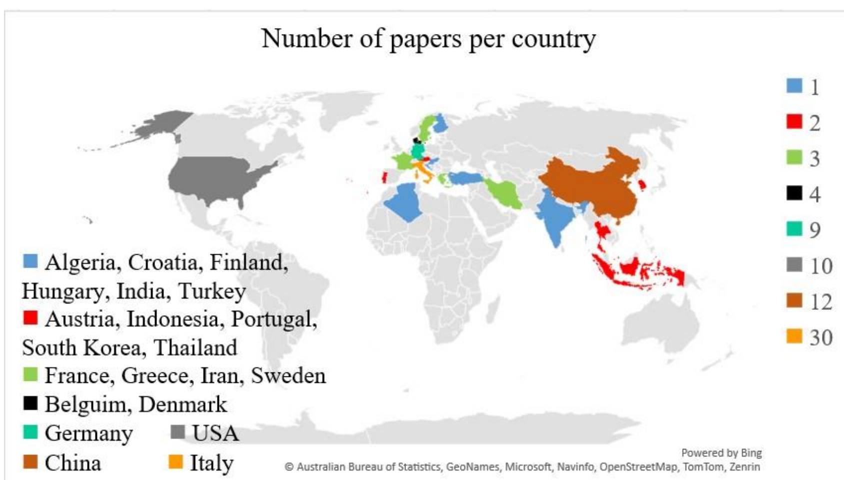

Figure 4.5. The map of research distribution all over the world

As we scanned the papers in the last round of review, "human-robot collaboration" is the most repetitive phrase among the keywords. Figure 6 depicts the network of 30 words that appear at least 10 times in the titles, abstracts, and keywords of all reviewed documents. The thicker the connecting line between words, the higher the popularity of paired words in papers. This is also true for the relation between the size of circles/fonts and the popularity of each keyword. Each color corresponds with a word cluster that contains the words with the strongest link among themselves and their connection with other words/clusters. Figure 4.6 shows task allocation is a more prevalent problem than assembly line balancing and scheduling among the reviewed papers.

The presence of ergonomics and safety in this network confirms their importance in the context of human-robot collaboration research. Although ergonomics is linked with assembly line balancing, task allocation, and scheduling problems, safety is not connected to the line balancing in the network which uncovers the lack of studies in this area of research. The Genetic Algorithm (GA) is popular among researchers for solving human-robot collaboration optimization problems and time is the productivity evaluation index in many of these studies. Simulation in the red cluster links with ergonomics, safety, time, and cost keywords while mathematical modeling in cluster yellow is connected with only cost and time. As a result, integrating ergonomics and safety into mathematical models remains a difficulty that requires further attention. Moreover, the purple cluster reveals the footprint of Industry 5.0 in this area of research. Ergonomics and safety relate to the human-centric pillar and flexibility relates to the resilience pillar in Industry 5.0. The third and last pillar is sustainability and future studies can integrate it into the collaborative assembly lines problems to enrich the literature and investigate moving from Industry 4.0 to Industry 5.0.

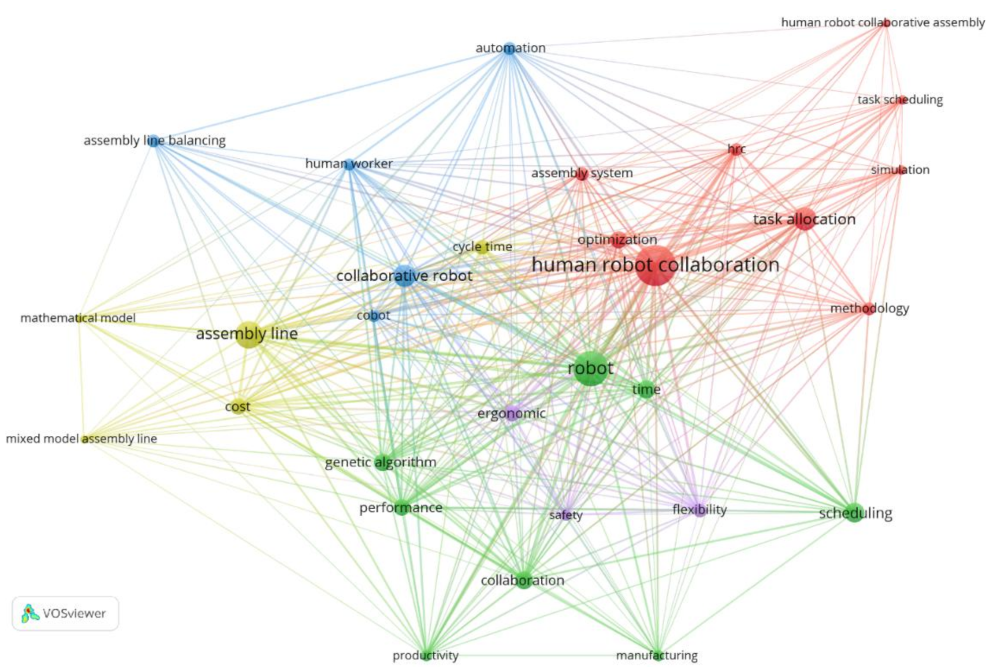

Figure 4.6. The network of the top 30 connected words in papers' title, abstracts, and keywords

4.3.2 Human-Robot Collaborative Assembly Line Optimization Problems

In the first round of reading papers, we divided them into three main types of optimization problems: Human-robot task allocation (35%), CRALBP (31%), and scheduling (34%). These three categories are the building blocks of section 4.3.2 and Table 4.2 summarizes the studied problems in each sub-section. The level of engaged decision-making (strategic, tactical, operational) is also provided in Table 4.2, which is based on a decision classification developed by Dolgui et al. (2022). The core of this review is analyzing the assembly line balancing problems in which humans and cobots collaborate in task execution. However, we start the review from one level before the line balancing decision, which is determining the potential automation level with task mode selection and allocation decisions. Then the review continues with studies on generating detailed task schedules after line balancing level. This section contains papers of these three categories in separate sub-sections each of which consists of a table of papers and explanations of the data presented.

Table 4.2. Decision categories in the CRALBP review

Section	Section title	Collaborative robotic assembly line problem (s)	Decision level
4.3.3	Human-robot task allocation	Task mode selection and task allocation among the workforces (4 modes: Human, Robot, Human or Robot, Human and Robot)	Strategic automation level
4.3.4	Collaborative Robotic Assembly Line Balancing	Task-to-station assignment or Task-to-resource-to-station assignment	Tactical line balancing
4.3.5	Human-robot collaborative task Scheduling	Task/Sub-task/Action allocation with sequencing and timing	Operational task scheduling

An assembly line balancing is a tactical or mid-term decision that researchers generally combine with strategic and operational decisions to improve the assembly line's performance. For instance, decisions like choosing the type of cobot or required skill are long-term or strategic and determine the automation level of assembly lines (Dolgui et al. (2022)) and some balancing problems integrate them into their model. Similarly, some other balancing problems address the optimization of task execution schedule which is a short-term or operational decision in assembly.

Integrating a collaborative robot into an assembly line not only alters the physical settings of the line but also changes some assumptions and concepts for planning and optimal decision-making. Human-robot task allocation problems find the best choice of workforce for executing tasks in an assembly station based on resource capabilities and tasks' complexity to optimize some objectives like time and cost. CRALB problems deal with assigning tasks to stations with the aim of minimizing the number of required stations, cycle time, or costs. Besides this primary decision, they mostly determine the responsible workforce (Human/Robot/Both) for executing each task in each station. Thus, instead of a traditional line balancing problem with a task-to-station assignment decision, planners face a task-to-station-to-workforce assignment decision. Finally, the scheduling problems address the sequence and timing of tasks assigned to a collaborative station. The presence of humans and robots in a fenceless workspace and cooperating on the same workpiece or parallel task execution requires scheduling decisions within the stations to ensure safety (Weckenborg et al., 2019). Therefore, decision-makers should constantly examine the requirements and existing conditions before generating a task execution schedule.

Each of the three presented subsections starts with an explanation of the general concepts of the problem and follows with a table summarizing the key characteristics of each research work. To identify studies with such configurations, all tables contain a column for ergonomics and safety to reveal studies that improve the ergonomics of work and ensure the safety of workers.

4.3.3 Human-Robot task allocation

This section aims to discuss two topics: the selection of the task mode and the allocation of tasks in a collaborative station. The two topics have an impact on the level of automation of the assembly system, which is a strategic decision. We examined these papers to find the key criteria for finding the optimal task executor agent in a collaborative workstation. As a result, it reveals which criteria have been considered to date and which criteria require further consideration in future studies. We combine both topics into one table (Table 4.3) so that we can easily compare evaluation criteria in articles that discuss one of the topics or both.

Diverse workers with different capabilities (human and robot) are available in a collaborative workstation. Also, the assembling process of a product consists of tasks varying in physical properties of engaged parts, assembly features like mounting direction, occupational risks, and joining methods such as screwing (Bilberg & Malik, 2019). Consequently, human and robot expertise in each task execution varies and depends on the degree of task complexity, accessibility, payload, and repeatability (Cai et al., 2022). In this manner, papers on two topics of task analysis and task allocation contribute to finding the best human/robot task match in an assembly operation.

The first group of studies breaks down the assembly process into tasks or sub-tasks and analyzes them according to criteria such as complexity, difficulty, and safety. Comparing these characteristics with resource capabilities, the tasks' automation potential is identified. There are four modes of performing a task in collaborative stations: Manual (H), Automated (R), Manual or Automated (H/R), and Collaborative (H&R). Therefore, the outcome of these studies clarifies which one of these four modes is applicable for performing each task and ultimately contributes to the long-term decision of selecting an assembly line automation degree. Lamon et al. (2019), Malik & Bilberg (2019b), and Dianatfar et al. (2019) are examples of these types of studies.

The second group deals with dynamic or static task allocation among the working resources inside a collaborative station given task automation potential and resources' availability. These task allocation decisions optimize criteria like assembly time, cost, safety, and ergonomics (Table 4.3). Bänziger et al. (2018), Karami et al. (2020), and Gjeldum et al. (2021) are some studies from the task allocation group of studies and the rest of them are available in Table 4.4. Many studies, such as those by Lamon et al. (2023), Gualtieri et al. (2023), Petzoldt et al. (2022), and Papetti et al. (Papetti et al.) do not separate the two topics. First, they analyze the tasks based on specific criteria, then determine the possible task modes, and finally allocate them to the best capable agent (human/robot/both).

A dynamic task allocation approach involves roles that do not remain static within the workers/robots, but instead change continuously according to a set of optimization criteria or workers' needs. The static approach, on the other hand, allocates a fixed set of tasks to the workforce without considering factors such as changes in worker conditions (Merlo et al., 2023). Compared to static task allocation, a dynamic approach is more human-centered, and flexible to cover the probable delays that may happen during the processes (Bruno & Antonelli, 2018). Although this is an advantage of a dynamic approach, it requires a monitoring system that is aware of the real-time condition of the workforce, tasks, and their environment to dynamically re-assign the tasks. Providing this real-time monitoring system imposes extra costs on the system which might not be beneficial, especially for small-medium businesses (SMEs).

Table 4.3. Task mode selection and task allocation evaluation criteria in the literature

paper	**Problem**	**Evaluation criteria**					**Problem**	**Evaluation criteria**					
	Task mode selection (H, R, H/R, H&R)	Part complexity	Skills for task execution	Process complexity	Safety	Ergonomics	Task allocation (S/D)	Time	Cost	Safety	Ergonomics	Resource utilization	Quality/ Errors
Johannsmeier & Haddadin, 2017	-						S	*			*		
Tsarouchi et al., 2017	✓		*				S	*				*	
Bänziger et al., 2018	-						S	*	*		*		
Bruno & Antonelli, 2018	✓	*	*	*			D	*					
Heydaryan et al., 2018	-						S	*		*	*		*
Bilberg & Malik, 2019	✓	*	*	*	*		D	*					
Dianatfar et al., 2019	✓	*	*	*		*	-						
Makrini et al., 2019	✓	*	*	*			D				*		
Lamon et al., 2019	✓	*	*	*		*	-						
Malik & Bilberg, 2019a	✓	*		*	*		-						
Malik & Bilberg, 2019b	✓	*		*	*		-						
Mateus et al., 2019	✓	*	*	*		*	S	*		*	*		
Karami et al., 2020	-						D	*					*
Liau & Ryu, 2020	✓	*	*				S	*			*	*	
Gjeldum et al., 2021	-						S	*	*		*		
Lippi & Marino, 2021	-						D	*			*		*
Malik & Brem, 2021	✓	*	*	*		*	D	*		*	*		
Tram & Raweewan, 2021	-						S	*	*		*		
Cai et al., 2022	✓	*	*	*		*	S	*			*	*	
El Makrini et al., 2022	✓	*	*	*			D	*			*		
Li et al., 2022	-						D	*			*	*	
Liau & Ryu, 2022	✓	*	*	*		*	S	*			*		
Merlo et al., 2022	-						D		*		*		
Papetti et al., 2022	✓	*		*	*	*	S	*	*	*			
Petzoldt et al., 2022	✓		*				D	*					
Zhang et al., 2022a	✓	*	*	*			S	*			*		
Alessio et al., 2022	✓	*	*	*	*	*	S	*		*	*		*
Wang et al. 2022b	✓	*	*	*			S	*				*	
Faccio et al., 2023	-						S	*		*			
Gualtieri et al., 2023	✓	*	*	*	*	*	S	*	*				*
Lamon et al., 2023	✓	*	*	*			D	*			*		
Merlo et al., 2023	-						D				*		

D: Dynamic task allocation; **S**: Static task allocation ; **Part complexity** relates to parts' physical features (size, weight, shape, stability, sensitivity) and part feeding method (part presentation and refilling) in an assembly line. ; **Process complexity** relates to mounting, assembly (insertion direction and resistance, holding after assembly), and joining methods (bending, gluing, screwing) of parts. ; **Ergonomics** relates to considering workers' payload capacity and fatigue level. ; **Skills for task execution** means the required accuracy, dexterity, speed, flexibility, repeatability, and Force for performing a task.

Few studies adopt criteria for finding the best human/robot-task match that is different from Table 4.4, such as the trust between humans and robots during job execution (Wu et al. (2017), Rahman & Wang (2018), Rahman et al. (2023)). Rahman & Wang (2018) consider human and robot speed as a performance measure during the assembly task and argue that lower difference between their speed increases human workers' trust in their robotic partners. They investigate the impact of trust between working partners on the human's mental load and eventually on the overall task performance. Not only humans' trust in robots is influential but also robots' trust in their human partner affects collaborative workload that includes mental, physical, and temporal demands as well as performance (speed), frustration, and effort (Rahman & Wang, 2018). Wu et al. (2017) also connect the uncertainty of human behavior with fatigue and trust issues. In a comprehensive approach, Rahman et al. (2023) propose a model to quantitatively compute the trust level in human-robot collaboration and its integration into the cobot motion planning algorithm.

4.3.4 Collaborative robotic assembly line balancing problem (CRALBP)

This study is primarily concerned with reviewing the literature pertaining to collaborative robotic assembly line balancing problems (CRALBP), which will be discussed in this section. Table 4.4 lists the relevant papers and their key features and is followed by more detailed explanations of the table's data. Our analysis of each paper is based on four factors: Assembly line environment characteristics, human-robot in a station, line optimization decisions, and the methodology to find the optimal solution (Figure 4.7). In this regard, Table 4.4 reveals the configuration of each assembly line, the level of human-robot interaction, ergonomics and safety of collaboration, and the methodologies for optimizing the line balance.

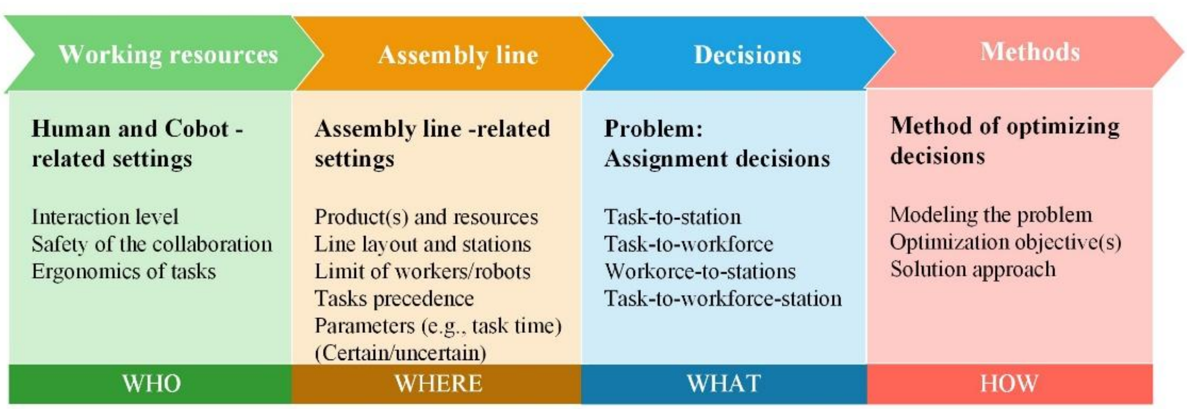

Figure 4.7. Building blocks of reviewed CRALBPs

Table 4.4. Collaborative Robotic Assembly Line Balancing Problem (CRALBP) literature

Reference	**Problem** *(s)*	**Assembly line features**	**H-R interaction level**	**Ergonomics/ Safety**	**Optimization criteria**	**Modeling approach**
Maganha et al., 2019	ALB Robot allocation Scheduling	2-P; UAL; one H and more than one R in a station;	Coexistence	-	Min number of robots	Heuristic (List algorithm); metaheuristic (stochastic descent)
Samouei & Ashayeri, 2019	ALB Resource selection	Multi model-P, SAL; **Demand uncertainty**	Collaboration	-	Min costs and cycle time	Mixed Integer Linear Programming (MILP) model and Robust model
Weckenborg & Spengler, 2019	ALB Scheduling	1-P; SAL; More than one R	Cooperation	Energy expenditure	Min costs per cycle	Mathematical model; GA
Yaphiar et al., 2019	ALB	Multi model-P; SAL; One cobot type	Collaboration	-	Min investment and operational costs	Mathematical model
Abdous et al., 2020	ALB Equipment selection	1-P; SAL; One H; one piece of equipment at each station	Cooperation	Workers' fatigue model	Min total costs and workers' fatigue	Nonlinear Programming (NLP) model; metaheuristic (Iterative Local Search)
Weckenborg et al., 2020	ALB Scheduling	1-P; SAL; One cobot type	Collaboration	-	Min cycle time	Mixed Integer Programming (MIP) model; GA
Rabbani et al, 2020	ALB	Multi model-P; Four-sided AL; More than one R	Synchronization	-	Min stations and H and R costs	Mathematical model, metaheuristic (particle swarm optimization (PSO))
Çil et al., 2020	ALB Scheduling	Multi model-P; SAL; More than one R	Cooperation	-	Min cycle time	MILP model, metaheuristic (Artificial bee colony)
Boschetti et al., 2021	ALB Scheduling	1-P; one station; one R	Cooperation	-	Min Makespan	Linear programming (LP) model
Dimény et al., 2021	ALB Scheduling	1-P; Simple AL; one R and one H in each station	Cooperation	-	Min workers, cobots, cycle time	MILP model and CPLEX solver
Koltai et al., 2021	ALB Scheduling	1-P, SAL; Shared and not-shared stations	Coexistence and Cooperation	-	Min stations and cycle time	NLP model; constraint programming (CP)
Kökhan & Baykoç, 2021	ALB	1-P; PAL; Given cycle time	Collaboration	-	Min labor cost and station opening	MIP model; metaheuristic (Simulated annealing (SA))
Li et al., 2021	ALB	1-P, SAL, several types of R	Synchronization	-	Min cycle time and cobot purchasing cost	MILP model, metaheuristic (migrating bird optimization (MBO))

Table 4.4. Collaborative Robotic Assembly Line Balancing Problem (CRALBP) literature (Continued)

Reference	Problem (s)	Assembly line features	H-R interaction level	Ergonomics/ Safety	Optimization criteria	Modeling approach
Nugraha et al., 2021	ALB	1-P; Two-sided AL; Renting R and tools	Collaboration	-	Min total costs (including training and equipment rental)	MILP model solved by CPLEX solver
Shan et al., 2021	ALB H and R allocation	1-P; Two-sided AL; Given number of stations; varied R capabilities; same H skills	Cooperation	-	Min cycle time and cost (including cobot purchase and employee hiring)	MIP model; non-dominant sorting genetic algorithm-II (NSGA-II)
Suer et al., 2021	ALB Scheduling	2-P, single station	Cooperation	-	Min cycle time and max output	Simulation; heuristic
Abdous et al., 2022	ALB Equipment selection	1-P; SAL; varying equipment task time	Cooperation	Fatigue level	Min investment cost and workers' fatigue	MILP model; ϵ-constraint method
Chutima & Khotsaenlee, 2022	ALB	2-P; PUAL; Normal and disabled workers	Coexistence	Limited Human tasks to avoid overload	Min time, workload, M2.5 emission, human workload; Max tax benefit	Mathematical model; metaheuristic (teaching-learning-based optimization (NSTLBO III))
Dalle Mura & Dini, 2022	ALB	1-P; Simple AL; H job rotation and skill level	Collaboration	Energy expenditure	Min assembly cost and workers' energy load	Mathematical model; GA
Dimény & Koltai, 2022	ALB; Cobot selection; Scheduling	1-P; SAL; Parallel and joint tasks; Given number of stations	Collaboration	humans' workload depend on the number of robots	Min number of robots and workload	Two MILP models solved by CPLEX
Keshvarparast et al., 2022	ALB; H & R allocation	1-P; One cobot type; Limited number of R; H experience level	Collaboration	Humans' workload: Borg score	Min cycle time and human physical workload	MILP model solved by GAMS
Kinast et al., 2022	ALB; Cobot allocation; Scheduling	1-P, mixed SAL and PAL, Limited number of R, given number of stations	Collaboration	-	maximize production costs and Makespan	CP model; metaheuristic (genetic-variable neighborhood search)
Nourmohammadi et al., 2022a	ALB; H & R allocation Scheduling	1-P; SAL: 2 stations; Given number of R and H; H skill level	Cooperation	-	Min cycle time	GA

Table 4.4. Collaborative Robotic Assembly Line Balancing Problem (CRALBP) literature (Continued and end)

Reference	**Problem *(s)***	**Assembly line features**	**H-R interaction level**	**Ergonomics/ Safety**	**Optimization criteria**	**Modeling approach**
Nourmohammadi et al., 2022b	ALB, H & R allocation Scheduling	1-P; SAL, H and R skill levels, limited number of H/R in each station	Collaboration	-	Min cycle time and number of workers	MILP model; SA
Pabolu et al., 2022	ALB Worker assignment	1-P; SAL; Given cycle time; **Learning-based task time** (prediction)	Collaboration	-	Min number of stations	MILP; Digital twin
Papetti et al., 2022	ALB in AL design problem	Mixed model-P; UAL; Industrial machines	Cooperation	Safety assessment; RULA and OCRA	Min cycle time, safety risk, costs, ergonomic risk, and Max flexibility	Virtual simulation by Technomatix
Sikora & Weckenborg, 2022	ALB; Cobot allocation; Scheduling	1-P; SAL; H presence at each station; Given number of stations	Collaboration	-	Min cycle time and Makespan	MILP model; Benders decomposition algorithm
Stecke & Mokhtarzadeh, 2022	ALB; Cobot allocation; Scheduling	Multi model-P, SAL	Collaboration	Energy expenditure	Min cycle time and ergonomic risk	MILP model, CP, Benders decomposition
Weckenborg et al., 2022	ALB	1-P; SAL, No parallel tasks	Cooperation	Energy expenditure	Min costs and workers' biomechanical load	MILP solved by Gurobi
Mura & Dini, 2023	ALB H & R allocation	Mixed model-P; Given cycle time; H job rotation and skill level	Collaboration	Noise exposure, energy expenditure	Min total cost and workload	A software tool based on GA (in MATLAB)
P: Product (e.g., 1-P: one product); **R:** Robot (in this context all robots are collaborative); **H:** Human worker**; AL:** Assembly Line**; ALB:** Assembly Line Balancing**; Assembly line layouts: SAL** (Straight assembly line with serially arranged stations); **PAL** (Parallel assembly line); **UAL** (U-shaped assembly line)						

A. Problem(s)

The purpose of an Assembly Line Balancing problem (ALBP) is to assign tasks to the workstations considering some requirements with the aim of optimizing one or multiple objectives to achieve efficiency (Battaïa & Dolgui, 2022). The presence of a Cobot that collaborates with a human partner in a fenceless workstation turns the ALBP into a Collaborative Robotic Assembly Line Balancing Problem (CRALBP). A CRALBP considers heterogeneous workforces (Human/Cobot) with different task times and capabilities in task execution. Some tasks may not be appropriate for cobots or humans due to technological constraints or safety and ergonomic concerns. Moreover, human workers and cobots can complete tasks together or in parallel in a workstation. These are the typical constraints that HRC imposes to a basic ALBP (Boschetti et al., 2021).

This section focuses on CRALBP, but these studies mostly hybridize ALB with other decisions. For instance, many CRALBPs assign tasks to the workforce (Humans/Robots/Both) and then to the workstation and integrate ALB and worker assignment decisions. Thus, the problem column of Table 4.4 contains all decisions covered by each paper. ALB with resource allocation and ALB with scheduling are two common combinations of decisions in the reviewed CRALBP literature.

- CRALBP with working resource selection/allocation

In I4.0, choosing the type of cobot is a strategic choice. (Dolgui et al., 2021). Li et al. (2021) integrate the assumption of different cobot types in a multi-objective CRALBP optimizing the cycle time and cobot purchasing cost. Human workers in this research are identical with similar skills as opposed to Mura & Dini (2019, 2022) and Samouei and Ashayeri (2019) who consider diversely skilled human workers. Mura & Dini (2019) minimize the number of skilled workers as an optimization criterion. Mura & Dini (2022) analyze the economic and ergonomic impact of adopting a workers' job rotation strategy. The CRALBP by Samouei & Ashayeri (2019) includes resource selection decisions assuming various capabilities among human workers as well as robots. In contrast, the assembly line in Abdous et al. (2020) research contains equipment (e.g., a robot) capable of performing all operations in the same way. Then, Shan et al., (2021) examine balancing and resource allocation problems in an assembly line with identical human workers and varied cobots' capabilities.

The decision on the optimal number of cobots is integrated into the study of Dimény & Koltai (2022) to achieve the desired level of human workload while satisfying the economic objective of CRALBP. 45% of the collaborative balancing problems in the review, combine the workforce selection/allocation with the balancing problem and 70% of them relate to 2022 or later. This increasing trend shows the interest of researchers in developing more comprehensive approaches to optimize human-robot collaboration in assembly operations. For instance, Sikora & Weckenborg (2022) extend a line balancing problem with a cobot assignment and scheduling program and propose a unified methodology for a range of decisions from strategic to operational.

With different settings in the assembly line, Maganha et al. (2019) merge the robot assignment, task allocation, and scheduling problems. Since the robots are mobile in that assembly line, robot allocation is not a strategic decision but operational. Clarifying exact boundaries between the categories of HRC studies is difficult as researchers merge multiple of them into their model and develop a more comprehensive methodology. Vieira et al. (2021) investigate the resource allocation and task scheduling problems in the HRC context with a recursive optimization-simulation approach that minimizes costs and Makespan respectively. The required number of robots per planning period is one of their model outputs. Some researchers like Malik & Brem (2021) investigate HRC cell layout optimization in which resource (robot, tools, etc.) selection is a part of the optimal decision. They address a variety of decisions from resource selection and task allocation to robot control programs and online collision detection. The resource-to-station allocation and task scheduling are also studied in a novel optimization-simulation approach. However, the HRC design problems are not within the boundaries of this review and recently Simões et al. (2022) explored the relevant literature.

- CRALBP with Scheduling

Some researchers from Table 4.4 (CRALBP literature) merge the line balancing problem with scheduling inside the collaborative stations to avoid interference of robots and humans during task execution (Weckenborg et al. (2019), Boschetti et al. (2021), Stecke and Mokhtazadeh (2022), and Nourmohammadi et al. (2022a, 2022b)). Here, the combination of task allocation and sequence planning is referred to as a scheduling problem. Scheduling becomes a critical decision in stations where humans and robots work in parallel or jointly in a shared fenceless workspace and the safety of humans will be as important as cost and time objectives. Although assembly line cobotization with parallel/joint tasks decreases the cycle time as an advantage (Koltai et al. (2021), Keshvarparast et al. (2022)), they generate safety challenges (Papetti et al., 2022). Therefore, the optimization models should offer an optimal task execution timing (schedule) that avoids any interference in the workforce's operations and satisfies the tasks' precedence relations at the same time. For the sake of obtaining the optimal result and considering safety issues, studies like Rabbani et al (2020), Li et al. (2021), and some others listed in Table 4.3 assume that parallel tasks are not allowed in the assembly stations.

Optimal scheduling of tasks in a human-robot collaborative assembly cell is the target of many studies without mixing it with a line balancing problem. To enrich our CRALBP literature, we do not remove these papers from the list and present them later in Section 4.3.5. Moreover, some studies that specifically relates to allocating tasks between human and robots are mentioned in 4.3.2.

B. Assembly line features

Each study deals with an assembly line with unique configurations and we summarized the main features in Table 4.4 In this regard, the layout of the assembly line (Straight, Parallel, U-shaped, Multi-sided, or Mixed), the number of products in the line (Single, multi, or mixed products), workers' characteristics (disabled, skilled, different task times), uncertainty of parameters, and specific policies such as job rotation and permitted parallel task execution are inspected. Definitions of assembly lines with different layouts and products are given in the table of definitions in paper Appendix 1. A common pattern found in the reviewed papers is the use of static and deterministic parameters in all but one case. Thus, we do not repeat this data for each paper and mention the only exception in Table 4.4.

C. H-R interaction level

Based on the five levels of interaction between humans and robots in an assembly line (Cell, Co-existence, Synchronization, Cooperation, and collaboration) and their features by Petzoldt et al. (2022), there is an H-R interaction level column in Table 4.4 Optimization models allocate the tasks to the workforce in 4 maximum possible ways: human, cobot, human or cobot, and both human and robot. Whenever a human and a robot perform a job simultaneously in a common space and share their time, it is called a true "collaboration" (Figure 4.8). However, in "cooperation", they execute the tasks in sequential orders in a shared area, unlike the "synchronization" level. Whenever the robots have cages or fences and work in a separate area from humans without sharing tasks or contact probability, it is a "Cell" level. "Coexistence" looks like a "Cell" without the robot's physical barriers (Petzoldt et al. 2022).

D. Ergonomics/ Safety

An objective of the new Industry 5.0 approach is to use technologies in a resilient way and shift manufacturing systems toward being more human-centric (Abdous et al., 2022). In this context, the ergonomics and safety of human workers in collaborative assembly lines, as well as the reduction of potential health risks, become important.

Researchers (Dimény & Koltai (2022), Weckenborg et al. (2020), and Tsarouchi et al. (2017)) argue that utilizing robots in assembly improves the safety and health condition of workers. In fact, cobots improve the ergonomics of the workplace by executing strenuous, repetitive, or boring tasks (Papetti et al., 2022). However, human-cobot interaction in a fenceless environment raises safety concerns and requires further attention to improve workers' safety during collaboration (Boschetti et al., 2021). For instance, a heavy part that increases the kinetic energy of the robot during manipulation is a threat to its human partner and increases safety risks (Malik & Bilberg, 2019b). Therefore, we examined the papers to find the problems that incorporate ergonomics and safety concerns into their developed methodologies or proposed framework. Such studies can be considered as the first steps toward Industry 5.0 with human-centric policies.

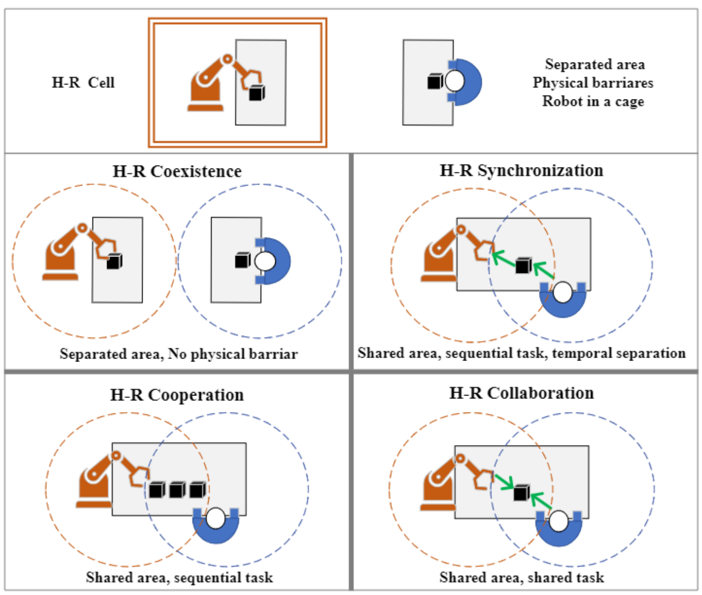

Figure 4.8. Four human-robot interaction levels

E. Optimization criteria

Optimization criteria evaluate the solutions obtained for assembly line balance problems (Boysen et al., 2007). Minimizing the number of open stations and minimizing the cycle time are two primary objectives in traditional assembly lines respectively known as ALB type 1 and ALB type 2. A column in Table 4.4 is dedicated to the criteria that evaluate the results of CRALBPs. In addition to these main objectives, CRALBPs utilize human workload, ergonomic risks, costs (e.g., labor costs, equipment costs), and the number of cobots or skilled workers as the evaluation criteria or objective functions in their developed models.

F. Modeling Approach

Developed methodologies for the reviewed CRALBPs are either Operation Research (OR)-based or simulation-based and the lack of learning-based techniques is significant. In the group of OR-based approaches, we can see a range of exact, heuristic, and metaheuristic algorithms. These methodologies generally begin with formulating the problem as a MIP, MILP, or MINLP model and then solve the model using constraint programming, benders decomposition, genetic algorithm, simulated annealing, and many other algorithms that are listed in Table 4.4 On the other hand, simulation-based approaches replicate the physical assembly line and its features in a virtual environment and evaluate the designed system in various situations to find the optimal decisions based on the situation.

Using the exact optimization techniques for solving CRALBPs is rare. Although they find the optimal solution for a problem, their performance highly depends on the size of the problem (e.g., number of operations and stations) and they are not suitable for large-scale problems (Stecke & Mokhtarzadeh, 2021). The most frequently used solution procedures to solve CRALBPs are heuristic and metaheuristics. They are often faster than exact algorithms and find good solutions in reasonable computational time. Nevertheless, it is difficult to guarantee the optimality of solutions when the problem's complexity grows, for example, due to the possibility of sequencing tasks in various ways (Weckenborg et al., 2020).

Rather than technology-driven designs, human-robot collaboration is moving towards a human-driven one to protect human health as a priority. To this end, it is required to consider the correlations between different drivers and features in a system with unpredictable human instead of static constraints and conditions. Simulation models provide the opportunity to discover the probable errors or risks (e.g., ergonomic risks) for human operators while analyzing the trade-off among multiple evaluation criteria. (Papetti et al., 2022). As human-robot collaborative assembly lines are complex systems with dynamic factors, simulation-based methods let us test the model in various conditions. However, developing a simulation model for a dynamic environment like a human-robot collaborative assembly line is difficult when model accuracy is critical to reliable results.

4.3.5 Human-Robot Collaborative Task Scheduling

This section aims to complement the literature review on assembly line balancing problems by listing some research works on scheduling problems. We refer to the studies on joint task allocation and sequencing problems as scheduling problems (Raatz et al., 2020) and investigate the methodologies for solving them in this section. The fenceless presence of a robot with a human operator working in parallel, concurrent, or sequential order in a common workplace requires planning the action of each working agent to satisfy the overall assembly necessities (e.g., task precedence) and optimization objectives (e.g., minimum assembly time). Thus, scheduling becomes essential for efficient human-robot collaboration. Table 4.5 contains the list of the research works on scheduling problems that we found while exploring the literature on assembly line balancing problems with Cobot. Note that some researchers (e.g., Mateus et al. (2020) and Wang et al. (2022b)) investigate the tasks' precedence generation methods for a product assembly process along with scheduling. The study of Wang et al. (2022b) contains a broad range of decisions from the decomposition of an assembly process into multiple tasks, finding the optimal sequence of executing tasks, determining the best responsible workforce with a task allocation model, and proposing the detailed tasks schedule using a genetic algorithm. However, reviewed articles in Table 4.5 assume that the precedence of executing tasks is predetermined.

Table 4.5. Task Scheduling Problems literature

Paper	**Uncertainty**	**Methodology**	**Optimization criteria**	**H-R interaction level**	**Ergonomics**	**Safety**
Wilcox & Shah, 2012	- D	Non-linear MIP model and an Adaptive Preference Algorithm	Min idle time, spatial interference	Synchronization	-	Check temporal/spatial interference
Chen et al., 2014	- D	Resource-Constrained Scheduling Problem; GA	Min assembly time and payment cost	Collaboration	-	-
Bogner et al., 2018	- S	Mathematical model, heuristic, metaheuristic	Makespan	Cooperation	-	Safety distance
Casalino et al., 2019	Human/ Robot task time S	Fuzzy-timed Petri Net with non-deterministic task time	Min human idle time	Collaboration	-	Safety zones to reduce robot speed

Table 4.5. Task Scheduling Problems literature (Continued)

Paper	Uncertainty		Methodology	Objective function	H-R interaction level	Ergonomics	Safety
Kousi et al., 2019	-	D	Combined Digital Twin and Artificial Intelligence techniques	Min Flow time, human payload, robot traveled distance; Max resource utilization	Collaboration	-	Collision-free trajectory planning
Wang et al., 2019	-	S	Simulation-based optimization	Min ergonomic load and cycle time	Collaboration	Lower Back Analysis (LBA) score	-
Mokhtarzadeh et al., 2020	-	S	Constraint Programming (CP)	Min Makespan	Collaboration	-	Safety distance limit
Nikolakis et al., 2020	Human presence	D	Two-level online ILP optimization model and event-based simulation	Min cycle time	Collaboration	-	Collision avoidance system
Raatz et al., 2020	-	S	GA and simulation	Min cycle time/ ergonomic risk	Collaboration	humans' posture and repetitive tasks	Assign harmful Jobs to robot
Yu et al., 2020	Environment	D	Reinforcement learning and Markov decision tree	Min job completion time	Cooperation	-	-
Zhang et al., 2020	Human task time	D	Nonlinear MIP model and GA	Min overall processing time	Collaboration	Human fatigue	-
Casalino, 2021	human task time	D	Markov model; Timed Petri Nets	Min idle time	Collaboration	-	Distance monitoring
Casalino et al., 2021	Human task time	D	Timed Petri Nets; Monte Carlo simulation	Min idle time; Max throughput	Collaboration	-	-
Ferreira et al., 2021	Task time	S	MIP model, Constraint Programming; GA	Min Makespan	Collaboration	-	-
Gualtieri et al., 2021a	-	S	A systematic framework; mathematical model	Min cycle time	Collaboration	Ergonomic evaluation	-
Pupa et al., 2021	-	D	Two-layer framework; MILP model and heuristic	Min idle time and execution time	Cooperation	-	Space and distance limits
Yu et al., 2021	-	D	Deep Q-network-based multi-agent reinforcement learning	Min task completion time	Synchronization	-	-

Table 4.5. Task Scheduling Problems literature (Continued)

Paper	**Uncertainty**		**Methodology**	**Objective function**	**H-R interaction level**	**Ergonomics**	**Safety**
Almasarwah et al., 2022	-	S	MILP model; shortest processing time rule; a heuristic	Min cycle time	Coexistence	-	-
Antonelli & Aliev, 2022	Human behavior	D	Real-time task allocation; Markov Decision Process, Dynamic Programming	Min completion time	Collaboration	-	-
Izghouti et al., 2022	-	S	GA	Min Makespan	Collaboration	-	-
Maderna et al., 2022	Human task time robot faults	D	Digital twin based on Timed Petri nets, simulation	Min completion time, idle time, part wait time	Collaboration	-	Wearable haptic bracelets
Monguzzi et al., 2022	-	S	Hungarian algorithm and MILP model	Min postural discomfort and cycle time	Cooperation	Human posture evaluation	-
Palacio et al., 2022	Task time	D	Flexible schedule by Reinforcement learning (RL) approach (Q-Learning)	Min assembly time	Cooperation	-	Safety zones
Pupa et al., 2022	-	D	Online framework for a resilient schedule-based AND/OR Tree; human skills included	Max actors' knowledge/skill level match	Cooperation	-	Human safety check in task assignment
Vieira et al., 2021	Human task time robot stoppage	D	Optimization-Simulation Approach: Two-level MILP model and discrete event simulation	Min operational costs and Makespan	Cooperation	-	Safety regulations (e.g., velocity)
Wang et al., 2022a	-	D	Digital Twin-based framework with GA	efficiency, safety, cost, and human factors engineering	Collaboration	H/R work ratio, human movement, power, and space	H/R conflicts/ contact, and robot work time in the collaborative area
Zhang et al., 2022c	-	S	Mathematical optimization model and GA	Min cycle time and human fatigue	Collaboration	Micro-breaks for recovery	Fatigue affects safety risk
Ren et al., 2023	-	S	MIP model; combined swarm optimization and GA: PSO-GA	Min completion time; production costs; automation level improvement	Collaboration	-	-

Table 4.5. Task Scheduling Problems literature (Continued and end)

Wang & Zhang, 2023	Task times	S	chance-constrained model; mathematical model with mixed-integer variables and nonconvex constraint	Min human/cobot reconfiguration cost and penalty costs for job delays	Collaboration	-	-
D = Dynamic task scheduling; **S** = Static/fixed task scheduling							

Human capabilities in performing an operation change over time in contrast with robot capabilities which are usually steady (Zhang et al., 2020). This change has roots in human trust, fatigue, task complexity, and other issues in the working environment. Thus, human is one of the dynamic factors in an assembly process. A column in the scheduling literature analysis (Table 4.5) shows whether the researchers captured any element of assembly uncertainty in their proposed static/offline or dynamic/online scheduling methodology. Dynamic task scheduling allows the model to apply system changes such as human performance and reschedule the activities of humans and robots based on the situation with the aim of avoiding useless waiting times and improving line performance (Pupa et al., 2021). On the other hand, the static approach considers a fixed sequence of operations and responsible agents without adapting to system changes. In human-robot collaborative systems, dynamic schedulers are more resilient to uncertainties, whereas static schedulers are incapable of providing flexible plans (Maderna et al., 2022).

