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Towards Human-Centric Assembly Lines: The Role of Fuzzy Expert Systems and Ergonomic Design

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

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Towards Human-Centric Assembly Lines: The Role of Fuzzy Expert Systems and Ergonomic Design

présentée par **Elham GHORBANI TOTKALEH**

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

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DEDICATION

To my dear parents, for their endless love, encouragement, and unwavering belief in me.

To my sisters, whose constant support and motivation have been a source of strength.

And to my fiancé, for his patience, understanding, and for being by my side throughout this journey.

Their collective support has been invaluable, and this achievement would not have been possible without them.

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RÉSUMÉ

L'industrie manufacturière repose fortement sur la conception et l'optimisation des lignes d'assemblage (LAs) pour améliorer la productivité, l'efficacité et la durabilité opérationnelle. Les problèmes traditionnels d'équilibrage des lignes d'assemblage (ALBPs) se sont principalement concentrés sur l'optimisation des indicateurs opérationnels, souvent au détriment des facteurs humains et de l'ergonomie (HF/E). Cependant, les environnements de production deviennent de plus en plus complexes en raison de la volatilité du marché et de la demande croissante pour des produits personnalisés. Par conséquent, il est nécessaire de mettre en place des systèmes de production plus flexibles et adaptatifs. Cette évolution souligne l'importance cruciale d'intégrer les considérations ergonomiques dès la phase de conception des LAs, afin de garantir que le bien-être des travailleurs soit priorisé, parallèlement à l'efficacité opérationnelle.

Cette thèse de doctorat répond à ce besoin en proposant de nouvelles approches basées sur la logique floue et les systèmes experts pour gérer les incertitudes inhérentes aux évaluations ergonomiques et à l'allocation des tâches. Contrairement aux méthodes traditionnelles d'ALBP qui reposent sur des modèles déterministes, cette recherche propose une approche centrée sur l'humain qui intègre l'ergonomie dès la phase de conception, ouvrant la voie à des systèmes de lignes d'assemblage plus adaptatifs et réactifs. La recherche est structurée autour de trois objectifs clés, chacun apportant des avancées uniques dans le domaine, présentées sous la forme de quatre articles distincts.

Le premier article, intitulé “Ergonomic Assembly Line Balancing Problems Evolution and Future Trends with Insights into Industry 5.0 Paradigm”, offre une revue complète des ALBPs, avec un accent particulier sur les aspects ergonomiques (Ergo-ALBPs) et le paradigme émergent de l'Industrie 5.0. Grâce à une analyse systématique de 57 études publiées entre 2011 et 2022, cet article explore l'intégration des indicateurs HF/E avec les facteurs opérationnels dans les problèmes d'optimisation. Il met en lumière les tendances significatives, les lacunes de la recherche et les opportunités futures dans le domaine des Ergo-ALBPs, en insistant sur l'importance de la conception centrée sur l'humain et de la collaboration entre les travailleurs et les technologies avancées, telles qu'explorées dans l'Industrie 5.0.

Le deuxième article, intitulé “Système Expert Flou pour l'Attribution des Travailleurs Ergonomiques et le Problème d'Équilibrage des Lignes d'Assemblage sous Incertitude”, introduit

un nouveau cadre en deux phases qui étend les méthodes traditionnelles d'ALBP en incorporant l'attribution des travailleurs avec un accent sur les risques ergonomiques. La contribution unique de cette approche réside dans sa capacité à gérer l'incertitude et les données imprécises concernant les temps de tâche et les capacités des travailleurs via un système expert flou. Cette approche se distingue des méthodes conventionnelles en introduisant une approche heuristique pour la faisabilité, combinée à une méthode d'évaluation ergonomique avancée, validée à l'aide de 96 instances synthétisées. Le cadre proposé comble une lacune importante dans les données orientées vers l'ergonomie, fournissant des solutions de haute qualité qui améliorent à la fois la sécurité des travailleurs et la productivité.

Le troisième article, “Conception de Lignes d'Assemblage Robotiques Centrée sur l'Humain: Une Approche par Système d'Inférence Flou pour la Gestion Adaptative des Charges de Travail”, fait progresser l'état de l'art en introduisant un nouveau modèle de fatigue spécialement conçu pour les LAs collaboratifs. Contrairement aux modèles déterministes existants, cette recherche intègre un système d'inférence floue qui capture la complexité et la variabilité des scénarios réels. L'intégration de robots collaboratifs est explorée dans le cadre de ce modèle, offrant des améliorations significatives de la productivité et des avantages ergonomiques. Cette étude est particulièrement innovante dans son exploration des principes de l'Industrie 5.0, mettant l'accent sur le bien-être des travailleurs en synergie avec les technologies d'automatisation avancées.

Le quatrième article, “Ergo4All-Pro: Promouvoir la Conception Centrée sur l'Humain à l'Ère Virtuelle”, présente le développement d'Ergo4All-Pro™, un modèle complet d'évaluation des risques ergonomiques adapté aux environnements virtuels et aux systèmes de modélisation numérique humaine (DHM). Ce modèle s'appuie sur les outils ergonomiques traditionnels en intégrant la logique floue pour fournir des évaluations plus précises et affinées des risques ergonomiques cumulatifs sur diverses parties du corps. La nouveauté d'Ergo4All-Pro™ réside dans sa capacité à opérer dans des environnements de réalité virtuelle et augmentée, répondant aux limites des outils existants pour évaluer les parties du corps et les risques cumulatifs. En comblant le fossé entre les méthodes traditionnelles et les environnements virtuels de pointe, Ergo4All-Pro™ permet de concevoir des lieux de travail plus sûrs et plus efficaces, notamment dans le contexte de l'Industrie 5.0.

Ensemble, ces contributions représentent une avancée significative dans la conception et l'optimisation des LAs, offrant un cadre robuste pour intégrer les considérations ergonomiques dès les premières étapes de la conception. Les méthodes proposées démontrent le potentiel d'atteindre des conceptions basées sur l'ergonomie avec un score ergonomique flou moyen de 0.7, tout en augmentant simultanément l'efficacité globale du système jusqu'à 77 %. De plus, l'intégration d'un modèle de fatigue floue pour l'optimisation des LAs robotiques devrait permettre de réduire les coûts du système jusqu'à 47%, notamment en période de pénurie de ressources humaines, en minimisant les besoins en récupération et les capacités supplémentaires nécessaires à l'atténuation de la fatigue. En outre, la troisième contribution de cette recherche, soumise en tant que brevet en collaboration avec Dassault Systèmes, introduit une invention de pointe dans un environnement de réalité virtuelle (VR). Cet outil permet de concevoir des lieux de travail ergonomiques avec des évaluations plus précises et sophistiquées. Il s'aligne non seulement sur les outils bien connus d'évaluation ergonomique (EAT), mais les améliore également grâce à sa capacité unique à évaluer les risques cumulatifs sur les parties individuelles du corps. Dans l'ensemble, cette thèse propose des solutions pratiques pour créer des LAs plus sûres, plus productives et plus adaptatives, faisant ainsi progresser de manière significative le domaine de la conception des LAs.

ABSTRACT

The manufacturing industry relies heavily on the design and optimization of assembly lines (ALs) to enhance productivity, efficiency, and operational sustainability. Traditional assembly line balancing problems (ALBPs) have focused primarily on optimizing operational metrics, often at the expense of human factors and ergonomics (HF/E). However, manufacturing environments are becoming increasingly complex due to market volatility and the rising demand for customized products. As a result, there is a growing need for more flexible and adaptive production systems. This shift highlights the critical need to integrate ergonomic considerations into the design phase of ALs, ensuring that worker well-being is prioritized alongside operational efficiency.

This Ph.D. thesis addresses this need by introducing novel approaches that leverage fuzzy logic and expert systems to manage the inherent uncertainties in ergonomic assessments and task allocations. Unlike traditional ALBP methods, which mostly rely on deterministic models, this research presents a human-centric approach that integrates ergonomics into the early design phase, paving the way for more adaptive and responsive assembly line systems. The research is structured around three key objectives, each contributing unique advancements to the field, presented in the form of four distinct articles.

The first article, titled "Ergonomic Assembly Line Balancing Problems Evolution and Future Trends with Insights into Industry 5.0 Paradigm," provides a comprehensive review of ALBPs, focusing specifically on ergonomic aspects (Ergo-ALBPs) and the emerging Industry 5.0 paradigm. Through a systematic analysis of 57 studies published between 2011 and 2022, this paper explores the integration of HF/E indicators alongside operational factors in optimization problems. It highlights significant trends, research gaps, and opportunities for future research in Ergo-ALBPs, with particular emphasis on the importance of human-centered design and the collaboration between workers and advanced technologies, as emphasized by Industry 5.0.

The second article, titled "Fuzzy Expert System for Ergonomic Assembly Line Worker Assignment and Balancing Problem under Uncertainty," introduces a novel two-phase framework that extends traditional ALBP methods by incorporating worker assignment with a focus on ergonomic risks. The unique contribution of this approach lies in its ability to handle uncertainty and imprecise data regarding task times and worker capabilities through a fuzzy expert system. This approach departs from conventional methods by introducing a heuristic approach for feasibility combined with an

advanced ergonomic assessment method, validated using 96 synthesized instances. The proposed framework addresses a significant gap in ergonomic-oriented data, providing high-quality solutions that enhance both worker safety and productivity.

The third article, "Human-Centric Robotic Assembly Line Design: A Fuzzy Inference System Approach for Adaptive Workload Management," advances the state of the art by introducing a novel fatigue model specifically designed for robotic ALs. Unlike existing deterministic models, this research incorporates a fuzzy inference system that captures the complexity and variability of real-world scenarios. The integration of supportive robots is explored as part of this framework, offering significant productivity enhancements and ergonomic benefits. This study is particularly innovative in its exploration of Industry 5.0 principles, emphasizing the role of human well-being in conjunction with advanced automation technologies.

The fourth article, "Ergo4All-Pro: Empowering Human-Centric Design in the Virtual Era," presents the development of Ergo4All-Pro™, a comprehensive ergonomic risk assessment model tailored for virtual environments and digital human modeling (DHM) systems. This model builds upon traditional ergonomic tools by integrating fuzzy logic to provide more accurate and refined assessments of cumulative ergonomic risks across various body parts. The novelty of Ergo4All-Pro™ lies in its ability to operate within virtual and augmented reality environments, addressing limitations of existing tools in assessing individual body parts and cumulative risks. By bridging the gap between traditional methods and cutting-edge virtual environments, Ergo4All-Pro™ enables safer, more efficient workplace designs, especially in the context of Industry 5.0.

Together, these contributions represent a significant advancement in the design and optimization of ALs, offering a robust framework for integrating ergonomic considerations into the early design stages. The proposed methods demonstrate the potential to achieve ergonomic-based designs with an average fuzzy ergonomic score of 0.7, while simultaneously increasing overall system efficiency up to 77%. Additionally, the integration of a fuzzy fatigue model for optimizing of robotic AL is expected to decrease system costs by as much as 47%, particularly during human resource shortages, by minimizing recovery needs and additional capacity requirements for fatigue mitigation. Furthermore, the third contribution of this research, submitted as a patent in collaboration with Dassault Systèmes, introduces a cutting-edge invention within a virtual reality (VR) environment. This tool enables ergonomic workplace design with more precise and sophisticated evaluations. It not only aligns with well-known ergonomic assessment tools (EATs) but also enhances them through its unique ability to evaluate cumulative risks on individual body parts. Overall, this thesis provides practical solutions for creating safer, more productive, and adaptable ALs, significantly advancing the field of AL design.