Operation research (OR), simulation, and Learning-based techniques are the three main groups of solution approaches to tackle the scheduling problems of the reviewed papers. OR-based methods including heuristic and metaheuristic algorithms find optimal solutions for well-defined problems, but they are suitable for static scheduling problems as proven by reviewed papers in Table 4.5. Also, heuristics and metaheuristics do not demonstrate good quality results for large instances within a reasonable time (Bogner et al., 2018). Combining optimization with simulation is another methodology that Vieira et al. (2021) developed to satisfy the objectives of the scheduling problem while iteratively evaluating the dynamics of processes using a simulation model and implementing them in the scheduling optimization model. Although this method is less complex in terms of modeling, it is difficult to guarantee the accuracy and optimality of results obtained from the recursive optimization-simulation loops (Vieira et al., 2021). Nikolakis et al., (2020) who applied a two-level optimization-simulation approach discuss that these hierarchical models cannot find the optimal solution and the quality of results is highly dependent on the composition method of stages. However, they are suitable for the automatic generation of good solutions in a reasonable time for system reconfiguration. The general advantage of simulation models is considering the dynamics of human-robot collaboration and rescheduling the tasks in a way that minimizes inactivity times and maximizes the throughput (Casalino, 2021). Finally, learning-based techniques are appropriate for presenting real-world problems due to their strength in handling complex problems and using human expertise in their algorithms (Palacio et al., 2022).

Many papers (Table 4.5) mention human-robot collaboration in their title, abstract, or context, but they do not necessarily convey the correct collaboration definition in which humans and robots share space and time to work jointly on the same task of product assembly. This raises the need to implement real collaboration settings into CRALBPs in future studies. To enrich the problems' review, the researchers' effort in improving humans' ergonomic factors or occupational health and safety (OHS) is recorded. We tend to investigate how extensively they address these core concepts of cobot integration into assembly lines. For instance, Gualtieri et al. (2021a) analyze the economic feasibility of their solution by calculating the payback period (PBP) as a primary key performance indicator. Accordingly, investment in occupational health and safety (OHS) by integrating cobots into the system is included in the PBP value and is eventually a part of the net profit.

4.4 Discussion on literature trend

This section discusses the trends in collaborative robotic assembly line problems based on the reviewed papers in section 4.3. CRALBPs of Table 4.4 have four main problem patterns based on optimization decisions: CRALBP; CRALBPs and resource (H/R) selection/allocation; CRALBP and scheduling; CRALBP with both resource allocation and scheduling. More than 90% percent of the proposed problems in the reviewed literature of collaborative line balancing considered deterministic parameters. Also, researchers mostly (92%) investigate multi-objective problems. The following pie charts (Figures 4.9 to 4.12) uncover the other general configurations of these CRALBPs.

The review is not limited to CRALBPs and investigated the task allocation and scheduling decisions as well. In fact, each group of papers reviewed in section 4.3 targets a distinct level of assembly line optimization problems: Strategic automation level decision through task mode selection and human-robot task allocation, Tactical line balancing decisions, and operational scheduling. The trend of these studies over time indicates the initial focus on human-robot task allocation and scheduling problems and then balancing problems that arise in literature to create a comprehensive task-resource-station assignment approach (Figure 4.13).

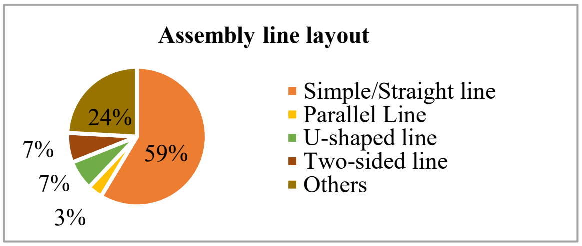

Figure 4.9. Assembly line layout in CRALBPs

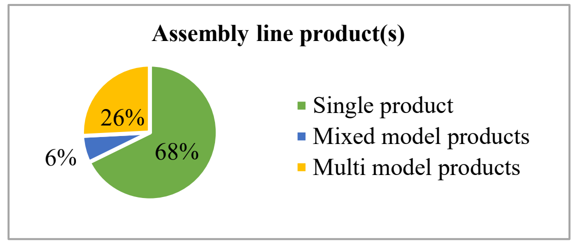

Figure 4.10. Product type in CRALBPs

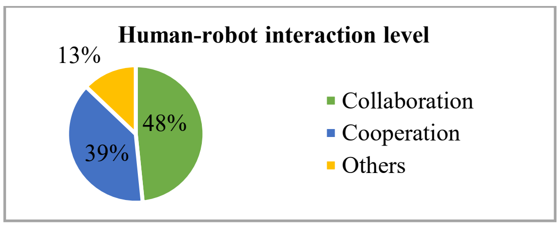

Figure 4.11. Human-robot interaction level in CRALBPs

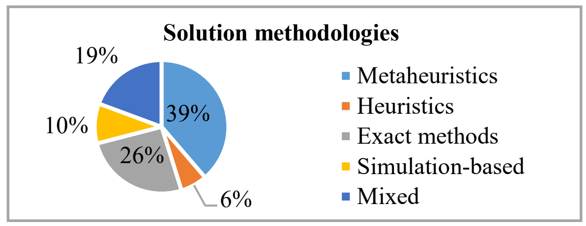

Figure 4.12. Methodologies applied to CRALBPs

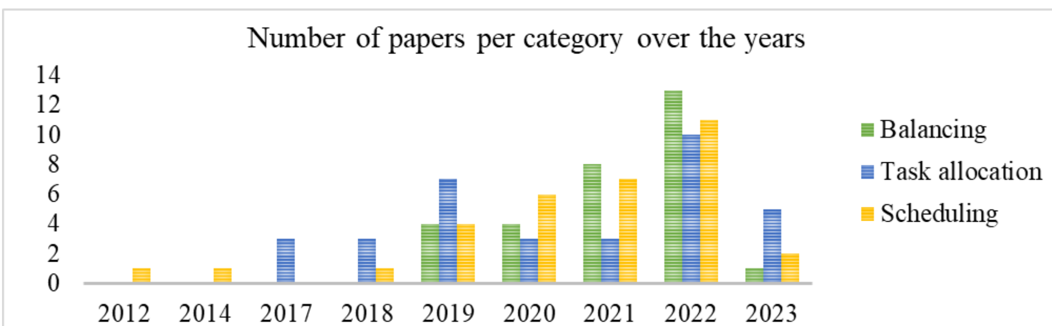

Figure 4.13. Number of papers in three main categories per year

The first group (Human-robot task allocation and task mode selection) relates to strategic decision-making of selecting a manual, robotic, or collaborative mode for each task. This finally defines the automation level of assembly lines. Humans and robots have different capabilities/ capacities that make them suitable for certain activities. This assumption is the starting point of many studies to investigate the suitable cobot type or required human skill for executing certain assembly tasks. These studies consider a group of abilities and limits for each working resource type and then compare them with the tasks' features to find the best mode (H, R, H/R, H+R) of all tasks. The complexity-based approach is the most utilized method for this decision. 80% percent of the reviewed task mode selection problems do not stop at this level and extend their approach to find a proper plan for allocating tasks to the resources in an assembly station. The best task-to-workforce assignment decision is mainly evaluated according to the optimal assembly time and then the ergonomics assessment of human operators in the literature (Table 4.3). Considering ergonomics in models could have two dimensions: first, regulating work condition boundaries to prevent human workers from fatigue/overwork; and second, determining the tasks in which the robot assistance would be beneficial for humans (Mateus et al., 2019).

All the researchers in Table 4.3, prefer a multi-objective task allocation approach rather than a single objective. Criteria such as production costs, safety, resource utilization, quality of the work, or probable errors in task execution are less adopted to evaluate the optimal assignment decision. Reducing time and improving ergonomics is the most common conflict in a human-robot collaboration that studies address in their problem. However, there are other conflicting objectives like time and safety or time and quality level. Collaborative areas are equipped with controlling devices and cobots have internal safety algorithms to prevent or reduce collision probabilities. For instance, the unexpected presence of a human in a robot's working area activates safety devices and algorithms to reduce the robot's speed or completely stop its action. Consequently, the assembly time will be increased to ensure the safety of a human operator. This dynamic environment requires dynamic allocation methodology which is considered in half of the reviewed papers in Table 4.3. The growing number of dynamic task allocation methods in recent years reflects the need for real-time approaches for safe healthy efficient human-robot collaborative environments. Some optimization models meet safety conditions by a spatial proximity constraint based on ISO 10218-1 and 2:2011 and ISO/TS 15066:2016 (e.g., Mokhtarzadeh et al. (2020), Pupa et al. (2021), Koltai et al. (2021)). A group of studies like Kousi et al. (2019) and Malik & Brem (2021) link task allocation and scheduling decisions with dynamic/online robot trajectory planning to ensure a safe collaboration. While these studies mainly investigate the collision risk, hazards are probable in exposure or contact levels which are neglected in the literature. Human exposition to radiation and vapors or contact with tools and cutting edges can be harmful (Mateus et al., 2019). Task analysis by Koltai et al. (2021) is one of the rare studies in which operation-related characteristics affect the human-robot safe distance.

The second group of reviewed papers (CRALBPs) basically relates to the tactical decision of optimally assigning the tasks to the stations known as assembly line balancing. After determining the proper stations, the balancing model should clarify which resource (H/R/Both) of collaborative stations is responsible for executing the assigned tasks. Therefore, worker assignment occurs inside a collaborative assembly line balancing problem. Few researchers develop a traditional-style line balancing problem while more than 80% of the studies in Table 4.4 combine it with other decisions mainly scheduling and resource selection/allocation to obtain more reliable outcomes. However, the assembly line features in these studies are still close to simple assembly line balancing problem characteristics. A simple serial assembly line with one product type and deterministic parameters that minimizes the cycle time or the number of stations. Moreover, as mentioned earlier, cooperation and collaboration terms are widely used interchangeably while they have different definitions. Sequential jobs as well as temporal and spatial separation of robots and humans are the strategies to decrease the complexities of collaborative environments like safety issues. Exploring the actual HRI level in balancing models proves that this area of research is in the infancy stage and needs more effort in developing methodologies that capture a real human-robot collaboration. Finally, 52% of the proposed solutions for CRALBPs are metaheuristic algorithms, specifically Genetic Algorithm (GA) with more focus on productivity metrics (minimum time, cost, and required resources) rather than ergonomics/safety objectives (Table 4.4).

The third group of reviewed papers is scheduling problems in the literature that control an assembly line at the operational level. When multiple resources work inside the same station, like the example of a human and robot, their action should be optimized to prevent any interference while taking advantage of their collaboration potential to improve the assembly process. For instance, parallel task execution decreases the cycle time, and robots can support human workers in heavy assembly operations and reduce the workload. However, humans and robots are two heterogeneous working resources, and their connection is not like two intelligent and flexible human agents. Thus, a great variety of studies are working on developing proper human-robot interfaces, human recognition algorithms for robots, and trajectory planning methods to improve their interaction. We removed these types of papers from this review and chose operational research-oriented methods like scheduling to investigate how researchers optimize H-R actions within a station. Like balancing problems, real human-robot collaboration is not necessarily addressed in the papers even if they use this term for actual H-R cooperation or synchronization. Furthermore, human behavior and intentions bring uncertainty into an assembly area. Fatigue decreases the human's reaction speed and generally reduces performance due to less concentration and the probability of failure in suitable response (Chen et al., 2014). However, around half (54%) of the studies reflect the dynamic or uncertain situation of assembly lines in their model. Selecting the optimal schedule is mainly based on minimum time (i.e., total completion time, cycle time, idle time) while other criteria such as safety and ergonomics are not included in all methodologies.

4.5 Future research directions

According to the analysis of content and exploring the literature trends, we developed a scheme for the existing studies and the future of research (Figure 4.14). The future of research works can go in two main directions. First, investigate the challenges of Cobot integration into assembly lines considering real or close to real constraints and features of assembly system environments. Second, tackling the complexity of proposed problems in the field of human-robot collaborative assembly line optimization using novel methodologies. Presented research areas of existing literature and future trends in each direction in Figure 4.14 are based on the 4 primary aspects of analyzed CRALBPs in 4.3.4 and Figure 4.7: Assembly line features, human-robot collaboration assumptions, hybrid decisions, and methodology development.

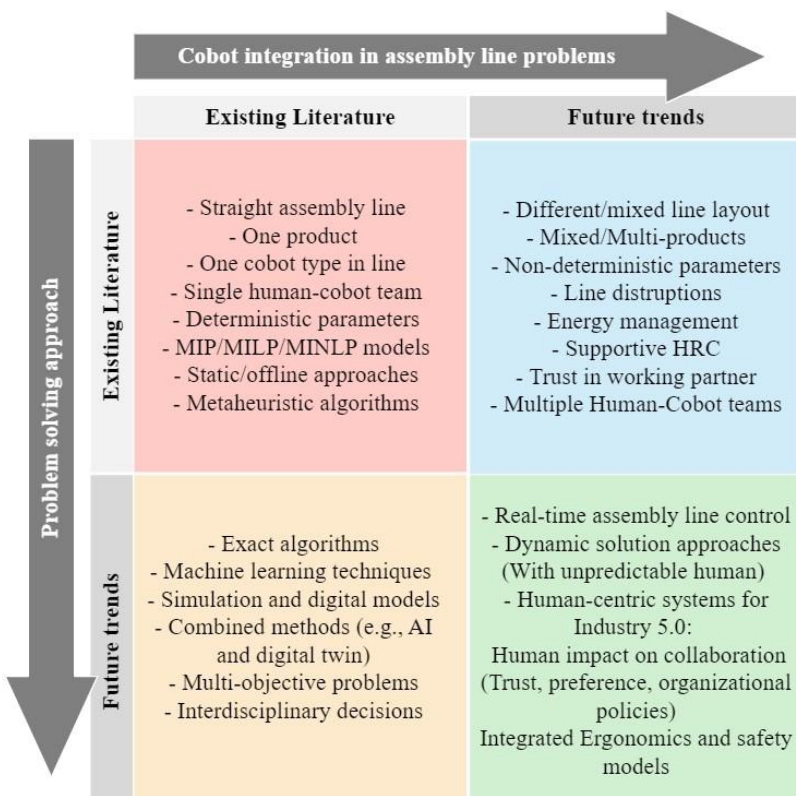

Figure 4.14. Existing literature and future trends for collaborative robotic assembly line optimization models

- Assembly line features

Straight assembly line (simple AL) with serially arranged stations is a common feature among most reviewed papers while researchers investigate parallel, U-shaped, or two-sided lines less, making them potential for further studies. Each of these line layouts has its own applications and is suitable for a different industry. For instance, parallel assembly lines perform operations at different mounting places at the same time contributing to satisfying the high volume demands for products (Kökhan & Baykoç, 2021). Two-sided lines are a special case of parallel lines but with stations that have a left-hand-side and a right-hand-side workspace (Boysen et al., 2007) which has the potential to be used for collaborative lines where humans and robots work together in different locations. As a result, future research has the potential to investigate various layouts to enrich the literature and help the manufacturers in finding a solution according to their industrial settings. Cobotics researchers claim that cobots are safe for close work with humans, but hazards could have other sources such as technological errors, contact with tools/materials, and human mistakes. Human-robot collaboration in performing tasks requires a short distance between them that may lead to collision and frequent collisions reduce the productivity in an assembly line (Malik & Brem, 2021). Therefore, there is an opportunity to study the impact of parallel/join operations on assembly performance (e.g., cycle time) along with physical or mental safety concerns in the optimization model. Furthermore, researchers have not addressed real human-robot collaboration adequately and task execution is mostly sequential in which humans and robots share the space, not the assembly time. Hence, more studies on true collaboration rather than the synchronization or cooperation of humans and cobots are essential for future research. Another promising research dimension is the selection of cobot type and its proper collaboration mode (Safety-rated monitored stop; Speed and separation monitoring; Hand guiding; power/force limitation) in transferring existing manual lines into a semi-automatic. Cobots are not widely used in many industries yet and this highlights the need for helping manufacturers decide about the best cobot type and its integration requirements. So that they can take the steps towards utilizing robots and managing the assembly lines with less difficulty and safety concerns. These topics mainly relate to the strategic decisions during the design phase but in the case of light cobots or mobile robots can change at lower levels (mid-term/short-term decisions). Finally, examining the impact of an organization's workforce strategy like hiring walking or temporary workers instead of fixed and high-skilled workers in a collaborative environment could be a potential avenue of research. High-skilled workers are usually expensive resources, and temporary or un-skilled workers may increase the safety risks in collaboration with cobots. Thus, decision-makers should clarify what are the essential skills required for collaborative assembly lines and then determine the suitable strategy for resource utilization.

- Collaborative assumptions

Considering close-to real-world assumptions in formulating an assembly line optimization problem is a key to more realistic results. Non-deterministic task execution time, human skills levels, demand fluctuations and uncertainties (e.g., human action/intentions, system breakdown), physical safety/ergonomic risks, social factors (trust), mental workload/fatigue, stress, environmental aspects, organizational supporting strategies regarding the cobot integration into the assembly lines are some elements that worth integrating with CRALBPs. Future research can explore these assumptions in strategic, tactical, and operational assembly line decisions for various industries. Humans are a source of uncertainty in collaborative work, and they can not perform a task in a certain time. Their performance may change over time due to fatigue or mental pressure and they may change their preference in executing tasks. Moreover, humans learn over time and researchers can capture the real nature of human workers by considering their learning curve for performing a task over time.

- Hybrid decisions

According to the recent review of Battaïa & Dolgui (2022) and papers in section 4.3, the recent trend in assembly line balancing is hybridizing with other decisions to develop a comprehensive framework for decision-making. A limited number of existing research in the collaborative assembly line area of research developed a framework that starts with the HRC design phase and continues to include decisions at all strategic, tactical, and operational levels. However, the literature on this kind of paper is new and requires more case studies in different industries. For example, combining the tactical assembly line balancing with robot type selection or required human skill level (Tactical and strategic decisions) is an example of a promising hybrid optimization problem for future studies.

- Methodology development

Although metaheuristics algorithms are promising methods according to the literature, other approaches like column generation, constraint programming, decomposition algorithms, and multi-agent systems (Sabar et al., 2009) for traditional assembly line problems can be updated and adapted for collaborative environments. Also, developing multiple models and comparing the developed methodologies in different industrial cases enrich the literature. Since many workpieces and resources are present in assembly line environments, this part of a production facility is dynamic and complex. Cobots with extra setups and proximity to unpredictable human workers in a fenceless environment increase the complexity and dynamics. However, recent I4.0 technologies in assembly lines provide the facilities with the required infrastructure for developing a digital model of physical assembly systems and predicting the events before their occurrence specifically in operational decisions. Accordingly, researchers can mix online simulation and optimization techniques to create digital models and tackle the uncertainties leading to more flexible and reliable assembly plans.

Learning-based techniques such as reinforcement learning, and deep learning are the other methods to confront complex problems. Papers in robot program development, robot path planning, and human recognition greatly utilize these techniques while few studies in the current literature review (task allocation, scheduling, and balancing problems) applied them. The human-robot collaboration happens in a human-centric environment in which robots must handle the uncertainty of their human partner to ensure a safe workspace. For instance, reinforcement learning, and deep learning can be utilized in task allocation, balancing, and scheduling to learn/understand the actions and intentions of humans in collaboration with a robot and update the task execution time based on the situation. In case of any change in the working environment, assembly parts/products, or human workers whose characteristics (body, habits, speed, etc.) are different, transfer learning employs its knowledge from previous learning to identify the new condition. Future research can examine hybrid techniques like the study of Lv et al. (2022) that combine reinforcement learning and transfer learning in the context of a human-robot collaborative assembly.

Finally, considering product quality, environmental or organizational goals, and occupational health and safety including ergonomic assessment ergonomics along with other objectives of the existing CRALB problems is another encouraging research path. HRC primarily aims at improving the worker's health conditions and many researchers evaluate human body workload as its measuring index. However, other occupational health and safety risks including collision risk, mental fatigue, and environmental hazards are not adequately integrated into task allocation, balancing, and schedule optimization methodologies. The joint optimization of safety aspects and other line productivity elements ensures a more reliable working environment for humans and affects their trust in cobots.

4.6 Conclusion

The article reviewed the research works on human-robot assembly task balancing decisions for the period of 2012-2023 based on their developed optimization methodologies. WOS and EV are the two main sources of the 97 final selected documents for the full content review. While the review primarily focuses on collaborative assembly line balancing models, task allocation and scheduling problems are included to enrich the review. The decisions of these models are within three main categories of strategic, tactical, and operational decision-making in assembly lines with cobots. According to the CRALBP literature, most researchers maintain the simple assembly line balancing characteristics and apply a metaheuristic algorithm for an optimal solution. Time, as a productivity indicator, is the most utilized decision evaluation criterion in all three main groups of problems. Moreover, the real dynamic environment of an assembly line such as uncertain human behavior and possible robot failures are not included in half of the reviewed papers. Researchers apply the cooperation and synchronization levels of HRI instead of collaboration to reduce the probable safety issues or avoid problem complexities. Thus, real human-robot collaboration and joint assembly task execution are still challenging and require more effort in solution methodology development.

Working on methodology development, considering various assembly line features, addressing the challenging features in HRIs, and hybrid problems are the four research directions for future studies based on the current literature review. Since CRALBP is in infancy levels, a mixture of characteristics from these four topics as well as conducting a specific case study from various industries forms novel problem configurations.

CHAPTER 5 ARTICLE 2: SAFETY-DRIVEN OPTIMIZATION OF HUMAN-ROBOT COLLABORATIVE ASSEMBLY LINE BALANCING

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Résumé

Dans le domaine dynamique de la fabrication avancée, l'intégration de robots collaboratifs (cobots) dans les chaînes d'assemblage s'impose comme une approche transformatrice visant à améliorer l'efficacité et la qualité du travail humain. Cet article traite le défi de la sécurité en collaboration humain-robot (HRC) dans le cadre d'un problème d'équilibrage de ligne d'assemblage (ALBP) visant à minimiser le temps de cycle. Un modèle basé sur la programmation par contraintes (CP) assigne de manière optimale les cobots aux postes de travail, répartit les tâches d'assemblage entre humains et cobots, et en détermine la séquence sur une ligne à modèle unique. Le modèle CP intègre une nouvelle politique de zonage au poste de travail, conçue pour éliminer les tâches parallèles présentant un risque moyen ou élevé dans un poste collaboratif. Des exemples numériques illustrent l'impact de cette politique. La comparaison des résultats optimaux obtenus avec et sans contraintes de zonage dans le HRC-ALBP montre une amélioration de la sécurité, au prix d'une légère augmentation du temps de cycle. Cette contribution aide à rapprocher les objectifs de sécurité en HRC et les objectifs opérationnels. Moyennant des modifications mineures, une seconde version du modèle minimise le nombre de cobots utilisés, offrant des perspectives supplémentaires sur l'optimisation de leur intégration. En considérant différentes fonctions objectif, des contraintes orientées sécurité et des enseignements managériaux, ce travail contribue à la création d'un outil d'aide à la décision aligné sur les principes de l'Industrie 5.0 centrés sur l'humain.

Abstract

In the dynamic field of advanced manufacturing, integrating collaborative robots (cobots into assembly lines has emerged as a transformative approach to improve efficiency and human job quality. This paper addresses the safety challenge of human-robot collaboration (HRC) in the context of an assembly line balancing problem (ALBP) aimed at minimizing cycle time. A constraint programming (CP)-based model optimally assigns cobots to workstations, allocates assembly tasks between humans and cobots, and sequence them on a single-model line. The CP model includes a novel workstation zoning policy to eliminate the medium and high-risk parallel tasks in a collaborative workstation. Numerical examples illustrate the impact of the proposed policy. Comparing the optimal results in the presence and absence of zone constraints in HRC-ALBP reveals improved safety at the cost of a minor increase in cycle time. This contributes to bridging the gap between HRC safety and operational goal. With minor modifications, a second version of the model minimizes the number of cobots used, providing further insight into the optimization of cobot integration. By considering different objective functions, safety-oriented constraints, and managerial insights, this work contributes to the creation of a decision-support tool that aligns with the human-cantered principles of Industry 5.0.

Keywords: human-robot collaboration, assembly line balancing, human-centred systems, occupational health and safety

5.1 Introduction

Robots are well-established in manufacturing environments, with diverse applications ranging from material handling and executing manufacturing operations to packaging the final product. Traditionally, industrial robots are enclosed by safety fences, preventing human operators from entering their designated work areas during active operations. Similar to self-driving cars, industrial robotics and automation aim to reduce or eliminate the need for human involvement in performing tasks. (Kolbeinsson et al., 2019). While automated processes hold the potential for throughput and quality enhancement, the cognitive capabilities of robots remain constrained. Consequently, fully automated systems encounter challenges in executing complex or adaptable tasks in dynamic or uncertain environments like assembly lines. (Johannsmeier & Haddadin, 2017).

Over the years, industrial evolution has led to a growing prevalence of customized products, resulting in increased variation in product orders. Manual assembly lines can adapt more flexibly to such variability but accuracy challenges and ergonomic issues due to repeatability exists. Human-robot collaborative (HRC) assembly lines are one of the solutions through which robots and humans can work together to achieve flexible, precise, and productive tasks (Boschetti et al., 2021). As one of the enabling technologies of Industry 4.0, collaborative robots (cobots) work alongside humans without physical barriers and are easier to program than traditional industrial robots. It enables companies to benefit from robot's precision and a human's intellectual flexibility (Papetti et al., 2022). Cobots are advantageous for disassembly and end-of-life products due to their high precision (Amirnia & Keivanpour, 2024)

Müller et al. (2017) identify four categories of human-cobot interaction in assembly processes: (1) Coexistence, where the human and cobot operate in separate workspaces without any direct interaction; (2) Synchronization, where they share the same workspace but work at different times; (3) Cooperation, where both work in the same workspace simultaneously but focus on different tasks; and (4) Collaboration, where the human and cobot work together simultaneously on the same task in the same workspace. These interaction levels can be employed at assembly workstations depending on task requirements, the capabilities and availability of humans and cobots, and productivity, ergonomics, or safety goals.

Cobots are defined as safe by design and other complementary devices like cameras and sensors are active in collaborative workstations to ensure a reliable human-robot collaboration. However, the reduced speed of cobots for safety purposes conflicts with the line’s productivity measures and bring inefficiency to the system (Chemweno et al., 2020; Berx et al., 2022; Krüger et al., 2009). According to Berx et al. (2022), 44% of human-robot collaboration risk factors relate to technology and 27% to humans. Considering technological vulnerability of safety system and inevitable human presence with potential errors, human-robot collaboration is not always flawless (Malik & Brem, 2021). As devastating human injuries cannot be tolerated, additional layers of safety assurance measures are required. On the other hand, safety systems of cobots and workstations namely proximity, property, and force-torque sensors adjust robot motions or stop their movement to minimize human-robot collision (Malik & Brem, 2021). A problem that arises from this context is how to reduce cobot task interruptions caused by safety systems without compromising productivity goals (e.g., cycle time).

Cobot types and the skills to use them are strategic decisions that impact the safety of HRC. Dynamic task scheduling and robot path planning are two methods at the operational level of collaborative workstation decisions to prevent unexpected contact between humans and cobots (Dolgui et al. (2022), Gualtieri et al. (2021b)). In this context, safe, warning and danger zones are defined around cobots to ensure human safety. According to ISO/TS 15066, “Safety Stop” operational mode forces the cobot to stop when a human enters a predefined safety zone. "Speed and Separation monitoring" and "Power and Force Limiting" modes use sensors to adjust Robot velocity, force, and pressure based on human distance and exposed body region. However, assembly lines with large-sized products or multi-manned layout apply zoning strategy to divide workstations into multiple workplaces where each worker are separated and perform tasks inside their dedicated zone. Therefore, the ALBP assigns the tasks to the workplaces (zones) inside the workstation and manages workforce scheduling in complex assembly processes and enhances material handling (Zangaro et al., 2023). ALBPs take advantage of zoning concept to define the connection or incompatibility of among tasks or stations in various assembly layouts (Yin et al., 2021; Fathi et al., 2019). Combining HRC and ALBP zoning concepts, we present a novel approach to safety assurance in collaborative assembly lines. The human-robot collaborative assembly line balancing problem (HRC-ALBP) has been discussed in the literature (Table 5.1), but optimal decisions are not influenced by safety factors.

The configuration of the assembly system (cobot assignment) and line balancing (task-resource-workstation assignment) are two investigated tactical decisions in the current study. Furthermore, scheduling the tasks inside each workstation is conducted to determine the sequence of task executions by human and cobot in collaborative workstations. This schedule is based on the precedence network of tasks for one product, availability of workforce, and safe zone constraints promoted as the "Safe Zone Policy" throughout the model. This policy focuses on a safe task assignment strategy independent of the cobot's internal safety mechanisms and eliminates the unnecessary proximity of the cobot to the human in a workstation causing hazards and process interruptions. A set of constraint programming (CP)-based mathematical formulations model our investigated single-model assembly line balancing problem with cycle time minimization objective, allowing parallel task execution under certain circumstances. CP approach has been widely used for worker assignment, balancing and scheduling problems due to its flexibility in modeling such complex problems. Studies by Vahedi-Nouri et al. (2024), Güner et al. (2023), and Işık & Yildiz (2024) discuss its performance over Mixed Integer Linear Programming (MILP) methods. Since cobot utilization is associated with costs, safety challenges, and line configuration changes, minimizing the number of used cobots is the other optimization objective investigated by the same CP model. Given the number of workstations and cycle time, it determines how many cobots can achieve a specific production goal.

In summary, this study promotes both efficiency and safety in manufacturing environments and contributes to the existing literature with the following characteristics:

•Conceptualized safety risks in a mathematical model by proposing the “Safe Zone Policy”. This model incorporates the risk of human-cobot proximity in collaborative workstations as a constraint while targeting productivity improvement by cycle time minimization. Considering the duration of human exposure to the potential source of hazards (Cobots) fills the literature gap of lacking a measurable safety factor integrated into line balancing decisions.

•Constraint programming (CP)-based formulations model a complex scheduling problem resulting from the proposed safe zoning policy in a compact manner. As an exact approach to solve the Human-Robot Collaborative Assembly Line Balancing Problem (HRC-ALBP), it finds the optimal solution using CP-SAT solver of python OR-Tools.

•A modified version of the CP model minimizes the number of cobots as a rarely explored objective function in literature. Exploring an alternative objective function with minor formulation adjustments highlights the flexibility of problem formulation approach and potentials to offer more insights into cobot utilization for SMEs.

•A focused discussion on incorporating Human-Robot Collaboration (HRC) risks into the assembly line's tactical decision-making process while exploring different objectives and impacts of constraints and parameters. This lays the groundwork to establish the foundations of a decision support system with human-centric industry5.0 perspectives in future research.

A literature review in section 5.2 investigates the existing studies about the relevant topics. Examining detailed specifics of papers and understanding the literature gaps clarifies the contribution of the present work. Section 5.3 starts with explaining the traditional ALBP and proposed HRC-ALBP differences and followed by a full description on the problem assumptions and applied methodology. The computational experiments are presented in section 5.4 to reveal the relationships among problem size, solution time, and optimal objective functions, as well as the impact of implemented safe decision-making strategy. Section 5.5 provides managerial insights into the results, offering valuable information for decision-makers. Current research on Human-Robot Collaborative Assembly Line Balancing Problems (HRC-ALBP) is still in its early stages, with significant potential for future exploration. In the conclusion (Section 5.6), we will outline promising directions for future research. Appendix A (5.7) presents an example of HRC-ALBP in illustrative form.

5.2 Literature review

5.2.1 Assembly Line Balancing Problem (ALBP)

Assembly line balancing has been extensively studied in the literature over the past few decades. Principals and basic definitions related to the assembly line balancing problem can be found in the work of Boysen et al. (2007). With the advancement of technology and market demands, production and assembly systems are continually evolving. Therefore, researchers have refined their assumptions about the assembly line balancing problem and developed improved methodologies based on real-world problems. Boysen et al. (2022) have reviewed the assembly line balancing research trend over the last fifteen years. Simple Assembly Line Balancing Problems (SALBPs) assign tasks of one homogenous product, according to their precedence, to sequentially arranged workstations, each with one worker type, and optimize cycle time or the number of workstations (Baybars (1986); Becker and Scholl (2006)). Extending SALBPs by more assumptions or optimizing other objective functions constitutes the category of General Assembly Line Balancing Problems (GALBPs).

Assuming diverse line layouts (U-shaped (Işık & Yildiz, 2024), two-sided (Huang et al. 2022), multi-manned (Michels & Costa, 2024), and parallel (Mao et al., 2025)), product model and number variations (single (Pınarbaşı & Alakaş, 2020), mixed (Huang et al. 2022), and multi models (Mao et al., 2025)), parameters uncertainty (Fathi et al., 2019), and specific task assignment criteria (e.g., resource skills (Vahedi-Nouri et al., 2024), ergonomics (Zhang et al., 2022), space and technological restrictions (Yin et al., 2021)) are among the main features that distinguishes the GALBPs from SALBPs. These features form the task assignment constraint in ALBPs. Problems with different objectives such as optimizing the number of workers (Katiraee et al., 2023), fatigue level (Abdous et al., 2022), equipment purchasing and operational cost (Zangaro et al., 2023), safety risk (Papetti et al., 2022), and energy consumption (Mukund Nilakantan et al., 2015) are in the category of GALBPs as well.

Technology has allowed machines and robots to work alongside humans on assembly lines, and thus researchers focus on GALBPs rather than SALBPs. Chutima (2022) provides a survey on robotic assembly line balancing and Dolgui et al. (2022) investigate different aspects of designing and managing an assembly system in the era of Industry 4.0. Lopes et al. (2017) investigate a robotic automotive assembly line in which multiple robots are presents in the same station for accomplishing the assembly tasks. To prevent spatial interference among robots' tasks, macro regions are determined on the product and an interference constraint is responsible for generating task assignment decision based on occupied regions and robot movements. Parallel robotic assembly line in Kubilay et al. (2024) consider zoning to introduce linked or incompatible tasks and avoid robots space overlap.

The current study solves a GALBP in which Collaborative Robots (cobots) are human co-workers. Given that technology-based safety systems and human operators are susceptible to errors, we propose a model that conceptualizes HRC risks in assembly line balancing decisions. Based on the reviewed literature, this is the first attempt to apply the zoning idea and propose a rule on zone utilization with safety implications in a Human-Robot Collaborative Assembly Line Balancing Problem (HRC-ALBP). A Constraint Programming (CP) model solves the proposed problem. The recent study of Vahedi-Nouri et al. (2024) demonstrates the capability of CP for solving complex scheduling problems in the presence of heterogeneous workforces in production lines. The following section reviews the HRC-ALBPs literature focusing on key findings of studies and their limitations, especially regarding HRC safety.

5.2.2 Human-robot collaboration (HRC) in Assembly Line Balancing Problem (ALBP)

5.2.2.1. Assembly task modes in HRC

Although cobots are a leading technology in recent assembly lines and crucial to be incorporated into ALBPs, human-robot collaboration complicates task assignment decisions. The human-robot collaboration complexities could cause by specific characteristics of agents (human/robot), system or environment, product, and task (Kiyokawa et al., 2023). Complexity and skill based are two widely used approaches to investigate compatibility of tasks with human or robot execution (Bruno & Antonelli (2018), Malik & Bilberg (2019), Mateus et al. (2019), Cai et al. (2022), Gualtieri et al. (2023)). They identify which tasks can be performed by humans, robots, both, or collaboratively by humans and robots. Upon identifying potential options for completing a task, criteria such as time, cost, quality, safety, and ergonomics are applied to select the most appropriate workforce (Bänziger et al. (2018), Gjeldum et al. (2021), Alessio et al. (2022), Faccio et al. (2023)). Thus, three possible task modes are manual (human), automatic (robot), or collaborative by human and robot.

5.2.2.2. Decision categories in HRC-ALBP

Having more than one working resource in a collaborative workstation and consequently different task execution modes is the primary difference between a SALBP and HRC-ALBP. As with multi-manned ALBPs, HRC-ALBPs assign tasks to workstations and determine the sequence within those workstations. Moreover, task time varies depending on the assignment decision (manual, automatic, collaborative). An HRC-ALBP therefore includes a sequencing problem with allocation-dependent task times (Weckenborg et al., 2019). The relevant literature refers to the fusion of task assignment and sequencing as a scheduling problem (Table 5.1).

Decision on the assignment of cobots to workstations is also important in HRC-ALBPs. Conventional industrial robots require permanent infrastructure while cobots are lightweight with plug-and-play features and short installation time that make them easy to install or move among workstations (Kumar et al., 2023). Since it is possible to displace them based on mid-term balancing decisions, most studies consider cobot assignment decision in their developed line balancing problem (Table 5.1). Also, Researchers may combine cobot type selection, cobot purchasing, or other assembly costs in the models (Li et al. (2021), Nugraha et al. (2021), Shan et al. (2021)).

5.2.2.3. HRC-ALBP constraints and optimization objectives

HRC-ALBP should be formulated according to the assembly line layout, the number of products, the priority relationship between tasks, resources (human/Cobot) availability and capability in performing tasks, the available number of resources with specific type or skill, assignment-dependent task times, safety, and ergonomic concerns. These conditions form the constraints of an HRC-ALBP mathematical model. Adhering to these constraints, the model optimizes one or multiple objective functions and determines a set of decisions for the assembly lines. Minimizing the number of workstations or cycle time are the two main optimization criteria in the ALBP literature. ALBPs with these objectives are categorized as Type-1 and Type-2 respectively. The cycle time is the interval between two workpieces entering a workstation where workers, machines, or robots perform repeated tasks (Boysen et al., 2007). Thus, the lower the cycle time, the higher the output quantity. Table 5.1 includes some studies with multi-objective problems that optimize other goals such as cost and workers' fatigue level besides the cycle time.

We minimize cycle time as the objective of our developed mathematical model given the number of workstations and available cobots. However, the target production quantities are sometimes predetermined, and cycle time is fixed to satisfy the production goals. When resources are insufficient to meet these objectives, extra working resources may solve the issue. The lightweight and easy installation characteristics of cobots have made them an ideal choice for such situations when manufacturers need to boost their processes. Thus, we explore minimizing the number of cobots as another rarely investigated objective using the same model to provide complementary information for decision-makers.

Table 5.1 includes 16 recent journal articles of the young HRC-ALBP literature with the most relevant problems to our research. These papers have some similar assumptions such as serially arranged workstations, a single product, similar human skills, deterministic parameters, and no safety-related discussions. However, each paper has pushed the boundaries of HRC-ALBPs further by considering a unique assembly line configuration and obtaining specific results. Their key findings can be categorized into three groups: First, managerial insights into the impact of HRC on assembly lines targeting the system's decision-makers. Second, investigation on the effect of assembly line and tasks' features such as line layout, number of workstations, and tasks' precedence relations on the complexity of the problem and results. Third, developing novel algorithms to efficiently solve the HRC-ALBPs and confront the challenge of satisfying multi-objectives.

Multi-manned workstation and the zoning theory

In addition to the resources' capability to perform the tasks, space restrictions are another real-world challenge that affect task assignment decisions in ALBPs. Workstation zoning in multi-manned assembly line layouts allows simultaneous task execution by multiple workers without interfering each other's tasks and prevent unnecessary waiting times caused by task priority requirement satisfaction (Pearce et al., 2019).

Table 5.1. Main features of the most recent HRC-ALBPs in the literature

Reference	Problem-specific features								Optimization criteria							Solution approach	Key findings
	Resource assignment	Line layout	Product model	Zoning constraint	Different robot types	human skill levels	Parallel tasks	Ergonomics/ Safety	Cost	Cycle Time	Safety /Ergonomic	Number of	Number of workers	Number of cobots	Makespan		
Samouei & Ashayeri, 2019	✓	SA	mt		✓				✓	✓						MILP	Applicable robust modeling. Satisfying demand requires lower cycle time and higher costs
Weckenborg et al. 2019	✓	SA	si				✓			✓						MIP, GA	Improved productivity by deploying cobots
Rabbani et al., 2020		4-side	mt	✓					✓			✓				PSO	The performance superiority of PSO compared to two methods
Çil et al., 2020	✓		mt		✓					✓						MILP, BA, ABC	The performance superiority of ABC compared to nine methods
Boschetti et al., 2021		1-w	si												✓	MIP	The tasks precedence graph impacts collaborative systems effectiveness
Koltai et al., 2021	✓	SA	si				✓			✓		✓				NLP, CP	Using cobots decreases cycle time but not necessarily the number of workstations
Li et al., 2021	✓	SA	si		✓					✓						MBO	High-quality Pareto solutions obtained by the MBO
Abdous et al., 2022	✓	SA	si		✓			E	✓		E					NLP	Economic investment and fatigue reduction by I4.0/I5.0 technologies are highly correlated
Dalle Mura & Dini, 2022	✓	SA	si			✓		E	✓		E					GA	HRC and job rotation improve ergonomics. Skill-based task assignments have a better impact than the job rotation policy.
Kinast et al., 2022	✓	SA	si				✓		✓						✓	CP, GA	The first cobot added to a line has more impact than the following cobots. GA is preferred over CP for large instances.
Nourmohammadi et al., 2022	✓	SA	si			✓				✓			✓			MILP, SA	The more humans and robots, the more cycle time reduction. SA is compared to GA, PSO, and ABC.
Papetti et al. 2022	✓	UAL	mi					E S	✓	✓	E S					Simulation	HRC mitigated ergonomic risks without dangerous events. The utilization rate of workstations increased by using cobots
Sikora & Weckenborg, 2022	✓	SA	si							✓						MILP, BD	Having more workstations for a fixed number of tasks reduces the complexity of HRC scheduling
Stecke & Mokhtarzadeh, 2022	✓	SA	si		✓			E		✓	E					MILP, CP, BD	Mobile robots can further reduce cycle time compared to immobile cobots. A mixed use of both robot types reduces ergonomic risks.
Weckenborg et al., 2022	✓	SA	si		✓			E	✓		E					MILP	An ergonomic-economic tradeoff: ergonomic improvement by cobot and exoskeleton at a minor cost increase.
Mao et al., 2025	✓	PAL	mt				✓			✓						MIP, TS	TS outperforms MIP, GA, and SA
This study	✓	SA	si	✓			✓	S		✓				✓		CP	"Safe zone policy" allows parallel tasks while reducing workers' exposure to safety risks without a substantial cycle time increase.
Table guide	Line layouts: Serial assembly line (SA), U-shaped assembly line (UAL), 4-sided workstation assembly line (4-side), 1 workstation (1-w), Parallel assembly line (PAL) Products: multi-model products (mt), mixed-model products (mi), single product (si) Solution approaches: Mixed integer programming (MIP), Mixed-integer linear programming (MILP), Non-linear programming (NLP), Benders decomposition (BD), Constraint programming (CP), Genetic algorithm (GA), Simulated annealing (SA), Particle swarm optimization (PSO), Bee algorithm (BA), Artificial bee colony (ABC), Migrating birds optimization (MBO), Tabu Search (TS)																

Zoning constraints relate to the compatibility or incompatibility of tasks to workstations or other tasks, typically because of line layout or space, tools, and equipment requirements (Fathi et al., 2019). Thus, researchers assume zone constraints mostly in problems with large-sized products and multi-manned workstations in straight lines, as well as multi-sided or parallel lines. Workstation zones are not usually shared among multiple workers in ALBP and defined as a dedicated workspace for each worker. However, the boundaries of collaborative stations are merged, and some areas are accessible to human and cobot while both can work in there. This difference is reflected in our zoning approach. A few examples of zoning applications in GALBPs and HRC-ALBPs for addressing tasks (in)compatibility or interference are Fathi et al. (2019), Pearce et al. (2019), Rabbani et al. (2020), Stecke & Mokhtarzadeh (2022), and Nourmohammadi et al. (2022b). Inspired by these studies and according to the literature, this is the first attempt to integrate zone constraint in a mathematical model of HRC-ALBP with the focus on promoting workers' safety.

5.2.2.4. HRC-ALBP solution approaches

Researchers have extensively deployed heuristic/metaheuristic algorithms for solving HRC-ALBPs (Table 5.1) since they are NP-complete problems in which instances cannot be solved in polynomial time. Heuristic and metaheuristic methods rapidly find well-enough solutions without optimality guarantee (Suer et al., 2021). For dynamic and online task planning (sequencing/scheduling) in a collaborative environment, the speed of finding a feasible solution to ensure the continuity and safety of the process is more important than the optimal solution. Thus, researchers divide a collaborative task into sub-tasks and schedule them by developing metaheuristics (Ren et al., 2023), simulations (Vieira et al., 2021), cyber-physical systems (Nikolakis et al., 2019), digital twins (Maderna et al., 2022), and machine-learning algorithms (Yu et al., 2021). This dynamic/online sub-task distribution to humans and cobots inside a workstation is a short-term operational decision. HRC-ALBP, however, is placed in a higher level of assembly line decisions as a mid-term tactical one infused with scheduling inside workstations.

Finding optimal solutions with exact methods is still applicable to HRC-ALBPs (Table 5.1). The use of decomposition methods and constraint programming (CP) is more effective in finding the optimal resolution than optimization software such as CPLEX and Gurobi to solve mathematical models (MILP, MIP, or NLP) (Table 5.1). CP model syntaxes resemble MIP models containing some decision variables, constraints, and possibly an objective function. Since optimization of an objective is not obligatory in a CP model, it can be formulated as a constraint-satisfactory model. Constraints can be linear, non-linear, and logical expressions in these models. CP solvers employ backtracking, branching, and constraint propagation methods to prune the domains of decision variables and the objective function value until the optimal solution is found (Bukchin & Raviv, 2018). Mokhtarzadeh et al. (2020) implemented CP to formulate a scheduling problem and minimize the makespan of a human-robot collaborative workstation. Kubilay et al. (2024) is a recent study on implementing CP for solving a robotic line balancing problem while Koltai et al. (2021), Kinast et al. (2022), and Stecke & Mokhtarzadeh (2022) in Table 5.1 address a collaborative balancing problem through CP. The superiority of CP over MILP for balancing and scheduling problems is also investigated by Bukchin & Raviv (2018), Abidin Çil and Kizilay (2020), Güner et al. (2023), Işık & Yildiz (2024), Vahedi-Nouri et al. (2024). Due to the proven performance of CP as an exact methodology and its suitability to our problem characteristics, we adopted this methodology to solve the proposed HRC-ALBP. All the reviewed CP models have been formulated and solved using the ILOG CP Optimizer (CPO). To the best of the authors' knowledge, this is the first study in the relevant literature to solve the CP model using the OR-Tools CP-SAT solver.

The developed CP model for HRC-ALBP primarily minimizes cycle time. With a minor modification to constraints, it is possible to explore cobot minimization as another objective function which is rarely studied in literature. This characteristic is an asset for the decision-makers who prefer to examine different objectives during the task planning.

5.2.3 Safety in human-robot collaboration assembly lines

ISO/TS 15066 introduces four collaborative modes for cobots working close to a human: Safety-rated monitored stop (SRMS), speed and separation monitoring (SSM), hand guidance (HG), and power/force limitation (PFL). Specific safety requirements are associated with each mode leading to a proper speed, power, and separation distance during collaboration. Violating a distance limit in SRMS and SSM modes makes the cobot reduce the speed or stop. There is some controlled contact between the human and the cobot in HG and PFL (ISO/TS 15066). Performing a task with HRC is controlled by a safety system containing risk assessment, virtual safety zones, sensors, and cameras to avoid or detect collisions (Gualtieri et al., 2021b). Cobot trajectory planning based on obstacle recognition by Ragaglia et al. (2018) and the collision identification system developed by

Ren et al. (2018) are examples of collision prevention and detection studies. Basic safety functions (e.g., stop button), tools, robotic systems, and humans are the four main sources of probable errors in a collaborative environment, leading to safety risks or process interruptions (Mukherjee et al., 2022). Cobots are designed for being safe in dynamic environments, but their collision is still probable and reduces the system's productivity. (Malik & Brem, 2021). Violating the space and distance limitations by operators is one of the human-related errors that highlights the criticality of proposed zoning policy.

Robot trajectory planning algorithms and task planning models are two approaches for minimizing the risk of human-robot collision or process interruption due to a detected/predicted collision. A digital twin of the assembly workstation was developed by Malik & Brem (2021) to generate an online cobot trajectory plan that meets safety requirements. Stecke & Mokhtarzadeh (2022) assumed more than half of the tasks in their HRC-ALBP cannot be performed simultaneously (parallel) because of safety issues. They used a Bernoulli distribution to determine which task pairs cannot be parallel to avoid human-robot collision. The study of Almasarwah et al. (2022) involves a collaborative assembly workstation with two products in which parallel tasks on two different products are prohibited to avoid any contact between the human and the cobot. Papetti et al. (2022) consider performing risk assessment during the design phase of collaborative assembly line as one of decision criteria in a simulation model. However, the other studies in Table 5.1 ignore parallel task execution by the human and cobot for safety reasons or only rely on safety standards in collaborative workspace for parallel tasks. For instance, parallel tasks are allowed in Koltai et al. (2021) model with certain restrictions due to task-specific characteristics. They assume safety issues are already considered when a task is eligible for being performed by a cobot.

Weckenborg et al. (2022) explain that the motion speed of a cobot will be reduced around a human worker for safety purposes and thus a higher execution time is associated with tasks performed by cobots. Malik & Brem (2021) acknowledge that reduced cobot speed causes a longer cycle time which can be improved by deploying better safety technologies or policies. Based on these arguments, the "Safe Zone Policy" acts as an additional safety layer besides the standards for parallel tasks and prevents unnecessary proximity. It defines a general rule for parallelization decision instead of random excluding concurrent tasks with vague reasoning. By parallelizing tasks, the cycle time and idle time of the stations are lowered, and the "Safe Zone Policy" ensures a safe distance between humans and robots.

5.3 The human-robot collaborative ALBP (HRC-ALBP)

Equally equipped workstations with one predetermined task mode (no processing alternatives), and no assignment restriction are among the SALBP assumptions (Scholl & Becker, 2006; Boysen et al., 2007) that cannot be true for the current HRC-ALBPs. We present a HRC-ALBP where some workstations are equipped with cobots, tasks have three processing options, and space-related constraints are present in addition to task precedence. Human-cobot collaborative workstations consist of a human and a cobot working together. Cobots have internal safety assurance algorithms for working with humans in a fenceless environment. These algorithms recognize human and other obstacles to avoid collision. External sensors and cameras in collaborative workstations continuously monitor the environment and working resources. HRC safety risk assessment verifies the potential manual, automatic, and collaborative tasks based on standards. The model assumes these safety protocols are already addressed in the design phase. In the balancing stage, the human and cobot of the collaborative workstation may complete collaborative tasks together or separate task on different parts in sequential or parallel manner. Simultaneous execution of separate tasks depends on human and cobot availability and the safe zone policy. Thus, task sequencing is essential to avoid duplicate assignments and any interference between the tasks respecting the workspace zone requirement. Workstation zones enable us to define a rule for keeping humans and robots apart during parallel tasks for safety reasons. Our problem therefore involves task assignment and sequencing decisions considering task precedence and working zone constraints to achieve a minimum cycle time.

5.3.1 Problem assumptions

Assembly line assumptions:

L.A1. One homogenous product and serially arranged workstations.

L.A2. Predetermined number of workstations

L.A3. A limited number of cobots of one type

Workstation assumptions:

W.A1. A maximum of two workforces in workstations: one human and one cobot

W.A2. One human worker is already employed in each workstation.

W.A3. Three zones in each workstation: Zone1 (accessible only by a human), Zone2 (accessible by a human and a cobot), and Zone3 (accessible only by a Cobot).

Task assumptions:

T.A1. A given number of tasks with known precedence graph and execution times

T.A2. A task is assumed to be completed without interruption when it is assigned.

T.A3. Three task modes: Manual (H), Collaborative (HC), and Automatic (C).

T.A4. Deterministic task time varies based on the task mode.

T.A5. Tasks occupy certain zones depending on the task mode and due to tool requirements, part size, etc.

Human and cobot assumption:

HC. A1. The same skills of human workers who can perform all tasks.

HC. A2. Some tasks are infeasible for automatic or collaborative modes mainly due to cobots' limited technical capabilities or task characteristics.

HC. A3. Allowed parallel execution of two separate tasks by a human and a cobot in addition to collaborative tasks through which they share task time and workspace.

Considering these assumptions and intending to minimize the cycle time, the developed mathematical model decides on assignment of cobots and tasks to workstations as well as their schedule. The problem is defined in a deterministic environment without considering the probable dynamics and uncertainties at this stage. Other conditions may exist in real-world assembly systems such as various resource requirements (industrial machines, tools, etc.), financial factors (assembly costs, cobot purchasing costs, etc.), and multiple conflicting objectives that are out of this research framework.

5.3.1.1. Task processing alternatives

The three alternatives of performing tasks are introduced in the model as H (by human), C (by cobot), and HC (by human and cobot). In HC mode, the human and cobot share workspace and time to perform sub-tasks sequentially or in parallel to deliver a final collaborative task. The concurrent availability of the human and cobot is obligatory for completing collaborative tasks, and none of the resources can process another task at the time of an ongoing collaborative task in the workstation. A task is assumed to be safe when HC mode is possible due to the maximum focus of external safety systems on the collaborative task and activated collaborative mode of cobot. But the safety of accomplishing a manual task by a human and an automatic task by a cobot in parallel, in the same station is still under question. The consequences can differ depending on the pair of tasks we parallelize.

The task modes are differentiated by task times. HC is associated with the lowest task time as it takes advantage of human's and cobot's abilities at the same time. The highest execution time of automatic tasks by cobots makes them the slowest option. Cobots operate at a minimum speed when working alone to ensure safety. In this problem, cobots have the same technical features such as power, speed, force, load weight, and axis. So, the assumed cobot type performs all tasks in the same amount of time. The human task time is a number between these two modes. Since humans have the same skills and one cobot type is considered, one manual time, one automatic time, and one collaborative time are considered for each task. More task time options will be required if there are more options for cobot type and human skill.

Some tasks are incompatible with automatic or collaborative modes because of task features and cobot's technical capabilities. However, we assume that human workers can complete all the tasks at this stage of the model. The task allocation decision finally determines the actual processing time of a task. Note that all the requirements for a collaborative task are considered at the design level and our model distinguishes it from the other modes only by the task processing time.

5.3.1.2. Workstation zoning policy

Operators who share their working environment with robots experience mental stress and psychological discomfort that impact their performance (Gualtieri et al., 2021b). Defining work zones and verifying conflicts before assigning parallel tasks is designed to prevent workers from feeling that their safety is at risk. The hierarchy of hazard control prioritizes hazard exposure elimination (ISO 12100:2010). Thus, we introduce a zoning rule into the assembly line balancing problem to eliminate risks arising from human-robot proximity. ISO12100 suggests a risk scoring system based on the severity and the probability of occurring a harm. Frequency and duration of exposure to the hazard, probability of occurring the hazardous event, and the possibility of avoiding or limiting the harm impact the probability score. The "safe zone policy" targets reducing the hazard exposure duration and avoid probable harms. Having fewer parallel tasks in the collaborative zone will result in a lower safety risk score and a safer HRC. Thus, the calculation of parallel task duration in the collaborative zone (zone 2) in the absence of zoning policy is the safety risk indicator in this study.

The studied HRC-ALBP model assumes three working zones in workstations based on the agents' accessibility to different points of the whole workspace. Zone 1 is only reachable by human workers; Zone 2 (collaborative area) is a common space accessible by both the human worker and cobot; and only the cobot has access to Zone 3 (Figure 5.1). Depending on the selected task mode, the working agent (human/cobot/both) will occupy one or two workstation zones. This zone engagement may relate to the task features, part size, required tools, etc. The collaborative task will always be completed in Zone 2. The developed CP model holds 0-1 parameters to indicate which zones are engaged in the other two modes. The problem assumption regarding workstation zoning is simplified to avoid overcomplication of the mathematical model (Figure 5.1). In real-world examples, the zone borders are blended and the probability of the human or cobot presence at a particular workstation point varies.

The dynamic safety zone around a cobot triggers it to change direction or stop if a collision is imminent. Our conditional zone separation policy generates task assignments that avoid such situations leading to both safe and efficient parallel task execution by human and cobot. Following the task precedence satisfaction and the availability of workers or cobots, the model verifies engaged zones through "safe zone policy" constraints. Parallel task pairs are only possible in situation 1 of Figure 5.2, where neither a human nor a robot is in the collaborative area (zone 2). When at least one working agent occupies the collaborative area (zone 2), zoning constraints prohibit parallel tasks (situations 2 and 3, Figure 5.1). As depicted in Figure 5.2, situation 1 is assumed to be low risk for parallel tasks as engaged zones are inaccessible by the other working agent. Situation 2 is categorized as a medium-risk parallelization with an ongoing task in the collaborative area while the other agent performs another task. Since the cobot task zone is as close as being accessible by the human, some human or technological errors may cause dangerous events or safety mechanisms may stop the cobot task. Likewise, dangerous events are more probable in situation 3 and the parallel tasks are associated with high safety or process disruption risks. Defined zoning constraints forbid all medium and high-risk concurrent task assignment decisions.

Consequently, scheduling the tasks within the workstation depends on the task precedence graph, availability/capability of working resources, and the associated risk level.

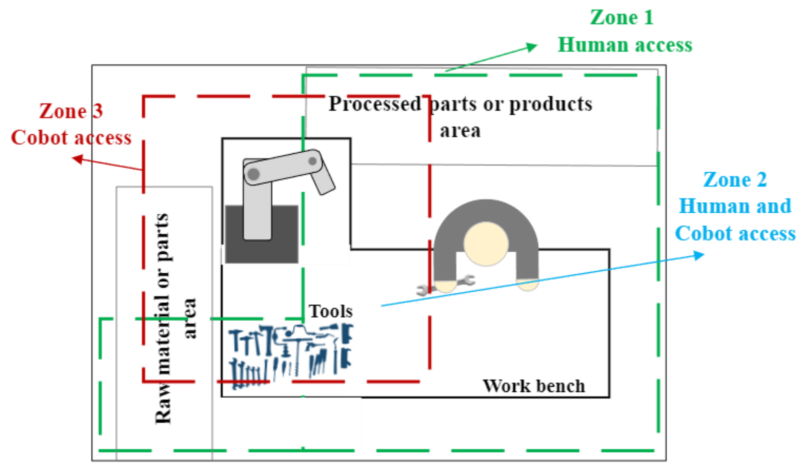

Figure 5.1. A basic illustration of a collaborative workstation from the top view. The whole space is divided into three zones according to the accessibility of a part of the workstation by the human worker and cobot

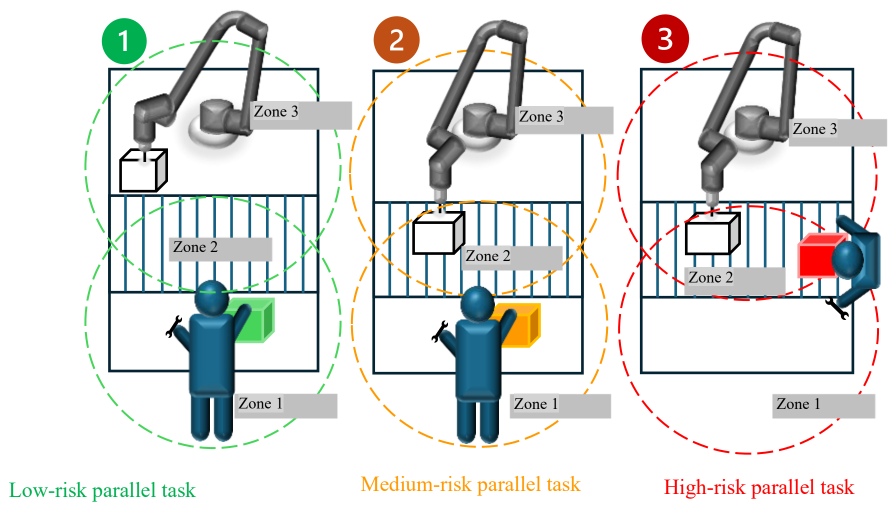

Figure 5.2. Three risk levels (situations) associated with parallel task execution by a human and a cobot inside the collaborative workstation of the assembly line

5.3.2 Constraint Programming Model

As a powerful exact method for solving balancing and scheduling problems, we use the constraint programming (CP) approach to mathematically model and solve the problem. Besides the conventional mathematical programming methods, CP takes advantage of computer science background and employs logical constraints, interval, and optional variables along with the conventional equality and non-equality constraints to formulate a problem. Thanks to CP, we can introduce an optional interval decision variable representing the task execution period to handle the complex relation among task times, mode selection, and zone engagement. In this section, the mathematical formulation of the problem is developed and then it has been represented with CP-specific syntax of CP-SAT solver in OR-Tools.

5.3.2.1. HRC-ALBP mathematical formulation

The following mathematical model uses a combination of equality, non-equality, and logical expressions to create the HRC-ALBP.

Indices

i, j Assembly tasks
w Workstation
$m, \acute{m}$ Task mode

Sets and Parameters

Nt Total number of tasks

Nw Total number of workstations
Nr Total number of collaborative robots
Tasks Set of all tasks {1, …, Nt}
Stations Set of all workstations {1, …, Nw}
Modes Set of all task modes {H (manual), HC (collaborative), C (automatic)}
Zones Set of workstation zones {1 (Human only), 2 (Mutual), 3 (Robot only)}
Z_{im} A subset of zones required for task i in mode m
P_i Set of immediate predecessors of task i
NA_m A subset of tasks that are not allowed to be done in mode m (Empty for m=1)
dt_{im} Duration of task i in mode m
Maxspan An upper limit for integer variables calculated by $\max(t_{im}) \times Nt$

Decision and auxiliary variables

X_{iwm} A binary variable equal to 1 if task i is in workstation w with mode m; 0 otherwise.
WS_w A binary variable equal to 1 if workstation w is open or used; 0 otherwise.

CR_w A binary variable equal to 1 if there is a cobot in workstation w; 0 otherwise.

CTW_w Integer variable for cycle time of workstation w

CT Integer variable for cycle time of the assembly line

sw_w Integer variable for starting time of workstation w

fw_w Integer variable for finishing time of workstation w

st_i Integer variable for starting time of task i

ft_i Integer variable for finishing time of task i

Y_{iwm} Interval variable for task execution equal to $[st_i, st_i + dt_{im} = ft_i]$ when $X_{iwm} = 1$

Using an interval variable in the mathematical model is one of the primary differences between MIP and CP models. Y_{iwm} is an optional interval variable containing the starting time, finishing time, and duration of a task upon the assignment of task to a specific mode ($X_{iwm} = 1$). Thus, other Y_{iwm}variables related to $X_{iwm} = 0$ will not be considered in the model leading to a more compact formulation.

Objective function:

Minimize CT (1)

Subject to:

$\sum_w \sum_m X_{iwm} = 1 \quad \forall\, i \in Taks$ (2)

$ft_j \leq st_i \quad \forall\, i \in Taks, j \in P_i$ (3)

$X_{iwm} = 1 \rightarrow ft_i - st_i \leq CTW_w \quad \forall\, i \in Taks, \forall\, w \in Stations, \forall\, m \in Modes$ (4)

$WS_w \leq WS_{w-1} \quad \forall\, w \in Stations: w \neq 1$ (5)

$sw_1 = 0$ (6)

$sw_w = fw_{w-1} \quad \forall\, w \in Stations: w \neq 1$ (7)

$sw_w + CTW_w \leq fw_w \quad \forall\, w \in Stations$ (8)

$CTW_w \leq CT \quad \forall\, w \in Stations$ (9)

$\sum_w CR_w \leq Nr$ (10)

$$CR_w = 0 \ \rightarrow \ \sum_i \sum_{m \neq 1} X_{iwm} = 0 \qquad \forall\, w \ \in Stations \tag{11}$$

$$\sum_m X_{iwm} \ \leq \ WS_w \qquad \forall\, i \in Taks, \forall\, w \ \in Stations \tag{12}$$

$$X_{iwm} = 1 \ \rightarrow \ st_i \ \geq \ sw_w \qquad \forall\, i \in Taks, \forall\, w \ \in Stations\ \forall m \in Modes \tag{13}$$

$$X_{iwm} = 1 \ \rightarrow \ ft_i \ - \ sw_w \ \leq \ CTW_w \qquad \forall\, i \in Taks, \forall\, w \ \in Stations, \forall\, m \in Modes \tag{14}$$

$$\sum_w X_{iwm} = 0 \qquad \forall m \in Modes, \forall\, i \ \in NA_m \tag{15}$$

$$\big(end(Y_{iwm}) \leq start(Y_{jw\acute{m}})\big) \vee \big(end(Y_{jw\acute{m}}) \leq start(Y_{iwm})\big) \tag{16}$$

$$\forall\, i,j \in Taks: i < j, \forall\, w \ \in Stations, \forall\, m, \acute{m} \in Modes, 2 \in \big(Z_{im} \cup Z_{j\acute{m}}\big)$$

$$\big(end(Y_{iwm}) \leq start(Y_{jw\acute{m}})\big) \vee \big(end(Y_{jw\acute{m}}) \leq start(Y_{iwm})\big) \tag{17}$$

$$\forall\, i,j \in Taks: i < j, \forall\, w \ \in Stations, \forall\, m, \acute{m} \in Modes, \big(Z_{im} \cap Z_{j\acute{m}}\big) \neq \emptyset$$

Equation (1) is the objective function of the model that minimizes the Cycle Time of the assembly line. We assume the time unit is seconds in this problem. Although the implemented zoning constraints may lead to fewer parallel tasks and thus a higher cycle time, the objective of minimizing cycle time compensates for the increased time through an optimal task allocation. Constraint 2 assigns each task to only one mode and one workstation. The precedence relationship between two tasks is guaranteed by constraint 3. Constraint 4 is a logical formulation to ensure that the cycle time of a workstation is greater than or equal to the duration of assigned tasks. Following the assumption of line layout, the workstations must be used sequentially (Constraint 5). Thus, the start time of the first workstation is set to zero (Constraint 6) and the finish time of each workstation is set to the start of the next one (Constraint 7). The cycle time of each workstation is calculated through constraint 8 and the overall line's cycle time (CT) is greater than or equal to these values (Constraint 9). CT will be equal to the maximum of all CTW_w. Since there are a limited number of cobots, constraint 10 is introduced to the model and CR_w will be zero for workstations without a cobot. Therefore, all X_{iwm} variables are enforced to be zero in the logical constraint 11 if there is not a collaborative robot ($\neg CR_w$) in the corresponding workstation. Upon assigning a task to a workstation, that workstation is officially used in the schedule (Constraint 12). Set of constraints 5 to 8 and 12 to 14 helps the model to gradually assign the tasks and initiate workstations one by one over the schedule. The start time of the assigned task will be the same as the start time of the workstation or after that (Constraint 13). The cycle time of a workstation can be presented as the difference between the task finishing time and station start time (constraint 14). Note that no buffer time is considered throughout the assembly line.

Based on the model assumptions, human workers can perform all assembly tasks. Certain tasks, however, are improper for collaborative or fully automatic modes. Constraint 15 sets the value of the relevant X_{iwm} to zero. A collaborative task requires the concurrent presence of a human and a cobot in the collaborative area (zone 2). In that timeframe, it is not possible to perform any parallel tasks. Moreover, the zone separation policy regarding parallel tasks should be met. Thus, constraint 16 prevents two tasks from being processed concurrently when zone 2 is occupied. Parallel task assignment to the human or cobot when they are already busy with a task is prohibited by Constraint 17. A workstation may consist of one human worker and one cobot, each performing only one task at a time. Thus, if a task is scheduled to be completed by a human at a workstation, it should be delayed until the previous task is completed. During solutions explorations, by setting X_{iwm} to 1, Y_{iwm} will take an interval value according to its definition in the variables list. This determines the interval of executing task i in station w with mode m in the current solution. Then the time overlap of two separate tasks in the same station will be verified through constraints 16 and 17. The combination of these two constraints guarantee that two tasks can only be executed concurrently if two distinct agents are responsible and zone 2 is not occupied.

5.3.2.2. Model with CP-SAT solver specific notation

The mathematical formulation in 3.2.1 is converted to the following model with constraint expressions specific to CP-SAT solver. Constraints 2, 4, 11, and 13–17 are updated to 2-a, 4-a, 11-a, and 13-a–17-a, respectively, with other constraints remaining unchanged.

Objective function:

Minimize CT (1)

Set of constraints:

(3), (5), (6), (7), (8), (9), (10), (12)

$$\boldsymbol{AddExactlyOne}\ (X_{iwm}) \qquad \forall\ i\ \in Taks \qquad \text{(2-a)}$$

$$(ft_i\ -\ st_i\ \leq\ CTW_w)\boldsymbol{OnlyEnforceIf}\ (X_{iwm} = 1)$$

$$\forall\, i \in Taks, \forall\, w\ \in Stations, \forall\, m \in Modes \qquad (4\text{-a})$$

$$\left(\sum_i \sum_{m\neq 1} X_{iwm} = 0\right) \boldsymbol{OnlyEnforceIf}(CR_w = 0\ ) \qquad \forall\, w\ \in Stations \qquad (11\text{-a})$$

$$(st_i\ \geq\ sw_w) \boldsymbol{OnlyEnforceIf}(X_{iwm} = 1\ )$$

$$\forall\, i \in Taks, \forall m \in Modes,\ \forall\, w\ Stations \qquad (13\text{-a})$$

$$(ft_i\ -\ sw_w\ \leq\ CTW_w) \boldsymbol{OnlyEnforceIf}\ (X_{iwm} = 1)$$

$$\forall\, i \in Taks, \forall\, w\ \in Stations, \forall\, m \in Modes \qquad (14\text{-a})$$

$$\boldsymbol{AddAssumption}(X_{iwm}.\boldsymbol{Not}) \qquad \forall m \in Modes, \forall\, i\ \in NA_m \qquad (15\text{-a})$$

$$\boldsymbol{AddNoOverlap}([Y_{iwm}, Y_{jw\acute{m}}])$$

$$\forall\, i,j \in Taks{:}\, i < j, \forall\, w\ \in Stations, \forall\, m, \acute{m} \in Modes, 2 \in \left(Z_{im} \cup Z_{j\acute{m}}\right) \qquad (16\text{-a})$$

$$\boldsymbol{AddNoOverlap}([Y_{iwm}, Y_{jw\acute{m}}])$$

$$\forall\, i,j \in Taks{:}\, i < j, \forall\, w\ \in Stations, \forall\, m, \acute{m} \in Modes, \left(Z_{im} \cap Z_{j\acute{m}}\right) \neq \emptyset \qquad (17\text{-a})$$

CP provides a more expressive and compact version of problem modeling than MIP. For instance, an additional constraint is required in MIP models that Y_{iwm} interval variable is impossible: $\mathrm{ft_i} \geq \mathrm{st_i} + \mathrm{dt_{im}x_{iwm}} \quad \forall\, \mathrm{i} \in \mathrm{Taks}, \forall\, \mathrm{w}\ \in \mathrm{Stations}, \forall\, \mathrm{m} \in \mathrm{Modes}$. Then, modeling the zone restriction policy (constraints 16,17) will be complicated without this variable due to additional indices, variables, and constraints required to convey the concepts that are easily applied by logical expressions of CP. Since non-linear formulations are probable in these cases, we utilize CP notations to avoid overcomplicating modeling process and focus on safety implications of the problem. The other MIP constraint replacements examples for equations 4, 11, 13, 14 are as follows:

$$ft_i\ -\ st_i\ \leq\ CTW_w + M(1 - x_{iwm}) \quad \forall\, i \in Taks, \forall\, w\ \in Stations, \forall\, m \in Modes \qquad (4\text{-b})$$

$$CR_w \geq\ \sum_{m\neq 1} X_{iwm} \qquad \forall\, i \in Taks, \forall\, w\ \in Stations \qquad (11\text{-b})$$

$$st_i + M(1 - x_{iwm})\ \geq\ sw_w \qquad \forall\, i \in Taks, \forall\, w\ \in Stations \forall\, m \in Modes \qquad (13\text{-b})$$

$$ft_i\ -\ sw_w\ \leq\ CTW_w + M(1 - x_{iwm}) \quad \forall\, i \in Taks, \forall\, w\ \in Stations, \forall\, m \in Modes \qquad (14\text{-b})$$

M is a very large number in these constraints.

5.3.2.3. CP model without zoning constraint

CP Models without and with safe zone policy differ in two constraints related to the engaged zones. The objective function and all constraints except constraints 16 and 17 remain unchanged in the model without zoning. These two constraints are replaced by equation (18) to ensure parallel task only to two distinct workforces (human and cobot) at a time without zone restrictions.

$$\big(end(Y_{iwm}) \leq start(Y_{jw\acute{m}})\big) \vee \big(end(Y_{jw\acute{m}}) \leq start(Y_{iwm})\big) \tag{18}$$

$$\forall\, i,j \in Taks\colon i < j, \forall\, w \;\in Stations, \forall\, m, \acute{m} \in Modes, (m, \acute{m}) \notin \{(H,C),(C,H)\}$$

The specific syntax of this constraint in CP-SAT solver is:

$$\boldsymbol{AddNoOverlap}([Y_{iwm}, Y_{jw\acute{m}}]) \tag{18-a}$$

$$\forall\, i,j \in Taks\colon i < j, \forall\, w \;\in Stations, \forall\, m, \acute{m} \in Modes, (m, \acute{m}) \notin \{(H,C),(C,H)\}$$

Figure 5.3 illustrates two different examples of workstation schedule with one human and one cobot in the presence and absence of "Safe Zone Policy". The model finds an ideal scheduling solution for tasks in which human and cobot waiting time is almost zero. However, this may not be true in other cases as it is guaranteed by the model. Without zone policy, Ta6 and Ta7 are parallel (yellow) with medium risk while Ta3 and Ta4 are parallel with high risk (red). Appendix A illustrates a problem with 20 tasks, 5 workstations, and 2 cobots in more detail.

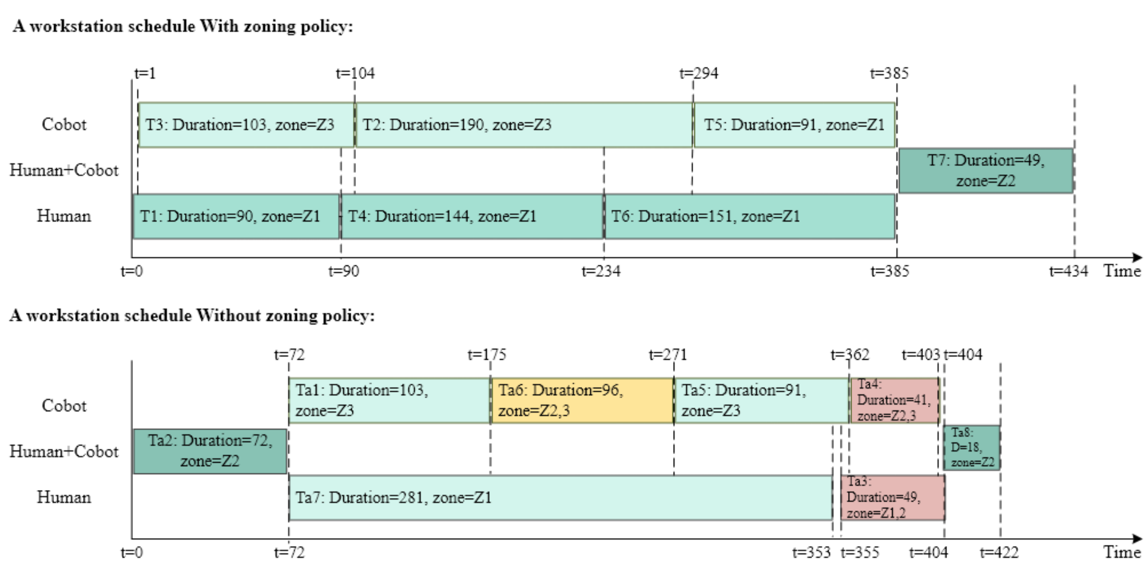

Figure 5.3. The schedule of tasks assigned to a collaborative workstation of the assembly line in the presence and absence of zoning restriction

We implemented the proposed CP model in Python and solved it with the CP-SAT solver of the OR-Tools package. It finds the optimal solutions for all the tested configurations of 25 samples randomly selected from the pool of instances from the Otto et al. (2013) dataset available at http://www.assembly-line-balancing.de website. Sections 5.4 and 5.5 contain all the details of the numerical experiments performed.