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LISTE OF SYMBOLS AND ABBREVIATIONS

3DSSPP	3D static strength prediction program
ABC	Artificial bee colony
ACO	Ant colony optimization
AI	Artificial intelligence
AL	Assembly line
ALBP	Assembly line balancing problem
ALDP	Assembly line design problem
ALWABP	Assembly line worker assignment and balancing problem
AR	Augmented reality
ARP	Accumulated risk of posture
AWCBC	Association of workers' compensation boards of Canada
BS	Beam search
CAD-CAM	Computer-aided design – computer-aided manufacturing
CALBP	Collaborative human-robot assembly line balancing problem
CALDP	Collaborative human-robot assembly line design problem
Cobot	Collaborative robot
COMSOAL	Computer method of sequencing operations for assembly line
COP	Combinatorial optimization problem
CP	Constraint programming
CT	Cycle time
DC	Duty cycle
DHM	Digital human modeling
EAT	Ergonomic assessment tool

EAWS	Ergonomic assessment worksheet
ECG	Electrocardiogram
EE	Energy expenditure
EMG	Electromyogram
Ergo-ALBP	Ergonomic assembly line balancing problem
Ergo-ALDP	Ergonomic assembly line design problem
Ergo-ALWABP	Ergonomic assembly line worker assignment and balancing problem
ERI	Effort-reward imbalance
ESI	Ergonomics stress index
ESI	Effort smoothness index
EWD	Ergonomic workplace design
FIS	Fuzzy inference system
FS	Feasible solution
FST	Fuzzy set theory
GA	Genetic algorithms
GALBP	General assembly line balancing problem
GP	Goal programming
GRASP	Greedy randomized adaptive search procedure
HARM	Hand arm risk-assessment method
HF/E	Human factors and ergonomics
ICA	Imperialist competitive algorithm
IEA	International ergonomics association
ILS	Iterated local search
IPG	Iterated pareto greedy

IoT	Internet of things
JCQ	Job content questionnaire
JSI	Job strain index
KIM	Key indicator method
KPI	Key performance indicators
LP	Linear programming
LS	Local search
MAE	Maximum acceptable effort
MAEE	Maximum acceptable energy expenditure
MBO	Migrating birds optimization
MIP	Mixed-integer programming
MILP	Mixed-integer linear programming
ML	Machine learning
MMALBP	Mixed-models assembly line balancing problem
MR	Metabolic rate
MRBCRS	Multiple rules based constructive randomized search
MSD	Musculoskeletal disorder
MVC	Maximum voluntary contraction
NIOSH	National institute for occupational safety and health
NSTLBO	Non-dominated sorting teaching-learning-based optimization
LS	Local search
OCRA	Occupational repetitive action
OWAS	Ovako working posture analysis
PALBP	Parallel assembly line balancing problem

PMES	Predetermined motion energy system
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
PSO	Particle swarm optimization
PTMS	Predetermined time motion systems
PWL	Physical workload
RA	Rest allowance
RALBP	Robot-assisted assembly line balancing problem
RALDP	Robotic assembly line design problem
RAMP	Risk assessment & management tool for manual handling Proactively
REBA	Rapid entire body assessment
RIPGA	Restarted iterated pareto greedy algorithm
RMS	Root means square
RPWT	Ranked positional weight technique
RULA	Rapid upper limb assessment
SA	Simulated annealing
SALBP	Simple assembly line balancing problem
SRL	Supportive robotic limb
SWD	Sheltered workcenter for disabled
TACO	Time-based assessment computerized method
TFN	Triangular fuzzy number
TSALBP	Time and space constrained assembly line balancing problem
UALBP	U-shaped assembly line balancing problem
VNS	Variable neighborhood search
VMS	Virtual manufacturing system

VR	Virtual reality
WD	Workplace design
WMSD	Work-related musculoskeletal disorder

LIST OF APPENDICES

CHAPTER 1 INTRODUCTION

The design and optimization of assembly lines (ALs) are foundational to the manufacturing industry, where the primary goals are to enhance productivity, efficiency, and sustainability. ALs are critical components of lean and mass production systems, enabling companies to reduce per-unit production costs by breaking complex tasks into simpler, repetitive processes. This pursuit of operational efficiency leads to assembly line balancing problems (ALBPs), which involve modeling problems and optimizing task distribution across workstations to eliminate bottlenecks, minimize idle times, and reduce in-process inventories. Traditionally, ALBPs have focused on balancing tasks based on process times to meet production targets, ensuring a uniform time-based workload distribution to maximize throughput and minimize costs (Boysen et al., 2007). However, this traditional focus on operational metrics often neglects critical aspects such as worker well-being, raising concerns about the long-term sustainability of such practices in modern industrial settings.

The growing complexity of manufacturing environments, driven by market volatility and increasing demand for customized products, requires more flexible and adaptive production systems. This flexibility often involves the inclusion of manual tasks, which introduce variability and significant ergonomic challenges (Vig, 2020). The performance of workers handling these manual operations directly impacts overall system efficiency. Additionally, workers in ALs are exposed to ergonomic risks and potential injuries due to the repetitive and prolonged nature of assembly tasks. As such, it is crucial to integrate ergonomic considerations into AL design from the outset to improve worker safety and well-being. This need has led to the emergence of the ergonomic assembly line balancing problem (Ergo-ALBP), a concept that balances both operational efficiency and worker well-being.

Over the past few years, the advent of Industry 5.0 has introduced a new paradigm emphasizing collaboration between workers and advanced technologies. This paradigm shift presents significant opportunities for advancing Ergo-ALBPs, with technologies like augmented reality (AR), virtual reality (VR), artificial intelligence (AI), and collaborative robots (cobots) potentially revolutionizing AL optimization. Industry 5.0 focuses on human-centric design principles, offering the possibility of improving worker comfort, productivity, and safety while fostering continuous learning and improvement. This thesis delves into the evolution and future trends of Ergo-ALBPs within the Industry 5.0 paradigm, highlighting its transformative potential and addressing the challenges of implementation in the manufacturing industry.

1.1 Background and Context

While traditional ALBPs have successfully optimized operational metrics, they often overlook the human aspect of the manufacturing process, particularly the ergonomic risks associated with repetitive and physically demanding tasks. This ignorance can result in work-related musculoskeletal disorders (WMSDs), caused by repetitive motions, awkward postures and forceful exertions required in many assembly tasks (Cimen et al., 2022). WMSDs negatively impact worker health, reduce productivity, and increase operational costs through absenteeism and turnover among others, underscoring the importance of incorporating ergonomic considerations into AL design (Ozdemir et al., 2021). The field of human factors and ergonomics (HF/E) aims to mitigate these risks by designing tasks, equipment, and workflows that align with human capabilities and limitations (Wilson, 2000).

In recent years, research has increasingly addressed these issues by integrating ergonomics into AL design and optimization, giving rise to Ergo-ALBPs. However, many of these efforts have focused on improving existing ALs rather than incorporating ergonomic principles during the design phase, Ergo-ALDPs. For instance, ergonomic workload balancing methods have been introduced to reduce physical strain by redistributing tasks more evenly among workers, considering both operational efficiency and ergonomic safety (Cirjaliu & Draghici, 2016). Despite these advances, there remains a gap in the systematic integration of ergonomic factors early in the design process, where critical decisions about task allocation, workload distribution, and workstation configuration are made.

In the design phase, it is essential to consider the uncertainties that can arise. These may stem from external factors, such as market fluctuations that affect demand, and internal factors, including production process imprecisions and unexpected equipment failures (Ghorbani et al., 2024d). Human-related variability, such as differences in task durations, and worker physical abilities, also contributes to uncertainty. Additionally, the inherent imprecision in the inputs of ergonomic assessment tools (EATs) can significantly impact the accuracy of results (Golabchi et al., 2016). Addressing these uncertainties is crucial to developing robust and sustainable AL designs (Ghorbani et al., 2024b).

Fuzzy expert systems offer a valuable solution to managing these complexities. By using fuzzy logic to handle uncertainties arising from incomplete and imprecise data, these systems can effectively model the decision-making processes of human experts (Tavana & Hajipour, 2020). This research leverages the strengths of fuzzy inference systems and expert knowledge to manage uncertainty, improving the efficiency and effectiveness of ergonomic practices in AL environments.

This thesis aims to bridge the existing gap by developing a fuzzy expert system that addresses uncertainties in ergonomic assessments and task allocations during the design phase, providing a more adaptive and human-centric approach to AL design. Digital human modeling (DHM) systems, when combined with fuzzy logic, offer powerful tools for simulating human interactions in ALs, predicting ergonomic issues before physical implementation, and enabling preemptive design adjustments (Dahibhate et al., 2023). This approach aligns with Industry 5.0, which emphasizes human-centric systems that enhance both worker well-being and operational resilience (Zhang et al., 2023).

1.2 Problem Statement

The design of ALs that prioritizes both productivity and worker well-being is a complex challenge, particularly given the variability and uncertainty inherent in real-world production environments. Traditional ALBP models assume fixed task times and uniform workloads, which oversimplifies the complexities of manual operations, in contexts where human operators are involved (Chica et al., 2011). The reliance on deterministic models can lead to suboptimal task assignments, as these models fail to account for variations in worker capabilities, fatigue, and ergonomic risks, all of which can negatively affect productivity and worker safety. Furthermore, failure to address ergonomic aspects during the design phase can lead to costly corrective actions in the future and the high cost of post-implementation redesigns to mitigate ergonomic issues underscores the importance of integrating ergonomic assessments into the design phase (Falck & Rosenqvist, 2014).

As global markets become more volatile and the demand for customized products grows, the need for adaptable and flexible production systems that can accommodate these dynamic environments has become apparent (Hu et al., 2011). While manual tasks within ALs can improve flexibility, they also introduce ergonomic and productivity risks, and the need to integrate HF/E into AL design from the outset, particularly under conditions of uncertainty, has become increasingly clear. This thesis aims to address these gaps to integrate uncertainty management into task allocation and workload balancing. Aiming to create safer, more efficient, and adaptable production systems, the system is designed to manage the imprecise nature of ergonomic assessments and task allocations, particularly in environments where human variability plays a significant role. For this purpose, a well-suited approach should be developed to handle imprecise and uncertain data in this research, making it an ideal approach for managing the complexities of ergonomic risk assessments and human variability in AL environments.

1.3 Significance of This Study

The significance of this research lies in its contribution to the field of AL optimization by integrating ergonomic considerations into the early design stages of ALs. While traditional ALBPs have largely neglected human factors, this study advances the state of the art by prioritizing worker well-being and safety, resulting in designs that not only improve operational efficiency but also enhance sustainability. By addressing ergonomic risks early in the design process, the fuzzy expert system helps prevent WMSDs and promotes long-term worker health and productivity. Moreover, the application of fuzzy logic to manage uncertainties in ergonomic assessments represents a novel contribution to the field, enabling more accurate and flexible designs that better reflect the realities of modern manufacturing environments (Azadegan et al., 2011).

Furthermore, this research aligns with the principles of Industry 5.0, which emphasizes the importance of human-centric values and the collaboration between human workers and advanced technologies in modern manufacturing environments. By integrating these technologies with ergonomic design principles, this study helps create safer, more efficient and adaptable ALs that can respond to changing market conditions and worker needs (Eriksson et al., 2024). This study also addresses the gap in worker assignment during the design phase by enhancing a sub-version of ALBPs, titled the assembly line worker assignment and balancing problem (ALWABP), to manage uncertainty and imprecise data regarding future operators through fuzzy logic and expert systems. This integration exemplifies the shift towards prioritizing worker well-being and personalized solutions, particularly in the context of Industry 5.0. The findings of this research are expected to revolutionize the way ALs are designed by shifting the focus towards human-centric, adaptive systems that prioritize both productivity and worker safety.

1.4 Research Questions

This research is guided by the following key questions:

- How can HF/E be effectively integrated into the design phase of ALs to improve worker safety and operational efficiency?

  This research seeks to explore methodologies for integrating HF/E principles into the initial design of ALs, ensuring that ergonomic considerations are not an afterthought but a key component from the outset. The aim is to balance worker safety, comfort, and health with the need to maintain or enhance operational productivity. This research will investigate the tools, frameworks, and best practices that can facilitate this integration, potentially identifying gaps in current design methodologies and proposing new approaches.
- What is the impact of some sources of uncertainty, including the imprecision of ergonomic assessments, on task allocations within ALs?

  Ergonomic assessments often involve a degree of uncertainty due to the variability in human workers' capabilities and environmental conditions. In addition, external sources of uncertainties like market situation and demand rate can affect time requirements in ALs. This question examines the nature of these uncertainties and their impact on task allocation in ALs. Therefore, by answering this question, we aim to address the inherent uncertainties in these assessments, enabling more adaptive and resilient decision-making processes that improve both ergonomics and task efficiency.
- How can experts' knowledge from ergonomists and industrial engineers be integrated into a decision-support system to simultaneously enhance ergonomic well-being and operational productivity in AL environments?

  This question focuses on exploring the development of a decision-support system that combines the domain knowledge of ergonomists (focused on human safety and well-being) with insights from industrial engineers (focused on productivity and efficiency). The research will delve into the system's planning, the integration of expert knowledge, and the validation methodologies that ensure its practical relevance and reliability in real-world industrial environments.

- How can uncertainty in the conventional fatigue evaluation methods during the AL design phase be modeled to better predict fatigue, optimize worker recovery needs, and reduce system costs through the use of cobots or supportive robots?

  To address the limitations of conventional fatigue models, this research tries to incorporate uncertainty into the design phase of ALs. It investigates appropriate modeling approaches that can capture the uncertainties inherent in ergonomic evaluations and task planning. The focus will be on how these models can improve decisions regarding recovery times and workload balancing, particularly in scenarios where cobots are deployed to reduce worker fatigue and enhance overall system efficiency.
- How can traditional EATs be adapted and integrated into DHM systems to overcome the limitations of existing commercial solutions within virtual environments?

  While current commercial DHM tools (e.g., Siemens Jack, DELMIA, IPS IMMA) already enable ergonomic assessments, this research will investigate how traditional EATs can be further customized and integrated into modern DHM systems within a virtual environment. The goal is to examine how virtuality can enhance the effectiveness of EATs by providing a more immersive and realistic platform for ergonomic analysis, and how these tools can be synthesized into DHM systems for more accurate simulations and ergonomic assessments in the design and planning of ALs.

1.5 Objectives and Contributions

The primary objective of this thesis is to develop and validate a decision-support framework for human-centric AL design, optimizing both ergonomic well-being and operational efficiency under uncertain conditions. In this thesis, the terms worker well-being and safety specifically refer to the domain of physical ergonomics, with an emphasis on minimizing risks associated with MSDs. Broader psychosocial or cognitive aspects are outside the scope of this work.

The key contributions of this research include:

- Development of a decision-support system that integrates ergonomic considerations into the design phase of ALs, offering a more human-centric approach to AL design.

  This contribution focuses on creating a structured framework that incorporates the expertise of ergonomists and human factors engineers into the early design process of ALs. The proposed system will balance worker well-being with operational goals by addressing the inherent variability and uncertainties present in human performance and ergonomic evaluations. By doing so, it will enable safer, more comfortable, and more efficient AL environments.

- Application of advanced uncertainty modeling to manage ergonomic assessments and task allocations in ALBPs and ALWABPs.

  This contribution addresses the challenge of uncertainty in ergonomic evaluations and task distribution in ALs. The research investigates methods, including knowledge-based systems and fuzzy logic, for handling variability in human worker capabilities, task complexity, and environmental conditions. The resulting system generates more flexible and robust solutions for task allocation, improving ergonomic quality and operational efficiency.

- Introduction of a novel fatigue modeling approach to optimize recovery time and mitigate ergonomic risks in AL environments.

  Conventional fatigue models often fall short in addressing uncertainty and human variability during the design phase. This contribution introduces a new modeling approach aimed at more accurately predicting worker fatigue, considering factors such as task difficulty, duration, and recovery needs. The model will help minimize the possible fatigue level, reducing the over cost of system and long-term ergonomic issues such as musculoskeletal disorders (MSDs). It also offers practical tools for managers to ensure workers remain productive without compromising their well-being.

- Exploration of supportive robots, such as supernumerary robotic limbs (SRLs), to enhance productivity and reduce ergonomic risks in ALs.

  This contribution involves investigating how advanced robotic systems like SRLs can complement human workers in AL environments. These robots could take over physically demanding or repetitive tasks, reducing the physical strain on workers. By examining the interactions between human workers and supportive robots, this research aims to identify optimal task-sharing strategies that boost productivity while lowering the ergonomic risks associated with manual labor. The integration of these robots will also provide insight into future human-robot collaboration in industrial settings.

- Customization of traditional EATs for integration into DHM systems within a virtual environment, providing predictive capabilities for identifying ergonomic issues early in the design process.

  The final contribution focuses on adapting existing EATs (tools traditionally used for assessing ergonomics) to fit into modern DHM systems in a virtual environment. By simulating various AL scenarios, these tools will provide predictive insights into potential ergonomic risks, allowing designers to address issues before the implementation in the real world. This virtual-based approach enhances the ability to visualize, test, and refine AL designs, ensuring that ergonomic considerations are prioritized and optimized during the early stages of planning.

Figure 1.1 illustrates the relation between research contributions, connecting the three research objectives to the key research questions.

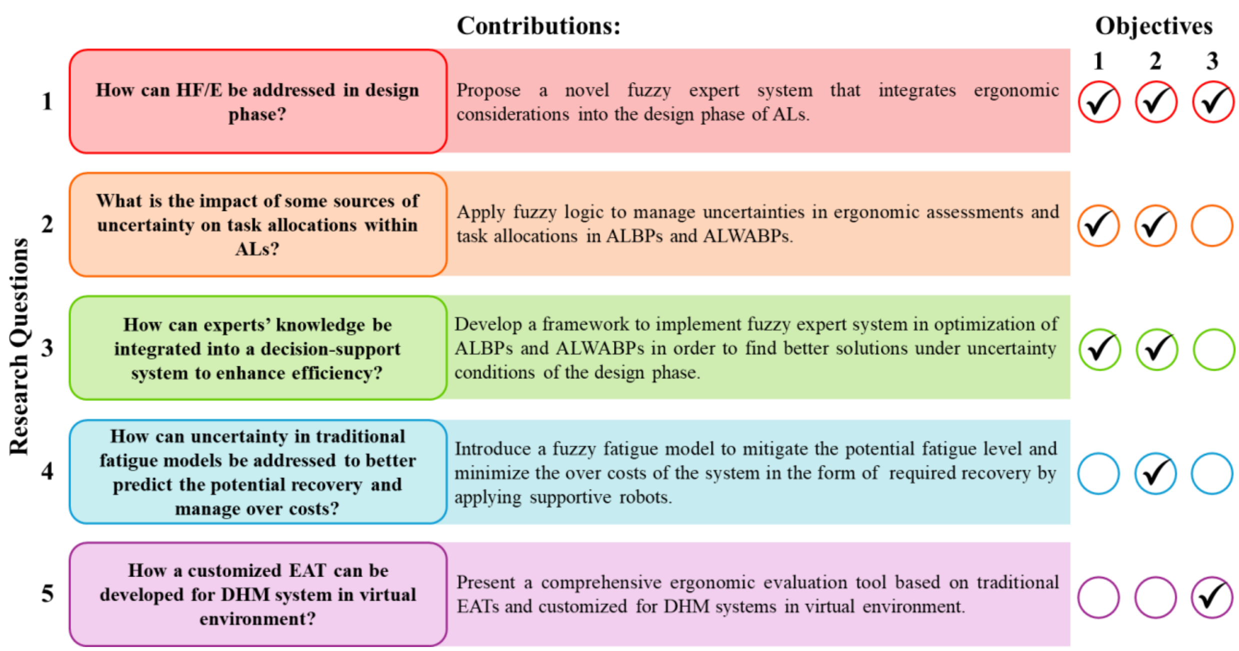

Figure 1.1 Contributions of this Ph.D. thesis to address research questions

The contributions of this research enable production system engineers to develop human-centric ALs that capture not only the HF/E aspects but also embed the vague and imprecise aspects to have more efficient and sustainable outcomes. The proposed approaches were tested on several synthesized datasets and scenarios and the results validated their effectiveness. The decision-support solutions, which employ knowledge-based and advanced uncertainty-handling techniques, can be applied across a variety of industrial applications. The outcomes of these contributions include:

- Three journal articles:
    - The first paper is a systematic review paper published in “CIRRELT Bureau de Montreal, Université de Montreal”. This article focuses on the evolution of Ergo-ALBPs with insights into Industry 5.0 paradigm to explore the future trends and research directions in this field of study.
    - The second article was published in the “Journal of Industrial and Production Engineering, Taylor & Francis”. This study develops a comprehensive framework based on fuzzy expert system and constructive heuristic method to optimize the Ergo-ALWABPs.
    - The third paper applies a fuzzy inference approach to develop a novel fuzzy fatigue model for optimizing the design of a robotic AL. It was published in the “International Journal of Advanced Manufacturing Technology, Springer Nature”.
- A submitted patent developed through reverse engineering of various EATs and based on an initial approach developed in Dassault Systèmes for DHM in virtual environment. This novel approach, named Ergo4All-Pro™, can integrate in the design phase of workplaces to help engineers estimate the potential ergonomic risk in each body part as well as upper limb.
- Three conference papers:
    - The first paper was presented in “IFIP 20th International Conference on Product Lifecycle Management (PLM23)” and published in conference proceedings titled “Product Lifecycle Management, Springer Nature”. This study proposes a primary optimization framework that considers the uncertain nature of ALBPs in the design phase. The proposed approach addresses the imprecise time factors and vague ergonomic aspects of ALs.
    - The second study was presented in “Applied Human Factors & Ergonomics (AHFE 2024)” and published in conference proceedings titled “Accessibility, Assistive Technology and Digital Environments”. This research develops a fuzzy ergonomic expert system to investigate and optimize ALDPs.

- The third research was presented in “Intelligent Systems Conference (IntelliSys 2024)” and published in conference proceedings titled “Intelligent Systems and Applications”. This paper presents a fuzzy fatigue model to address the uncertainty of ergonomic aspects in the design phase, applying a conventional fatigue model (Potvin, 2011).

As a result, this thesis compiles the findings and documents in the four articles incorporated into this thesis, three journal papers and one patent. As journal papers were the comprehensive version of conference papers, all three conference articles were added to the annex of this thesis. Figure 1.2 illustrates the four main articles along with three conference papers involved in this Ph.D. research journey along with the three research objectives involved.