5.4 Computational Experiments

5.4.1 Design of experiments

There is no specific benchmark data for our proposed HRC-ALBP in the literature. So, we conduct numerical experiments to validate the proposed model and solve various instances with and without the proposed "Safe Zone Policy". A dataset for SALBP from Otto et al. (2013) is available at http://www.assembly-line-balancing.de website. We accessed this website in February 2024 and used it as the primary source of instances for performing our numerical experiments. Otto et al. (2013) use different distributions for task times to systematically generate their instances. Inspired by the method that Weckenborg et al. (2020) used for adjusting parameters using the same dataset of Otto et al. (2013) for a human-robot collaborative assembly line problem, we generated the required parameters for our problem. Weckenborg et al. (2020) extensively discuss ALBPs dataset settings and the collaborative robot integration impact on their configurations. They explain the rational pattern of parameter generation for HRC-ALBP such as task times and infeasible tasks for collaborative or automatic execution.

We randomly selected 25 samples from the pool of 525 records of problems with 20 tasks and tried three levels for the number of workstations (5, 8, and 10). Also, the examples are tested with 0, 1, 2, and 4 cobots available in the assembly line. Data on task durations for manual mode and task precedence relation graphs are from Otto et al. (2013). Moreover, 25 instances with 50 tasks are selected and joined with 5,8, and 10 workstations each of which tested with 2,4, and 6 available cobots (Table 5.2). Then, we generated task times for collaborative and automatic modes inspired by Weckenborg et al. (2020). The collaborative mode of a task is 30-40% faster than human mode and the automatic mode is 30-40% slower due to the decreased speed of cobots for safety purposes. These times are randomly generated using the uniform distribution in Excel (collaborative time = manual time*(0.6*(0.1*RAND())) and automatic time = manual time (1+0.3*(0.1*RAND()))). Even though human workers can perform all tasks manually, collaborative and automatic modes are not always possible. A ratio of 0.5 is assumed for the task members of NA_m sets when m=2 and m=3 meaning that 10 out of 20 tasks cannot be assigned to collaborative or automatic modes.

Each workstation is divided into three zones based on the accessibility of humans and cobots. A human or cobot may occupy one or two zones to perform a task in one of the three modes (H, HC, C). Zone 1 in mode H, zone 2 in mode HC, and zone 3 in mode C are always engaged. Human workers or cobots may access zone 2 to complete some tasks in H or C mode. This could be due to required tools, part size, task features (e.g., rotating, moving), etc. The Zone 2 Engagement (ZE) ratio represents the percentage of tasks that occupy zones 1 and 2 in human (H) mode, or zones 2 and 3 in cobot (C) mode. We randomly generated the parameter of zone engagement for each task in three modes with two ratios of 0.3 and 0.5 for manual or automatic tasks. The ZE equal to 0.3 means 30% of tasks will occupy Zone 1 and Zone 2 in the manual (H) mode or Zone 2 and Zone 3 in the automatic (C) mode. The significance of the ZE ratio lies in its role in applying the "safe zone policy," where parallel task pairs are prohibited from occupying Zone 2 simultaneously. A higher ZE potentially reduces parallel tasks causing increased cycle time. Overall, 850 instances were generated and solved, 475 of which relate to 19 combinations of 25 samples for 20 tasks and 375 relate to 15 combinations of 25 samples for 50 tasks problems. (Table 5.2)

Table 5.2. Parameters combinations in solved instances

Number of tasks	**ZE rate**	**Number of workstations**	**Number of cobots**	**Zoning policy**	**Total combinations**
20	0.3, 0.5	5	0, 1, 2	Yes	19
		8, 10	0, 1, 2, 4		
		5	1, 2	No	16
		8, 10	1, 2, 4		
50	0.3, 0.5	5	0, 2, 4	Yes	15
		8, 10	0, 4, 6		
		5	2, 4	No	12
		8, 10	4, 6		

As part of our study, we also solved examples without zoning constraints to examine the impact of the proposed policy on optimal cycle time and arising risks. Consequently, 400 instances with 20 tasks and 300 instances with 50 tasks were solved without applying zone restrictions (Table 5.2).

They uncover the cycle time (CT) change and duration of parallel tasks within zone 2 with medium to high-level risks to human safety or task interruption. All these instances are tested with cycle time minimization.

With minor modifications to the primary model, it is possible to change the objective function from cycle time to the minimization of used cobots. This allows further interpretation of various configurations impact on the results. Variable CR_w indicate cobot-to-workstation assignment decisions in the primary CP model. A second version of the model minimizes the sum of CR_w when cycle time (CT) is set to a fixed number. Thus, constraint (10) is eliminated, and the new objective function is defined as Minimize $\sum_{w \in Stations} CR_w$. Other constraints remain the same as described in the primary CP model in 3.2.1. The average of obtained cycle times from previously solved examples with ZE=0.3 is the baseline of the cycle time parameter in the second version of the CP model. Then $\pm 10\%, \pm 13\%, and\ \pm 15\%$ of average CT for 20 tasks is examined to find the minimum number of cobots. Considering 5, 8, 10 workstations and ZE=0.3, 21 combinations and 525 instances are tested. Some instances were not feasible when cycle time was reduced by 10% of the optimal average or more, so the presented results include the average of feasible cases. Since the majority of 50 task instances were not feasible by reducing 10% or more of the cycle time, only -5% is applied for these examples.

5.4.2 Analysis of results and discussion

This section contains all the outputs of solved examples in Python via CP-SAT solver of the OR-Tools package using a laptop Intel Core i7 with 16GB RAM. A limit of 10800 seconds has been set to solve the examples with 20 tasks and 14400 seconds for 50 task examples. The model finds optimal solutions for all the teste instances within the time limit.

Due to the increased problem complexity in 50-task instances, we adjusted two CP solver parameters to be able to solve them. CP-SAT does not parallelize solution search algorithms by default and sequentially explores them making it time consuming and sometimes redundant. Therefore, we activated the parallel utilization of diverse algorithms by setting the "number of search workers". The number of search workers is one by default, which is used for 20-task examples, and we increased it by 20 for 50-task examples to take advantage from more diverse techniques in parallel search phase. The search workers can be increased by 64 depending on computer hardware specifications (CPU, Memory, and Logical processors).

Another changed parameter for 50-task examples is the probing level. Probing is a technique that fixes variables and examines its consequences on the solution. By increasing the probing level to 4, we sacrifice 30-120 seconds at the beginning of the solution search to let the solver pre-solve the model and simplify it as much as possible by fixing variables. In the configuration of 50 tasks, 10 workstations, and 4 cobots; the 1651 variables created by model is decreased to 1135 after the pre-solve step. Moreover, the initial 113367 constraints decreased to 5748 mainly by simplifying "NoOverlap" constraints for optional interval variables, updating initial variable bounds, and reducing symmetries in the scheduling decisions.

5.4.2.1. Optimal Cycle Time and Computational Efficiency

The time spent running the CP model and obtaining the optimal task and cobot assignment decisions for 20 task and 50 task examples are presented in Table 5.3. The maximum average run time for manual assembly lines (0 cobots) is less than 6 minutes while activating parallel search worker of CP-solver drops this time to less than a minute for 50 task examples. As cobots are added to the assembly lines, the zoning constraints will be activated to check the parallel tasks, and thus more time is required to reach the optimal solution. Increasing the number of tasks has more impact on the solution time. The run time increases by adding the first 2 cobots to perform 20 tasks in 5, 8, and 10 workstation configurations while 4 cobots have a minor impact or even decrease the time (Figure 5.4). This trend is also true for the 50-task instances. Table 5.3 reveals increasing the number of cobots doesn't necessarily increase the problem's difficulty, but a combination of factors like 50 tasks, 10 workstation, 4 cobots and ZE=0.5 may cause more complicated scheduling decisions. Boschetti et al. (2021) state that the task precedence graph could influence the effectiveness of collaborative systems. Our investigation of the 20-task instances reveals that this graph also impacts the run time. Whenever the tasks' order strength is low in the precedence graph, there are more opportunities for parallel execution. This prolongs the run time for finding the optimal task schedule. The standard deviations of solution times also show that other problem parameters, one of which is the precedence graph, impact the difficulty level of finding the optimal decision.

Increasing the number of workstations and cobots for completing a fixed number of tasks reduces the cycle time (Table 5.4, Figure 5.5). Figure 5.5 demonstrates that the number of workstations has a greater impact on cycle time drop than integrating cobots. In contrast, changing the ZE ratio from

0.3 to 0.5 causes a minor increase in cycle time. This cycle time change with ZE ratio variation is slightly greater, still minor, in 50-task examples compared to 20-stasks. Higher ZE ratios means more manual/automatic tasks require Zone 2 and cycle time increases due to fewer parallel tasks in the safe zone policy.

Table 5.3. The average Run Time (RT) (seconds) for finding optimal solutions and the standard deviation (std) of calculated average times (safe zone policy applied)

Average CPU time (Run Time (RT)) in seconds			**W = 5**		**W = 8**		**W = 10**	
			ZE=0.3	ZE=0.5	ZE=0.3	ZE=0.5	ZE=0.3	ZE=0.5
Nt=20	Nr = 0	**RT**	113		358		259	
		std	146		607		285	
	Nr = 1	**RT**	588	749	602	595	454	730
		std	782	727	867	1231	640	1255
	Nr = 2	**RT**	505	874	483	502	712	964
		std	596	1056	701	823	1309	1115
	Nr = 4	**RT**	-	-	351	403	689	994
		std	-	-	483	439	1252	1431
Nt=50	Nr = 0	**RT**	13		37		45	
		std	6		20		13	
	Nr = 2	**RT**	2344	5479	-	-	-	-
		std	1269	2658	-	-	-	-
	Nr = 4	**RT**	1768	3910	2595	5631	3126	7234
		std	1700	1917	1286	2501	1063	2402
	Nr = 6	**RT**	-	-	1444	3893	2083	5079
		std	-	-	608	2182	695	2244

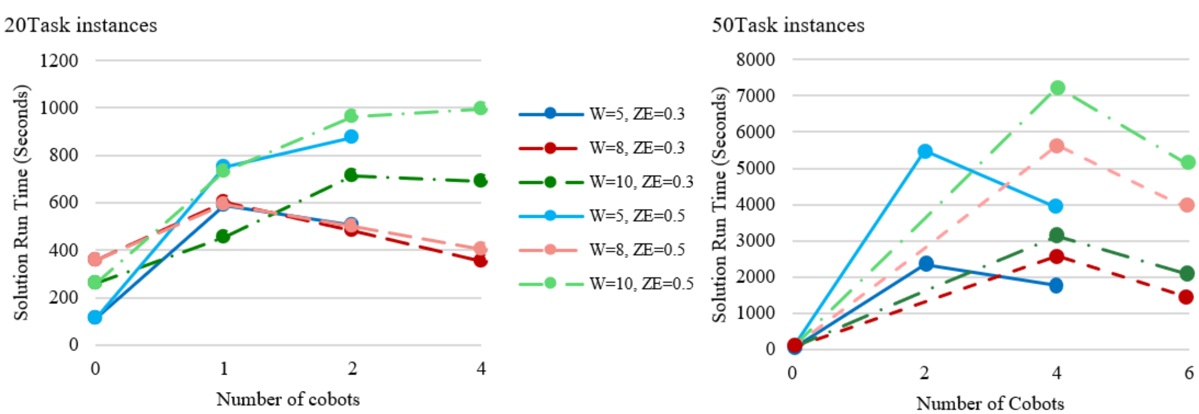

Figure 5.4. The run time for optimal solution varies based on the number of workstations and cobots (W=Workstation, ZE= Zone Engagement ratio)

Table 5.4. The average optimal Cycle Time (CT) in seconds for 25 samples with 20 and 50 tasks and a combination of Workstation-cobot-ZE (safe zone policy applied)

Average optimal Cycle Time (CT) and solution Run Time (RT) in seconds			**W = 5**		**W = 8**		**W = 10**	
			ZE=0.3	ZE=0.5	ZE=0.3	ZE=0.5	ZE=0.3	ZE=0.5
Nt=20	Nr = 0	**CT**	1346		879		725	
		std	641		423		323	
	Nr = 1	**CT**	1190	1201	804	810	691	692
		std	570	576	380	386	306	306
	Nr = 2	**CT**	1070	1097	754	761	674	674
		std	508	524	344	350	293	293
	Nr = 4	**CT**	-	-	694	703	634	639
		std	-	-	307	314	260	264
Nt=50	Nr = 0	**CT**	2047		1299		1041	
		std	415		265		208	
	Nr = 2	**CT**	1686	1744	-	-	-	-
		std	346	352	-	-	-	-
	Nr = 4	**CT**	1513	1595	1025	1062	854	876
		std	304	325	209	217	178	177
	Nr = 6	**CT**	-	-	968	1014	803	835
		std			195	203	165	169

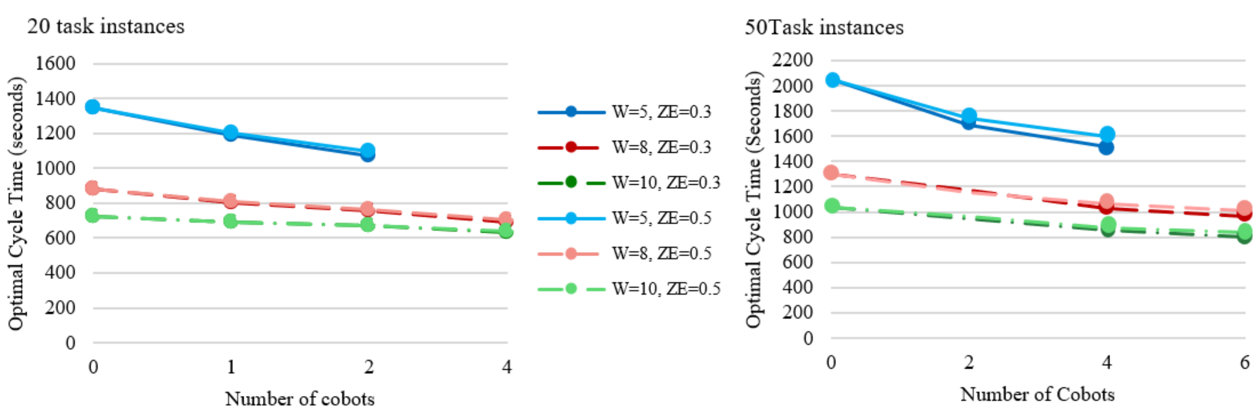

Figure 5.5. The average cycle time of 25 samples was reduced by increasing the number of workstations and cobots (W=Workstation, ZE= Zone Engagement ratio)

For a fixed number of tasks, adding cobots has less impact on cycle time reduction for higher number of workstations. This is crucial for decision-makers to know that increasing the number of cobots doesn’t significantly reduce cycle time or increase the output. They should be aware that the ratio of tasks to workstations and cobots is a key factor in reducing cycle time, as shown in

Table 5.4. For example, the cycle time remained unchanged in almost half of the 10-workstation assembly line instances after adding one or two cobots and cycle time becomes equal to the maximum task time. As a result, expecting CT improvement is unreasonable when extra resources (workstation/cobot) are available to accomplish all the tasks. However, when we had 50 tasks in 10 workstations adding cobots always led to cycle time reduction.

5.4.2.2. "Safe Zone Policy" impacts

To understand the impact of the zoning policy, Table 5.5 compares the cycle time before and after affecting the policy. CP model finds the optimal solution significantly faster (up to 95% for some cases) when the zoning constraints are ignored (Table 5.6).

Examples without zoning constraints showed a decrease in cycle time of between 0 and 4.28% for 20-task examples but 3.99 to 12.42% decrease in cycle time happened for 50 task problems (Table 5.5). However, these cycle time reductions are at the cost of concurrent Zone 2 utilization by cobot and human while performing different tasks on different pieces (Table 5.7, Figure 5.6 and 5.7). The 20 task, 10 workstation, one cobot configuration is an example of unchanged cycle times in the presence and absence of zoning policy with potential medium and high-risk parallel tasks by ignoring zoning policy (Table 5.5 and 5.7).

Comparing the average duration of parallel tasks in high-risk and medium-risk situations for different assembly line configurations in Table 5.7 and Figures 5.6 and 5.7 reveals a descending trend when more workstations are available for 20 task cases. On the contrary, when we have 50 tasks to complete in the same number of workstations, ignoring the zone policy offers more parallel task opportunities, especially with medium and high risk. Figures 5.6 and 5.7 better illustrate the level of parallelization for different explored configurations. They contain some bars indicating the average cycle time related to each configuration. If the duration of medium or high-risk parallel tasks exceeds half of the cycle time, the bars will be red, otherwise they will be green. These bars are all red for 50 task configurations highlighting the criticality of medium and high-risk tasks. Upon occurring an error during concurrent tasks in these cases, both safety risks and negative affect on assembly line outputs are expected.

Table 5.5. Average of minimum cycle times (seconds) in the optimal solutions

Task	Workstation	Cobot	Without zoning	With Zoning ZE=0.3	Change (%)	With zoning (ZE=0.5)	Change (%)
20	5	1	1186	1190	0.33	1201	1.25
		2	1050	1070	1.87	1097	4.28
	8	1	802	808	0.74	810	0.99
		2	749	754	0.66	761	1.58
		4	686	694	1.15	703	2.42
	10	1	691	691	0	692	0.14
		2	672	674	0.30	674	0.30
		4	632	634	0.31	639	1.10
50	5	2	1614	1686	4.28	1744	7.46
		4	1397	1513	7.67	1595	12.42
	8	4	973	1025	5.08	1062	8.39
		6	903	968	6.72	1014	10.95
	10	4	820	854	3.99	876	6.4
		6	763	803	4.99	835	8.63

Table 5.6. Average model run time (seconds) to find the optimal solution

Task	Workstation	Cobot	Without zoning	With Zoning ZE=0.3	Change (%)	Without zoning	With zoning ZE=0.5	Change (%)
20	5	1	202	588	65.65	200	749	73.30
		2	216	505	57.22	205	874	76.54
	8	1	302	574	47.39	282	595	52.61
		2	249	723	65.56	217	502	56.77
		4	99	351	71.79	100	403	75.19
	10	1	144	569	74.69	144	730	80.27
		2	197	718	72.56	202	964	79.05
		4	370	748	50.53	360	994	63.78
50	5	2	342	2344	85.41	355	5479	93.53
		4	206	1768	88.35	217	3910	94.46
	8	4	363	2595	86.02	355	5631	93.7
		6	193	1444	86.64	188	3893	95.18
	10	4	534	3126	82.92	510	7234	92.95
		6	310	2083	85.12	313	5079	93.84

Table 5.7. The average duration (seconds) of using Zone 2 by parallel tasks (without safe zone policy)

Task	Workstation	Cobot	Average Cycle Time	ZE=0.3			ZE=0.5		
				Two tasks in Zone 2	One task in Zone 2	Total	Two tasks in Zone 2	One task in Zone 2	Total
20	5	1	1186	74	256	430	149	504	653
		2	1050	148	590	738	471	833	1304
	8	1	802	13	188	201	142	297	438
		2	749	70	357	427	332	458	791
		4	686	80	663	743	466	745	1210
	10	1	691	62	86	148	83	157	240
		2	672	51	221	272	175	301	476
		4	632	60	500	560	326	622	948
50	5	2	1614	189	757	946	666	1022	1688
		4	1397	380	1195	1575	961	1498	2459
	8	4	973	253	994	1247	679	1296	1975
		6	903	366	1224	1590	977	1481	2458
	10	4	820	249	906	1155	637	1073	1710
		6	763	356	1002	1358	881	1293	2174

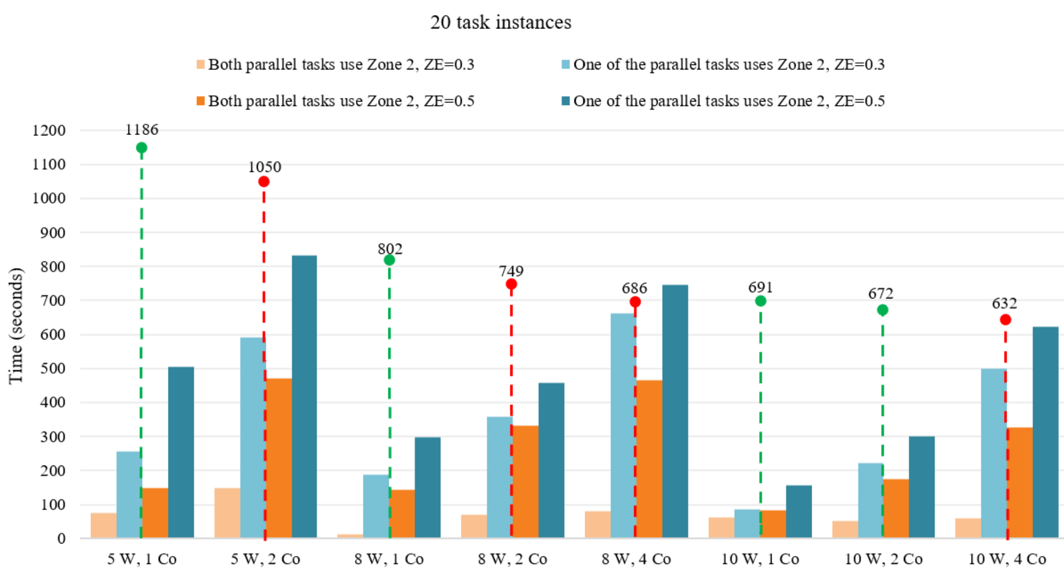

Figure 5.6. The average duration of Zone 2 engagement in parallel tasks without zoning constraint and their comparison with the average cycle time of the relevant configurations (20 Tasks, W=Workstation, Co=Cobot)

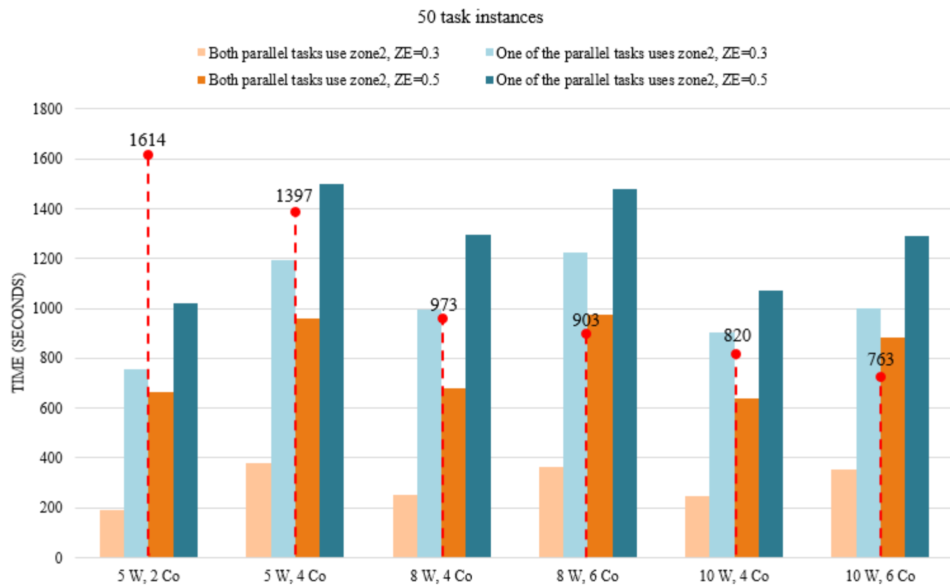

Figure 5.7. The average duration of Zone 2 engagement in parallel tasks without zoning constraint and their comparison with the average cycle time of the relevant configurations (50 Tasks, W=Workstation, Co=Cobot)

5.4.2.3. Cobot minimization objective

The experiments include a secondary model with a cobot minimization objective function to expand the discussion on different assembly line configurations. This model is a modified version of the primarily developed CP seeking the minimum number of collaborative robots for assembly lines given the cycle times and number of workstations. A manufacturer may use this approach to determine how many cobots are required to accomplish the desired cycle time. By introducing the cobot minimization objective we tend to prove that it is not mathematically complicated to switch from one objective function to another within our developed model.

Table 5.8 presents the results of experiments with different cycle times and the minimum cobots as the objective function. Based on the average optimal cycle time of solved instances for 5, 8, and 10 workstations, we conduct a sensitivity analysis of the objective function on the same cases as the primary model. Table 5.8 shows the variation in the optimal number of cobots given a range of cycle times and workstations and thus, a feasible range of cycle times is found for a specific number of cobots. For example, in the assembly line with 20 tasks, 5 workstations, minimum cycle time is 1346 in manual mode (Table 5.4) and adding one cobot to this line can reduce it to 1082 while the maximum cycle time would be 1323 seconds, depending on task assignment and scheduling decisions (Table 8).

Table 5.8. Minimum number of cobots given the cycle time (seconds) and number of workstations (with zoning constraints; ZE=0.3)

Task	CT range	5 Workstation		8 Workstation		10 Workstation	
		CT	Min cobot	CT	Min cobot	CT	Min cobot
20	-15%	1022	3	668	5	579	6
	-13%	1046	3	684	4	593	5
	-10%	1082	1	713	3	620	3
	Average	1202	1	786	2	681	1
	+10%	1323	1	865	1	749	0
	+13%	1359	0	888	0	770	0
	+15%	1383	0	904	0	783	0
50	-5%	1519	4	947	7	787	7
	Average	1599	3	996	5	828	5
	+10%	1759	2	1096	3	911	3
	+13%	1807	2	1126	2	936	2
	+15%	1839	1	1146	2	953	2

Th optimal configurations obtained by cycle time and used cobots minimization objectives are combined in Figures 5.8 and 5.9. Figure 5.8 shows the expected cycle times according to the number of used cobots. This provides the decision makers with the line's capacity in cycle time reduction with the same number of cobots. Then, Figure 5.9 shows the cycle time variation according to the number of workstations. This figure confirms that increasing the number of cobots has less influence on reducing cycle time when the number of workstations rises. Given that cobot utilization does not significantly reduce cycle time in some cases and gives rise to safety challenges, minimizing number of cobots besides minimizing the cycle time offers an approach to efficient cobot deployment.

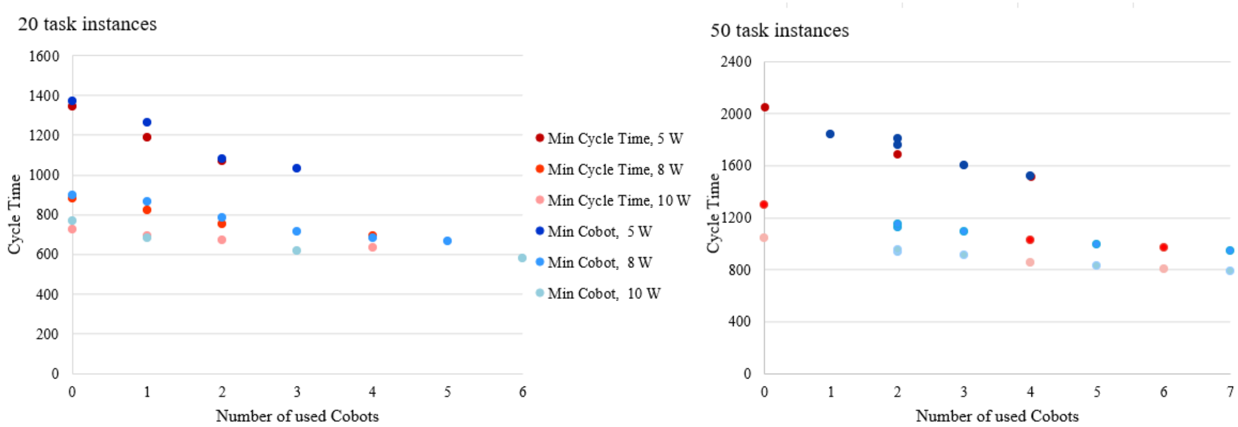

Figure 5.8. Cycle Time variation according to the number of cobots (results with two different objectives, ZE=0.3, with zoning policy)

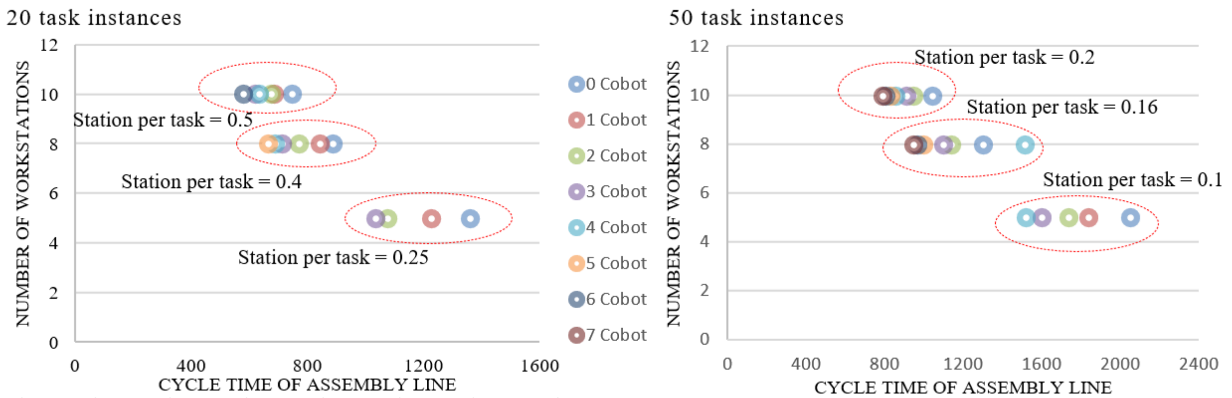

Figure 5.9. Cycle Time variation according to the number of workstations and cobots

5.4.3 Model limitations

The proposed model focused on introducing zoning constraints to an HRC-ALBP to ensure human safety and task continuity when strong safety systems are activated in a collaborative workstation. We simplify some assumptions about the studied assembly system to avoid a complex model. Task time are assumed to be deterministic while their variation may cause some bottlenecks in the absence of buffer time. This leads to delays at certain workstations, idling downstream stations, and ultimately reducing the overall output. Therefore, future incorporation of buffer time, maintenance plans, task preemption, task time variability, etc. into the model will result in a more realistic model. Assuming one worker, in each workstation, who can perform all tasks with same skill level is a simplification of real-world problems. The idle time of workers and cobots is not guaranteed to be minimum in our model and can be a topic for further investigations. Considering one cobot type and a maximum of one cobot in each workstation simplifies the balancing and scheduling decisions. Multiple cobot types will lead to more available task modes and additional constraints on schedule overlaps for human-robot teams in cases with more than one human and cobot in workstations.

Including the safety risk into the model in the form of specific zone separation regulation constraints does not present details regarding the risk scores as it is known with safety risk assessment methods. Future research can incorporate a novel risk assessment technique into the model and calculate the risk score along with cycle time optimization. Another limitation of the presented work is the developed methodology and the size of solved examples. All the analyzed results relate to the problems with 20 and 50 assembly tasks. According to Otto et al. (2013), their dataset for 20 and 50 tasks are suitable for testing exact methods like CP and 100 tasks samples should be used for heuristic algorithms. However, comparison of the currently developed CP model with other methods is a promising track for further research.

5.5 Managerial Insights

The reason behind employing the safe zone policy constraints is guaranteeing the physical safety of human workers by eliminating the source of probable hazards (human-cobot proximity) from collaborative workspace when the presence of human and cobot is not necessary. Even if there are no threats to human safety, cobot safety algorithms dynamically adjust their trajectory and actions based on workspace events and unexpected human presence may interrupt their work. On the other hand, working with a cobot in close distance without physical safety barriers imposes a psychological burden to human workers when they are not confident enough with working with cobots or do not fully trust the cobots. Considering probable risks during tactical decision for line balancing besides the design stage and online operational modifications, allows humans to feel safer around cobots as their safety is a priority in every stage of the decision making. According to the obtained results, a minor cycle time reduction can cost a significant increase in hazardous task assignment decisions. So, it is suggested to bear slightly higher cycle time and prioritize human workers as one of the primary values of human-centered systems in Industry 5.0. The proposed approach is also beneficial to promoting other aspects of Industry 5.0: By reduced safety challenges, cobots offer SMEs a sustainable solution with low energy consumption and waste. Besides, safe zoning policy reduces potential process interruptions by creating a more reliable assembly line.

The results also show that excessive cobot utilization is not a wise solution for cycle time reduction in all assembly lines. Long enough cycle times and more stations provide human workers sufficient time and space to complete more tasks when other factors like ergonomics do not apply. Investigating the minimum number of cobots given the cycle time has three hidden benefits for the assembly line: lower costs (cobot purchasing, safety devices, and energy fees), simpler task planning, and reduced human safety challenges. This intrinsically supports our fundamental research goal of maintaining efficiency while addressing safety concerns. It is important to note that high human wages, scarcity of skilled workers, and ergonomic issues may conflict with this objective and increase the necessity of cobot deployment.

5.6 Conclusion and future research

This study presents a novel approach to building a balanced assembly line efficiency and human workers' safety. The proposed Human-Robot Collaborative Assembly Line Balancing Problem (HRC-ALBP) utilizes a Constraint Programming (CP) model to minimize the cycle time given the number of workstations and cobots. The model finds the best workstations for placing the cobots and assigns the tasks to the working resources of each workstation. Then, the optimal cycle time is applied to the same model as a parameter to minimize the number of used cobots. The minimum number of cobots meets assembly constraints (e.g., a predetermined cycle time) and intrinsically imposes lower costs, planning difficulties, and safety risks. The minimized cycle time corresponds to line efficiency and safety satisfaction is implemented through zoning constraints as a policy for executing parallel tasks by human and cobot. Any technological problem in safety devices or human-related errors during task execution may create hazardous events or task operation interruption. So, the model proposes the "safe zone policy" to eliminate the unnecessary human-cobot proximity and avoid unintended contact between them.

Our results demonstrate that zoning restriction removes the medium and high-risk parallel task pairs with less than 5% and 13% deviation from the optimal cycle time for 20-task and 50-task instances respectively. This cycle time change is compared to the duration of medium and high-risk parallel increased by more than cycle time, meaning that any collision or task interruption will directly affect the number of assembly line outputs. Moreover, integrating the results of minimized cycle time instances with examples of minimized number of cobots shows the variation of cycle time achievable by a certain number of cobots and vice versa.

Overall, the proposed problem and the solution approach based on CP contribute to advancing the integration of human-robot collaborative ALBPs with human-centered fields of research like safety. Developing a model that is versatile in optimizing different objectives, handles the complex constraints is an asset for the manufacturing planners enabling them to try various configurations and compare their results. On the other hand, joining the human safety concerns with a mathematical assembly line balancing decision initiates the building blocks of a decision tool with human-centered goals enabling Industry 5.0. Moreover, the proposed zone regulations will minimize unexpected human-cobot interactions that reduces potential process interruptions and enhances the overall reliability of the system. Building human trust in cobots through a safe decision-making approach facilitates cobots utilization in SMEs, leveraging their energy efficiency and precision (resulting in less waste) to align with the sustainability goals of Industry 5.0.

Future research may focus on the current model limitations and develop improved methodologies suitable for more real-world applications. There could be three main directions: First, the assumptions related to cobot integration such as the number and type of cobots, human skills, and human-cobot teams in the assembly lines and the relevant challenges such as financial factors, ergonomics, safety issues, energy management, environmental concerns, human and cobot trust in their co-workers, human preference impact on task performance, etc. Addressing any of these challenges promotes industry 5.0 goals. The second research direction could compare the developed CP with other methods or customize it for better performance; investigate the advanced methodologies for addressing similar problems and those that can efficiently solve large-scale and complex problems dynamically or online. Multi-objective models (cycle time and number of cobot and workers; cycle time and safety risk score; cycle time and idle time), decomposition methods, simulation and digital models, machine learning algorithms, and a mix of methodologies tailored to the problem requirements. Starting from the current research and investigating these two research directions provides a foundational framework for industries looking to integrate human-robot collaboration while maintaining high safety standards. Finally, researchers and practitioners across various domains such as logistics and manufacturing of continuous products can explore the potential risks of HRC in their industry. Novel approaches are still needed to combine qualitative methods such as risk assessment with quantitative mathematical optimization models for the car manufacturing and space industry where HRC is widely used. This helps to pave the way for innovative solutions that meet specific challenges of each industry and enhance human-robot collaboration outcomes.

5.7 Appendix A

A numerical instance of the HRC-ALBP model is presented in detail in this section. Consider an assembly line with 5 workstations for performing 20 tasks. The priority of executing tasks must follow the tasks precedence graph in Figure 5.10. A human works in each workstation and 2 cobots are assigned to stations. Humans and cobots perform tasks in three modes with different durations while respecting tasks precedence (Figure 5.10). It is assumed that 50% of tasks cannot be collaborative or automatic, therefore, Tasks {1, 2, 3, 6, 9, 11, 12, 14, 15, 16} cannot be collaborative, and {1, 2, 3, 5, 6, 7, 8, 9, 13, 17} cannot be done automatically only by Cobot (NA_2 and NA_3 sets). ZE parameter is 0.3 in this example meaning 30% of the tasks require zone 2. Tasks {1,2,4,8,13,14} in human mode (m=1) and {4,6,12,13,15,18} in Cobot mode (m=3) will need zone 2 during their execution (Z_{im} parameter). Manual and automatic modes occupy Zones 1 and 3 for the remaining tasks, respectively. We used a uniform distribution to randomly determine the list of possible task modes and zone 2 requirements.