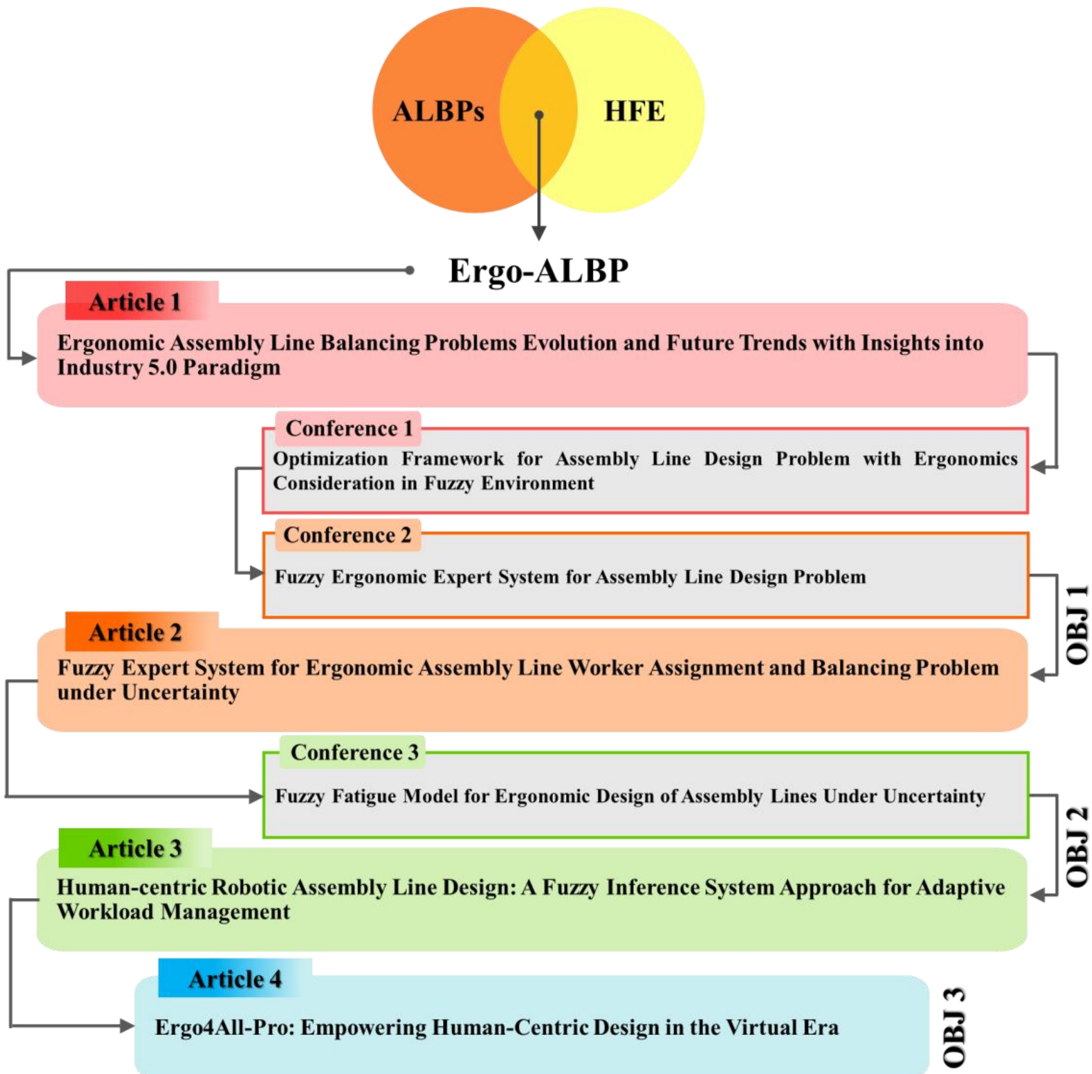

Figure 1.2 Outcomes of this Ph.D. thesis related to each research objective

1.6 Thesis Structure

This thesis contains nine chapters as follows:

- Chapter 1: Introduction – Provides an overview of the research context, problem statement, significance, research questions, objectives, and contributions.
- Chapter 2: Literature Review – Explores background about ALBPs and HF/E considerations and reviews existing literature on Ergo-ALBPs, identifying research gaps and justifying the need for this research.

- Chapter 3: Methodology – Describes the research methodologies used to investigate the research questions, including the development and validation of the fuzzy expert system, and the specific methods employed to achieve each research objective.
- Chapter 4: Article 1 – Conducts a systematic literature review of Ergo-ALBPs, exploring the future study and paradigm shift of Industry 5.0 to find critical research gaps and develop the research direction toward contributing to the literature in this field.
- Chapter 5: Article 2 – Presents the first research objective of this thesis that proposes an ergonomic fuzzy expert system for optimizing the ALWABP under uncertainty.
- Chapter 6: Article 3 – Presents the second research objective of this thesis. It proposes a novel fuzzy fatigue model through a fuzzy inference system (FIS) to find an optimum or near optimum solution for robotic AL.
- Chapter 7: Article 4 – Proposes the third research objective of this thesis. It develops a comprehensive novel EAT based on traditional methods which is proper for integrating in DHM and virtual environment.
- Chapter 8: General Discussion – Discusses the implications of the findings, comparing them with existing studies and highlighting the contributions of this research.
- Chapter 9: Conclusion – Summarizes the research findings, addresses the limitations, and suggests directions for future research.

This structured approach ensures a comprehensive exploration of the research questions and objectives, offering a holistic view of the methodologies used to advance the field of human-centric design and optimization of ALs. Figure 1.3 presents the different stages of this thesis, their achievements and deliveries. The subsequent chapters will delve into the specific details of the research process, methodologies, and findings, providing a robust framework for understanding the complex interaction between ergonomics, uncertainty, and operational efficiency of AL environments.

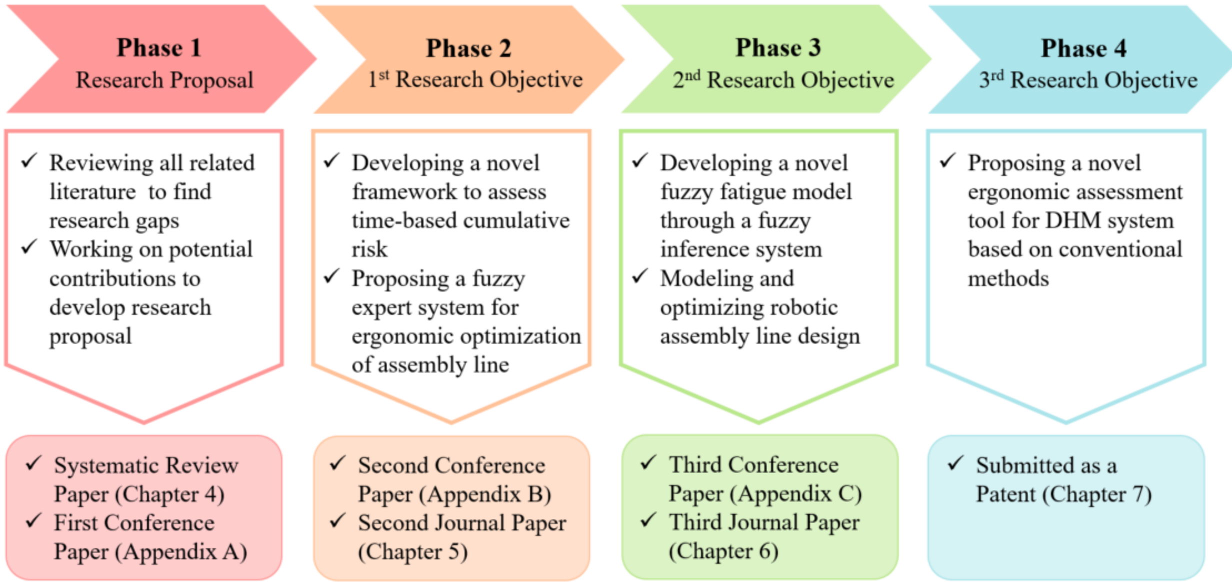

Figure 1.3 Various phases of this Ph.D. thesis

CHAPTER 2 LITERATURE REVIEW

In this chapter, a comprehensive literature review is presented on the studies that have been done on ALBPs by considering ergonomic aspects of workplace design (WD) to understand the theoretical background of Ergo-ALBP. For this reason, a review study is done on two main parts of this research: ALBPs and EATs, separately, to identify the fundamental aspects and define categories and their measuring indicators. Figure 2.1 depicts the structure of this chapter and explains the key aspects of each section. The focus point of this literature review is in the third part of this chapter (Ergo-ALBP), while in the first and second sections, the two main areas of the research (HF/E and ALBPs) are explained in detail.

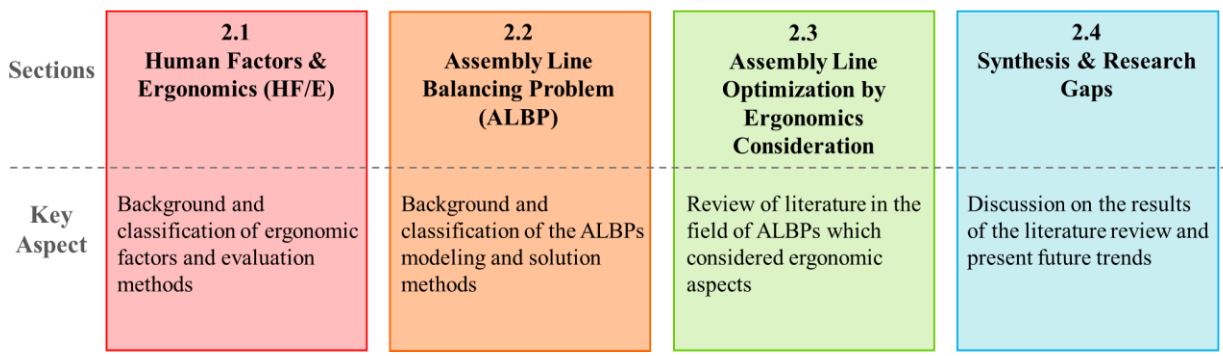

Figure 2.1 Outline of the literature review chapter

2.1 Human Factors and Ergonomics (HF/E)

Physically demanding jobs can result in fatigue, MSDs, and cumulative injuries. Thus, it is essential to establish a framework that evaluates tasks considering all possible risks. Adequate understanding of human capacity, comprising biomechanical and physiological factors, is critical in measuring physical demands (Chengalur et al., 2004). Ergonomic principles aim to adapt job activities to ensure worker welfare, safety, and enhanced productivity (Bautista, Batalla, & Alfaro, 2013). Ergonomic factors such as repetitive tasks, awkward postures, prolonged activity, and mental stress can contribute to ergonomic risks, which may affect both worker well-being and job satisfaction. Consequently, EATs have been developed to evaluate workplace risks, ranging from simple assessments to more sophisticated approaches requiring specialized knowledge (Tkitek & Triki, 2022).

This subsection defines key ergonomic indicators, introduces EATs, and classifies various HF/E criteria. Recent advancements in DHM have further integrated ergonomic evaluations into WD, emphasizing the importance of ergonomics in both physical and digital environments.

2.1.1 Background

Short-term task evaluations are typically categorized under biomechanics and muscle strength assessments. Biomechanical evaluations analyze internal forces affecting muscles, joints, and tendons to measure moments around specific body parts. This analysis assesses the impact of unusual load or awkward postures. For physically demanding tasks performed over longer periods, fatigue evaluation is crucial, focusing on the task's duration and the adequacy of recovery time.

WMSDs remain a major concern, accounting for one-third of all workplace injuries. The primary causes are excessive physical workload (PWL), including manual handling, repetitive movements, and awkward postures (Rajesh et al., 2021). WMSDs not only affect individual workers but also incur significant economic costs. Therefore, considering HF/E aspects is a vital approach to addressing these risks, ensuring a user-centered workplace design that promotes productivity and reduces injuries.

The quantification of ergonomic risks requires consideration of task demands, workplace conditions, environmental factors, and psychological aspects like stress (Joshi & Deshpande, 2019). Ergonomic risks associated with tasks can be analyzed by considering postural load, repetitive movements, and manual handling (Ghorbani et al., 2023).

2.1.2 Classification of Ergonomic Assessment Tools (EATs)

Chengalur et al. (2004) categorized EATs into three primary groups based on the data type:

1. Qualitative EATs are based on observational data and often analyzed through checklists or safety studies.
2. Semi-quantitative EATs combine qualitative and quantitative data for rapid analysis and risk classification (e.g., REBA, RULA, OCRA).
3. Quantitative EATs use objective data to assess risk factors in detail, these methods are ideal for ergonomic job design.

Furthermore, based on the method applied for data collection, EATs can be divided into four types: direct (instrumental), observational, subjective (self-reports), and psychophysiological methods.

Direct methods use physiological indicators like blood pressure, oxygen consumption, electromyogram (EMG), electrocardiogram (ECG), and heart rate to measure PWL. Observational methods evaluate body posture, force exertion, and movement frequency, while subjective methods, such as self-reports, are commonly used for ease and validity in ergonomic evaluations (Lorenzini et al., 2023).

Additionally, popular EATs can be grouped into posture-based, biomechanics-based, and multi-aspect methods. Figure 2.2 presents some samples of the well-stablished EATs based on this categorization. While each method has strengths, no single tool is universally superior. The selection of a suitable method depends on the specific ergonomic risks being evaluated (Arkouli et al., 2022).

Posture-based

RULA (Rapid Upper Limb Assessment) evaluates ergonomic risks linked to upper-limb disorders.

REBA (Rapid Entire Body Assessment) assesses risks for both upper and lower body parts.

OWAS (Ovako Working Posture Analysis) analyzes hazardous postures, assigning scores based on body position.

HARM (Hand Arm Risk-assessment Method) analyzes risks in the arm and hand based on duration and forces of tasks.

Biomechanical

ESI (Ergonomics Stress Index) evaluates the mechanical loading and biomechanical stresses placed on different body parts during work tasks.

3DSSPP (3D Static Strength Prediction Program) developed by the University of Michigan to predict muscle forces, joint moments, and spinal compression.

AnyBody is a software system designed for musculoskeletal analysis. It is used to simulate the human body and analyze the mechanics of muscles, bones, and joints.

Multi-aspect

OCRA (Occupational Repetitive Action) evaluates the risk of repetitive work for upper limbs.

JSI (Job Strain Index) focuses on the upper extremities (wrist and hands) particularly for analyzing repetitive jobs.

KIM (Key Indicator Method) is a screening method targeted at the manual handling of loads.

EAWS (Ergonomic Assessment Worksheet) is a quick screening tool that covers four risk areas: body postures, action forces, manual materials handling, and upper limbs (with a focus on high frequency).

NIOSH (National Institute for Occupational Safety and Health) lifting equation determines acceptable lifting loads to reduce risk.

Figure 2.2 Some samples of EATs

2.1.3 Digital Human Modeling (DHM)

DHM plays a critical role in optimizing workstation design and reducing ergonomic risks by facilitating early-stage ergonomic assessments within virtual manufacturing system (VMS). By implementing ergonomic constraints and factors in the design phase, DHM enables the development of preventive ergonomic strategies to improve workplace safety and efficiency (Schaub et al., 2012).

The origins of DHM can be traced back to the late 1960s when Springer et al. (1969) at Boeing developed a digital dummy to evaluate reach distances inside aircraft cockpit based on anthropometric data. This marked the birth of virtual ergonomics. Over the decades, DHM has evolved significantly, particularly with the commercialization of DHM systems such as Dassault Systèmes' CATIA-DELMIA in 2000. Initially, DHM tools operated as "standalone" system (independent software), but they have since been integrated into advanced computer-aided design – computer-aided manufacturing (CAD-CAM) platforms, which are widely used by industrial designers and engineers. This integration allows for the ergonomic assessment of work environments within virtual design frameworks, helping to accommodate the variability of anthropometric characteristics in diverse workforces (Charland, 2016).

DHM tools have proven effective in minimizing WMSDs by allowing physical and some organizational ergonomic risks to be identified and addressed in the early stages of the design process. Chaffin (2005) emphasized the proactive application of DHM tools during the design phase, highlighting the importance of addressing ergonomic concerns before physical prototypes are developed. By anticipating and mitigating potential ergonomic issues at the design stage, organizations can minimize the risks of WMSDs and ensure safer, more efficient work environments.

Recent advancements in DHM have focused on the dynamic simulation of human movement, enabling real-time ergonomic assessments. De Magistris et al. (2013) contributed to this development by enhancing the dynamic control capabilities of DHM, allowing for more accurate simulations of human motion. This is particularly important in dynamic work environments where posture-related risks are prevalent. Their work underscores the value of real-time simulations in identifying and correcting ergonomic risks related to posture and movement.

The ability to simulate and analyze human interactions with workstations, tools, and tasks in a virtual environment eliminates the need for costly physical prototypes and allows for iterative testing and optimization. For example, Paudel et al. (2022) introduced a 3D human pose estimation framework that uses video and image sequences to evaluate ergonomic postures in real-time. Their approach, which incorporates assessment methods such as OWAS, REBA, and RULA, demonstrated high accuracy in scoring postural risks, reinforcing the significance of precise posture analysis in preventing injuries in industrial settings.

DHM systems are becoming increasingly indispensable across a wide range of industries, not only for workstation design but also for product development. By simulating different body types and postures, DHM systems allow designers to create products and work environments that cater to a diverse workforce, enhancing both safety and comfort (Dahibhate et al., 2023). This integration of ergonomic considerations from the outset contributes to the overall effectiveness of the product development process and reduces the risk of injuries.

In their research, Alexopoulos et al. (2013) integrated ergonomic assessment techniques with VMS and DHM to develop the “ErgoToolkit”, which analyzes ergonomic factors in the early stages of the manufacturing process. The use of dynamic human task simulation allows the identification of ergonomic issues before physical production begins. Similarly, Caputo et al. (2019) developed a method for ergonomic validation using several EATs in a virtual space. Their approach, which combines numerical analysis and virtual simulations, has proven useful for both ergonomists and designers in optimizing human-centered workplace designs.

Understanding the capabilities and limitations of various DHM systems is crucial for advancing ergonomic assessments. Poirson and Delangle (2013) conducted a comprehensive comparative analysis of different human modeling tools, providing valuable insights into their strengths and weaknesses. This analysis is particularly useful for researchers and practitioners when selecting the most appropriate DHM tools for specific applications. Dahibhate et al. (2023) also highlighted that certain DHM systems are better suited for ergonomic assessments or industrial scenarios, guiding more informed decision-making.

Based on the work of Poirson and Delangle (2013) and Dahibhate et al. (2023), four of the most popular DHM software platforms for ergonomic assessments are CATIA-DELMIA, Jack, RAMSIS, and AnyBody. These tools offer some ergonomic assessment capabilities, allowing for more precise analysis of ergonomic risk factors and effective design interventions.

2.2 Assembly Line Balancing Problems (ALBPs)

This section explains the fundamental aspects of ALs in manufacturing and investigates ALBPs in the relevant research literature. ALs play a crucial role in production systems, particularly from a lean manufacturing perspective. As the closest point to the market within the production process, ALs are flexible systems that can efficiently respond to demand fluctuations and market developments. Their importance lies not only in their role in final product assembly but also in their impact on upstream sections of the production system, where changes and improvements in ALs can lead to better overall management.

The optimization of ALs has become a prominent focus in literature due to their critical function in most manufacturing systems. Serving as the pacemakers of production, balanced and optimized ALs are essential for maintaining continuous flow and supporting the implementation of efficient pull systems. Balancing ALs is key to ensuring that production operates smoothly and in line with demand.

Given the importance of this topic, this section reviews ALBPs and provides a preliminary definition of ALs and ALBPs. It also explores the literature to present a comprehensive classification of ALBPs, providing insights into the design and optimization of production lines. Finally, various methods used to solve ALBPs are discussed, particularly in relation to ergonomic considerations.

2.2.1 Background

Since Henry Ford's introduction of mass production, ALs have evolved significantly, transitioning from fast-paced, single-model lines to more adaptable systems. Nowadays, there are various types of ALs, and substantial research has contributed to their development in numerous aspects.

ALs generally consist of a series of workstations arranged in a specific sequence to produce products by performing predefined tasks. The primary goal of ALs is to efficiently produce and deliver large quantities of standardized products. This focus on productivity has driven the modeling and solution of ALBPs, which were first mathematically formulated by Salveson (1955). ALBPs involve assigning tasks to workstations to meet production rates, satisfy constraints, and optimize one or more objectives.

In the design of ALs, the main challenge is assigning tasks to a sequence of workstations with a specified cycle time (CT) while satisfying precedence constraints and optimizing performance measures (Becker & Scholl, 2006). ALBPs become more complex due to constraints such as occurrence, precedence, and capacity limitations. The objectives of ALBPs can be grouped into three categories: capacity-related, cost-related, and profit-related objectives (Eghtesadifard et al., 2020).

While the overall goal of ALBPs is to improve the efficiency of the AL, different industries, with their unique conditions and restrictions, prioritize different objectives. Common optimization objectives in the literature include minimizing the number of workstations, CT, workload variation, idle time, setup costs, and equipment costs, as well as maximizing production efficiency and line throughput (Razali et al., 2019).

Assembly line design problems (ALDPs) further complicate ALBPs by considering not only tasks assignments but also the selection and assignment of tools or equipment to workstations (Finco et al., 2019). ALBPs are central to medium-term production planning (tactical planning), while ALDPs represent long-term, strategic decisions with significant financial implications. The objectives of ALDPs must align with the factory's strategic goals, such as cost reduction and profit maximization. One of the key performance indicators (KPIs) is line utilization, which is closely tied to CT and the number of stations (Becker & Scholl, 2006).

2.2.2 Classification of Problems

Baybars (1986) provided the most widely known classification of ALBPs, dividing them into two groups: simple ALBP (SALBP) and general ALBP (GALBP). According to Becker and Scholl (2006), SALBPs focus on a straight, one-sided AL designed for mass production of a homogeneous product, with a deterministic CT and the objective of optimizing performance while considering two types of constraints on task assignment (Bautista, Batalla, & Alfaro, 2013):

- Precedence constraints: These define the allowable sequence of task execution.
- Cumulative constraints: These limit the total time spent at each workstation.

SALBPs are the simplest form of ALBPs, and they can be further classified into four categories based on specific characteristics (Rekiek et al., 2002). ALBP-1 minimizes the number of workstations with a given CT, ALBP-2 minimizes the CT with a fixed number of workstations, ALBP-E finds the most efficient combination of workstations' number and CT, and ALBP-F checks the feasibility of any combination of workstations' number and CT (Boysen et al., 2007). However, when additional considerations such as constraints, limitations, and other objective functions are added, the problem becomes more complex and falls into the GALBP group.

Although extensive research has been conducted on SALBPs, real-world ALs often present more complex challenges that require the consideration of GALBPs. Over the past decade, there has been a growing trend toward incorporating additional constraints and diverse objectives to address these more realistic and complicated scenarios (Mutlu & Özgörmüş, 2012). Comprehensive surveys by Becker and Scholl (2006) and Boysen et al. (2007) laid the foundation for the classification of GALBPs, and more recent studies have continued to expand on this body of knowledge.

In their systematic review paper, Eghtesadifard et al. (2020) identified four specific considerations for classifying ALBPs. Figure 2.3 presents a synthesized classification of ALBPs based on the most frequently cited categories in the literature. Baybars's classification (represented in red) provides a general framework, dividing ALBPs into two groups: SALBPs and GALBPs. However, more detailed classifications have emerged, considering additional aspects of ALBPs.