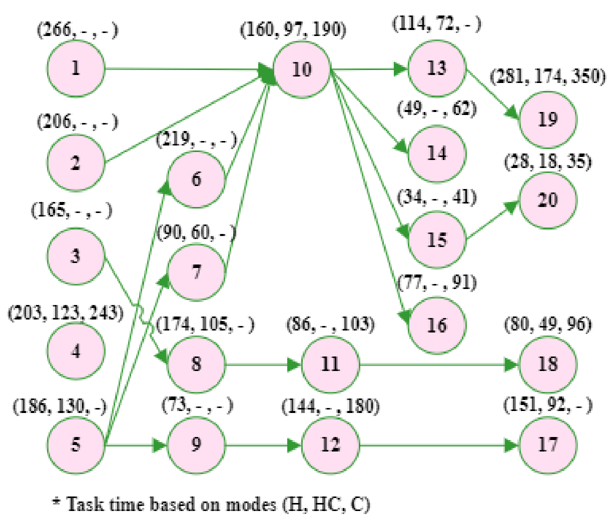

Figure 5.10. Tasks precedence graph including task times of three modes

Objective Function = CT = 434
Station 1, 0 Cobot, Cycle time 431
Station 2, 0 Cobot, Cycle time 433
Station 3, 0 Cobot, Cycle time 425
Station 4, 1 Cobot, Cycle time 434

Station 5, 1 Cobot, Cycle time 431
Task 1, Station 1, mode H, start 165, finish 431, use zone 1, 2
Task 2, Station 3, mode H, start 867, finish 1073, use zone 1, 2
Task 3, Station 1, mode H, start 0, finish 165, use zone 1
Task 4, Station 5, mode H-C, start 2043, finish 2166, use zone 2
Task 5, Station 2, mode H, start 433, finish 619, use zone 1
Task 6, Station 3, mode H, start 1073, finish 1292, use zone 1
Task 7, Station 4, mode H, start 1301, finish 1391, use zone 1
Task 8, Station 2, mode H, start 692, finish 866, use zone 1, 2
Task 9, Station 2, mode H, start 619, finish 692, use zone 1
Task 10, Station 4, mode C, start 1405, finish 1595, use zone 3
Task 11, Station 4, mode C, start 1302, finish 1405, use zone 3
Task 12, Station 4, mode H, start 1391, finish 1535, use zone 1
Task 13, Station 5, mode H-C, start 1797, finish 1869, use zone 2
Task 14, Station 5, mode C, start 1735, finish 1797, use zone 3
Task 15, Station 5, mode H, start 1735, finish 1769, use zone 1
Task 16, Station 4, mode C, start 1595, finish 1686, use zone 3
Task 17, Station 4, mode H, start 1535, finish 1686, use zone 1
Task 18, Station 4, mode H-C, start 1686, finish 1735, use zone 2
Task 19, Station 5, mode H-C, start 1869, finish 2043, use zone 2
Task 20, Station 5, mode H, start 1769, finish 1797, use zone 1

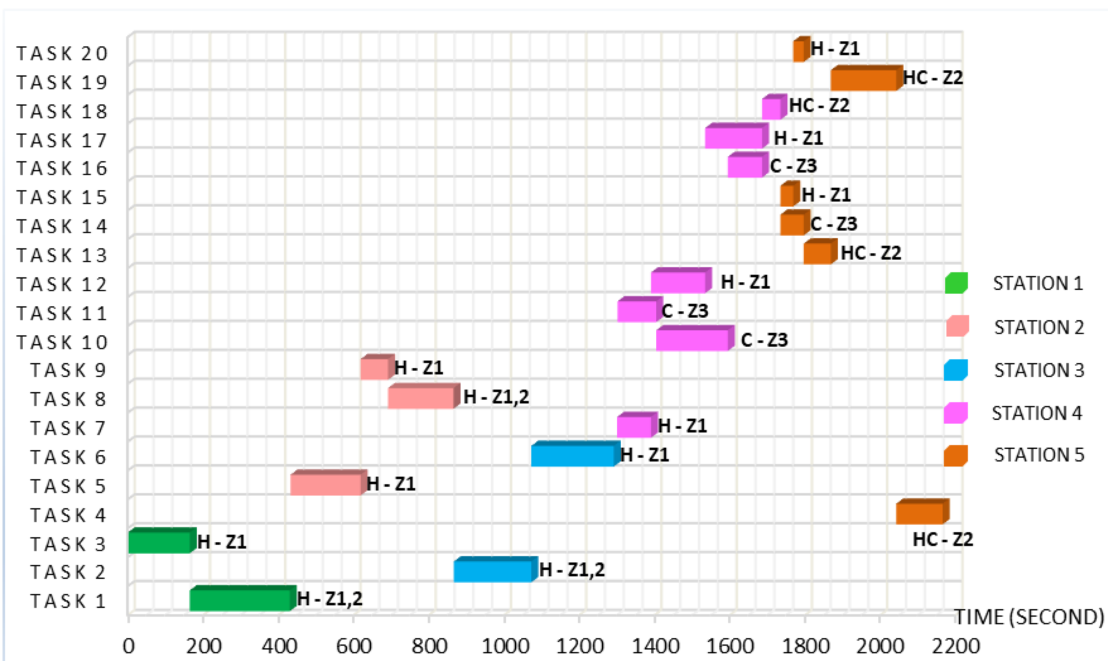

Figure 5.11. An example of the optimal task assignment and schedule includes zones (With "Safe Zone Policy")

In the model output, the optimal cobot assignment, task- workstation, and task-mode decisions are determined. Moreover, the detailed starting and completion time of each task is presented. The overall cycle time of the assembly line is equal to the maximum cycle time among the workstations.

Figure 5.11 shows the schedule of all 20 tasks with their responsible agent (H, C, HC) and the engaged zones (Z1, Z2, Z3, Z1,2). The detailed results reveal that all defined constraints are satisfied. The “safe zone policy” is applied to the parallel task pairs (7 and 11, 10 and 12, 16 and 17, 14 and 15, 14 and 20) in workstations 4 and 5. The human and cobot avoid zone 2 during parallel task execution. Figure 5.12 illustrates the same problem in the absence of zoning policy. The cycle time is 422 in this solution but the zone separation in parallel task is not considered leading to medium (tasks 6,12,16,18,19) and high-risk (tasks 2,4,14,15) situations.

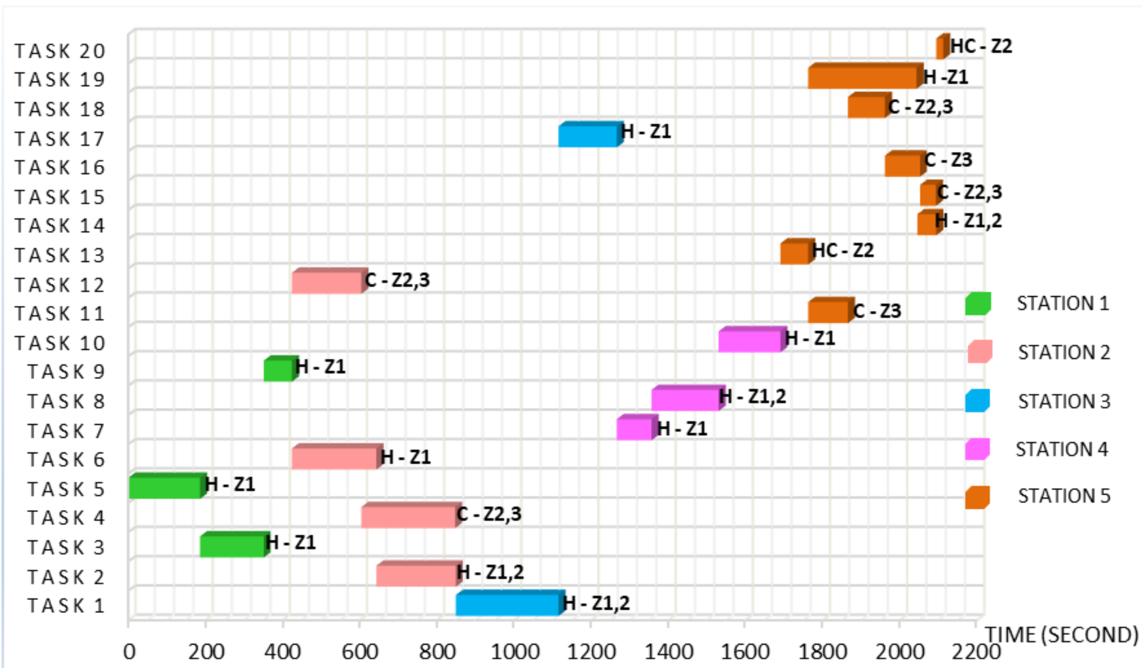

Figure 5.12. An example of the optimal task assignment and schedule includes zones (Without “Safe Zone Policy”)

CHAPTER 6 ARTICLE 3: BALANCING PRODUCTIVITY AND SAFETY: A RISK-AWARE FRAMEWORK FOR HUMAN-ROBOT COLLABORATIVE WORKFLOWS

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This chapter is almost identical to the submitted version with minor additional explanations for better conceptual clarification in the final department submission.

Résumé

Cet article aborde le problème d'équilibrage de ligne d'assemblage (Assembly Line Balancing Problem, ALBP) dans un contexte de collaboration humain-robot (HRC), en intégrant les risques de défaillance des tâches au moyen d'un cadre inspiré de la PFMEA (Process Failure Modes and Effects Analysis). Ce cadre couvre plusieurs catégories d'effets de défaillance, dont la sécurité, et les traduit en un indice de priorité de risque alternatif (ARPN). Un modèle d'optimisation fondé sur la programmation par contraintes (CP) est proposé au niveau tactique, afin de déterminer l'affectation des tâches aux postes et l'allocation des ressources humaines et robotiques. À la différence des travaux existants, majoritairement centrés sur l'évaluation des risques en phase de conception ou sur des mécanismes de contrôle dynamiques au niveau opérationnel, l'ARPN est ici intégré directement au modèle tactique d'ALBP, permettant une optimisation bi-objectif du temps de cycle (CT) et du risque de défaillance. Par ailleurs, une contrainte orientée sécurité est introduite pour limiter la sévérité des conséquences lors de l'exécution parallèle de tâches humain–cobot. Des expérimentations numériques sur diverses configurations d'assemblage mettent en évidence l'influence des compétences humaines et de l'intégration des cobots sur le compromis entre les objectifs, et montrent la capacité du modèle à réduire les chevauchements de tâches dangereux, notamment lorsque la disponibilité des compétences est limitée. En structurant une prise de décision informée par le risque au niveau tactique, cette contribution fait progresser la modélisation du HRC-ALBP vers des systèmes d'assemblage à la fois sûrs et performants, et rapproche les cadres d'optimisation des exigences industrielles en matière de sécurité.

Abstract

This paper addresses the Assembly Line Balancing Problem (ALBP) in the context of Human-Robot Collaboration (HRC), integrating task failure risks through Process Failure Modes and Effects Analysis (PFMEA)-inspired framework. The framework captures multiple categories of failure effects including safety and translates them into an Alternative Risk Priority Number (ARPN). A Constraint Programming (CP)-based optimization model is developed at the tactical level of decision-making, where task-to-workstation and workforce allocation is determined. Unlike existing research focused mainly on design-phase risk assessments or dynamic operational level controls, this study embeds ARPN directly into the tactical ALBP model, enabling a bi-objective optimization of Cycle Time (CT) and failure risk. Additionally, a safety-aware constraint is introduced to limit the severity of safety consequences during parallel human-cobot task execution. Computational experiments across diverse assembly configurations reveal the role of human skills and cobots in objectives trade-off. They also demonstrate the model's ability to reduce hazardous task overlaps, especially under limited worker skill availability. By establishing risk-informed decision-making at the tactical layer, the study advances HRC-ALBP modelling toward safe and productive assembly systems, thereby bridging the gap between theoretical optimization frameworks and practical safety requirements.

Keywords: Human-Robot Collaboration; Assembly Line Balancing Problem, Collaborative Robot, Manufacturing Safety, Task Failure Risk, Constraint Programming

6.1 Introduction

In modern manufacturing systems, the integration of collaborative robots (cobots) into assembly lines is increasingly pursued to enhance productivity and operational flexibility (Bilberg & Malik, 2019; Weckenborg et al., 2019). However, Human-Robot Collaboration (HRC) introduces unique challenges, particularly in balancing efficiency and safety within task assignments and scheduling decisions (Gualtieri et al., 2021b). Physical barriers between human and robots are removed in collaborative workstations with the intention of creating human-robot physical interaction opportunities in a shared workspace. These environments are not risk free due to the probable undesired collisions or contacts between humans and robots that imply hazardous situation and potentially affect operator safety and process continuity (Murino et al., 2023).

To address these challenges, manufacturers mostly rely on applied safety standards, operator training, and advanced sensor technologies for real-time monitoring and hazard prevention (Li et al., 2024). While such practices are essential, they typically operate at the design or operational levels, for example, safe-by-design standards (ISO 10218, ISO/TS 15066) that regulate safe robotic workspace layouts and cobot integration, or real-time monitoring systems that reactively detect and mitigate hazards through trajectory and task schedule modifications (Ragaglia et al., 2018; Liu et al., 2020). What remains largely overlooked, however, is the tactical decision-making layer, where task-to-workstation allocation and resource assignment choices are made. Relying solely on design-phase safeguards or operational monitoring can lead to corrective actions that increase costs and reduce productivity, leaving a critical gap in proactive planning (Berx et al., 2022). Current literature largely neglects the integration of potential process failure risks in tactical assembly planning decisions, even though inappropriate task assignments, particularly under varying task characteristics, execution modes, and operator proficiency, can create unsafe conditions and workflow disruptions (Zhao et al., 2025). This study adopts a proactive approach that directly embeds safety risk directly into decisions for allocating tasks to workstations and resources to achieve more reliable and resilient workflows, as well as fulfilling this crucial need in literature.

The complexity of incorporating risk into human-robot task allocation stems from the variability of interaction dynamics and their impact on key performance indicators such as cycle time, scrap rates, and hazardous events (Huck et al., 2021). Each task may involve different failure modes and consequences depending on the execution mode in which it is performed (Antonelli & Stadnicka, 2019). When these variations are combined with differences in human worker proficiency, task sequencing and resource allocation become even more challenging. In this paper, we introduce a Constraint Programming (CP)-based model for HRC-ALBP that redefines assembly line efficiency by incorporating the critical failure risk of tasks directly into the Cycle Time (CT) optimization framework. The model employs a Process Failure Mode and Effect Analysis (PFMEA)-inspired approach to frame the overall potential failure risk of tasks assigned to workstations, denoted by Alternative Risk Priority Number (ARPN), and minimize it along with CT. The ARPN value covers the scores for task processing failure effects on safety, time, quality, and performance to involve a broader range of HRC risks into the balancing decision.

Nine possible task execution modes are captured in the model, which represent three levels of worker proficiency (beginner, intermediate or trained, expert), three levels of cobot speed (low, moderate, high), and three collaboration choice of joint worker proficiency level and moderate cobot speed. There has been HRC-ALBPs with different human skills in the literature (Dalle Mura & Dini, 2022; Nourmohammadi et al., 2022b), however, they apply the same time for cobot tasks due to the assumption that they operate at reduced speeds for safety reasons. As a result, options for cobot speed are neglected, and this study fills the literature gap by examining these alternatives. While the proficiency of human workers and the speed at which cobots carry out tasks vary, a safety-aware constraint controls parallel operations in potentially high-risk scenarios, such as the presence of a beginner-level worker in a collaborative workstation. Moreover, the CP model employs a bi-objective optimization framework to minimize both cycle time and cumulative risk scores (ARPN), addressing productivity and safety simultaneously.

Therefore, this research contributes to the HRC-ALBP field with the following features:

- A novel CP-based optimization model that integrates PFMEA-inspired risk indicators into the HRC-ALBP framework with different human workers proficiency levels and varying cobots speeds, resulting in nine potential task modes.

- Simultaneous optimization of productivity (via cycle time minimization) and task failure risk (via ARPN minimization), offering a structured approach to evaluate trade-offs.

- A safety-aware constraint that sets a threshold for the severity of safety effect in parallel task assignments between humans and cobots, ensuring safer collaboration with preserved productivity.

The remainder of this paper is organized as follows. Section 6.2 presents a literature review on Human-Robot Collaboration (HRC) in the context of Assembly Line Balancing Problems (ALBPs), with particular emphasis on reliability and safety challenges that motivate the integration of task failure risk and cycle time minimization. Section 6.3 describes the problem assumptions and outlines the proposed optimization model framework. Section 6.4 details the parameter design procedures adopted for numerical experiments. Section 6.5 presents and analyzes the experimental results, highlighting key findings and discussing the main limitations of the proposed model. Section 6.6 provides managerial insights and practical implications for decision-makers. Finally, Section 6.7 concludes the paper by summarizing the contributions and outcomes and proposes promising directions for future research.

6.2 Literature Review

In the era of Industry 5.0, Human–Robot Collaboration (HRC) within assembly lines offers promising benefits in productivity and customization. However, optimizing such collaboration demands careful consideration of tasks' coordination, safety risks, and failure management from design to operational phase. Berx et al. (2022) disclose 254 HRC risk factors that 44%, 27%, and 14% of them relate to technology, human, and collaborative workspace respectively and highlight the criticality of facing emerging HRC challenges throughout the legislation and all decision-making stages for such systems. This section starts with introducing the existing studies on various short-term to long-term decisions in a human-robot collaborative assembly system and highlights the addressed problems and the applied solution methods so. It synthesizes key contributions from the literature on Human-Robot Collaborative Assembly Line Balancing Problems (HRC-ALBP) in more detail. Then, studies that address HRC risks are discussed based on the impact they have on safety, time, quality, and performance. Through reviewing the literature, emphasis is placed on exploring HRC-ALBPs, human-robot interaction risks, and constraint-based formulations to enhance operator safety and the reliability of human-centric assembly systems.

6.2.1 Human-Robot Collaborative Assembly

6.2.1.1. Problem features

The integration of cobots into assembly lines has driven a surge of interest in models that support hybrid work distribution between human and robot agents. The first group of studies approached this integration by exploring cobot types and investment prospects, optimizing the workstation layout and evaluating task characteristics to categorize tasks possible to be performed by a human, cobot, or both independently or decomposed into subtasks suitable for collaborative execution (H, C, H/C, H+C). According to the assembly decision layers, these choices constitute long-term strategies. Complexities related to cobot properties, parts' physical features or processes, required skills, as well as the safety and ergonomic factors are the key evaluation criteria in studies by Bruno & Antonelli (2018), Bilberg & Malik (2019), Dianatfar et al. (2019), Lamon et al. (2019), Malik & Brem (2021), Cai et al. (2022 & 2025), Alessio et al. (2022), Gualtieri et al. (2023) on task allocation.

The second types of studies involve short-term decisions such as dynamic task scheduling at the operational level of assemblies. A human-robot collaborative workstation constitutes a dynamic and highly complex environment, wherein a network of integrated sensory systems continuously monitors operational conditions to enable real-time adaptations such as automated adjustments to speed, force, and proximity, as well as intelligent task reallocation. These dynamic or online task modifications consider operational efficiency metrics besides ergonomics and safety obligations in response to unplanned events during human-robot interactions. Tsarouchi et al. (2017), Bogner et al. (2018), Mokhtarzadeh et al. (2020), Pupa et al. (2021), Maderna Petzoldt et al. (2022), Li et al. (2022), et al. (2022), Merlo et al. (2023), Ren et al. (2023), Tchane Djogdom et al. (2024) have investigated such task allocation/re-allocation and scheduling models. Implementing advanced approaches like learning algorithms, dynamic fatigue models, Augmented Reality (AR), Internet of Things (IoT), Digital Twin (DT), digital human and motion recognition are among the most recent topics in dynamic task planning research which can be found in the studies by Yao et al. (2024), Cimino et al. (2024), Sandrini et al. (2025), Gao et al. (2025), Ajidarma & Nof (2025), Yang et al. (2025), Amirnia & Keivanpour (2025), Nicoletti & Appolloni (2025).

A third group of studies investigates mid-term assembly decisions in the presence of cobots where task categories (H, C, H/C, H+C) are predetermined and online monitoring systems handle unexpected interactions among human, robot, and collaborative environment. Assigning cobots, workers, and tasks to the workstations are the primary decisions in this group which is the topic of the current study as well. Basic HRC-ALBP literature such as the studies of Weckenborg et al. (2020), Çil et al. (2020), Sikora & Weckenborg (2022), Huang et al. (2024) implement traditional ALB features and solution approaches in HRC setup with minimal modifications in available resources and task execution modes. Next level of HRC-ALBP studies seek minimization of costs, number of cobots or workers in addition to the cycle time or number of workstations, known as the conventional objective functions in ALBPs. Such papers by Samouei & Ashayeri (2019), Rabbani et al. (2020) Koltai et al. (2021), Kinast et al. (2022), Nourmohammadi et al. (2022), Zhang et al. (2024), and Mao et al. (2025) involve mixed-product, diverse line configurations, the deployment of multiple cobots, and varying levels of human operator skill. They contribute to greater realism in modeling and deal with a substantially increased complexity of decision-making process in the solution approach.

Next expanded category of HRC-ALBPs is enriched by merging human factors into the time-cost improvement goals. Major investigations by Weckenborg et al. (2022), Stecke & Mokhtarzadeh (2022), Dalle Mura & Dini (2022), Abdous et al. (2023), Keshvarparast et al. (2025), Yin et al. (2025), Celik & Ozcelik (2025) concentrate on HRC ergonomics through human fatigue and energy expenditure models. Rare studies, such as those by Papetti et al. (2022) and Kheirabadi et al. (2025), explicitly incorporate the criticality of safety risks arising from decision-making consequences in human-robot collaborative line balancing. Starting with the strategic decision, Papetti et al. (2022) provides a conceptual framework for investigating task features to find suitable execution modes and then as a mid-term decision assigning tasks to workstation using a multicriterial framework evaluating ergonomics, safety, effectiveness, flexibility, and costs. The ranked weighted sum of all evaluation criteria determines the best solution. They use Pilz Hazard Rating (PHR) technique through which the safety risk is obtained by multiplication of scores for the degree of possible harm, probability of occurrence, possibility of avoidance, and frequency of exposure. A safe zone policy is proposed by Kharabadi et al. (2025) within the CP-based framework of an HRC-ALBP. This policy controls the proximity of workers and cobots as well as the duration of exposure to high-risk task executions by eliminating simultaneous, but non-collaborative, tasks performed by humans and cobots in the same workstation zone. However, Nourmohammadi et al. (2024) rely on safety sensors and other technologies to enable multiple humans and cobots presence in the workstations and Mokhtarzadeh et al. (2020) assume pair of tasks that do not meet the safety distance requirement. This literature gap highlights the necessity of current research and reveals future opportunities for reflecting more human safety factors in line balancing models. Using the principles of FMEA, this paper integrates a quantitative risk metric into the mathematical model of HRC-ALBP and optimizes it along with cycle time, which is not explored in previous works. The next sub-section will dive into safety and other risk factors in HRC assembly literature.

6.2.1.2. Solution approaches

Depending on the research objectives and the complexity of the proposed HRC-ALBP, researchers have applied a variety of exact, heuristic, metaheuristic, and hybrid solution methods. One stream of research focuses on incorporating diverse features of HRC- ALBPs into the solution approach, while another stream concentrates on exploring and comparing various methodologies to identify the most effective one. Mixed-Integer Linear Programming (MILP), Benders Decomposition (BD), Constraint Programming (CP), Simulated Annealing (SA), Genetic Algorithm (GA), Particle swarm optimization (PSO), Bee Algorithm (BA), Artificial bee colony (ABC), Migrating bird optimization (MBO), and Tabu Search (TS) are the applied techniques in the reviewed papers in the previous sub-section. Advanced learning methods, simulations, and digital twins have not yet been widely adopted for addressing HRC-ALB models. Instead, they are more commonly applied to online/dynamic task planning or cobot trajectory optimization, where real-time responsiveness is prioritized over optimality of the solution (Ragaglia et al. (2018), Kousi et al. (2019), Nikolakis et al. (2020), Yu et al. (2021), Maderna et al. (2022), Wang et al. (2023)). Although instant decisions are not involved in HRC-ALBPs, the complexity of assumptions is the motive for exploring alternative approaches to the conventional MIP models. Decomposition algorithms and Constraint Programming are the primary substitutes and their superiority in finding optimal solutions for balancing/scheduling problems is largely investigated in literature by Bukchin & Raviv (2018), Pinarbasi et al. (2019), Michels et al. (2019), Abidin Çil & Kizilay (2020), Zohali et al. (2021), Güner et al. (2023), Işık & Yildiz (2024). In the context of HRC, Mokhtarzadeh et al. (2020), Koltai et al. (2021), Sikora & Weckenborg (2022), Stecke & Mokhtarzadeh (2022), Dimény & Koltai (2023), Huang et al. (2024), Vahedi-Nouri et al. (2024), Nourmohammadi et al. (2025) reveal how CP and Benders Decomposition (BD) exceed MIP approach.

Constraint Programming (CP) is a methodology for solving combinatorial problems by specifying a set of constraints that define the desired solution properties, rather than outlining the steps to find it. The solution is then obtained by searching for variable assignments that satisfy all constraints simultaneously and probably optimizing a target function (Apt, 2003). A set of constraints, variables and their domains form the model fundamentals in which variables represent decision points, domains define the possible values each variable can take, and constraints restrict the combinations of variable assignments (Apt, 2003; Bukchin & Raviv, 2018). A powerful feature of CP is its ability to naturally model discrete decision problems with logical, temporal, spatial, and resource-based constraints suitable for complex scheduling or assembly line balancing decisions (Bukchin & Raviv, 2018). Moreover, CP does not require constraints to be linear or the objective function to be continuous which is well-suited for discrete, highly constrained, and non-linear decision problems. This flexibility is particularly relevant to characteristics of our investigated HRC-ALBP, where logical expressions could handle relationships between task modes and worker skills. Additionally, task mode selection in parallel executions and safety risk controlling constraint benefit from logical and temporal separation expressions of CP while linearization of such constraints increases model complexity. CP solvers combine constraint propagation, which reduces the domains of variables by eliminating inconsistent values, and systematic search techniques, such as backtracking or branch-and-bound, to efficiently explore the solution space (Apt, 2003). Thus, we are using CP as a previously proven suitable methodology for modeling our unique HRC-ALBP. Thus, we are using CP as a previously proven suitable methodology for modeling the unique complexities of our HRC-ALBP, where task-to-workstation and workforce allocation, skill-dependent processing times, and safety-aware parallel task restrictions must all be resolved simultaneously.

6.2.2 Reliable and safe HRC

Human-Robot Collaboration (HRC) in manufacturing environments introduces new dimensions of risk, reliability, and complexity of a system. Ensuring safe interaction between humans and robots is essential for the successful deployment of collaborative robotic systems, especially in dynamic assembly lines and hazardous operations. The collaborative workspace requires not only physical safety mechanisms but also reliable task allocation, real-time risk assessment, and robust system architectures that can respond to failures or uncertainties (Li et al., 2024; Gualtieri et al., 2021b). Berx et al. (2022) identify 254 HRC-specific risk factors and categorize them into five groups of humans, technology, collaborative workspace, enterprise, and external. Industrial risk assessment methods for robotic/cobotic applications are explored by Chinniah (2016) and Huck et al. (2021). This sub-section reviews the studies on assembly line decision-making across strategic, tactical, and operational levels, with particular attention to how each research approach challenges related to human-robot collaboration safety other categories of risks.

Design-phase safety controls relate to long-term approaches like workstation layout design, cobot design and programming, standards and risk management at the beginning of cobot integration into the manufacturing environment. Operational level safety risk controls focus on collaborative work condition adherence to the standards, regulations, and goals, following by instant adjustments on human and cobot sub-tasks or actions as the short-term decisions. The middle stage of controls in tactical level assembly decisions should verify the safety of human-robot collaboration while distributing tasks and resources to the workstations to achieve certain given the existing constraints.

While the literature is expanded for design and operational level controls, the influence of task and resource assignment on safety of collaborative assembly lines is significantly neglected.

6.2.2.1 HRC risks impacts

An adopted HRC risk assessment framework is derived from Process Failure Mode and Effects Analysis (PFMEA) by Antonelli & Stadnicka (2019) and evaluates the Risk Priority Number (RPN) of tasks' based on risk failure influence on four distinct categories of safety, time, quality, and performance. This categorization supports a structured analysis of how task execution failure affects HRC reliability and helps guide risk mitigation strategies from long-term to short-term decisions.

Safety-driven risk analysis: The most direct and critical impact of failure in HRC systems pertains to safety. Numerous studies have addressed collision avoidance, dynamic risk assessment, and danger zone prediction to protect human operators in shared workspaces. For example, Saenz et al. (2020) consider safe human-robot distance during the design of collaborative spaces and Liu et al. (2020) developed an active response strategy based on real-time risk evaluation. Similarly, Lacevic et al. (2023) proposed the use of explicit danger zone modeling, while Scalera et al. (2022) advocated for adaptive dynamic safety zones to optimize both fluency and protection. Formal methods like HAZOP-UML and SAFER-HRC have also been introduced to enhance safety assurance through hazard modeling and verification (Guiochet, 2016; Askarpour et al., 2016). Alenjareghi et al. (2024) explored real-time job hazard detection using AI and computer vision. These approaches are particularly useful in robot trajectory and task planning in risk assessment tools and automation frameworks at the operational level that support safe HRC configurations (Poot et al., 2018; Huck et al., 2021) and provide additional design-time solutions for long term.

Time-oriented risk impacts: Failures that disrupt task timing, such as robot malfunction, delayed handovers, or sensor misreads, constitute the time risk category. These failures typically lead to production delays or synchronization breakdowns. Research by Zhao et al. (2025) and Wang et al. (2023) illustrates how flexible and adaptive scheduling mechanisms can absorb such temporal disturbances in real-time. Scalera et al. (2022) emphasize collaboration fluency and productivity improvement besides human safety assurance and develop an online scaling of dynamic safety zones that reduces idle times. Furthermore, simulations using hidden semi-Markov models (Wang et al., 2023) and digital twins (Liu et al., 2025) have been developed to proactively handle time-sensitive risks. These methods mostly provide short-term reactive solutions to the dynamics of a collaborative environment and target reducing time-loss while safety requirements are met.

Quality-related failure effects: Failures in this category primarily affect output quality, either due to inaccurate part placement, inconsistent force application, or misalignment between human and robotic actions. Studies such as Realyvásquez-Vargas et al. (2019) and Gualtieri et al. (2022) incorporate quality feedback loops and ergonomic guidelines to mitigate such risks. Realyvásquez-Vargas et al. (2019) focus on validating successful operations during collaborative workstation design starting from the cobot installation to the worker training step and explore probable hazards such as mechanical, electrical, vibration, pressure, and health risks associated with cobot. Then they score the probability and severity of certain hazards in the scale of 1-5 and multiply them to obtain the associated risk. They highlight the analysis of risks associated with cobots, validation procedures for cobot integration in the assembly station, and operators training as the three main stages of reducing HRC risk. Maisano et al. (2020) develop a distributed-Process FMEA (dP-FMEA) framework for risk assessment in distributed manufacturing tracing various failures including the quality-related issues across different production systems. They tackle how to conclude on the SOD parameters and RPN value in the FMEA method when various experts from around the world assess and score each potential failure risk parameters.

Performance-impacting factors: Performance-related risks influence efficiency and throughput. These group of studies adopt a system thinking approach, where performance is seen as the outcome of multiple interrelated factors namely cost, safety, ergonomics, time, quality, and technological infrastructure. Rather than optimizing a single aspect, these works address the trade-offs or synergies among various dimensions of risk to ensure overall effectiveness of the human-robot collaborative system. Michalos et al. (2018) demonstrate how seamless integration of HRC in automotive assembly affects system throughput, emphasizing the co-dependence of all these factors on performance. Faccio et al. (2023) model task allocation considering variable cobot speeds, accounting for safety margins, cycle time, and ergonomic impacts to optimize performance. Zhao et al. (2025) propose a safety-efficiency integrated task allocation framework, explicitly balancing safety risk, task duration, and adaptability to support overall HRC performance. Bonini et al. (2024) present a risk-aware task sequencing method that factors in multiple safety and operational constraints, enabling more coherent collaboration workflows. Antonelli & Stadnicka (2019) propose an FMEA based risk assessment method to capture potential collaborative assembly errors affecting time, safety, quality, and overall performance. Note that human cognitive-related factors such as mutual trust and preferences in task execution could impact HRC performance as well (Rahman & Wang, 2018; Noormohammadi-Asl et al., 2025). As with the studies of this category, they try to address combination of risk effects (safety, time, and quality) to ensure a reliable HRC. However, none of the reviewed papers have analyzed the role of decision policies in task distribution among the assembly workstations and conventional ALBP objectives such as cycle time minimization alone might lead to HRC risks in the collaborative assembly lines.

6.2.2.2 Integrating Safety in HRC-ALBP Models

Despite growing attention to HRC risks and safety challenges, they haven't been integrated as a quantitative parameter within optimization-based Assembly Line Balancing Problems (ALBPs). Already reviewed papers in previous subsections address these risks in a single workstation at design or operational levels. FMEA and PFMEA (Lee & Yam, 2012; Stone et al., 2021; Antonelli & Stadnicka, 2019; Maisano et al., 2020; Murino et al., 2023), Job Hazard Analysis (JHA) (Alenjareghi et al., 2024); HAZOP (Hazard and operability study) (Guiochet, 2016), Fault Tree Analysis (FTA) (Bensaci et al., 2017), and Pilz Hazard Rating (PHR) (Papetti et al., 2022), are the applied risk assessment methods to identify and assess HRC risks in collaborative workstations. Marvel et al. (2015) and Faccio et al. (2023) utilized standard ISO 15066 as the main reference for setting the parameters and risks evaluation during task distribution between human and cobot. Relevant standards such as ISO 10218 and ISO/TS 15066 provide guidance for cobot integration, but practical implementation requires context-sensitive risk analysis.

JHA, HAZOP, and FTA are valuable in safety assurance and design reviews, yet they are difficult to embed directly into an ALBP optimization framework because their outputs are not inherently optimization-ready: JHA is typically local to a job step, making it sensitive to operator behavior and situational factors and therefore hard to translate into stable, consistent task-station-mode coefficients; HAZOP is powerful for systematic deviation analysis (best for "what-if" deviations), but it can expand combinatorially with the deviation trees, which does not map well to the compact structure of ALBP; and FTA provides a rigorous causal logic for top events and yields risk representations that are not naturally time-dependent (e.g., exposure during parallel work) nor easily decomposed into scalable linear constraints for assignment and sequencing. As a result, these methods typically require an intermediate translation into per-task risk scores or constraint rules before optimization. In contrast, PFMEA aligns naturally with ALBP because it produces structured, assembly processes (tasks)-level, quantifiable parameters (S, O, D) that can be indexed by task i, workstation w, and execution mode m, aggregated as objective terms or constraints, conditioned on human/cobot execution modes via mode-specific risk coefficients, and adjusted through model-controlled design choices (e.g., improved detection via reduced occurrence via safer allocations and overlap restrictions), enabling scalable risk-aware optimization without inflating model complexity.

Existing studies treat safety as a design/operation-time evaluation or as an external assessment without embedding it into mid-term decision models such as ALBP. As a result of underdeveloped risk-aware ALBP, there is a significant opportunity to establish the utilization of structured risk assessment methods outputs within deciding for assigning the cobots and human operators to the workstations and then distributing the tasks among workstations and workforces. In this context, the present study builds on literature by introducing a CP-based model for ALBP that explicitly integrates tasks' critical failure impact parameters categorized into safety, time, quality, and performance inspired by PFMEA model proposed by Antonelli & Stadnicka (2019). By doing so, it offers an inclusive approach for optimizing the efficiency of collaborative assembly lines by minimizing the cycle time while maintaining worker well-being and system robustness through mitigating potential task execution failure effects.

6.3 Problem description

6.3.1 Human-Robot Collaborative Assembly Line Balancing (HRCALB)

An HRCALB problem investigates a proper approach to finding the best station for human operators and robots based on their capabilities and distributes the tasks to stations given the availability of these working agents. The balancing decision generally considers assembly line layout configuration, task requirements, and workforce characteristics as the problem constraints while fulfilling certain goals. Figure 1 illustrates the assumed assembly line with available workforce, the tasks to be assigned to the workstations respecting a predetermined precedence graph, and the available modes to perform these tasks. Since the fenceless collaboration of humans and robots challenge proper and punctual performance of assembly processes, the proposed HRCALB problem incorporates the outputs of a PFMEA risk assessment methodology as the additional parameters during finding the optimal values for decision variables. Moreover, this model minimizes a weighted objective function consisting of cycle time and maximum accumulated risk of tasks failures among stations. The reasoning behind choosing PFMEA risk parameters for this model is explained in 3.2. Any failure during tasks execution may impact deadlines, quality goals, safety requirements, and ultimately the overall performance of the assembly line. By bonding root causes and balancing decisions, this approach redefines the efficiency improvement of a collaborative assembly line. The assumptions of the studied balancing problem are as follows:

- a1 Serially arranged stations in the assembly line of one product type.
- a2 Fixed number of workstations
- a3 A maximum of one cobot and one human worker can be allocated to each station.
- a4 One cobot type with three speed level control
- a5 Labeled human workers in three levels based on their training, skills, and experience in performing all tasks.
- a6 A total of 9 possible modes for performing tasks depending on human skill, cobot engagement, and speed level.
- a7 Due to technological limitations or high risk-related parameters, some modes are impossible for certain tasks, but there is at least one feasible mode for each task.
- a8 The most critical failure of all tasks and their required parameters are predetermined and given by the risk assessment team
- a9 Severity, which is divided into four categories of effects (safety, time, quality, performance), occurrence, and detectability scores are the failure risk-related parameters.
- a10 The level of severity, occurrence, and detectability difficulties vary as per task mode.

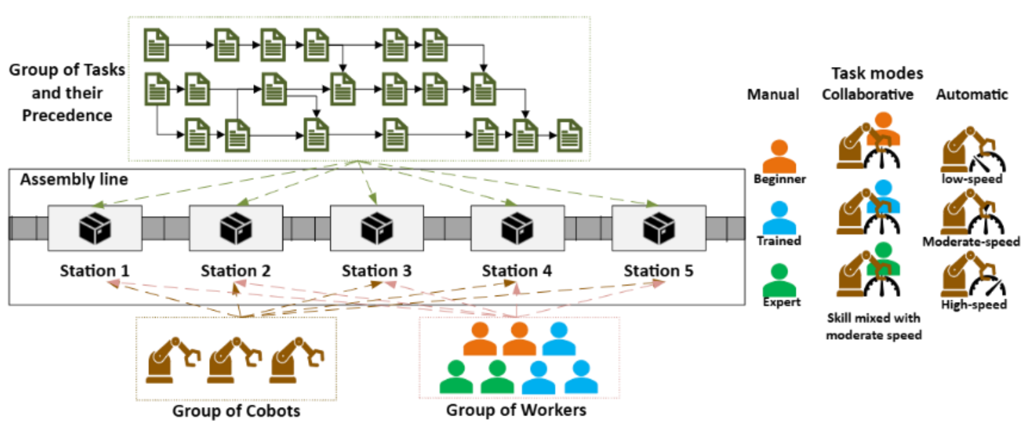

Figure 6.1. Illustration of assembly line layout, workforces, tasks precedence and available modes

6.3.2 Failure risk reduction basis

FMEA, FTA, and HAZOP are the frequently applied techniques in the context of HRC (Murino et al., 2023). HAZOP is a qualitative method to identify potential hazards and operability issues in a process/system and FTA starts with a specific defective state and uses a logic diagram to understand cause-effect chains. Both methods are cause-oriented tools while FMEA has some derivatives with a process-oriented approach (PFMEA) that better merge in ALBP. Unlike design-stage FMEA, process FMEA focuses on risks during manufacturing and assembly processes. Despite FMEA utilization in design-stage HRC, PFMEA has not been sufficiently integrated into production decision models such as assembly line balancing. It systematically evaluates potential failure modes, their causes, and effects on process outcomes, assigning scores for severity (S), occurrence (O), and detection (D) to compute a Risk Priority Number (RPN) or its variants such as the Alternative RPN (ARPN) (Carlson, 2012; IEC 60812:2018). Authorities use this list of ranked failures to start mitigation actions, and the next round of assessments verifies no additional hazards raised from process modifications. In PFMEA, the expert team provides a list of potential failures and ranks them based on their criticality. Higher priority is usually assigned to the higher RPN, which is calculated by the multiplication of S, O, D, or higher ARPN, which is the sum of S, O, D. However, decisions for treatment may be influenced by the severity of the failure mode, meaning that if there are failure modes with similar or identical RPN/ARPN, the failure modes that are to be addressed first are those with the high severity rating (IEC 60812:2018).

The developed HRC-ALBP model uses ARPN as the failure risk representative instead of widely used RPN. S, O, and D parameters scale between 1 to 10, and their multiplication (RPN) will result in non-continuous numbers between 1 and 1000 which makes ranking and comparing risks across tasks less straightforward. Thus, ARPN is suggested by international standard of FMEA (IEC 60812:2018) as the modified version of RPN to provide a continuous scale for the assessment of criticality by aggregation of S, O, and D. The ARPN values are usually lower than those from the RPN method and being less sensitive to small changes in parameters. For instance, risk parameters of a task in mode 1 are $S_1 = 10, O_1 = 1, D_1 = 1$ leading to $RPN_1 = 10, ARPN_1 = 12$ while in mode 2 are $S_2 = 5, O_2 = 5, D_2 = 5$ leading to $RPN_2 = 125, ARPN_2 = 15$. The RPN value here could be misleading for the managers in the task mode selection as a moderately risky task mode appears much “riskier” than an extremely severe but rare failure. However, ARPN preserves the catastrophic signal of mode 1 and the catastrophic but rare event is still comparable in importance to modes with medium risks. Moreover, tuning parameters and risk threshold setting are more transparent with ARPN values than with RPN, where certain values are skipped without explanation, making it harder for managers to interpret the risk shifts. In real-world assembly systems, managers often want to test “what-if” scenarios by tightening or relaxing risk thresholds to evaluate trade-offs between safety and productivity. With ARPN, such adjustments are intuitive: increasing the threshold directly increases the allowance for cumulative risk in predictable, proportional increments. In contrast, tuning RPN thresholds produces nonlinear and sometimes abrupt changes, since the product structure magnifies interactions between S, O, and D. This can lead to inefficient outcomes, such as admitting extremely severe but rare risks (e.g., $9 \times 3 \times 2 = 54$) while excluding moderate ones (e.g., $4 \times 4 \times 4 = 64$).

Based on a worst-case logic, we assume one top failure risk and the relevant S, O, and D parameters for each possible mode of assembly tasks are determined and given by the risk assessment team. Since we aim at minimizing the accumulated risk of tasks assigned to workstations and find a balanced plan in terms of risk and time efficiency, considering the most critical failure of each task intrinsically cover the remaining lower-level failures. Thus, maximum potential failures will be minimized. Then, we incorporate these parameters into the constraints and objective function of an ALBP. Inspired by applied PFMEA in collaborative workstation by Antonelli & Stadnicka (2019), we assumed that Severity of a failure is given into four categories of effects on safety, time, quality, and overall performance (which is influenced by other three effects); each associated with different values depending on the selected task mode. Besides overall risk reduction in the objective function, the model includes a limitation for the safety effect severity in case of assigning two tasks in parallel. If the total effect on human safety exceeds a certain threshold, this constraint permits parallelization only when the associated failure risks are either infrequent or detectable.

Although summation (ARPN) and multiplication (RPN) of S, O, D parameters can both be modeled in CP, cumulative workstations ARPN constraints propagate better and make threshold adjustments more stable (fewer “sudden” feasibility shifts in the solution space) due to values continuity. The multiplicative structure of RPN creates an inconsistent feasible region for the risk variable, leading to a weak pruning procedure that removes values from the variable domain when they correspond to invalid solutions. For optimization models like ALBPs, this continuity of ARPN values helps ensure smoother objective functions and reduces the chance of artificial “jumps” in risk calculations. Therefore, ARPN could better represent the required risk variable in our developed HRC-ALBP and the target numerical experiments. NOTE that in the provided CP model, “$\mathrm{EPN}_{\mathrm{ew}}$” of workstation “w” represents the sum of SOD parameters associated with all assigned tasks to the station in severity effect category “e” and ARPN will take the maximum value of sum of station’s EPN values among all workstations.

6.3.3 Optimization model HRC-ALBP

Indices:

i, j	Assembly tasks
w	Workstation
$m, \acute{m}$	Task mode
e	Effect of failure
k	Human skill level

Sets and Parameters:

Nt	Total number of tasks
Nw	Total number of workstations
Nr	Total number of collaborative robots
Nh_k	Total Number of human workers with skill level k
Effects	Set of the group of effects caused by probable failures {Safety, Time, Quality, Performance}
Tasks	Set of all tasks {1, …, Nt}
Stations	Set of all workstations {1, …, Nw}
Skills	Set of human workers skill levels {1 (b=beginner), 2 (t=trained), 3 (x=expert)}
Speed	Set of Cobot’s speed levels {l(low), m (moderate), h (high)}
Modes	Set of all task modes {1 (H_b), 2 (H_t), 3 (H_x), 4 (H_bC), 5 (H_tC), 6 (H_xC), 7 (C_l), 8 (C_m), 9(C_h)}
P_i	Set of predecessors of task i

NA_m	A subset of tasks that are not feasible for mode m
dt_{im}	Duration of task i performed in mode m
ν_1	Weight of safety related objective function element (ARPN)
ν_2	Weight of efficiency related objective function element (CT)
S_{eim}	Severity of effect e in the critical failure of task i performed in mode m
O_{im}	Occurrence level for the critical failure of task i performed in mode m
D_{im}	Detection difficulty level for the critical failure of task i performed in mode m
α	Safety severity level that prohibits occurrence and detection levels higher than β
β	Accumulated occurrence and detection limit upon safety severity higher than α
Maxspan	An upper limit for integer variables calculated by $max(t_{im}) \times Nt$

Variables:

X_{iwm}	Binary	$\begin{cases} 1 & if\ task\ i\ is\ assigned\ to\ workstation\ w\ with\ mode\ m \\ 0 & otherwise \end{cases}$
WS_w	Binary	$\begin{cases} 1 & if\ task\ i\ is\ assigned\ to\ workstation\ w\ with\ mode\ m \\ 0 & otherwise \end{cases}$
Co_w	Binary	$\begin{cases} 1 & if\ a\ Collaborative\ Robot\ is\ assigned\ to\ the\ workstation\ w \\ 0 & otherwise \end{cases}$
hu_{kw}	Binary	$\begin{cases} 1 & if\ a\ human\ worker\ with\ skill\ k\ is\ present\ at\ the\ workstation\ w \\ 0 & otherwise \end{cases}$
L_{ij}	Binary	$\begin{cases} 1 & if\ task\ i\ and\ task\ j\ are\ being\ performed\ in\ parallel \\ 0 & otherwise \end{cases}$
WCT_w	Integer	Worktation w Cycle Time
CT	Integer	Cycle Time of the line
sw_w	Integer	Starting time of workstation w
fw_w	Integer	Finishing time of workstation w
st_i	Integer	Starting time of task i
ft_i	Integer	Finishing time of task i
max $\_st_{ij}$	Integer	Maximum time between starting time of tasks i and j

$\min\_ft_{ij}$ Integer Minimum time between finishing time of tasks i and j

Y_{iwm} Interval Task time interval: $[st_i, st_i + dt_{im} = ft_i]$ when $X_{iwm} = 1$

EPN_{ew} Integer Effect priority Number (EPN) for effect e in workstation w

ARPN Integer Cumulative effects Alternative Risk Priority Number of the assembly line

The following Constraint Programming (CP)-based model consists of linear mathematical and logical expressions to formulate the problem characteristics with an objective of minimizing cycle time and accumulated risk in the assembly line. This form of representing the model indicates the most similarities with conventional MILP with the aim of creating better understanding. Later in 3.4, the model with more solver-oriented style of expressions will be provided.

Objective function: Minimize $(\nu_1 * \text{ARPN} + \nu_2 * \text{CT})$ (1)

Subject to:

$\sum_w \sum_m X_{iwm} = 1 \qquad \forall\, i \in Tasks$ (2)

$ft_j \le st_i \qquad \forall\, i \in Taks, j \in P_i$ (3)

$X_{iwm} \rightarrow hu_{kw} \quad \forall\, i \in Tasks, \forall\, w \in Stations, \forall\, m \in \{1, 2, 3\}, \forall\, k \in Skills: k = m$ (4)

$X_{iwm} \rightarrow hu_{kw} \quad \forall\, i \in Tasks, \forall\, w \in Stations, \forall\, m \in \{4, 5, 6\}, \forall\, k \in Skills: k = m - 3$ (5)

$\sum_k hu_{kw} = 1 \qquad \forall\, w \in Stations$ (6)

$\sum_w hu_{kw} \le Nh_k \qquad \forall\, k \in Skills$ (7)

$\sum_w Co_w \le Nr$ (8)

$Co_w = 0 \rightarrow \sum_i \sum_{m \ge 4} X_{iwm} = 0 \qquad \forall\, \text{w} \in \text{Stations}$ (9)

$\sum_w X_{iwm} = 0 \qquad \forall m \in Modes, \forall\, i \in NA_m$ (10)

$\left(end(Y_{iwm}) \le start(Y_{jw\acute{m}})\right) \vee \left(end(Y_{jw\acute{m}}) \le start(Y_{iwm})\right)$

$\forall\, i, j \in Taks: i < j, \forall\, w \in Stations, \forall\, m, \acute{m} \in Modes: \acute{m} = m$ (11)

$\left(end(Y_{iwm}) \le start(Y_{jw\acute{m}})\right) \vee \left(end(Y_{jw\acute{m}}) \le start(Y_{iwm})\right)$

$\forall\, i, j \in Taks: i < j, \forall\, w \in Stations, \forall m, m':\ (\{m, m'\} \cap \{4,5,6\} \neq \emptyset) \wedge (m \neq m')$ (12)

$\sum_m X_{iwm} \le WS_w \qquad \forall\, i \in Taks, \forall\, w \in Stations$ (13)

$X_{iwm} = 1 \rightarrow st_i \ge sw_w \qquad \forall\, i \in Taks, \forall\, w \in Stations$ (14)

$$WS_w \leq WS_{w-1} \quad \forall \text{ w} \in \text{Stations: w} \neq 1 \quad (15)$$

$$sw_1 = 0 \quad (16)$$

$$sw_w = fw_{w-1} \quad \forall \text{ w} \in \text{Stations: w} \neq 1 \quad (17)$$

$$sw_w + SCT_w \leq fw_w \quad \forall \text{ w} \in \text{Stations} \quad (18)$$

$$X_{iwm} \rightarrow ft_i - sw_i \leq WCT_w \quad \forall\, i \in Tasks, \forall\, w \in Stations \quad (19)$$

$$WCT_w \leq CT \quad \forall \text{ w} \in \text{Stations} \quad (20)$$

$$\max\_st_{ij} = \max(st_i, st_j) \quad \forall\, i,j \in Tak \quad (21)$$

$$\min\_ft_{ij} = \min(ft_i, ft_j) \quad \forall\, i,j \in Tak \quad (22)$$

$$L_{ij} = 1 \rightarrow \min\_ft_{ij} - \max\_st_{ij} > 0 \quad \forall\, i,j \in Taks \quad (23)$$

$$\sum_{j \neq i} L_{ij} \leq 1 \quad \forall\, i \in Taks \quad (24)$$

$$L_{ij} = 0 \quad \forall\, i \in Taks, \forall\, j \in P_i \quad (25)$$

$$S_{eim} * X_{iwm} + S_{ej\acute{m}} * L_{ij} \geq \alpha \rightarrow (O_{im} + D_{im}) * X_{iwm} + (O_{j\acute{m}} + D_{j\acute{m}}) * L_{ij} \leq \beta \quad (26)$$

$$\forall\, i,j \in Taks: i < j;\ \forall\, m, \acute{m} \in Modes: m \neq \acute{m};\ \forall e \in \{\text{safety}\}, \forall \text{ w} \in \text{Stations}$$

$$EPN_{ew} \geq \sum_i \sum_m (S_{eim} + O_{im} + D_{im})\, X_{imw} \quad \forall e \in Effects;\ \forall \text{ w} \in \text{Stations} \quad (27)$$

$$ARPN \geq \sum_e EPN_{ew} \quad \forall \text{ w} \in \text{Stations} \quad (28)$$

Equation (1) minimizes the weighted sum of Alternative Risk Priority Number (ARPN) and Cycle Time (CT) of the assembly line. Each task should be assigned to one workstation in one mode (Constraint 2). A task can be started only if all its predecessors are already completed (constraint 3). Constraints (4)-(6) relate to the assumption of human skills and ensure that only one human (one skill level) is in each workstation and the assigned task modes should be in accordance with the available skill level in that workstation. For instance, performing a task in mode H_t or H_tC means assigning a trained operator to the workstation. Since each workstation has only one human, no other task at that station can be performed in modes requiring different human skill levels (H_b, H_x, H_bC, H_xC). The number of workers at each skill level and available cobots are limited (constraint 7, 8), and we can have collaborative and automatic modes only if a cobot is assigned to the workstation (constraint 9). Not all the tasks can be performed in all defined modes (constraint10). Due to the maximum availability of one human and one cobot at each workstation, constraint 11 prohibits the assignment of more than one task to the human or the cobot at a time. Upon selecting a collaborative mode for a task (m=4,5,6) in which both human and cobot are occupied, no other task can be performed in parallel (constraint12). Constraints (13)-(18) relate to initiation and utilization of the workstation in the assembly line. Constraints (19) and (20) determine the value of cycle time of the workstation (WCT) and assembly line (CT). The variable L_{ij} represents the concurrent execution of task pairs (i, j) and constraints (21)-(25) control when it should take the value of 1 or 0. Constraints (26)-(28) relate to failure risk parameters integration into ALBP. If the severity of a task or two parallel tasks hits the limit (α), constraint 26 guarantees that the accumulation of occurrence and detection score will be lower than (β). This constraint ensures that tasks with high cumulative safety risk severity are not performed concurrently by the human and cobot at a workstation, unless their failures are rare and highly detectable. The thresholds α and β represent managerial policy parameters, derived from decision-makers' or experts' judgments, which capture the system's tolerance for safety consequences associated with parallel tasks. An EPN value is calculated for each severity effect group (safety, time, quality, performance) at each workstation in constraint 27 through the sum of S, O, D parameters associated with all tasks assigned to that station. The maximum total EPN (i.e., the sum across all effect groups) among the workstations is defined as the overall ARPN, representing the assembly line's accumulated risk (Constraint 28). This measure is minimized jointly with the assembly line's cycle time (CT).

6.3.4 CP model in solver-specific syntax

The literature of CP-based modeling for HRC-ALBP usually represents the constraints by IBM CPLEX software- specific expressions, while we have used CP-SAT solver of open source OR-Tools in Python to model our problem. It is possible to create most linear constraints as they are in this solver besides the existing specific built-in syntax to represent the logical relations or interval variables.

Minimize $(\nu_1 * \text{ARPN} + \nu_2 * \text{CT})$ (1)

Set of constraints:

(3), (7-8), (13), (15-18), (20), (24-25), (27-28)

$\boldsymbol{AddExactlyOne}\ (X_{iwm})$ $\quad \forall\ i\ \in Taks$ (2II)

$(\sum_i \sum_{ḿ} X_{iwḿ} = 0)\boldsymbol{OnlyEnforceIf}\ (hu_{kw})$ $\quad \forall\ w\ \in Stations, \forall\ k \in Skills$ (4,5II)

$where\ ḿ\ are\ members\ of\ a\ set\ including\ restricted\ modes\ for\ skill\ k$

$\boldsymbol{AddExactlyOne}\ (hu_{kw})$ $\quad \forall\ w\ \in Stations$ (6II)

$(\sum_i \sum_{m>3} X_{iwm} = 0)\boldsymbol{OnlyEnforceIf}(Co_w.\boldsymbol{Not}())$ $\quad \forall\ w\ \in Stations$ (9II)

$\boldsymbol{AddAssumption}(X_{iwm}.\boldsymbol{Not})$ $\quad \forall m \in Modes, \forall\ i\ \in NA_m$ (10II)

$\boldsymbol{AddNoOverlap}([Y_{iwm}, Y_{jwḿ}])$ (11II)

$\forall\ i,j \in Taks: i < j, \forall\ w\ \in Stations, \forall\ m, ḿ \in Modes: ḿ = m$

$\boldsymbol{AddNoOverlap}([Y_{iwm}, Y_{jwḿ}])$ (12II)

$\forall\ i,j \in Taks: i < j, \forall\ w\ \in Stations, \forall m, m^{'}:\ (\{m, m'\} \cap \{4,5,6\} \neq \emptyset) \wedge (m \neq m')$

$(st_i\ \geq\ sw_w)\boldsymbol{OnlyEnforceIf}(X_{iwm})$ $\quad \forall\ i \in Taks, \forall m \in Modes,\ \forall\ w\ Stations$ (14II)

$(ft_i - sw_w \leq CTW_w)\boldsymbol{OnlyEnforceIf}\ (X_{iwm})$ (19II)

$\forall\ i \in Taks, \forall\ w\ \in Stations, \forall\ m \in Modes$

$\boldsymbol{AddMaxEquality}(\text{max\_}st_{ij}, [st_i\ , st_j])$ $\quad \forall\ i,j \in Taks: i \neq j$ (21II)

$\boldsymbol{AddMinEquality}(\text{min\_}ft_{ij}, [ft_i\ , ft_j])$ $\quad \forall\ i,j \in Taks: i \neq j$ (22II)

$(\text{min\_}ft_{ij} >\ \text{max\_}st_{ij})\ \boldsymbol{OnlyEnforceIf}(L_{ij})$ $\quad \forall\ i,j \in Taks: i \neq j$ (23II)

$(S_{eim} + S_{ejḿ} \geq \alpha)\boldsymbol{OnlyEnforceIf}(X_{iwm}, \text{S\_}met_{im})$ (26-aII)

$(S_{eim} + S_{ejḿ} < \alpha)\boldsymbol{OnlyEnforceIf}(X_{iwm}, \text{S}_{met_{ij}}.\boldsymbol{Not}())$ (26-bII)

$((O_{im} + D_{im}) + (O_{jḿ} + D_{jḿ}) \leq\ \beta)\boldsymbol{OnlyEnforceIf}(X_{iwm}, \text{S\_}met_{im})$ (26-cII)

$\forall\ i,j \in Taks: i < j, \forall\ w\ \in Stations, \forall\ m \in \text{Modes},\ \forall\ e \in \{safety\}$

In CP-SAT, $AddExactlyOne\ (var)$ ensures avoiding multiple assignment of a variable (i.e., task to a mode and workstation assignment and human skill in each station) and $AddNoOverlap(var1, var2)$ avoids variables overlaps over the schedule (i.e., tasks executing time window). The expression of "$(constraint)OnlyEnforceIf(var)$" is used to impose a constraint upon satisfying a binary variable (var=1). For example, collaborative and automatic modes are excluded from available modes ($\sum_i \sum_{m>3} X_{iwm} = 0$) of tasks if no cobot ($Co_w.Not()$) is assigned to the workstation (constraint (9II)). Enforcing a constraint could be dependent to more than one variable like three parts of constraint 26-II where two variables satisfaction is necessary to apply the relevant constraints. $AddMaxEquality$(max_st_{ij}, [st_i , st_j]) and $AddMinEquality$(min_ft_{ij}, [ft_i , ft_j]) assign the maximum and minimum value of two variables ((st_i,st_j) and (ft_i,ft_j)) to a new variable (max_st_{ij} and min_ft_{ij}) to help with finding the parallel task pairs.

To implement constraint 26 in CP-SAT style, a new Binary variable (S_met_{ij}) is defined and used to verify the truth of left-hand side expression in constraint (26). If this condition (left-hand side formula) is true and S_met_{ij}=1, then the right-hand side expression must be fulfilled. This is called the reification technique that turns a logical condition or constraint mostly into a binary variable. Thus, we define the relation between binary variable (S_met_{im}) and left-hand side condition ($S_{eim} * X_{iwm} + S_{ej\acute{m}} * L_{ij} \geq \alpha$) as the first step and full reification; then enforce right-hand side condition if S_met_{im} takes value. The partial form of reification called implication is previously used in the constraints 4,5,9,14,19, and 23 using "OnlyEnforceIf" and existing binary decision variables.

6.3.5 Objective variables scaling

Although both ARPN and CT are represented as integer values, they differ in unit/scale. To enable their combination in a single weighted objective function, we applied the following normalization procedures (Figure 6.2) to bring them onto a comparable scale prior to minimization. This procedure is the first step of solving the model in experiments to make sure that the objective weights are properly determined according to the parameters of each example.

For $\boldsymbol{\nu_1 = 0}$:

Create the model with constraints (2)-(28)

Solve model with objective function = Minimize CT

$$\boldsymbol{Min\ CT = f_{min}^{CT}}$$

For $\boldsymbol{\nu_2 = 0}$:

Create the model with constraints (2)-(28)

Solve model with objective function = Minimize ARPN

$$\boldsymbol{Min\ ARPN = f_{min}^{ARPN}}$$

Calculate scaled weights $\boldsymbol{\nu_1}$ and $\boldsymbol{\nu_2}$:

$$\boldsymbol{\nu_1 = \frac{f_{min}^{CT}}{f_{min}^{ARPN} + f_{min}^{CT}}}$$

$$\boldsymbol{\nu_2 = \frac{f_{min}^{ARPN}}{f_{min}^{ARPN} + f_{min}^{CT}}}$$

For scaled $\boldsymbol{\nu_1}$ and $\boldsymbol{\nu_2}$ for objective function elements:

Create the model with constraints (2)-(28)

Solve model with objective function = Minimize $(\boldsymbol{\nu_1 * \mathrm{ARPN} + \nu_2 * \mathrm{CT}})$

Figure 6.2. Solution Approach algorithm

6.4 Design of experiments

The numerical experiments serve two main purposes, aligned with the primary research objective of balancing risk and cycle time. First, they analyze model behavior and results under different system configurations, highlighting how productivity-risk trade-offs vary with operator skill levels, the degree of cobot integration, and the weighting of cycle time and risk in the objective function. This analysis highlights that assigning cobots to all workstations of an assembly line with predominantly unskilled operators is a major source of operational risk. Moreover, adjusting the cycle time weight (±50%) and consequently risk weight, shifts the optimization focus between minimizing cycle time and risk creating an assembly line that is more “output-oriented” or more “risk-conscious”. Second, comparison experiments on safety severity controls for parallel task execution demonstrate the model’s capability in hazardous conditions reduction.

6.4.1 Task times and risk-related parameters

Due to the lack of benchmark data for the developed risk integrated HRC-ALBP in literature, we generated numerical experiments to solve various instances and validate the proposed model in different assembly line configurations. The required data for the basis task times and the tasks precedence graph are obtained from Otto et al. (2013), which is a systematically generated database for ALBP and widely used by studies for performing numerical experiments in this research area. Since they emphasize that the examples with large number of tasks are suitable for testing heuristic and metaheuristic algorithms, we randomly select 25 samples with 20 tasks from this database to proceed with our experiments. Using the same data source, Weckenborg et al. (2020) proposed task times for cobot or collaborative mode as well as a certain percentage of infeasible tasks for specific mode(s). In this regard, we considered the task times from Otto et al. (2013) as the time for trained human skill level ($dt_{im=2}$). Işık & Yildiz (2024) work on ALB with worker assignment problem considered three skill levels, each with 10% additional time by decreasing levels. Inspired by their approach, we generated human task times for beginner (m=1) and expert levels(m=3) with 10-20% increase and decrease from the trained level, respectively (dt_{i1}=dt_{i2}+dt_{i2}*(0.1+(0.1*RAND())), dt_{i3}=dt_{i2}*(0.8+(0.1*RAND()))). Using $dt_{im=2}$ as the basis of time generation for all modes and following the proposed approach by Weckenborg et al. (2020), collaborative mode with trained human is 30–40% faster than human mode and the automatic mode with average speed is 30–40% slower due to the reduced cobot speed for safety purposes (dt_{i5}= dt_{i2}∗(0.6∗(0.1∗RAND()), dt_{i8}= dt_{i2}*(1+0.3∗(0.1∗RAND()))). Then task times for other modes with different skill or speed are generated like the manual modes with random 10-20% difference. A ratio of 0.5 is assumed for the task members of NA_m sets for the beginner level operators, collaborative mode with beginner operator, and high-speed cobot modes. This is applied to create constraints closer to real conditions where there are technical limitations, skill prerequisites, or high failure risks for executing certain task-modes. However, trained and expert operators are allowed to perform all tasks. This infeasibility ratio will respectively decrease to 0.4 and 0.3 as the collaborative mode engage trained and expert humans or the cobot speed is reduced to medium and low.

Failure risk parameters (S, O, D) are basically represented as integer values ranging from 1 to 10 by the risk assessment experts and the FMEA standard IEC 60812. Since we have already excluded some random tasks from executing in particulars modes due to expressed reasons including high risk, we generate the SOD parameters of each feasible task-mode from range 1 to 8. In fact, extreme scores 9 and 10 relate to conditions such as high risk of severe human injury, scrap part/product, extensive delivery delay or complete operation failure that are assumed to be fixed before the balancing stage. Accordingly, in this study, the SOD parameters of each feasible task-mode combination were assumed within the range of 1 to 8 to form a simulated dataset provided by a team of experts for computational experiments of line balancing optimization. This design choice ensures that the model evaluates realistic but manageable risk levels while excluding extremely hazardous conditions. It should be noted that, in practice, S, O, and D values would be determined by a cross-functional risk assessment team (e.g., engineers, safety specialists, and production managers) using PFMEA guidelines and empirical data. Thus, while the current dataset serves as an academic proof of concept for testing the proposed HRC-ALBP model, the approach remains fully adaptable to real-world assessments once such expert evaluations are available.

Antonelli & Stadnicka (2019) divide the severity (S) of a task failure into four categories of effects on safety, time, quality, and performance. Similarly, we generated random values from 1 to 8 for S_{eim} for $e \in Effects$ except performance. Since performance will be affected by the other three categories, starting range its parameter generation starts with the maximum value of other effects. For instance, $S_{safety,i,m} = 4$, $S_{time,i,m} = 6$, and $S_{quality,i,m} = 3$, $S_{performance,i,m}$ cannot be lower than 6. It must be noted that this condition is logically applied to the scores difference among skill levels and cobot speed. For instance, if safety risk effect of a task by an expert human is 5 ($S_{safety,i,3} = 5$), lower levels like trained and beginner operators are associated with safety effects higher than 5. Similarly, the time effect score of 3 for the minimum/low speed cobot mode intrinsically leads to higher scores on high-speed mode due to its lower task time that any interruption imposes extra influence on cycle or completion time.

6.4.2 Experimental scenarios

To focus on the objectives' trad-off and the influence of human skills and cobot integration level throughout the experiments, the number of tasks is assumed fixed (20) and the number of workstations is set to 5. Since the number of available cobots might be less than the number of workstations, the availability of 3 and 5 cobots are both examined. Moreover, the number of available human operators in each skill level (expert(x), trained(t), beginner(b)) is limited and three strategies are explored to reflect their impact: Balanced skills (2x, 2t, 3b), skill dominance (3x, 1t, 3b), and skill shortage (1x, 2t, 4b). The α and β threshold parameters are set to 12, and 14, respectively. Considering the range of SOD parameters from 1 to8, α=12 ensures that tasks can be concurrent without limiting their chance of occurrence and detection (O, D) if both have severity levels lower than 6 or one with S=8 and the other S=4 or lower, representing low safety severity effect. However, if $S_{safety,i,m}$=8 and $S_{safety,j,m}$=5 ,for instance, their total O and D parameters must be less than 14 which ensures at least two low O and D parameters are associated with parallel tasks. This means that either the failure risk rarely occurs, or it is highly detectable. We have tested various combinations of α and β to examine possible SOD parameters and conclude that 12, and 14 properly enforce a moderate level of safety control to the experiments. These parameters are selected only for solving numerical examples in the current study and the decision makers could tune α and β thresholds based on the company's risk tolerance policies and standards, extendable to the judgments of risk assessment team for scoring and rating failures and their related factors. Proposing these limits makes the model more adaptable to real-world industrial applications where managers investigate various approaches to find the best practice in assuring safety and productivity based on the existing production requirements/conditions.

Combining the defined parameters leads to unique assembly line configurations, each with a name in table 1 for better indication of our notion in testing that specific mix of parameters. Since the number of tasks and workstations as well as the α, β values are fixed, they are excluded from this table. Calculation of balanced objective weights ν_1 and ν_2 are explained in subsection 3.5. For the experimental goals, we tried ±50% of the CT weight and to decrease and increase its impacts. Since the total CT and ARPN weights should be equal to 1, the ARPN weight changes respectively. The reported weights in table 1 are the average of 25 weights obtained in each tested configuration. Designing 18 unique configurations from the combination of parameters for 25 selected samples from Otto et al. (2013) resulted in 450 examples, analyzed in the next section.

To further discuss the applied limits to the severity of safety effect in parallel tasks, we performed additional experiments on the configurations with CT-focused objective function (3, 6, 9, 12, 15,18) without constraint 26 containing α and β parameters. A comparison of concurrently assigned tasks to stations with and without this limitation demonstrates the consequences of overlooking this constraint. This result in additional 150 examples, leading to a total of 600 unique tested examples in the numerical experiment phase. Section 5 provides the average of obtained results mostly in the form of figures and tables.

The word "config" in the following sections is used as the abbreviation of configurations introduced in Table 1 and it represents a particular combination of parameters in the solved examples.

Table 6.1. Parameters configurations for numerical experiments

No.	Configuration name	Nr	Nh_x	Nh_t	Nh_b	v_1	v_2
1	Partial cobot-Balanced Skill-Balanced CT&ARPN	3	2	2	3	0.87	0.13
2	Partial cobot-Balanced Skill-Relaxed CT					0.94	0.06
3	Partial cobot-Balanced Skill-CT focused					0.73	0.27
4	Partial cobot-Skill Dominance-Balanced CT&ARPN		3	1	3	0.87	0.13
5	Partial cobot-Skill Dominance-Relaxed CT					0.94	0.06
6	Partial cobot-Skill Dominance-CT focused					0.73	0.27
7	Partial cobot-Skill Shortage-Balanced CT&ARPN		1	2	4	0.87	0.13
8	Partial cobot-Skill Shortage-Relaxed CT					0.94	0.06
9	Partial cobot-Skill Shortage-CT focused					0.73	0.27
10	Full cobot-Balanced Skill-Balanced CT&ARPN	5	2	2	3	0.87	0.13
11	Full cobot-Balanced Skill-Relaxed CT					0.94	0.06
12	Full cobot-Balanced Skill-CT focused					0.73	0.27
13	Full cobot-Skill Dominance-Balanced CT&ARPN		3	1	3	0.87	0.13
14	Full cobot-Skill Dominance-Relaxed CT					0.94	0.06
15	Full cobot-Skill Dominance-CT focused					0.73	0.27
16	Full cobot-Skill Shortage-Balanced CT&ARPN		1	2	4	0.87	0.13
17	Full cobot-Skill Shortage-Relaxed CT					0.94	0.06
18	Full cobot-Skill Shortage-CT focused					0.73	0.27

6.5 Analysis of results and discussion

The outputs of designed numerical experiments in section 4 are presented here in detail. All the examples are implemented in Python environment and solved using OR-Tools CP-SAT solver in a laptop Intel Core i7 with 16GB RAM. A limit of 14,400 seconds has been set to solve the model which was enough to find the solution for all the tested instances. As a default setting, CP-SAT sequentially explores potential solutions without concurrent search in different directions of the solution space. Thus, we adjusted the solver settings to make it suitable for our complex decision-making model and to benefit from the solver capabilities.

Number of search workers in CP-SAT determines how many and which search algorithms are used to investigate potential solutions. This number is set to one by default and we raised it to 20 to activate parallel utilization of diverse search algorithms. Depending on this solver parameter, logical processors of the computer are separately engaged with exploring the solution space using an specific method and update the best solution details whenever they found a better one. This must be noted that the search workers can be raised by 64 depending on computer hardware specifications (CPU, Memory, and Logical processors) in order to solve more complicated problems. Probing parameter of the solver is also set to 4 instead of 1 (default) as a technique to fix some variables in advance and examine the consequences on the solution space as well quickly inspecting the constraints. Using this parameter, we perform a pre-solve stage that tries to simplify the model as much as possible with fixing some variables, tuning variable boundaries, or managing the constraint redundancies. Pre-solving usually takes less than 2 minutes but allows the solver to better interpret and simplify the formulations before starting the main search phase. For instance, symmetrical solutions are very probable in scheduling decisions and will be checked at this level.

6.5.1 CT and ARPN minimization trade-off

"Increasing the automation capacity (more cobots) and human skill levels consistently reduce the cycle time, while the risk metric (ARPN) reduction mostly depends on human skills improvement". Table 6.2 contains the average of optimal objective function and time of finding this solution per designed configuration. The objective function is calculated from the weighted sum of Cycle Time (CT) and Alternative Risk Priority Number (ARPN) variables, and they are reported in Table 6.2 as well. CT and ARPN correspond to the cycle time and the total sum of SOD parameters for the tasks assigned to the workstation that attains the maximum of these values among all workstations. ARPN increases with higher task SOD parameters unless the balancing model reallocates tasks to achieve a lower ARPN. The model doesn't set thresholds for CT and ARPN and finds the lowest possible values that reflect better line balancing performance. Assigning more tasks with longer durations to a workstation results in higher cycle time. Similarly, assigning more tasks with higher SOD parameters could increase the ARPN values. Following the FMEA framework, failure criticality is primarily driven by severity; therefore, we incorporate a constraint on safety-effect severity to allow managerial threshold setting on this parameter.

Since the model aimed at simultaneous minimization of ARPN and CT, assigning a higher weight to one of them, (e.g., ν_1), in the objective function drops the value of its corresponding variable (ARPN) but raises the other (CT). Due to the nature of the problem and task time parameters, CT values are intrinsically greater than ARPN. Higher CT weight leads to higher objective function values, whereas balanced weight distributions and increased ARPN weights respectively yield intermediate and the lowest objective values. (Table 6.2, Figure 6.3). The variation of CT and ARPN weights among the examples are represented in Figure 6.4.

Table 6.2. Average objective function with its composing variables and the average solution time per config

Config	Cobot - Skill (x, t, b) - weights (ν_1, ν_2)	CT (sec)	ARPN (Risk)	Objective	solution time (sec)
1	3 - (2, 2, 3) - (0.87, 0.13)	952	120	205.31	1659
2	3 - (2, 2, 3) - (0.94, 0.06)	1040	113	156.89	1233
3	3 - (2, 2, 3) - (0.73, 0.27)	877	133	283.83	1657
4	3 - (3, 1, 3) - (0.87, 0.13)	893	113	194.59	1085
5	3 - (3, 1, 3) - (0.94, 0.06)	982	107	147.95	787
6	3 - (3, 1, 3) - (0.73, 0.27)	852	122	272.13	1264
7	3 - (1, 2, 4) - (0.87, 0.13)	1041	138	232.22	2037
8	3 - (1, 2, 4) - (0.94, 0.06)	1121	132	178.42	1145
9	3 - (1, 2, 4) - (0.73, 0.27)	956	156	318.49	2538
10	5 - (2, 2, 3) - (0.87, 0.13)	900	119	199.55	1162
11	5 - (2, 2, 3) - (0.94, 0.06)	996	111	152.81	877
12	5 - (2, 2, 3) - (0.73, 0.27)	834	134	274.81	1124
13	5 - (3, 1, 3) - (0.87, 0.13)	849	112	188.51	680
14	5 - (3, 1, 3) - (0.94, 0.06)	916	106	144.44	538
15	5 - (3, 1, 3) - (0.73, 0.27)	795	123	260.15	647
16	5 - (1, 2, 4) - (0.87, 0.13)	975	137	225.17	1435
17	5 - (1, 2, 4) - (0.94, 0.06)	1057	128	172.61	946
18	5 - (1, 2, 4) - (0.73, 0.27)	906	154	302.93	1499

Comparing configs 1-9 with configs 10-18 reveals that increasing the automation capacity (more cobots) and human skill levels consistently reduce the cycle time, while skill levels are more influential in risk (ARPN) reduction. The ARPNs values associated to the configurations with skill shortage are the greatest risk amounts in Table 6.2 and configs 5 and 14 with the highest skilled workers and different numbers of cobots produce the minimum average ARPN values. As a result, cobot integration does not increase risks on its own; rather, operators' expertise is more influential on collaborative assembly lines. Availability of 5 cobots for an assembly line with 5 stations, eliminates the decision for cobot-to-station assignment decision and reduces model complexity. Therefore, the time for finding the solution in configs 10-18 is always lower than their similar configs (1-9) only with 3 cobots. Moreover, configs with more expert humans (4-6, 13-15) are less time consuming in finding the best solution compared to the rest of configs as the solver requires less searching time to assign a skilled human to a workstation. Accordingly, availability of more skilled workers or cobots relative to the number of workstations contributes to faster solution convergence.

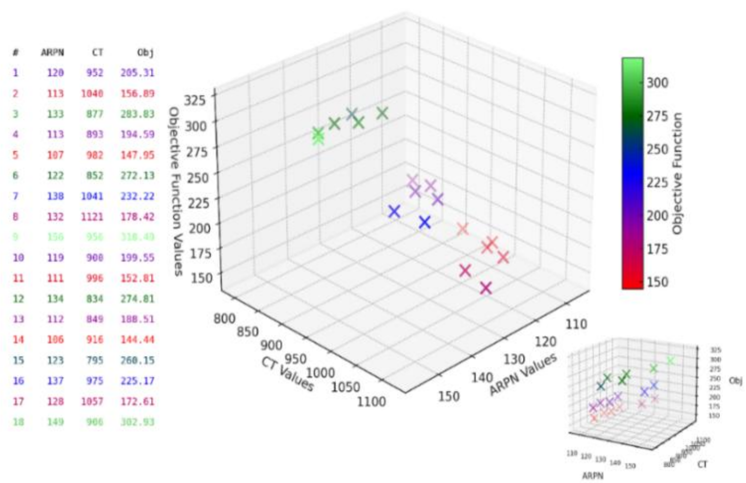

Figure 6.3. 3D visualization of average CT, ARPN, and objective function values per configuration

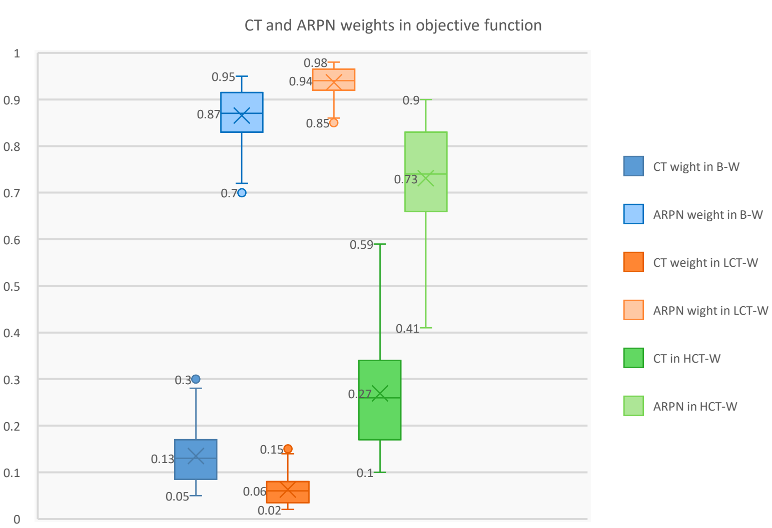

Figure 6.4. CT and ARPN weights in the objective function

A clear understanding of how the assembly line depends on cobots and varying levels of human skill supports wiser decisions in resource management to achieve a reliable productive system. Table 6.3 represents the average percentage of each task mode utilization across 18 tested configs and Figure 6.5 visualizes these distributions. A general observation across all configurations is the prevalence of expert-driven modes, particularly expert human (H_x) and expert human collaborating with cobot (H_xC). These modes dominate the charts in several configurations (e.g., 4-6 and 13-15), suggesting that expertise, whether human alone or combined with robotic support, is central to effective task execution. Expert operators and expert-cobot collaborations intrinsically complete tasks more quickly and with fewer errors, which directly supports the cycle time and risk minimization objectives of the model. The high engagement of these modes reflects system setup to emphasize precision and consistency through expertise. At the same time, a noticeable underutilization of beginner-level human (H_b) and collaborative beginner (H_bC) modes across the

Table 6.3. Task mode utilization percentage per tested config

Config/Mode	H_b	H_t	H_x	H_bC	H_tC	H_xC	C_l	C_m	C_h
1	5	25	27	3	8	25	6	1	0
2	4	25	30	2	9	20	9	1	0
3	5	27	20	5	7	31	3	1	1
4	6	11	40	2	5	31	4	1	0
5	4	12	44	1	4	27	7	1	0
6	7	10	36	2	6	35	3	1	0
7	10	29	16	7	10	14	11	2	1
8	9	31	17	6	8	14	13	1	1
9	14	27	9	7	14	20	6	2	1
10	3	16	19	4	14	30	11	2	1
11	2	19	23	3	14	26	11	2	0
12	3	15	17	4	19	32	7	2	1
13	2	7	30	4	8	41	6	2	0
14	2	8	34	2	8	36	9	1	0
15	3	6	24	4	9	46	5	2	1
16	7	22	12	9	17	17	12	3	1
17	6	22	13	7	17	16	18	1	0
18	8	18	10	11	20	19	9	2	3

most configurations implies that the system avoids allocating tasks to less experienced personnel, potentially due to performance or safety concerns. Moreover, under skill shortage conditions (Configs 7-9 and 16-18), a higher proportion of tasks shift to manual or automatic modes, which aligns with expectations. The preference for intermediate (H_t, H_t C) and expert-level engagement also suggests a risk-averse strategy that still balances task distribution across skill levels to maintain operational efficiency.