SALBP	Simple ALBP (straight AL, minimize CT with a given numbers of workstation & vice versa)
GALBP	General ALBP (all problems which cannot be categorized as simple)
SMALBP	Single model of ALBP (there is only one type of product)
MuMALBP	Multi-model of ALBP (there are more than one type of product produced in batches)
MMALBP	Mixed model of ALBP (several models of a product which produced in mixed situation)
SALBP	ALBP for a straight AL
UTALBP	ALBP for a U-shape AL
PALBP	ALBP for a parallel AL
2S-ALBP	ALBP for a two-sided AL
Hybrid ALBP	Combination of different layout of AL
Paced	Fixed timeframe for the movement of parts from one workstation to another
Unpaced	There is no definite timeframe and parts are moved occasionally

Figure 2.3 Classification of ALBPs

For example, ALBPs can be categorized based on workstation layouts (green category) or the type(s) number of products being manufactured (orange category). Another important classification distinguishes between paced and unpaced (buffered) ALBPs, based on the timing of part and material movement between workstations (Becker & Scholl, 2006). In the literature, paced lines are sometimes referred to as synchronous lines.

Additionally, new classifications have emerged based on advancements in production systems. Abdous et al. (2020) categorized ALs into three types based on the level of automation: manual, semi-automated, and automated lines. While most ALBP research has historically focused on manual ALs, there is an increasing interest in developing robust models for semi-automated and automated systems. This has led to the development of collaborative human-robot assembly line balancing problems (CALBPs) and robotic assembly line balancing problems (RALBPs) (Stecke & Mokhtarzadeh, 2022).

Figure 2.3 presents these common classifications, but it is important to note that some studies introduce new classification methodologies. For instance, Cakir et al. (2011) classified ALBPs based on task time characteristics, dividing them into deterministic and stochastic models. However, other stochastic elements beyond task time, such as variations introduced by improvements in manufacturing processes, can also influence these problems (Becker & Scholl, 2006).

Eghtesadifard et al. (2020) classified ALBPs based on objective functions into three categories: cost-related, profit-related, and capacity-related objectives. However, Hazır et al. (2015) categorized profit as a sub-class within composite models, proposing a classification consisting of cost-oriented models, capacity-oriented models, and composite models.

Therefore, as more realistic models continue to emerge, hybrid ALBPs have become increasingly common, integrating various classes of problems to create more accurate representations of real-world manufacturing challenges.

2.2.3 Solution Methods

The ALBP was first mathematically formulated by Salveson (1955) as a linear programming (LP) model. Halgeson and Birnie (1961) were the first to propose a technique for solving these problems. However, for the first 40 years, ALBPs were primarily solved through trial-and-error methods (Unuigbe et al., 2016).

ALBPs fall under the broader category of combinatorial optimization problems (COPs), which involve searching for an optimal solution from a finite set of FSs. Battaïa and Dolgui (2013) reviewed 300 research articles on ALBPs, concluding that the primary focus in the literature has been on developing methods to solve multi-objective problems. Despite advancements in this field, there remains a gap between the mathematical models and the complexities of real-world problems, with ongoing efforts to integrate more task features, performance indicators, and objective functions.

Much of the research in this area has focused on solving SALBPs (Battaïa & Dolgui, 2013). SALBPs have been proven to be NP-complete problem (Wee & Magazine, 1982), and the same is true for GALBPs, which are even more complex (Becker & Scholl, 2006).

Various computational methods have been used to solve ALBPs, including exact, heuristic, and meta-heuristic approaches (Battaïa & Dolgui, 2013). Common exact methods include dynamic programming, branch-and-bound, and other mathematical techniques. However, since NP-hard problems like ALBPs cannot be efficiently solved using exact methods, more advanced algorithms are needed to find near-optimal solutions. Numerous studies have demonstrated the effectiveness of heuristic and meta-heuristic methods in addressing ALBPs. Heuristic methods are solution strategies that rely on trial-and-error to produce acceptable solutions within a reasonable time frame. Meta-heuristic algorithms, on the other hand, utilize trade-offs between randomization and local search, generally outperforming simpler heuristics.

Among the most commonly used heuristic methods in ALBPs are the ranked positional weight method and Kilbridge & Webster's method. Frequently applied meta-heuristic algorithms include genetic algorithms (GA), particle swarm optimization (PSO), and ant colony optimization (ACO). Other meta-heuristic methods used in the literature include memetic algorithm, simulated annealing (SA), Petri net, tabu search, and the neural network (Eghtesadifard et al., 2020).

In recent years, there has been a growing trend toward the use of hybrid algorithms, which combine two or more meta-heuristic methods to improve solution quality by overcoming the limitations of individual methods. When it comes to solving ALDPs, which involve the assignment of equipment and balancing/sequencing procedures, exact methods are generally inefficient. As ALDPs are considered a variant of ALBPs with different layouts (Baykasoglu et al., 2017), they are also NP-hard, and heuristic algorithms are most often used to find solutions that are close to optimal (Hazır et al., 2015).

2.3 Assembly Line Optimization by Ergonomic Considerations

Most ALs still rely on manual systems, as these offer the most flexibility to adapt to market fluctuations and technological developments (Ozdemir et al., 2021). Due to the nature of assembly tasks, workers in ALs are often exposed to one or more ergonomic risk factors, which commonly result in WMSDs. The severity of these risks is determined by the frequency, intensity, and duration of exposure (Mutlu & Özgörmüş, 2012). Therefore, ergonomic criteria are essential in designing sustainable, modern ALs, balancing workers' well-being and system performance (Weckenborg & Spengler, 2019).

Traditionally, the primary goal of ALBPs has been to maximize profit by focusing on economic parameters such as production rate, time efficiency, and operational costs. Conventional approaches, however, tend to overlook the indirect costs associated with poor ergonomic conditions, such as absenteeism, healthcare expenses, and long-term injury-related losses (Alexopoulos et al., 2013). Ignoring these factors leads to significant penalties for organizations, both financially and in terms of workforce sustainability.

Increased ergonomic risks often result in chronic injuries that impose high costs on both companies and society at large (Bautista, Batalla-García, et al., 2015). Hendrick (2008) found that "Good ergonomics projects typically yield a direct cost-benefit ratio of 1 to 2, up to 1 to 10, with a typical payback period of 6–24 months." Nonetheless, focusing solely on operational factors like CT optimization, without addressing ergonomic issues, can lead to decreased worker productivity. Low ergonomic standards in the workplace may result in disability (increased absenteeism) or severe fatigue (reduced efficiency) (Battini et al., 2011).

Before 2011, ergonomic risks were rarely considered in ALBPs. However, more recent studies have increasingly integrated ergonomic considerations into AL optimization. In this section, we review published articles since 2011 that address Ergo-ALBPs, focusing on the use of EATs, technical aspects, and the mathematical models applied. The emerging trends in Ergo-ALBPs, particularly within the context of Industry 4.0, are also discussed. While a comprehensive systematic review of Ergo-ALBP literature is provided in the first article of this thesis (Chapter 4), this section offers a condensed summary of the key studies and trends.

2.3.1 Ergonomic Tools Applied in Optimization Models

AL tasks inherently carry ergonomic risks due to their repetitive and prolonged nature. These risks often lead to WMSDs, making ergonomics a critical consideration in the design and optimization of ALs. Integrating ergonomic principles with operational efficiency is vital to prevent injuries and optimize performance simultaneously. Gunther et al. (1983) were among the first to include ergonomic risks in ALBPs, setting a foundation for what has become a growing area of interest. Their study constrained the maximum level of operators' energy expenditure, marking an early acknowledgment of ergonomic concerns in assembly line design.

Despite this early progress, limited advancements were made in this field until Otto and Scholl (2011) introduced ergonomics as a key objective in optimization models. This research acted as a turning point, spurring increased interest in Ergo-ALBPs, with many studies following their lead (Otto & Battaïa, 2017). Recent studies have expanded these models to incorporate more comprehensive ergonomic considerations (Calzavara et al., 2019; Daria et al., 2018).

The efficiency of manual AL systems is strongly influenced by how ergonomic factors are integrated into the balancing process (Ozdemir et al., 2021). Research in Ergo-ALBPs aims to achieve this integration. Although universally superior EAT does not exists, these tools are crucial for evaluating ergonomic risks in the workspace. However, as Takala et al. (2010) note, no single method is applicable to all situations, and each EAT has its own strengths and limitations. While section 2.1.2 provides an overview of numerous EATs, the evaluation methods in Ergo-ALBP studies remain limited. The selection of EAT often depends on the specific requirements of the assembly environment and the types of tasks being analyzed.

Chengalur et al. (2004) highlighted that semi-quantitative and quantitative methods are often inappropriate to job design, although they can be useful for job evaluation. Consequently, qualitative and semi-quantitative approaches are typically used in Ergo-ALBPs (Abdous, Delorme, Battini, Sgarbossa, et al., 2023). Table 2.1 presents a summary of the most commonly applied EATs in Ergo-ALBP literature.

Table 2.1 Summary of most applied EATs in various research on Ergo-ALBPs

References	**EAT**
(Otto & Scholl, 2011), (Otto, 2014), (Bautista, Alfaro-Pozo, et al., 2016), (Bautista Valhondo et al., 2015), (Bautista, Batalla-García, et al., 2015), (Bautista, Alfaro-Pozo, et al., 2016), (Baykasoglu et al., 2017), (Tiacci & Mimmi, 2018), (Akyol & Baykasoğlu, 2019), (Finco et al., 2020), (Zhang et al., 2020), (Cimen et al., 2022)	OCRA
(Bautista, Alfaro-Pozo, et al., 2016), (Bautista Valhondo et al., 2015), (Bautista, Batalla-García, et al., 2015), (Barathwaj et al., 2015), (Bautista, Alfaro-Pozo, et al., 2016), (Dalle Mura & Dini, 2019)	RULA
(Polat et al., 2015), (Bortolini et al., 2017), (Polat et al., 2018), (Kahya & Şahin, 2019), (Vollebregt, 2021), (Yetkin & Kahya, 2022)	REBA
(Otto & Scholl, 2011), (Bautista, Alfaro-Pozo, et al., 2016), (Bautista Valhondo et al., 2015), (Bautista, Batalla-García, et al., 2015), (Bautista, Alfaro-Pozo, et al., 2016)	NIOSH
(Otto & Scholl, 2011), (Otto, 2014)	EAWS
(Battini et al., 2015), (Battini, Calzavara, et al., 2016), (Dalle Mura & Dini, 2019), (Stecke & Mokhtarzadeh, 2022), (Dalle Mura & Dini, 2022)	(Garg et al., 1978)
(Battini, Delorme, et al., 2016), (Chutima & Khotsaenlee, 2022), (Quenehen et al., 2023)	PMES
(Battini et al., 2017), (Finco et al., 2018), (Weckenborg & Spengler, 2019), (Finco et al., 2020), (Finco et al., 2021)	(Price, 1990)
(Katiraee et al., 2023), (Keshvarparast et al., 2022)	(Borg, 1990)
(Abdous et al., 2020), (Abdous, Delorme, Battini, Sgarbossa, et al., 2023), (Abdous, Delorme, Battini, & Berger-Douce, 2023)	(Ma et al., 2010)

Although OCRA is the most frequently employed EAT in Ergo-ALBPs, there have been studies that compare or integrate the results of OCRA with other methods. For example, several studies have combined OCRA with RULA and NIOSH (Bautista, Alfaro-Pozo, et al., 2015; Bautista, Alfaro-Pozo, et al., 2016; Bautista, Batalla-García, et al., 2016; Bautista Valhondo et al., 2015). The last five rows of Table 2.1 list various methods used to evaluate energy expenditure (EE) and fatigue in ALBPs.

2.3.2 Modeling of Ergonomic Oriented Problems

In the past decade, a growing number of research efforts have integrated HF/E indicators into ALBPs (Kahya & Şahin, 2019). Traditionally, Ergo-ALBPs have focused on two main objectives: minimizing the number of workstations (Type 1) and minimizing the cycle time (Type 2). However, ergonomic considerations have become increasingly essential, adding new dimensions to optimization models.

Otto and Scholl (2011) pioneered research on the impact of ergonomic assessments in AL rebalancing. They demonstrated that incorporating ergonomic risks into ALBPs does not necessarily require significant additional investment. In more than half of their cases, ergonomic considerations did not increase the number of workstations. They proposed two methods for addressing ergonomic risk in the SALBP-1. The first method involved adding constraints to limit the maximum permissible ergonomic risk, while the second introduced a new objective function aimed at minimizing overall ergonomic risk. A weighting coefficient was then used to combine the objective with the initial goal of minimizing the number of workstations. The authors utilized three EATs: the revised NIOSH equation, the OCRA method, and the EAWS method.

Rajabalipour Cheshmehgaz et al. (2012) focused on operator posture by applying the OWAS postural risk assessment method. Their optimization aimed to balance the physical workload across workstations while minimizing the accumulated risk of postures (ARPs) index, which quantifies risks to various body parts (legs, back, and arms) based on workload distribution.

Bautista, Batalla and Alfaro (2013) addressed a crucial trade-off: increasing the number of workstations to improve ergonomic conditions can lead to higher costs by altering the layout. To manage these conflicting goals, they proposed a model that integrated time, space, and ergonomic risks. Their novel "time and space-constrained ALBP" (TSALBP) was the first to mathematically model such a problem using linear programming (LP). Later, they extended this model by incorporating additional ergonomic risk factors like posture, repetitive tasks, and handling activities, creating a mixed-integer linear programming (MILP) model (Bautista, Batalla, Alfaro, et al., 2013). Both models were solved using exact approaches, emphasizing the feasibility of balancing ergonomic risks with operational efficiency.

To further advance TSALBP, Bautista, Alfaro-Pozo, et al. (2015) developed a metaheuristic approach, the greedy randomized adaptive search procedure (GRASP), which focused on minimizing the maximum ergonomic risk across workstations. Their case study on Nissan's engine company demonstrated the efficiency of GRASP, comparing its output with solutions generated by LP.

Battini, Delorme, et al. (2016) made significant contributions by introducing the concept of "smoothness" factors in ALBPs. In their multi-objective SALBP-2 model (minimizing CT with a fixed number of stations), they utilized the predetermined motion energy system (PMES), first developed by Garg et al. (1978), which breaks down tasks into basic movements like lifting, carrying, and walking. The authors also applied Pareto optimality analysis to evaluate trade-offs in their case study, providing deeper insights into how energy expenditure can be incorporated into ALBPs (Battini, Delorme, et al., 2016).

While the use of PMES allowed for energy-based ergonomic optimization, it overlooked individual worker differences (e.g., age, gender, weight). Dalle Mura and Dini (2019) addressed this gap by developing a GA for multi-objective SALBP-1, which minimized the number of workstations while considering operators' physical capabilities and technical skills. They used the RULA method to evaluate ergonomic risks and workload variance at each station.

Daria et al. (2018) also tackled the challenge of individual differences in ergonomic considerations by introducing the VR-Ergo Log system. This system combined motion capture technology with immersive reality and heart rate monitoring to assess ergonomic performance. They evaluated several ergonomic KPIs and incorporated human variability factors such as gender, age, and physical characteristics into their AL design evaluation.

Katiraee et al. (2019) reviewed the literature on ALBPs and noted that human diversity factors, while gaining attention, are often limited to age and experience. They emphasized the need for future research to include a broader range of diverse factors and ergonomic methods that consider anthropometry and gender.

Otto and Battaïa (2017) provided a comprehensive review of ALBP optimization methods that accounted for physical ergonomic risks and MSD risks. They categorized the literature based on whether ergonomic risks were treated as constraints or objectives, highlighting the prevalence of heuristic methods like GA, local search (LS), ACO, SA. The authors suggested for future research to develop exact solution algorithms to improve the precision of ergonomic-oriented ALBPs.

Bortolini et al. (2017) extended ergonomic optimization to the assembly station level, focusing on task assignment and component picking. Their multi-objective model minimized CT and ergonomic risks, yielding optimal task assignment and storage location strategies.

Finally, Zhang et al. (2020) introduced a U-shaped AL optimization model, where CT and ergonomic risks were minimized using an iterated pareto greedy (IPG) method. Their work contributed to expanding ergonomic considerations in more complex AL layouts.

2.3.3 Assembly Line Planning in the Industry 4.0 Era

While the majority of Ergo-ALBPs have traditionally focused on manual ALs, there is an increasing trend towards the integration of Industry 4.0 technologies. This shift is motivated by the need for production systems that are both flexible and adaptive, particularly to meet the demands of mass customization that define the Industry 4.0 era. Recent research has begun exploring RALBPs. The inclusion of robots introduces new advantages but also presents challenges related to task allocation, line balancing, and scheduling decisions (Kheirabadi et al., 2023). These challenges highlight the need to not only optimize technical processes but also prioritize the ergonomic well-being of the workforce.

The evolution towards Industry 5.0 builds upon these developments by emphasizing a more human-centric approach to automation. This paradigm shift seeks to combine the precision of robotic systems with human intelligence, emphasizing worker well-being while maintaining high levels of operational efficiency. Ergo-ALBPs are increasingly focused on CALBPs, which promote sustainable and resilient manufacturing systems (Ghorbani et al., 2023).

In manufacturing, human-robot interactions are typically classified into four types: coexistence, interaction, cooperation, and collaboration (Wang et al., 2020). These categories represent varying levels of synergy, from independent operation in the same environment to direct collaboration on tasks. Ergonomic considerations are increasingly integrated into these interactions, particularly in collaborative settings where humans and robots share tasks and workspace. By incorporating ergonomics, these interactions address significant challenges while improving both the safety and efficiency of ALs.

Pioneering studies like Weckenborg and Spengler (2019) highlighted the importance of integrating ergonomic considerations into cost-oriented approaches for CALBPs. They utilized models like

Price (1990) to balance EE and reduce physical workload. Subsequent research by Stecke and Mokhtarzadeh (2022) and Weckenborg et al. (2022) further explored the role of EE in CALBPs, using the Garg et al. (1978) model and a biomechanical approach, respectively. These models were solved by applying exact methods within a mixed integer programming (MIP) framework. Alternatively, studies by Chutima and Khotsaenlee (2022) and Quenehen et al. (2023) employed the PMES to measure EE in CALBPs, employing hybrid metaheuristic approaches to solve the resulting models.

Dalle Mura and Dini (2022) applied GA to address the job rotation problem in collaborative Als. Their objective was to minimize the cost of assigning workers with varying skill levels while accounting for the installation of cobots and other equipment. Additionally, they sought to minimize variation in EE between workstations by considering workers' movements, physiological characteristics, the degree of collaboration with robots, and job rotations. Keshvarparast et al. (2022) introduced a bi-objective optimization model for CALBPs, aiming to minimize both CT and workers perceived physical workload, which was measured using the Borg scales. They solved this model by applying a Pareto front approach.

Abdous et al. (2020) proposed an optimization model within the CALDP context, with the goal of minimizing equipment costs and ergonomic risks. Their model assessed dynamic muscle fatigue using a formula developed by Ma et al. (2009) to evaluate the impact of tasks assigned to each workstation. Building on this study, Abdous, Delorme, Battini and Berger-Douce (2023) developed a multi-objective optimization model to address CALDP, focusing on minimizing equipment and production costs, optimizing space utilization, and reducing fatigue risks, utilizing the model proposed by Ma et al. (2010).

2.4 Synthesized and Research Gaps

While ALBPs have been extensively studied, Ergo-ALBPs have received relatively limited attention, particularly in the design phase. Neglecting ergonomic considerations during the initial design stages can lead to significant long-term health issues for workers. According to Falck and Rosenqvist (2014), addressing these issues in existing ALs and in the form of corrective actions is 9.2 times more expensive than implementing preventive measures early during design step. However, most research focuses on optimizing existing ALs, leaving Ergo-Assembly Line Design Problems (Ergo-ALDPs) underexplored. A few notable studies, such as Baykasoglu et al. (2017), and Finco et al. (2019), have studied Ergo-ALDPs. Baykasoglu et al. (2017) utilized a heuristic approach for SALBP during the design phase, while Finco et al. (2019) developed a semi-automatic AL design aimed at minimizing both ergonomic risks and design costs. Their research emphasized the importance of addressing ergonomics at the design stage. Early integration of ergonomics in assembly process planning would create more efficient and sustainable systems.

This Ph.D. research aims to address the gaps in literature, focusing on two key dimensions related to the design phase of Ergo-ALBPs:

- Uncertain conditions: In real-world scenarios, various sources of uncertainty impact Ergo-ALDPs, affecting modeling objectives. Uncertainty in these problems can be classified into two main categories: environmental and system uncertainty (Ho, 1989). Environmental uncertainty relates to external factors such as market fluctuations and customer behavior, while system uncertainty includes production process variations, particularly those influenced by human factors.

  Among these uncertainties, demand uncertainty and task time variability are the most critical (Hazır et al., 2015). Unlike automated ALs, manual systems are subject to significant variability in task times due to factors like worker fatigue, differing skill levels, age, and experience. Additionally, demand, which heavily influences optimization objectives, is not deterministic during the design stage. Therefore, designers and decision-makers must effectively address these uncertainties when designing ALs to ensure more realistic and sustainable solutions.

- Ergonomic evaluation methods: Despite the wide variety of available EATs (Takala et al., 2010), few methods have been leveraged in optimization models of ALs. The literature shows that only a limited number of ergonomic criteria are suitable for addressing design phase and solving ALDPs, as most existing EATs were developed for operational or already-existing ALs (Otto & Battaïa, 2017). Moreover, ergonomic evaluations during the design phase suffer from imprecision, particularly when staffing decisions and task assignments have yet to be finalized. Several studies (Golabchi et al., 2017; Golabchi et al., 2016) highlight the imprecise nature of inputs used in EATs, which can significantly affect the results. Therefore, there is a need for research to explore a broader spectrum of ergonomic evaluation methods that can be applied during the design stage, particularly under uncertain conditions.

To the best of our knowledge, among all studies on Ergo-ALBPs up to 2022, Tiacci and Mimmi (2018) were the only researchers to address uncertainty by modeling stochastic task times in ALBPs. Their approach introduced penalties for instances where ergonomic constraints and/or predicted CTs were not met. Sikora et al. (2022) highlighted two primary approaches for dealing with variability in processing times in ALBP literature: "no reaction" and "active reactions". In the "no reaction" approach, planners accept variability as an inherent aspect of the system, akin to unpaced (asynchronous) ALBPs. Tiacci and Mimmi (2018) incorporated an unpaced AL into their study and, to address the complexity of their problem, applied a simulator for model validation.

Although a limited number of studies have addressed the uncertain nature of ALBPs, the gap is even more apparent in the domain of Ergo-ALBPs. In most existing research, deterministic models dominate, assuming fixed task times and static conditions. This simplification neglects the variability present in real-world environments, where task times and human capabilities fluctuate due to fatigue, experience, skill levels, and other factors.