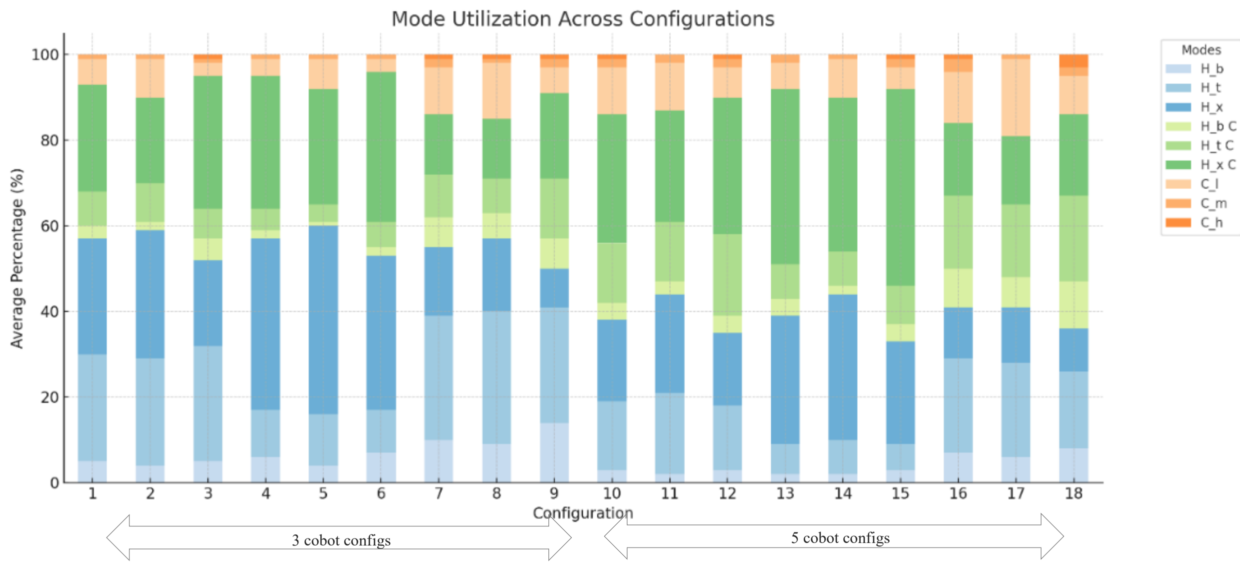

Figure 6.5. Visualization of task mode utilization percentage per tested config

Distinct patterns emerge by factoring in the cobot integration levels where configs 1-9 involve 3 cobots and configs 10–18 involve 5 cobots. In lower-integration configs (1-9), the reliance on human-only modes is more pronounced, especially H_t and H_x, while collaborative and robot-only modes are present but restrained due to limited cobot availability. With the system transitions to higher cobot integration in configs 10-18, there is a marked shift by more frequent collaborative modes (H_tC, H_xC) and robot-only modes (C_m, C_h). This is the result of expanded automation capacity that allows offloading more tasks to collaborative or autonomous modes. Some configurations stand out despite the general trend. For example, config 16 have the most evenly distributed mode utilization, suggesting a configuration capable of leveraging diverse resources/modes effectively at the condition of skill shortage. Conversely, config 15 (with 5 cobots) is highly skewed toward H_xC, indicating a strong reliance on expert collaborative work and minimal use of standalone human or automatic modes.

Next analysis of results is dedicated to the objectives trade-off. The Pareto front between Cycle Time (CT) and Aggregated Alternative Risk Priority Number (ARPN) in Figure 6.6 identifies the configurations that represent efficient trade-offs between production speed and operational risk: reducing CT generally comes at the expense of higher ARPN, while lowering ARPN tends to increase CT. A configuration appears on this front if no other tested configuration example achieves a strictly lower CT and a strictly lower ARPN simultaneously. In other words, each Pareto-optimal solution is non-dominated: improving one performance criterion inevitably degrades the other. Solutions plotted in red in Figure 6.6 correspond to Pareto-optimal solutions that satisfy this non-dominance criterion. Non-Pareto points (not red) lie inside the objectives trade-off space, indicating they are outperformed by at least one pareto-optimal configuration sample point in both dimensions. Configurations at the lower-left segment of the front represent balanced compromises, while those at the extremes emphasize either aggressive CT reduction at elevated risk or significant risk reduction at the expense of production speed.

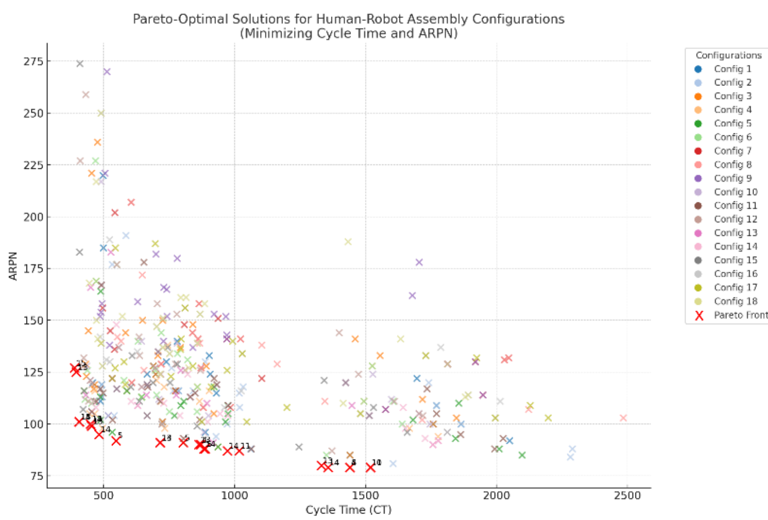

Figure 6.6. Pareto-Optimal Solutions in the scatter plot of all results

Pareto-front points act as rational choices for decision-makers and selecting any non-pareto configuration would imply the existence of another configuration with both a lower CT and a lower ARPN. From an operational perspective, the identified pareto front allows decision-makers to consciously navigate the productivity-risk trade-off among various combinations of available resources and system parameters while ensuring that no dominated (suboptimal) configs are chosen. For instance, repeated presence of certain configurations (e.g., 13, 14) in pareto front points reflects a robust balance between automation efficiency and controlled operational risk, making them more adaptable to varying production conditions. Accordingly, those parameters are useful starting points for seeking a collaborative assembly that balances productivity with risk (including safety).

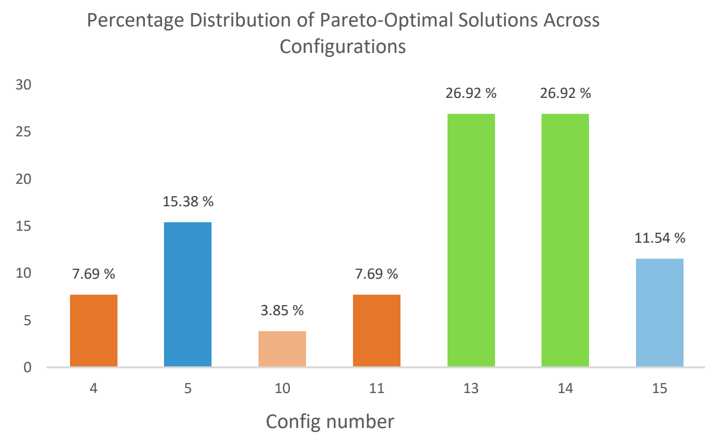

Figure 6.7. Prevalence of configs in the pareto-optimal points

According to findings, the Pareto-optimal set includes configs 4, 5, 10, 11, 13, 14, 15, which are characterized mostly by high cobot deployment combined with either balanced or high-skilled worker strategies (Figure 6.7). These designs leverage automation to achieve substantial CT reductions without disproportionately inflating risk, keeping ARPN at competitive levels. For example, Config 15, with full cobot deployment and more expert humans, occupies the lower-left region of the Pareto front, indicating its ability to maintain short CTs while controlling the overall risk. Almost 54% percent of pareto-optimal points belong to configs 13 and 14, which have the same high cobot counts (5) and human skills (3 experts). Higher cobot counts tend to push solutions toward shorter CTs, but if paired with beginner-heavy skill distributions, they can elevate ARPN due to elevated SOD parameters. Consequently, such configurations are frequently excluded from Pareto-optimality. This observation highlights that variations in joint cobot allocation and worker skill distribution can shift a solution closer to or farther from the Pareto frontier, featuring the link between system design parameters and multi-objective performance.

Pareto solutions for all configurations except #15 are associated with balanced ν_1 and ν_2 or lower ν_2; indicating that a greater focus on cycle time than on risk reduction may have a negative effect on system reliability (higher risk), whereas a more focused approach to risk control does not necessarily result in a major cycle time increase. These results further confirm that, in human-robot collaborative assembly systems, the interplay between technological integration, human resource skill distribution, and the composition of objective function weights is decisive in determining multi-objective efficiency. Figure 8 provides a better representation of the correlation between design choices and optimal outcomes. This heatmap is based on Pearson linear correlation values and the color intensity reflects the strength and direction of each relationship with red shades representing positive relationships and blue shades representing negative ones. It primarily highlights that achieving efficient and safe assembly line configuration is not solely dependent on one variable but rather emerges from a carefully tuned interplay of resource composition and objective weighting.

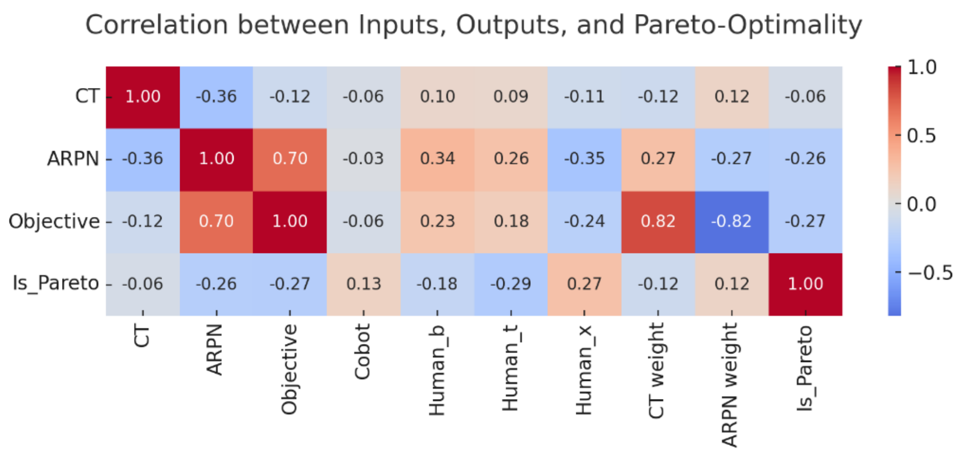

Figure 6.8. Heatmap correlation between key design parameters and optimization objectives

Correlation heatmap demonstrates the correlation between the designed configurations input parameters and the objectives values: Cycle Time (CT), Aggregated Alternative Risk Priority Number (ARPN), the composite Objective function, and Pareto-optimality. The heatmap highlights how strategic parameters such as available skilled workers drive operational efficiency and risk outcomes. CT and ARPN demonstrate negative correlations with Pareto membership, as expected, lower values in both contribute to optimality. reported in Table 2. Since ARPN appears slightly more influential than CT in pareto presence, the effectiveness of risk-aware system design is highlighted. Additionally, ARPN weight shows a positive correlation with being Pareto-optimal (Is_Pareto), while CT weight correlates negatively, suggesting that prioritizing risks over speed in the objective function increases the likelihood of reaching pareto-efficient solutions in the tested configurations. A moderate negative correlation (−0.36) is observed between CT and ARPN, indicating that shorter cycle times are generally associated with higher risk levels, and conversely, as previously reported in Table 2. Interestingly, ARPN appears slightly more influential than CT in determining optimality status, reflecting the effectiveness of risk-aware system design.

As human skills improve, the positive correlation between skills and CT and ARPN gradually decreases, eventually becoming negative for expert operators. This suggests that more skilled teams tend to achieve more favorable outcomes compared to less experienced ones. Furthermore, the correlation analysis indicates that the number of cobots has a negligible direct influence on system performance, implying that increasing the number of cobots from 3 to 5 does not systematically improve production efficiency or risk outcomes within the explored configurations. The slightly positive association with pareto-optimality indicates that configurations with a higher cobot presence may contribute marginally to achieving balanced trade-offs, although the effect remains weak. Overall, these results highlight that system performance depends more on the strategic deployment and coordination of cobots with human workers skills than on their absolute number. This figure reinforces that achieving efficient and safe assembly line configurations is not solely dependent on one variable but rather emerges from a carefully tuned interplay of resource composition and objective weighting.

6.5.2 Safety effect severity control impact

"The application of the safety constraint suppresses high-risk parallel tasks while reconfiguring allocations toward safer collaborative modes, demonstrating the system's adaptive capacity to preserve productivity under safety requirements." The original optimization model considers all four categories of risk severity parameters effects on safety, time, quality, and performance in the ARPN variable in the objective function. However, the severity of a risk is always under watch by risk management team mostly due to safety reasons. For example, the team prioritize the risks with higher severity score upon having the same RPN in the FMEA method. Inspired by this mindset, we have included a constraint in the model that set a threshold for safety effect severity in independent parallel task executions by human and cobot.

The comparative analysis of mode utilization (Figure 9) reveals a shift in task assignment strategies depending on whether the safety severity constraint on high-risk parallelism is enforced. Striped bars in Figure 9 represent the "Without" constraint condition for visual distinction. Across all configurations, the removal of the constraint leads to a higher reliance on robot-only modes. In contrast, when the constraint is applied, the system compensates by slightly increasing the use of human-cobot collaborative modes (H_bC, H_tC, H_xC), maintaining productivity while adhering to safety limits. The utilization of human-only modes (H_b, H_t, H_x) remains generally stable, indicating that the constraint primarily affects how robotic resources are deployed in shared workspaces.

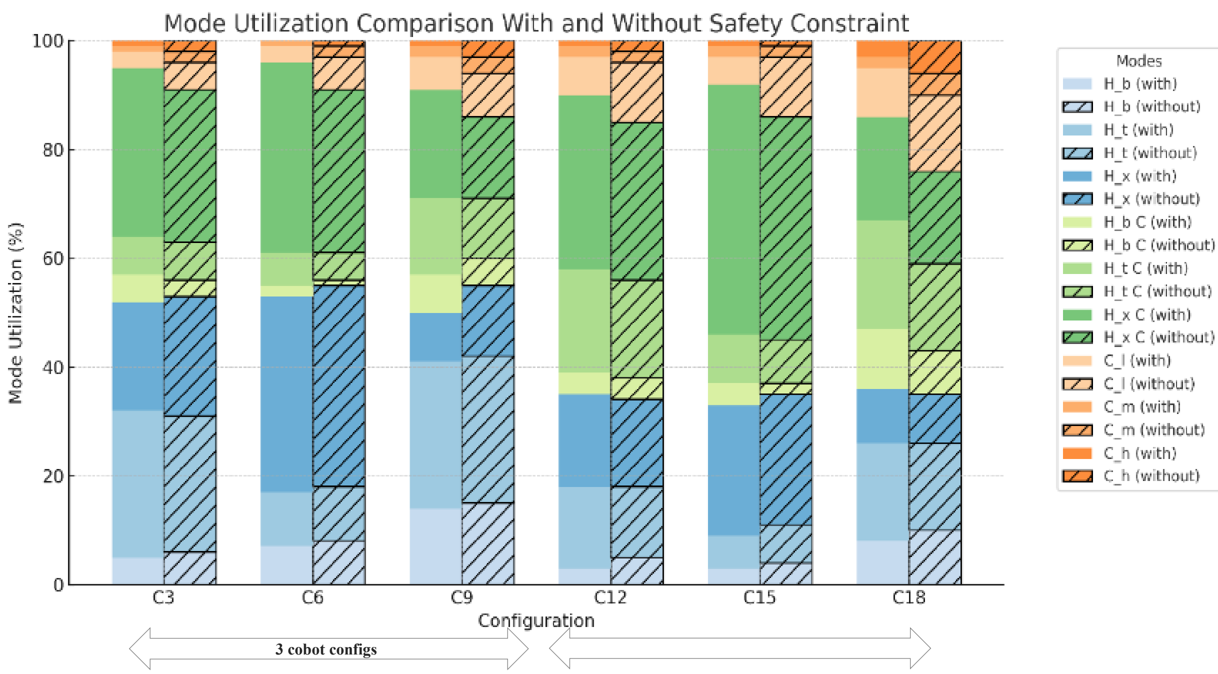

Figure 6.9. Task mode utilization percentage per config with/without safety severity limit

This shift in strategy is further validated by the parallel task duration analysis (Table 6.4). Safety severity threshold prevents tasks concurrency when the cobot should be active with maximum speed and the operator is unskilled, while this hazardous condition happens by ignoring the constraint. Without the safety severity limitation, the cumulative average duration of parallel tasks per configuration is significantly higher. For instance, configuration 3 shows a total of 2452 seconds without the constraint versus only 677 with it and a dramatic reduction observed consistently across all configurations. The unconstrained system exploits more opportunities for concurrency, especially in modes involving high-speed cobots (C_h), which are very restricted when the constraint is active. In the constrained setting, parallelism still exists but is reallocated to safer, slower configurations involving lower risk cobot modes (C_l, C_m) and highly skilled human involvement (H_t, H_x), reflecting a deliberate trade-off between safety and efficiency. In other words, this supports the idea that while riskier forms of concurrency are suppressed, the system seeks alternative means to retain productivity by favoring safer overlaps. In turn, this reinforces

Table 6.4. Average duration of parallel task modes per config with/without safety severity limit

Average parallel tasks duration per config/mode		*With limit*			*Without limit*			*With limit*		*Without limit*	
		H_b	H_t	H_x	H_b	H_t	H_x	CT	ARPN	CT	ARPN
3	C_l	260	0	68	363	371	384				
	C_m	0	155	194	311	155	148	877	133	851	132
	C_h	0	0	0	457	211	52				
Sum		677			2452						
6	C_l	221	0	81	325	406	322				
	C_m	0	0	130	280	60	197	852	122	829	121
	C_h	0	0	0	457	204	0				
Sum		432			2251						
9	C_l	341	366	0	395	436	285				
	C_m	254	155	0	213	341	0	956	156	931	155
	C_h	0	0	214	377	270	148				
Sum		1330			2465						
12	C_l	263	300	40	290	415	306				
	C_m	250	93	0	134	287	219	834	134	779	130
	C_h	0	168	0	289	320	310				
Sum		1114			2570						
15	C_l	130	0	0	360	325	325				
	C_m	250	74	40	250	243	151	795	123	762	120
	C_h	0	168	0	191	308	0				
Sum		662			2153						
18	C_l	296	148	0	472	428	197				
	C_m	250	276	0	290	264	23	906	149	821	154
	C_h	0	248	0	331	439	330				
Sum		1218			2774						

the mode utilization findings, where collaborative execution modes gain relative prevalence under safety constraints. Taken together, the analysis features the adaptive capacity of the system that actively reconfigures task allocations in response to safety constraints by reducing risky concurrency, extending collaborative engagements, and preserving safe forms of parallelism.

The comparison of Cycle Time (CT) and Alternative Risk Priority Number (ARPN) across configurations with and without the safety effect constraint reveals a nuanced trade-off. In all configurations, the application of the safety constraint results in a moderate increase in CT, indicating a slowdown in production likely caused by reduced opportunities for parallel execution. This aligns with earlier findings where the constraint led to fewer and shorter concurrent tasks. However, ARPN values do not consistently decrease under the constraint. It is conceptually immature to equate the improvement of safety (achieved through constraints) with the total disappearance of risk. Although the constraint successfully limits high-severity safety risks, it may inadvertently force the system to adopt alternative task assignments that carry higher risks in other dimensions, such as time or quality. Therefore, applying the safety constraint introduces a multi-dimensional risk redistribution, emphasizing the importance of balancing safety enhancements with overall system efficiency and operational risk in human-robot collaborative environments. Decision-makers should note that mitigated effects in one risk dimension may adversely affect other risk dimensions and evaluate whether such increased impacts are acceptable.

For further analysis of safety effect constraint impact, we have calculated the total sum of SOD parameters associated with parallel task pairs in four categories of safety, time, quality, and performance, which is represented as EPN value in Figure 6.11. Labeled data in this figure present the average sum of S, O and D scores for one pair of parallel tasks (EPN value) in each effect category across six configurations and two compared assignment strategies: “With” and “Without” constrained severity of safety effect for parallel task execution. The constrained model reduces the likelihood of risky task overlapping while the unconstrained model allows unrestricted parallel execution, regardless of associated risk. Having few EPN values in Configs 3, 6, and 15 in the presence of constraint (no blue box appeared in the plot) reflects a deliberate model behavior, where the constraint effectively filters out risky parallelism during scheduling those configurations. Also “With Constraint" results consistently show lower average parallel pair EPN values in the safety category compared to other effects, which highlights the direct impact of the constraint on safety risk mitigation. Conversely, the "Without Constraint" group allows more flexibility, resulting in higher average EPN values in general.

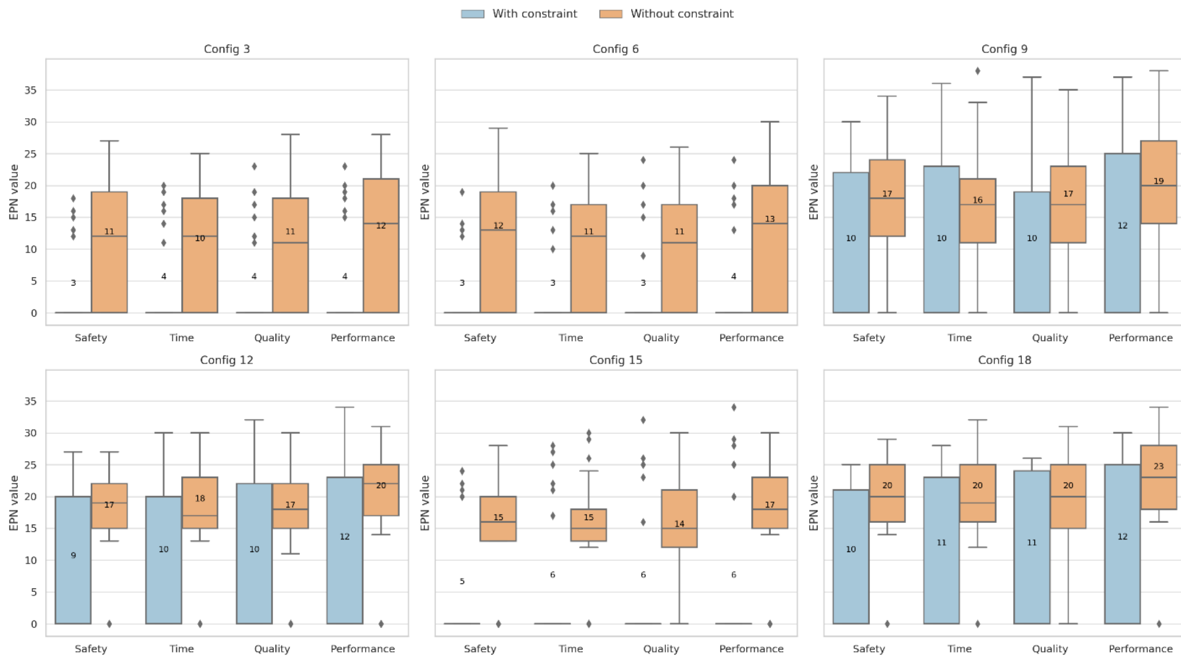

Figure 6.10. Average EPN=S+O+D per severity effect category among configs compared with/without safety threshold constraint

Deploying more cobots (configs12,15,18 compared to configs 3,6,9) is associated with higher EPN values in all effect categories, either in presence or absence of the safety threshold constraint. However, significantly lower EPN values in the constrained group of these configs (12,15,18) suggest that greater automation (more cobots) enhances the flexibility needed to meet safety constraints. Regardless of the number of available cobots, lack of expert operators escalates the overall risk of parallel task pairs. The lowest EPN average relates to configs 6 and 15 where the number of expert workers is higher than other configs. On the other hand, lack of human expertise in configs 9 and 18 resulted in the highest average EPN values. The highest risk profile in config 18 illustrates the difficulty in forming safe task overlaps during balancing an assembly line with fully cobotic stations without the support of highly skilled labor. Finally, comparison results for the proposed controlled concurrency constraint highlights the value of integrating safety-aware logic in promoting balanced operational efficiency and worker protection for Human-Robot Collaborative Assembly Line Balancing Problems.

6.5.3 Limitations

First group of model limitations relates to the problem's assumptions about the assembly line characteristics such as line layout, product counts/models, homogeneous cobot type, and discrete levels for human skill and cobot speed. Changing each of these features will need fundamental modifications to the parameters, variables, and constraints of the optimization model. Secondly, the risk-related parameters are simplified to prevent model from over complications and leave the room for emphasizing on the novelty of its integration with ALBP and following impacts. For instance, the most critical failure and its associated S, O, and D parameters are considered for each task, whereas in practice a task may involve multiple potential failure risks, each with its own uncertain SOD values. Such complexity could be more realistically captured in future work using stochastic programming techniques or Monte Carlo simulations that capture probability distributions of these parameters. Additional failures risk parameters significantly increase the number of variables and constraints, demanding new solution approach and higher computational capacity. All the risk parameters are inspired by PFMEA technique whereas other methods may not necessarily utilize severity, occurrence, and detectability scores to assess HRC risks.

In this study, the S, O, and D parameters were assigned values between 1 and 8 to focus on realistic but non-catastrophic conditions, excluding extreme cases that in practice would already be mitigated before line balancing decisions. In real industrial settings, however, these parameters are not arbitrarily chosen but assessed by cross-functional teams whose judgment and contextual knowledge play a crucial role. Collecting SOD data across diverse tasks and modes is resource-intensive, requiring expertise, historical failure records, and detailed operational insights. While our constructed dataset/numerical experiments do not replicate the full complexity of industrial environments, it enables testing the model under varied conditions and demonstrates its potential. This controlled setup strengthens the credibility of the findings by ensuring transparency and reproducibility, while highlighting a pathway for future validation through real-world case studies that promote the practicality of the proposed model.

Although extending the failure risk beyond the safety effect and assigning distinct parameters to the time and quality effects of a probable task failure brings novelty to HRC-ALBP, it requires adjustments to the risk assessment team procedures in advance. Moreover, it is not always straightforward to differentiate among individual failure effects or to account for the synergistic impact of multiple factors. Assuming a safety severity constraint using α and β threshold parameters is another model limitation that can be further investigated by trying multiple combinations, experts' opinions, or decision-makers preferences. However, all these innovations stem from careful investigations into the fundamentals and requirements of HRC, as well as the decision-making structure of ALBP, which together establish the foundation for developing novel decision-support tools that not only ensure operational efficiency from a balancing perspective but also enhance reliability in HRC.

From the methodological perspective, the current model implements a scalarization method to minimize the weighted sum of cycle time and aggregated ARPN in a single objective framework. However, ARPN could be replaced by RPN (the original risk priority number from FMEA approach) or combined with other objectives including operational and investment costs, number of stations, and number of human operators. Moreover, other techniques capable of handling multiple objectives such as Lexicographical method, epsilon-constraint method, and Non-dominated Sorting Genetic Algorithm II (NSGA-II) could be implemented for expanding the current experiments in future research. Numerical experiments performed in this study are designed in a way that focuses on joint CT-ARPN optimization outcomes rather than exclusive influence of cobots integration into assembly lines. Thus, the numbers of tasks and stations are fixed, and the experiments concentrate on varying task modes and objective weights. Examining a wider range of cases with greater parameter diversity in future research would likely yield more conclusive results.

6.6 Managerial insights

The numerical experiments confirm that in Human–Robot Collaborative Assembly Line Balancing Problems (HRC-ALBP), productivity and operational risk are inseparably linked; optimizing one often involves concessions in the other. Cycle Time (CT) minimization and ARPN reduction compete for priority, and the balance point ultimately depends on managerial preferences and risk tolerance. By embedding a safety-severity constraint that limits the combined severity of safety effects in parallel human–cobot tasks, the proposed model elevates safety to near-equal priority with productivity. This dual emphasis reflects real-world conditions in industries where risk exposure carries regulatory, financial, and reputational consequences. While cost is not explicitly modeled, cobot availability and workforce skill distribution indirectly influence overall expenditure, making cost integration a promising avenue for future research where it may add further tension to existing trade-offs.

The safety-severity constraint aligns directly with established global collaborative robotics safety frameworks, such as ISO 10218 and ISO/TS 15066, which emphasize minimizing hazardous force interactions and maintaining safe separation distances. In practical terms, the constraint operationalizes these principles by reducing high-risk parallel task combinations, thereby lowering overall risk metrics and, in effect, reducing the likelihood of costly accidents, compliance breaches, or production stoppages. This approach provides a virtual testing ground conceptually aligned with digital twin principles, enabling managers to examine task allocations and configurations against safety requirements prior to deployment. From a managerial perspective, this alignment positions the model not only as a productivity tool but also as a proactive compliance strategy that strengthens long-term operational resilience.

Configuration analysis further reveals that balanced or expert-heavy skill distributions consistently outperform beginner-heavy setups in reducing risk, particularly when paired with higher cobot counts. Continuous training can shift operations toward these safer, more productive configurations while improving worker confidence and reducing execution errors and fostering a safer work environment with extended benefits beyond physical risk controls. The results also warn against indiscriminate automation: increasing cobot numbers without adequate skill readiness can reduce CT but raise ARPN, often excluding such setups from the Pareto front. This supports a phased deployment strategy by gradually increasing cobot integration as workforce proficiency matures and suggests integrating the safety-severity constraint into scheduling systems to dynamically reassign tasks and avoid unsafe parallel operations.

Pareto front results offer actionable guidance for managers. Configurations 13 (Full cobot- Skill Dominance- Balanced CT&ARPN) and 14 (Full cobot- Skill Dominance- Relaxed CT) dominate, demonstrating strong performance in balancing CT and ARPN through the combination of high cobot counts, strong human skills, and effective objective weight composition. Configurations 5 and 15 also appear frequently, leveraging human expertise under varying cobot numbers and weight priorities. In contrast, configurations that never appeared in pareto front reflect trade-offs that may be less attractive in practice. Correlation analysis between parameters such as skill distribution and objective weights reveals predictable patterns that could underpin predictive analytics tools capable of forecasting risk escalation before it occurs. Together, the pareto dominance patterns, correlation findings, and constraint impacts provide managers with a decision-support roadmap (Figure 6.12) for selecting configurations that fit operational priorities, available resources, and safety expectations. We suggest this approach as an operationally viable balance between automation efficiency and human well-being in modern assembly industry.

For industrial applications of the proposed model, accurate PFMEA data is required from a dedicated risk assessment team and the convention PFMEA method should be modified to accommodate the four categories of severity effects needed as the model parameters. Moreover, as with all collaborative environments, installation of reliable safety devices and advanced monitoring systems are crucial and the developed model for mid-term balancing decisions has a complementary role to risk control methods. Finally, validating skills of current human operators is an essential step in introducing cobots into assembly lines, as supported by the results. Therefore, managers should invest in operator training in addition to cobot acquisition if the ultimate goal is improved productivity with reduced safety consequences.

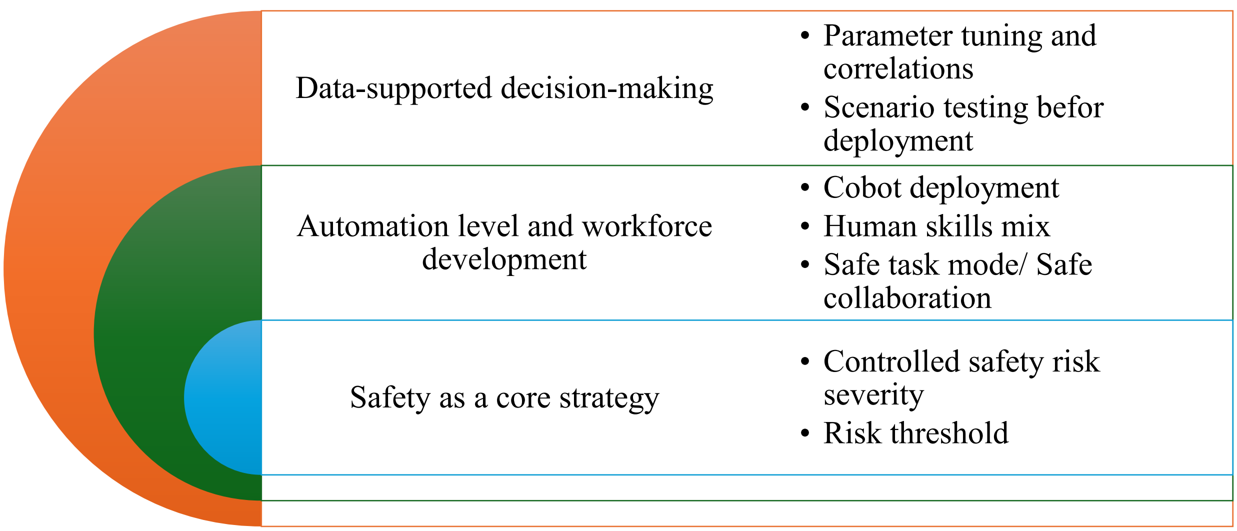

Figure 6.11. Managerial roadmap to safe and efficient human-robot collaborative assembly line

6.7 Conclusion

This study introduces a novel constraint programming (CP)-based optimization framework for the Human-Robot Collaborative Assembly Line Balancing Problem (HRC-ALBP), integrating PFMEA-inspired risk indicators and accommodating varying worker proficiency levels alongside multiple cobot operating speeds. By jointly optimizing cycle time (CT) and aggregated Alternative

Risk Priority Number (ARPN), the model offers a structured means of evaluating the inherent trade-offs between productivity and operational risks. The additional constraint on the task failure risk severity of safety effects for parallel human-cobot tasks offers a proactive policy that prevents unsafe operations concurrently in a workstation.

The numerical experiments reveal that productivity and risk mitigation cannot be optimized in isolation; instead, their interaction is highly dependent on the interplay of human skill distributions, cobot availability, and objective weight settings. Configurations characterized by balanced or expert-heavy skill mixes, combined with high cobot counts dominate the Pareto front, offering superior CT-ARPN trade-offs. In contrast, beginner-heavy configurations with elevated cobot counts are often able to achieve shorter CTs at the cost of increased ARPN, leading to their exclusion from Pareto-optimality. These findings emphasize that automation scaling should proceed in parallel with workforce skill enhancement to prevent risk and specifically safety degradation. The relationship between input parameters and outcomes (CT and ARPN) underscores the potential for predictive analytics tools to anticipate risk escalation, enabling managers to perform timely interventions before inefficiencies or safety incidents occur. Moreover, the safety-severity constraint was shown to reduce both the prevalence and duration of high-risk parallel operations, trading marginally slower parallel task execution for substantial reductions in exposure to severe failure effects. This trade-off is useful for developing a high-reliable manufacturing environment.

In summary, the proposed model advances the state of the art in HRC-ALBP by embedding structured risk metrics within a multi-objective optimization framework. It bridges the gap between HRC risk assessment model and HRC assembly line balancing decisions, offering an approach that is one step closer to practical deployment of risk assessment team outputs in mathematical optimization models. This approach suggests establishing a decision-support tool for managers seeking to achieve sustainable, safe, and productive assembly systems. Future research should explore limitations of the current model, push the boundaries of addressing novel HRC challenges and solve problems with features closer to real industrial settings. More complex assumptions regarding the assembly line characteristics and parameters should be examined. Researchers may implement other methods to integrate operational risks with balancing decisions or compare results of various risk assessment techniques. Simple weighted approach for treating the current bi-objective model should be compared with more sophisticated methodologies in future studies.

More importantly, developing unique solution approaches based on heuristic, metaheuristic, or learning algorithms is required for large-sized experiments or industrial case studies where exact methods become highly time-consuming. The entire optimization framework is proposed in a static environment while each component could contain an uncertainty factor in industrial cases. Such extensions would not only improve the realism of the model but also provide decision-makers with richer insights into the risks' distribution, ultimately supporting more resilient and safety-aware assembly line planning.

CHAPTER 7 GENERAL DISCUSSION

This thesis set out three linked objectives: (i) to clarify the decision space of collaborative assembly lines and expose the gap around the tactical level and safety criticality (Paper 1), (ii) to embed a safety constraint based on space zoning that governs parallel execution in collaborative stations (Paper 2), and (iii) to internalize process (task)-failure risk directly in tactical balancing through a FMEA-inspired ARPN objective alongside CT (Paper 3). Taken together, these steps move the conversation from "how fast can we balance?" to "how do we balance fast and safely when humans and cobots share workspace?" The primary contribution of this thesis is not the development of a novel solution algorithm, but rather a conceptual reframing of safety itself that transformed it from an external check into a primary, integrated element of tactical balancing decisions, where safety functions as a preventive driver that shapes feasible task combinations before hazardous situations arise, rather than as a reactive constraint imposed after productivity objectives are defined.

7.1 Theoretical Implications of the Safe Tactical Decisions

The work translates into the first step of this research and takes a step towards recentering the tactical layer of decision space. The literature review paper summarizes a young field while it specifies the point of analysis where safety has been missing. Design-phase compliance and operational monitoring are becoming mature while the tactical layer (task-to-workstation decisions, mode choices, and resource pairing) remained underdeveloped not only in safety terms but also in various realistic problem assumptions and advanced solution methods. Establishing that layer as the proper position for risk-aware balancing matters because decisions there shape the feasible envelope for line performance: which tasks can be parallel, which modes are tolerable, and which skills must co-locate to avoid risky overlaps. Methodologically, this reframing acknowledges that HRC systems involve logical or non-linear dependencies and combinatorial choices that make Constraint Programming (CP) more suitable than purely linear formulations. Conceptually, it provides a clean separation of concerns: design sets capabilities and limits; tactics compose safe/efficient work packages; operations adapt in real time. By clarifying the role of tactics, the thesis supplies a platform for future models to incorporate safety into the part of the system where it will systematically influence outcomes.

The second phase of the research reframes safety as an intrinsic property of the feasible solution space in HRC-ALBP, rather than a pre- or post-processing metric. The safe zone policy introduced in the second article translates an occupational-safety principle into explicit feasibility rules: Simultaneous execution of two tasks is permitted only if human and cobot activities remain confined to their respective zones, while tasks requiring shared or cross-zone engagement are prohibited from parallelization. Human-cobot separate but concurrent tasks are classified as low-risk when confined to separate zones, medium when one agent enters the collaborative/other agent's zone, and high when both tasks occupy same zone(s). Prohibiting medium- and high-risk combinations reshapes feasible solutions and fundamentally alters the optimization landscape, by preventing hazardous concurrency at the planning stage rather than compensating for it through downstream monitoring or emergency interventions. Solutions constrained through the zoning policy consistently exhibit low risk parallels and greater reliance on safe overlaps or sequential execution without significant time loss. This safety-driven model highlights the structural consequences of embedding safety directly into feasibility rules in which concurrency opportunities are no longer simply a function of task timing but of safety-classified accessibility. Thus, ignoring this rule imposes operators to med- to high-risk parallel task pairs. Moreover, the model reveals the effects of design-level factors on mid-term decisions, where changes in task-zone engagement combined with zone threshold policies can shift a system from feasible to infeasible, producing a different task assignment and scheduling strategy. In these cases, cycle time extends because of replacing parallel with sequential execution to ensure that safety is fully preserved; interpreted as a preventive stabilization mechanism that reduces the likelihood of unplanned interruptions, operator hesitation, and risk-induced stoppages during execution.

In the third step, risk is internalized in the objective function to shape a time-risk tradeoff landscape. Introduced safe and efficient human-robot assembly balancing model frames the failure risk of task inside the objective using the ARPN term. Defined ARPN aggregates S, O, and D associated with tasks additively, producing smoother and more interpretable marginal effects than multiplicative RPN in the computation experiments. Theoretically, this yields a trade-space where many dominated points disappear, meaning solutions that "win" on CT by exploiting risky parallelism now carry an explicit ARPN penalty and slide off the Pareto set unless compensated by safer execution mode choices. Therefore, unsafe configurations are discouraged before they are selected and promote inherently safer execution patterns as first-class candidates in the solution space. This explains the empirical pattern that expert-heavy or balanced skill distributions appear frequently on the frontier that enable safe parallelism and keep ARPN in check. Just as important, the distinction of ARPN into four categories of safety, time, quality, and performance clarifies the redistribution of risks when safety is tightened by additional constraints. This shows that safety improvements may displace risk into other dimensions, reinforcing the importance of evaluating the full vector of ARPN effects rather than a single aggregated score.

A relevant concern is whether combining a safety constraint with a risk-based objective amounts to ‘double counting’ which is not the case. The two mechanisms serve different but complementary roles. The constraint establishes a strict boundary by prohibiting high-severity concurrent hazards, which mirrors regulatory expectations. In contrast, the risk objective guides optimization within that safe boundary, steering the system toward lower overall risk levels across time, quality, and performance dimensions. This dual-lever design ensures that one mechanism guarantees a floor of protection, while the other tunes efficiency and residual risks, together shaping outcomes not only in CT and ARPN but also in exposure duration, mode choices, and average EPN (S+O+D) value patterns for parallel task pairs.

Across experiments of the bi-objective model, a consistent pattern emerges at certain configurations with human skills beating the cobot speed. Upon the higher cobot availability, increments in human skill (especially toward expert levels) deliver larger joint improvements in CT and ARPN than increments in cobot speed when the safety constraint is active. The explanation is structural: skilled humans expand the set of safe parallel pairings (more tasks can run concurrently without breaching severity limits), whereas speed increases may be restricted by the same constraint. This clarifies why some configurations with more cobots underperform on ARPN (and leave the frontier). Thus, speed alone cannot offset risk when unsafe pairings are eliminated. The theoretical message is that skill and speed are non-substitutable in the presence of safety thresholds; their payoffs differ by threshold policies. This reinforces the idea that human expertise functions as the basic enabler of safe concurrency, whereas cobot speed functions as an amplifier once safety is already ensured.

From an operations research perspective, the applied methodology contributes beyond its specific optimization results in two important ways. First, it demonstrates how safety knowledge from the domain can be built directly into the model as logical constraints rather than just treated as penalty terms. Doing so allows the solver to systematically rule out unsafe options early in the search process, making it easier to handle large and complex decision spaces. Second, it shows the value of using an additive risk measure (ARPN) instead of the traditional multiplicative RPN. Because ARPN is additive, it allows managers and researchers to test "what-if" scenarios on severity, occurrence, or detection values and to see how small changes affect overall risk. By contrast, multiplicative RPN can create sudden jumps that make results harder to interpret. Together, these features mean the model is not just a mathematical solution approach but a planning framework that can support sensitivity analysis, reveal risk redistribution across categories, and link tactical balancing with broader organizational goals of resilience, compliance, and productivity.

7.2 Practical Implications of Safe Policies

The work translates into four concrete managerial policies that extend the insights of the models into practice:

- **Safe parallelism policy**. The safe zoning policy and severity-based threshold are not merely rigid barriers but tunable controls. Managers can start conservatively, ensuring stability and operator confidence, and progressively relax thresholds as training, sensing technologies, and workplace maturity advance. This makes safety constraints a proactive lever rather than a static limit, positioning safety as a preventive control that reduces exposure, stabilizes execution, and supports continuous operation rather than merely restricting throughput. The model quantifies the "safety cost of parallelism," offering a clear measure of how much productivity is traded off when stricter safety boundaries are enforced. This allows managers to negotiate acceptable compromises while maintaining compliance.
- **Skill-first deployment**. Results consistently show that investing in operator expertise yields safer concurrency and lower ARPN values than relying only on cobot speed or numbers. In practical terms, this suggests sequencing investments as prioritizing training and upskilling before expanding cobot fleets or increased robot speed modes. Skilled human resources unlock safe parallelism and provide resilience in scenarios where cobot upgrades alone cannot compensate for safety concerns.
- **Configuration screening via Pareto presence**. The Pareto front provides a built-in ranking of feasible line setups under varying conditions. Configurations that frequently appear on the frontier (e.g., 13 and 14) can be treated as "robust candidates" for pilot deployment, while those that almost never appear are unlikely to deliver strong results

without structural redesigns, such as task regrouping. This offers managers a data-grounded tool for pre-screening the system before committing to costly changes on the shop floor.

- **Interpreting risk redistribution**. Presence of safety risk besides the cycle time in the objective function, drives the balancing decisions towards enhanced productivity without sacrificing operator's safe working condition. The safety constraint reduces high safety severity overlaps but redistributes risk into other categories, such as time or quality, due to shifts in task execution modes. This outcome is not a failure of the model but a reflection of trade-offs in real operations. The managerial lesson is to adopt a dashboard view of risk and track ARPN components separately across safety, time, quality, and performance rather than relying on a single aggregate score. This ensures that improvements in safety are not offset by intolerable losses elsewhere, and that management remains aware of displacement effects across risk categories.

The practical contributions of this thesis are most relevant in multi-station collaborative lines where humans and cobots can work in parallel, skill levels among operators vary, and robots operate at more than just minimum speed. In such environments, the model's insight into safe task allocation and risk redistribution provides direct managerial value. However, the findings have limited relevance in highly constrained micro-task settings, where robots already function under strict speed and force reductions with enforced separation distances. The framework is particularly suited for organizations prepared to formalize safety thresholds in consultation with safety teams and to use tactical planning as a decision-support tool that proactively manages both throughput and risk.

A key implication for Industry 5.0 is that safety and human-centric values can be embedded directly into tactical decision-making, rather than being left to strategic design stages or reactive operational controls. By formalizing safety both as an optimization objective and as a feasibility constraint, the framework produces assembly plan that is explainable and aligned with Industry 5.0 principles of resilience and human-centricity. This represents a shift from efficiency-only planning toward prevention-oriented decision-making, where workers' protection is considered through line balancing decisions, and throughput stabilization and long-term competitiveness are strengthened by avoiding safety-related disruptions rather than their correction.

Importantly, adopting these ideas does not demand extensive data infrastructures. Three building blocks are sufficient: (i) a jointly defined safety severity and zone separation threshold, (ii) zone engagement and structured SOD parameters assessments for eligible task-modes, and (iii) a realistic estimate of workforce skill distribution and applicable cobot speeds. With these inputs, the model can generate both a "safe plan" and a "relaxed plan". Comparing these two quantifies the productivity trade-offs and the risks potentially reintroduced, offering managers a concrete basis for investment decisions in training, sensing technologies, or task/station redesign. In this way, the model functions as a practical decision-support mechanism rather than a purely academic theory.

In sum, the applied objectives demonstrate that the placement of safety within tactical optimization fundamentally reshapes assembly line balancing. By embedding safety as both a constraint and an objective, and by quantifying its impact on cycle time (CT), risk (ARPN), duration of human exposure to unsafe operations, mode utilization, and average EPN=S+O+D of parallel task pairs, the framework provides managers with a structured roadmap for navigating trade-offs. It also positions safety as a preventive system property that actively shapes performance outcomes, rather than as a limiting factor accepted only when productivity must be compromised. The contribution lies not only in generating safer or faster plans, but in producing plans that are manageable, transparent, and consistent with the sustainable, human-centric manufacturing systems envisioned under Industry 5.0.

7.3 Limitations and Future Research

While this thesis advances the field of Human–Robot Collaborative Assembly Line Balancing Problems (HRC-ALBP) by embedding safety into tactical optimization models, several limitations remain that construct directions for future studies (Figure 7.1). One central limitation lies in the modeling assumptions and availability of real-world data. The model simplifies spatial interactions by dividing each workstation into three predefined zones with tasks engaging one or more of these zones depending on execution modes. While this assumption provides a structured way to model parallelism and enforce safety constraints, it does not fully capture the fluid nature of real assembly operations. In practice, task boundaries are not always so clear: human reach, cobot trajectories, and tool usage often extend beyond these fixed zones, and movements may blend across zone borders. As a result, risks of interference or unsafe proximity could occur even when tasks are modeled as operating in separate zones. This abstraction, while useful for optimization, may therefore understate real-world uncertainty in spatial overlaps. Future work could address this by incorporating improved workspace mapping and probabilistic zone engagement to better align the model with actual human–robot interaction patterns.

Failure risk parameters (Severity, Occurrence, Detection) were represented as deterministic integer scores on a bounded scale consistent with FMEA conventions, yet in this research they were constructed for experimentation rather than derived from industrial datasets. In practice, such values are assessed by cross-functional teams with contextual knowledge, drawing on operational history and incident records. Moreover, severity assessments are often debated, and occurrence and detection may fluctuate with operator training, maintenance policies, or sensing technologies. Collecting comparable data across a full range of tasks and cobot modes is both resource-intensive and sensitive to organizational practices. As such, the numerical experiments in the research should be read as proof-of-concept demonstrations rather than direct reflections of industrial reality. Future work should aim to validate and calibrate the framework with empirical datasets from industrial partners, which would substantially enhance external validity and practical adoption.

Another limitation arises from the scope of failure risk modeling. Each task was associated with only its most critical failure mode, mirroring the prioritization logic of classical FMEA but simplifying the complexity of real-world assembly where multiple risks may coexist with compounding effects. This assumption underrepresents cumulative uncertainty, especially when risks differ in probability and severity. Future research could overcome this by applying stochastic programming or Monte Carlo simulations to incorporate multiple potential failure modes and their probabilistic interplay. Such approaches would allow exploration of robustness under uncertainty, offering richer insights into how risks propagate across assembly lines and providing managers with a more nuanced decision basis.

The design of the safety constraints also represents a bounded perspective. First, safety was modeled through a zoning-based rule that restricts unsafe parallel execution, effectively eliminating medium- and high-risk overlaps. While this approach proved effective in filtering hazardous concurrency, it does not capture other important safety dimensions such as cumulative ergonomic strain and operator fatigue. In the extension, the model introduced explicit thresholds for cumulative SOD parameters in the safety effect category for concurrent tasks. These thresholds, while useful for ensuring feasibility and offering decision-makers a clear boundary of acceptability, remain fixed values in the current formulation, leaving space for policy makers to adjust them.

Relying on fixed thresholds risks oversimplifies the dynamic and context-sensitive nature of safety management. Future research should therefore move beyond static cutoffs toward more adaptive mechanisms such as probabilistic severity models or cumulative risk measures across multiple parallel tasks. By integrating these dimensions, future models can better reflect the complexity of human–robot collaborative environments and support managers in balancing productivity with a richer and refined understanding of safety.

Methodologically, Constraint Programming (CP) was well-suited to capture the logical constraints and combinatorial nature of HRC-ALBP, yet scalability remains an important issue. The computational experiments in this thesis involved configurations of limited size, whereas industrial environments may involve hundreds of tasks, diverse products, and dynamic disturbances. Solving such large-scale problems may require hybrid solution approaches, combining CP with heuristics, decomposition, metaheuristics, and learning-based methods to achieve practical runtimes. Future research should investigate scalable and adaptive methods capable of supporting near real-time tactical planning, which is crucial for industrial deployment.

The generality and transferability of findings also present limitations. While the tested configurations span a wide decision space by varying tasks, stations, cobot counts, worker skill distributions, and objective weights, they remain conventional abstractions of actual production systems. Real-world manufacturing introduces additional complexity such as product variety, stochastic task arrivals, and unexpected disruptions that were not modeled in this work. Expanding the framework to accommodate these complexities, and linking tactical planning with operational re-scheduling modules, could provide an integrated decision-support system capable of bridging multiple decision layers.

Finally, although this thesis aligns conceptually with Industry 5.0 values of human-centricity, resilience, and sustainability, this integration is largely implicit. Future work should explicitly measure the long-term benefits of safety-aware tactical planning, such as reductions in accident costs, improvements in worker well-being, and avoidance of downtime. Coupling optimization models with digital twins may play an important role here, allowing managers to virtually test line configurations and safety policies before implementation. Since humans' behavior, unpredicted presence, and errors affect the safety of collaborative environment, the future research should greatly work human-centricity aspect of Industry 5.0 study the influence of operators' trust on their cobot co-worker, cognitive overload, training, and learning curves on occupational health and safety. These subjects could be part of enhancing organizational readiness for cobot integration. In this way, future research could move from conceptual alignment to measurable contributions to Industry 5.0 goals.

Taken together, these limitations highlight not only the boundaries of the present work but also opportunities for future contributions. Addressing them would allow researchers to ground tactical HRC-ALBP optimization in empirical reality, expand the range of modeled uncertainties, integrate broader safety dimensions, and ensure scalability to real industrial contexts. In so doing, the research community can progressively transform tactical optimization from a controlled academic exercise into a robust decision-support framework that embodies the principles of safety, resilience, and human-centricity central to Industry 5.0.

Figure 7.1. Current limitations and Future extensions

CHAPTER 8 CONCLUSION

This thesis has proposed and validated a safety-oriented modelling framework for Human–Robot Collaborative Assembly Line Balancing Problems (HRC-ALBP), advancing both the theoretical foundations of operations research and the practical application of collaborative manufacturing. The central ambition of the research was to bridge two domains that have traditionally been addressed in isolation: productivity-focused optimization and safety-focused risk management. The growing adoption of collaborative robots (cobots) makes this integration not only timely but essential, as shared human-robot workspaces expose operators to risks that cannot be mitigated by productivity-oriented models alone. By embedding safety into tactical balancing decisions on task assignments, resource allocations, and execution modes, this thesis presents assembly line balancing as a problem in which safety risk, and efficiency are inseparable.

The research progressed through three complementary stages, each corresponding to a published or submitted paper. The first stage filled an important knowledge gap by delivering the first systematic literature review on HRC-ALBP. At the time, no consolidated mapping of decision layers, collaboration modes, and safety challenges existed, despite the rapid growth of interest in collaborative manufacturing. This review highlighted how safety was largely absent from tactical decision models and provided a conceptual map that emphasized where research should advance. Beyond cataloguing existing work, the review served as a strategic intervention: it identified tactical balancing as a critical but overlooked layer where neglecting safety could create impractical or dangerous solutions.

The second stage moved from conceptual groundwork to operational modeling by introducing a Constraint Programming (CP)-based formulation that embedded station zoning into the balancing solutions. The safe-zone policy translated distance-based safety principle into explicit feasibility rules, prohibiting medium- and high-risk parallel executions. This approach demonstrated how safety could be treated not as an external check but as a structural property of the feasible solution space. Results showed that hazardous overlaps could be eliminated with only small trade-offs in cycle time, shifting the definition of "optimality" toward solutions that harmonize efficiency with compliance. For industry, this contribution provided a tactical planning tool that makes safety auditable and enforceable during task allocation, not just after deployment.

The third stage extended the framework by incorporating risk parameters inspired by Process Failure Mode and Effects Analysis (PFMEA). Using the Alternative Risk Priority Number (ARPN) as an additive and more interpretable measure of overall risk, the model evolved into a bi-objective optimization framework that simultaneously minimized cycle time and cumulative risk. A targeted safety-severity constraint ensured that the most hazardous forms of parallelism were explicitly prohibited, while the ARPN objective penalized broader categories of risk, including time, quality, and performance effects. This expansion marked a decisive step from safety-only to multi-dimensional risk-aware optimization. Empirical results showed that configurations with stronger human expertise consistently dominated, while aggressive cobot deployment without skilled operators often degraded safety and removed configurations from Pareto optimality.

The significance of these contributions advances in two dimensions. Theoretically, the thesis repositions the tactical layer of assembly decision-making as a critical point for embedding safety. Strategic-level compliance measures and operational-level monitoring are well studied, but tactical optimization, where the distribution of tasks, workers, and cobots is decided, remained underexplored. By showing that this layer can absorb safety constraints and risk objectives without collapsing efficiency, the research expands the methodological boundaries of ALBP modeling. It also enriches the operations research toolkit by demonstrating how logical safety constraints and additive risk measures can be encoded in CP formulations, yielding models that are both tractable and explainable.

From a managerial perspective, the thesis offers actionable insights for balancing productivity and safety in real-world collaborative lines. The results demonstrate that while safety constraints can slightly extend cycle time, these increases are modest compared to the avoided costs of accidents, compliance breaches, or unplanned stoppages. The models function as virtual testbeds, comparable to digital twins, enabling the evaluation of 'what-if' scenarios, systematic comparison of safe versus relaxed task allocations, and assessment of the efficiency trade-offs associated with varying safety rules. Findings also highlight the decisive role of human expertise: investing in workforce training and upskilling consistently unlocking safer concurrency and lowering cumulative risk more effectively than increasing cobot speed or counts alone. These insights caution managers against over-reliance on automation and reaffirm the Industry 5.0 principle that human competence remains central to resilient and sustainable manufacturing.

The work also acknowledges its limitations. The SOD risk parameters were generated under controlled assumptions rather than drawn from industrial datasets, constraining external validity. Task zone engagement was assumed discrete, whereas in practice spatial boundaries may overlap or blur. Only the dominant risk per task was modeled, neglecting the probabilistic interplay of multiple potential failure modes. Constraint Programming, while powerful, may not scale efficiently to very large or real-time problems. These limitations are not weaknesses alone but directions for future research: validating the models with industrial partners, expanding risk modeling with stochastic programming or simulations, integrating additional safety dimensions such as ergonomics and fatigue, and developing hybrid solution methods to address scalability.

In conclusion, this thesis has shown that efficiency and safety are not inherently conflicting objectives in HRC-ALBP but can be jointly optimized when safety is elevated to a first-class element of tactical decision-making. By progressing from conceptual mapping to zoning-based feasibility constraints and finally to multi-dimensional risk optimization, the research has delivered a coherent and comprehensive framework that advances both academic understanding and industrial practice. The findings demonstrate that the “where” of safety matters: embedding it into tactical balancing transforms assembly line planning into a process that is not only efficient but also explainable, controllable, and aligned with Industry 5.0 values of human-centricity, resilience, and sustainability. In doing so, the thesis lays a conceptual and methodological foundation for the next generation of collaborative manufacturing systems in which systems are designed not only to be faster and more flexible, but fundamentally safer and more sustainable.

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APPENDICES

APPENDIX A: ARTICLE 4: A REVIEW ON COLLABORATIVE ROBOT ASSEMBLY LINE BALANCING PROBLEM

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Abstract

Assembly line balancing problems have been the subject of numerous studies for decades. The recent advantages of technologies in the Industry 4.0 era and integrating collaborative robots into the assembly systems have created task allocation, workload balance, and scheduling challenges. This paper provides a brief literature review on the existing collaborative assembly line balancing problems comparing their main characteristics and suggests some research directions for future studies.

A.1 Introduction

The current manufacturing paradigm in Industry 4.0 (I4.0) deals with mass customization, and production plants need to develop flexible and costly-efficient processes (Malik and Brem, 2021). This change is the result of altered customers' demands. Variability and short lifecycle are two essential features of the products in the current market. As a result, the manufacturing paradigm shifted from large-scale production to small batches to meet the fluctuating and unpredictable market demands. This market change challenges manufacturers in managing the related costs of providing a flexible system suitable for producing customized products (Wojtynek et al., 2017). However, the emergence of Industry 4.0 (I4.0) technologies has made the assembly processes more flexible, reliable, and efficient in the current mass customization paradigm and shaped Assembly 4.0 (A4.0) (Cohen et al., 2019). Dolgui et al. (2021) and Cohen et al. (2019) explain the significant impacts of I4.0 technologies on assembly lines' strategic, tactical, and operational decisions and how challenging their actual applications are. One of the recently emerging I4.0 technologies is the collaborative robot (cobot) that allows taking advantage of both manual and automated processes while having low production costs (Weckenborg and Spengler, 2019). These new industrial robots can collaborate with humans in a fenceless environment. Although robots provide higher production speed and accuracy, humans are more intelligent, creative, and flexible (Hashemi-Petroodi et al., 2020). Thus, robots' lack of cognitive capabilities has become the main challenge in establishing a fully automated system (Johannsmeier and Haddadin, 2017). However, cobots are developed to deliver the desired level of flexibility and automation (Weckenborg and Spengler, 2019) in assembly lines and reduce the costs of engaged human workers (Cohen et al., 2019; Çil et al., 2020).

As cobots offer a variety of advantages and are becoming more prevalent in assembly lines, it is essential to integrate them into decision-making as a new resource. For instance, finding the right work balance between humans and robots is vital for reaching the Human-Robot Collaboration (HRC) goals to improve human ergonomic conditions. (Stecke and Mokhtarzadeh, 2021). Assembly line Balancing Problem (ALBP), the subject of countless studies for decades, is one of the related topics that would face a challenge in modeling and developing solution methodologies by integrating the cobots into the system. Therefore, this research highlights the critical aspects of studies dealing with ALBP with cobots and potential research directions. These papers can be considered a new research path called Collaborative Robot Assembly Line Balancing Problem (CRALBP). Compared to the Robotic Assembly Line Balancing (RALB), integrating the cobots into the systems as a new trend in RALB increases the complexity of problems (Chutima, 2020). There is a detailed review of robotic assembly line balancing problems done by Chutima (2020). This study categorizes the papers based on the type of their assembly layout at first and then clusters each of them according to the concept of 4M (Man, Machine, Material, Method). However, the discussion on papers with collaborative robots is limited to a few documents in this study. There is no review paper of the CRALB problems to the best of the authors' knowledge. Here, we provide a brief review of the main characteristics of CRALBP studies and some other related processes that have been complicated due to using cobots in assembly lines. CRALBPs are not mature enough to conduct an extensive review, but this study tries to give the researchers clear insights to enrich this subject in the future.

The remainder of the paper is organized as follows: In section A.2, the research methodology is described. Then the analysis of the results is presented in section A.3. Finally, according to the analyzed results, some future research directions are suggested and discussed in section A.4.

A.2 Research Methodology

A systematic approach inspired by the studies of Acerbi et al. (2021) and Dolgui et al. (2021) has been adopted to find the papers through the web of science without a time limit and then select the most related documents for literature review. The primary goal of the study is investigating the collaborative robots within the assembly line balancing problems, and the following strategy is selected after several attempts of different keyword combinations: ((collaborative robot OR human-robot collaboration OR cobot) AND (assembly) AND (balancing OR planning OR task allocation OR scheduling)). This search strategy in the title, keywords, and abstract of papers leads to 149 documents spanning 2003 to 2022. The process of selecting records is shown in Fig 1. The design of HRC workspaces is out of the paper's scope and recently was reviewed by Simões et al. (2022). Investigating the human-cobot relationship challenges is one of the main aspects of this study. So, the papers without a human worker engagement, such as collaborative robotic teams, are excluded from the results, leaving us with 129 documents. Among these papers, only 11 articles directly mention the assembly line balancing problem with the presence of cobots in their context. To ensure the cover of all CRALBP studies, we investigated the references of obtained results and found three other CRALB articles not included in the records. ALBPs generally optimize task allocation considering sequential relations (Li et al., 2021). However, integrating cobots into these problems gives rise to other challenges such as resource selection (robot/human), scheduling, and human/robot variable task times (Weckenborg et al., 2019). Thus, the articles on resource allocation, scheduling, task allocations, and sequencing are not excluded, and we discuss them as complementary resources.

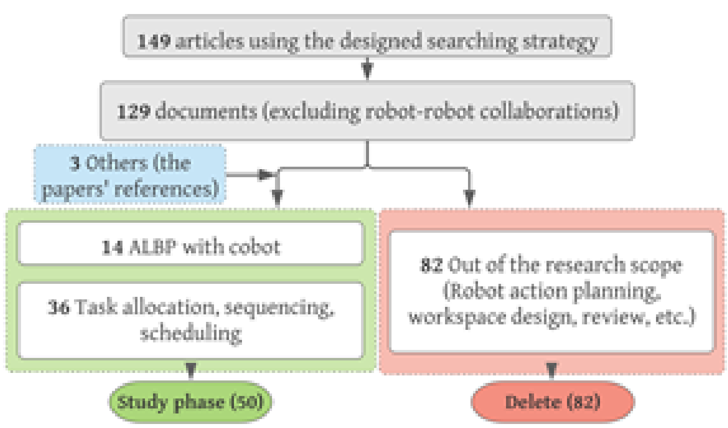

Figure A.1. Papers' selection procedure

Based on the challenges of collaborative assembly line balancing represented by Weckenborg et al. (2019), in section A.3, we group the 50 documents into three categories of issues addressed in their proposed problem. Also, a table summarizes the key characteristics of reviewed CRALBP papers.

A.3 Content Analysis

According to the obtained papers on CRALB, table1 represents the key elements of these problems. Although the traditional assembly line balancing problem is about assigning the tasks to the workstations considering specific precedence, the presence of the cobots in a system makes it more challenging (Weckenborg et al., 2019). In this section, we discuss how researchers try to address these challenges in their studies. In collaborative scenarios, tasks can be performed by a human, cobot, or both with different task times. Thus, more than one type of work resource is available. Some papers investigating this problem are mentioned in 3.1. With the simultaneous assignment of humans and robots to a station, task scheduling is essential and included in reviewed papers (section A.3.2 and table A.2). Moreover, it is required to determine which tasks should be done by human/cobot/both. Section A.3.3 represents an overview of this problem. Finally, fig 2 briefly depicts our study's framework created based on assembly line challenges with cobots by Weckenborg et al. (2019).

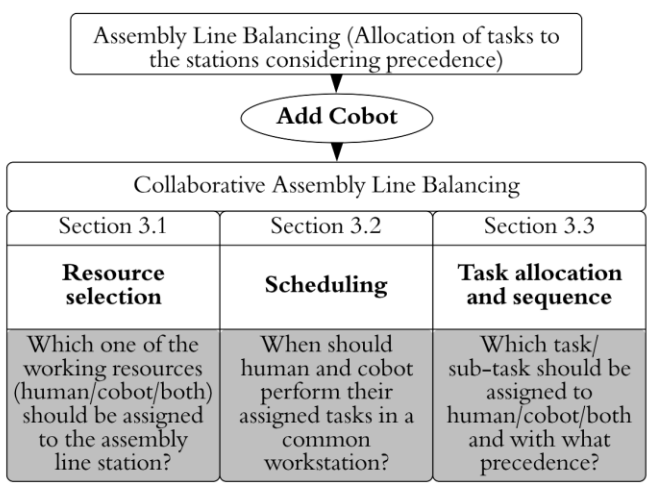

Figure A.2. Literature review framework

A.3.1 Working resource selection and allocation

Selecting the type of cobot is a strategic decision in A4.0 (Dolgui et al., 2021). The CRALB studied by Li et al. (2021) includes several types of cobots with different purchasing costs. They develop a multi-objective optimization approach to minimize both the cycle time and cobot purchasing cost. In this study, human workers have the same level of skills. Similarly, Dalle Mura and Dini (2019, 2021), and Samouei and Ashayeri (2019) investigate the CRALBP involving workers with different skills. They have reflected this characteristic in the objective function of problem to find the optimal resource selection strategy. Cobots are considered a working resource in all the CRALBPs and they deal with optimal allocation of humans, cobots, or both to the stations. However, these studies have different approaches in the objective function definition and problem formulation as represented in table A.1. Sometimes, studies address more than one problem. Kinast et al. (2021) combine the assignment of cobots to the stations with a jobshop scheduling and find a balance of costs and makespan.

A.3.2 Scheduling

Some CRALB papers are enriched by addressing a scheduling problem. In all of these researches (Weckenborg et al., 2019; Boschetti et al., 2021; Stecke and Mokhtazadeh, 2021; Koltai et al., 2021; Weckenborg and Spengler, 2019; and Dimény et al., 2021), scheduling is performed in the stations where the parallel working of cobot and human workers is allowed. Therefore, the planners must create a schedule for these stations to satisfy the tasks' precedence constraints and avoid interference. According to Koltai et al. (2021), parallel execution of jobs reduces the overall cycle. This is a benefit in assembly line balancing. Still, half of the listed CRALBPs have not considered parallelism in their problem, probably because of safety issues. Scheduling is also the subject of many investigations that focus on HRC in a work cell rather than in an assembly line with several stations. These studies can be categorized into static (offline) and dynamic (online or real-time) scheduling. In most of these papers, scheduling refers to a combination of task allocation and sequencing. Execution of parallel or shared tasks by humans and cobot (Bogner et al. 2018; Zhang et al., 2021; Casalino et al., 2021; Raatz et al., 2020; Mokhtarzadeh et al., 2020; Chen et al., 2014; Nikolakis et al., 2018) are considered in half of these papers. As previously mentioned, the positive impact of parallel task execution by humans and cobots is in reduced cycle time (Raatz et al., 2020). Besides, the ergonomic risk, a leading enabler of cobot utilization, has been evaluated and addressed in some of the mentioned (Zhang et al., 2021; Gualtieri et al., 2021; Raatz et al., 2020) scheduling problems.

Referring to table A.2, some researchers developed a model to optimize the schedule in real-time. This way, they try to overcome some uncertainties of a collaborative environment.

Table A.1. Collaborative Robot Assembly Line Balancing Problems (CRALBPs)

Reference	Problem	Assembly layout	Objective	Solution approach	Parallel / joint tasks	Considering human safety/ Ergonomic factors
Weckenbor et al., 2019	ALB with scheduling	Single-product, Simple AL, One cobot type	Min cycle time	Mathematical model (MIP) and genetic algorithm	Parallel/ joint	No
Weckenborg, and Spengler 2019	ALB with scheduling	Single-product, Simple AL, More than a cobot	Min costs per cycle	Mathematical model and genetic algorithm	Parallel	Ergonomic load evaluation by energy expenditure
Dalle Mura et al., 2019	ALB: different human skills	Single-product, Simple AL, More than a cobot	Min costs, skilled workers, worker's energy load	Mathematical model and genetic algorithm-based software	Joint	Ergonomic load evaluation by energy expenditure
Yaphiar et al., 2019	ALB	Multi-product, Simple AL, One cobot type	Min investment and operational costs	Mathematical model and a numerical example	Joint	No
Samouei and Ashayeri, 2019	ALB: resource selection and demand uncertainty	Multi-product, Simple AL	Min costs (certain model), Min costs and cycle time (uncertain model)	Mathematical model (MILP) and Multi-objective robust optimization model	Joint	No
Rabbani et al, 2020	ALB	Multi-product, Four-sided AL, More than a cobot	Min stations and human/robot costs	Mathematical model, particle swarm optimization	No	No
Çil et al., 2020	ALB with scheduling: assessing nine algorithms	Multi-product, Straight (simple) AL, More than a cobot	Min cycle time	Mathematical model (MILP), Bee algorithm and artificial bee colony	No	No

Table A.1. Collaborative Robot Assembly Line Balancing Problems (CRALBPs) (continued and end)

Boschetti et al., 2021	ALB with scheduling	Single-product, Single-station layout, One cobot	Min makespan	Mathematical model (LP)	Parallel	No
Stecke and Mokhtar zadeh, 2021	ALB with scheduling: decision on cobot numbers	Multi-product, Serially arranged stations	Min cycle time and ergonomic risk	Mathematical model (MILP), Constraint programming, Benders decomposition	Parallel/ Joint	Ergonomic load evaluation by energy expenditure
Li et al., 2021	ALB	Single-product, Straight AL, several types of cobot	Min cycle time and cobot purchasing cost	Mathematical model (MILP), multi-objective migrating bird optimization	No	No
Dalle Mura et al., 2021	ALB: human job rotation and different skills	Single-product, Simple AL	Min assembly cost and workers' energy load	Mathematical model and genetic algorithm	Joint	Ergonomic load evaluation by energy expenditure
Suer et al., 2021	ALB with scheduling	Two products, Single-station	Min cycle time and max output	Simulation and a heuristic method	No	No
Koltai et al., 2021	ALB with scheduling: Shared or not-shared station	Single-product, Simple AL	Min stations and cycle time	Non-linear mathematical model and constraint programming	Parallel	No
Dimény et al., 2021	ALB with scheduling	Single-product, Simple AL, at most one cobot and one human in each station	Min workers, cobots, cycle time	Mathematical model (MILP) and CPLEX solver	Parallel (not always)	No

A.3.3 Task allocation and sequences

One of the primary goals of integrating collaborative robots is to reduce the human workload. Many studies represent the ergonomic risks evaluation or safety-related issues as an essential part of their task allocation problem. Maximizing worker effort reduction (Gjeldum et al., 2021), minimizing workload on the human body (Makrini et al., 2019), task difficulty/human fatigue (Zhang et al., 2022; Tram and Raweewan, 2021; Lamon et al., 2021), and ergonomic score based on human physical overexertion and robot assistance (Mateus et al., 2019) are among the objectives that can be used to find optimal task distribution between humans and cobots with ergonomic concerns. There are other objective functions such as cycle time (Bilberg and Malik, 2019; Bänziger et al., 2018; Dianatfar et al., 2019; Malik and Bilberg, 2019), costs (Johannsmeier and Haddadin, 2017; Wu et al., 2017), idle time (Karami et al., 2020) in the task allocation problems. All the mentioned studies with ergonomic metrics do not have a single objective, and authors try to balance multiple criteria in the assignments. Besides, humans and cobots can not perform all assembly tasks because of their complexity or unique skills requirements. Tsarouchi et al. (2017) propose a framework for task allocation in which the payload capability of the resources is one of the task assignment criteria. With a different approach, Bruno and Antonelli (2018) classify the tasks based on the safety requirements and assign the tasks dynamically using historical data and a decision tree. They state that HRC in a shared space with physical contact (including a common workpiece) is the most challenging scenario in terms of safety. To tackle this challenge of jointly working on a workpiece, some researchers (Dianatfar et al., 2019; Rahman et al., 2015; Rahman and Wang, 2018; Mateus et al., 2020) divide the tasks into sub-tasks to better manage the HRC using cobot speed control (Dianatfar et al., 2019) or collision evaluation (Mateus et al., 2020). After determining the tasks of human/robot/both, the order of tasks should be selected. This process is called assembly sequencing. Faber et al. (2017) create a static graph-based sequence planner that reduces the switches between human, robot, and tools. However, Aliev et al. (2019) propose a robot program that generates a real-time sequence during the task executions. All CRALBPs in the table A.1 assume a predefined tasks sequence, but human workers are a source of uncertainty in a collaborative scenario. Thus, having a fixed order of tasks may lead to an unrealistic plan in assembly lines.

A.4 Discussion and Future studies

The primary purpose of this survey is to review assembly line balancing problems with cobots and highlight their key features. This research area is in the infancy stage, and we need to explore more collaborative cases in different industries. Therefore, we propose three future research directions based on the reviewed papers and practical problems to investigate.

Table A.2. Methodology of scheduling problems

Reference	Static/dynamic model	Methodology	Objective function
Maderna et al., 2022	Dynamic	Digital twin based on Petri nets, simulation	Min costs
Yu et al., 2020	Dynamic	Reinforcement learning and Marcove decision tree	Min job completion time
Bogner et al., 2018	Static	Mathematical model, heuristic and metaheuristic algorithms	Makespan
Zhang et al., 2021	Static	Mathematical model, Epsilon Constraint Method, Genetic algorithm	Min job cycle time and human fatigue
Casalino et al., 2021	Dynamic	Petri Nets with non-deterministic human task time	Min human/robot idle time
Gualtieri et al., 2021	Static	A systematic framework with the mathematical model	Min cycle time
Raatz et al., 2020	Static	Multi-objective optimization with Genetic algorithm	Min costs
Mokhtarzadeh et al., 2020	Static	Constraint Programming and Multi-agent planning	Min makespan
Yu et al., 2021	Dynamic	Deep Q-network based multi-agent reinforcement learning	Min task completion time
Chen et al., 2014	Static and dynamic	Resource-Constrained Project Scheduling model with a genetic-based revolutionary algorithm	Min assembly time and cost
Casalino et al., 2019	Static	Fuzzy-timed Petri Net with non-deterministic task time	Min idle time
Nikolakis et al., 2018	Dynamic	Decision-making framework with multicriteria based on an intelligent search	Min flow time
Kinast et al., 2021	Static	Genetic algorithm	Min costs and makespan
Vieira et al., 2021	Dynamic	Recursive Optimization-Simulation Approach	Min costs and makespan

A.4.1 Assembly line features

All the CRALBPs have a simple straight assembly line, while U-shaped, Two-sided, or Parallel lines are potential layouts for further studies. Cobots are safe for close work with humans and it is an opportunity to benefit from parallel jobs that save time. Secondly, the concept of human-robot collaboration in a task is not yet fully addressed in the literature. Human and cobot sequentially execute tasks in some studies and only share the space, not the time. So, we need more reflections on real collaboration rather than the coexistence of humans and cobots. These decisions on the type assembly line and automation level are strategic topics that could be investigated in further studies. Besides, workforce strategies (walking workers, temporary workers, etc.) and planning are among the other subjects that are not addressed by existing CRALBPs and could be a potential avenue of research.

A.4.2 Collaborative assumptions

To obtain a realistic assembly plan, we should formulate a problem with actual assumptions. Non-deterministic task times, different human skills, system uncertainties (demand, human action, system breakdown, etc.), human-robot collision/ergonomic risks, social factors (trust), and reflecting environmental effects of cobots are some elements that can be considered in CRALBPs. These factors may affect all levels (strategic, tactical, operational) of assembly line decisions.

A.4.3 Methodology development

Assembly lines are complex and dynamic environments involving many workpieces and resources. Cobot increases these characteristics as they need extra setups when working with an unpredictable human in a fenceless environment. However, real-time data gathered using I4.0 technologies help to create a digital model of physical assembly systems and predict the events before their actual occurrence. This impacts the operational level of assembly decisions. Accordingly, studies can combine simulation and optimization models, create digital models to tackle some uncertainty of the system, and develop more flexible and reliable plans. Moreover, combining product quality and human safety or ergonomics with other objectives of CRALB problems could be a research path. One of the main concepts in HRC is improving the worker's health conditions. Although some researchers have evaluated human body workload, all injury risks (collision, mental and physical fatigue, etc.) of HRC need to be integrated into methodologies. Then we will have a joint optimization of safety aspects and other productivity elements that ensures a reliable working environment for humans and affects their trust in cobots.