Stochastic programming models offer one solution by treating specific parameters, such as task times, as stochastic variables, thus allowing for the incorporation of variability. However, in the context of Ergo-ALBP, Tiacci and Mimmi (2018) study remains the only one that included stochastic task times. Another approach is applying fuzzy logic, which introduces fuzzy numbers to handle imprecise or insufficient historical data. This approach is particularly useful in scenarios where data uncertainty is prominent, such as ergonomic assessments and task allocations. A small number of studies have applied fuzzy set theory in the form of fuzzy programming to manage conflicting objectives in ALBPs (Mutlu & Özgörmüş, 2012; Ozdemir et al., 2021; Rajabalipour Cheshmehgaz et al., 2012). Thus, the application of fuzzy logic in this field remains limited.

This thesis aims to contribute significantly to the existing literature by addressing these critical research gaps. Specifically, it extends the field of Ergo-ALBP by introducing a fuzzy expert system to model and manage uncertainty while developing a comprehensive and customized EAT. The fuzzy expert system leverages ergonomic expert knowledge and the underlying logic of conventional approaches to create a robust framework that accounts for imprecision in data, particularly in task times, worker capabilities, and ergonomic risks.

Through the development of a comprehensive fuzzy risk assessment approach, this thesis tackles the above gaps and forms the foundation for the three research articles presented in Chapters 5 to 7. These contributions are detailed as outlined in the Figure 2.4:

- The first objective introduces a novel two-phase framework that extends traditional ALBP methods by integrating worker assignment with a focus on ergonomic risks. The unique contribution lies in its ability to handle uncertainty and imprecise data regarding task times and worker capabilities through the application of a fuzzy expert system. This method departs from conventional approaches by employing a heuristic approach for feasibility, combined with an advanced ergonomic assessment method validated using 96 synthesized instances. By addressing the gap in ergonomic-oriented data, this framework generates high-quality solutions that simultaneously enhance worker safety and productivity.
- The second objective advances the field by introducing a novel fatigue model tailored to robotic ALs. Unlike existing deterministic models, this research leverages a fuzzy inference system to capture the complexity and variability of real-world scenarios. Additionally, it explores the integration of supportive robots, highlighting their potential for enhancing both productivity and ergonomic outcomes. This approach is particularly innovative within the context of Industry 5.0, as it emphasizes human well-being alongside advanced automation technologies. The research contributes to Industry 5.0 principles by fostering harmony between robotic precision and human intelligence.
- The third objective presents the development of Ergo4All-Pro, a comprehensive ergonomic risk assessment model specifically designed for virtual environments and DHM systems. Unlike conventional ergonomic tools, Ergo4All-Pro leverages fuzzy logic to deliver more accurate and detailed assessments of cumulative ergonomic risks across various body parts. Its novelty lies in its ability to operate within virtual and augmented reality environments, bridging the gap between traditional ergonomic methods and the requirements of Industry 5.0. This framework enables safer and more efficient workplace designs, addressing the limitations of existing tools, particularly when evaluating individual body parts and cumulative risks.

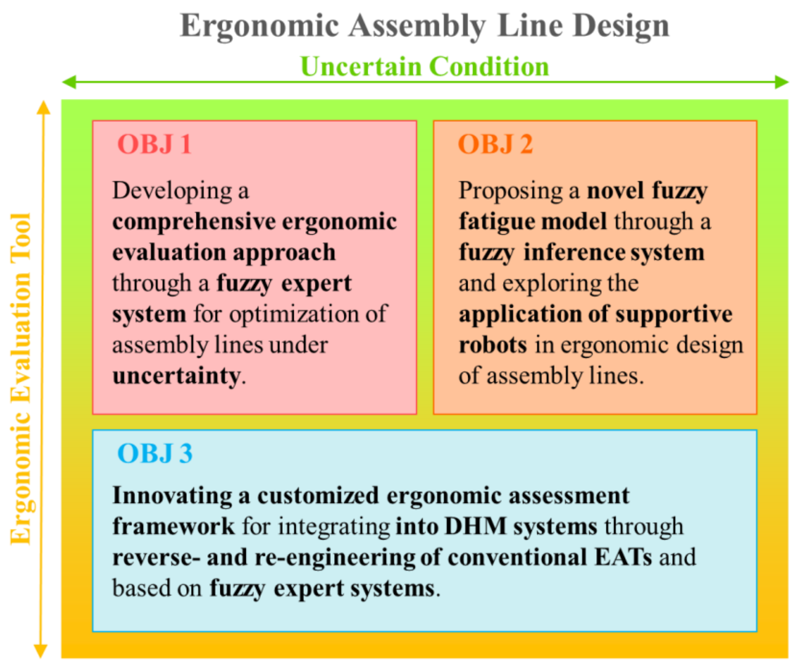

Figure 2.4 Research gaps and the main contributions in the form of three objectives

CHAPTER 3 RESEARCH METHODOLOGY

This Ph.D. research presents a comprehensive framework and methodology to introduce novel approaches that leverage fuzzy logic and expert systems for managing the inherent uncertainties in ergonomic assessments during the AL design phase. Unlike traditional ALBP methods, which rely on deterministic models, this research adopts a human-centric approach that integrates ergonomic considerations into the early stages of design, facilitating the development of more adaptive and responsive AL systems. Through the application of fuzzy expert systems, the proposed models capture the expertise and knowledge of ergonomists and industrial engineers to support more resilient and flexible designs.

Conventional EATs are predominantly designed for evaluating existing workplaces in real-world settings. However, a significant gap remains in the design phase, particularly in virtual environments, where evaluation tools suitable for DHM systems are still lacking. The proposed models and frameworks aim to adapt traditional EATs for implementation during the design phase and within virtual systems, assisting engineers and designers in developing human-centric ALs that prioritize worker well-being.

This research is structured around three key objectives, each contributing unique advancements to the field. These objectives are explored in the form of three distinct studies, each addressing a specific aspect of the AL design process. In the following subsections, the applied methodologies to achieve each research objective are explained in detail. Figure 3.1 provides an overview of the chapter's four main sections and summarizes the key points of the methodology discussed in each part.

Before detailing the methodological choices per objective, the use of fuzzy expert systems is defined and justified. A fuzzy expert system is a rule-based artificial intelligence method that leverages fuzzy logic to model human reasoning and manage uncertainty and imprecision in decision-making processes. Unlike conventional models that rely on precise numerical data, fuzzy expert system is suited to handle vague or incomplete information, making it an appropriate choice for ergonomics, where assessments often depend on subjective evaluations and expert judgments. The rationale behind adopting fuzzy expert system in this research is threefold:

(1) Uncertainty Management: Ergonomic and fatigue assessments inherently involve human variability and incomplete data.

(2) Expert Knowledge Formalization: FES provides a platform to integrate the implicit knowledge of ergonomists and domain experts.

(3) Flexibility for Early Design Phases: Early AL design typically lacks precise data, making fuzzy systems suitable for generating reliable insights in such contexts.

While fuzzy logic was the primary tool used, alternative methods (e.g., stochastic modeling) were reviewed but deemed less suited for directly capturing expert judgment and qualitative assessments.

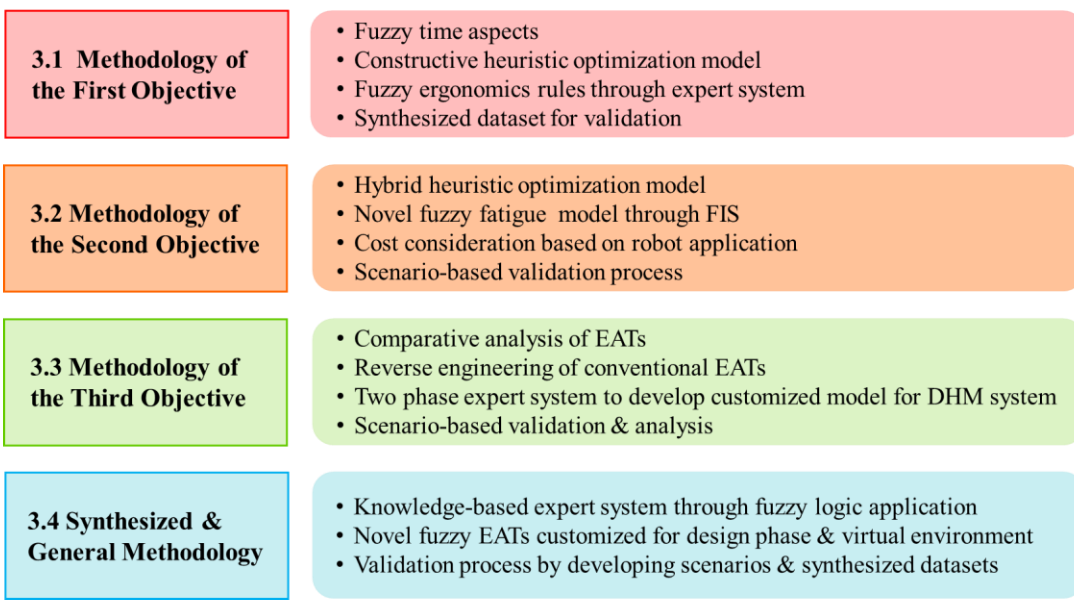

Figure 3.1 Sections of this chapter and their main points

The research process followed a design science methodology comprising four main steps:

- Problem Identification and Analysis: This involved a systematic literature review, identifying gaps in integrating HF/E into AL design under uncertainty.
- Model Development: For each research objective, models and frameworks were developed based on operational needs and ergonomic considerations.

- Expert Consultation and Rule Elicitation: A panel of five ergonomists and two industrial engineers were consulted to formalize expert knowledge into fuzzy rules.
- Validation and Evaluation: The models were validated using benchmark datasets, synthesized scenarios, and a real-world case study.

Each objective followed this general process, with adjustments based on specific research questions

3.1 Methodology of the First Objective

To achieve the first research objective, a two-phase optimization framework is proposed to optimize the ergonomic ALWABP (Ergo-ALWABP) using a fuzzy expert system under uncertainty. The methodology consists of three key steps:

1. Modeling Uncertainty in Task Times: The first step involves developing a mathematical model based on operational constraints such as CT, determined by the desired takt time, the number of operators, and task precedence relationships. Task times are represented as triangular fuzzy numbers (TFNs) to reflect uncertainty during the design phase when detailed information about the operators assigned to specific workstations may be insufficient. Each task is defined by a triplet of values: minimum, average, and maximum execution times, representing the fuzzy range of possible task durations. These values account for variability in workers' characteristics, skills, experience, and abilities, which influence task execution times. The use of TFNs allows for a flexible and realistic representation of task durations, accommodating uncertainties and diversity in worker performance during the early design stages.
2. Ergonomic Risk Assessment Using Fuzzy Expert System: A fuzzy expert system incorporates ergonomic experts' knowledge into a set of fuzzy rules to assess the ergonomic risk at both the workstation and AL levels. These rules translate expert insights into quantifiable measures of ergonomic risk. The model evaluates task-level risk as an input and assesses the risk exposure at the workstation level based on the proportion of time allocated to tasks with different risk levels (low, medium, or high) in each CT. Drawing on studies such as Gallagher and Heberger (2012) and Potvin (2011), five fuzzy rules are applied to predict ergonomic risk, depending on the cumulative execution time of high-risk

and low-risk tasks relative to the CT. At the AL level, a fuzzy ergonomic score is generated to assess the overall ergonomic quality of the design, with low-risk solutions scoring highest (1) and high-risk solutions scoring lowest (0).

3. Optimization Method: A constructive heuristic approach is utilized to explore potential task sequences and assignments to generate feasible solutions (FSs). This approach systematically generates and evaluates task assignments using customized priority rules initially developed by Akyol and Baykasoğlu (2019), which consider factors such as task execution times and precedence relationships. These rules guide task selection to ensure operational constraints from the first step are met. The final optimization step focuses on selecting the best FS with the maximum ergonomic score, ensuring that the chosen solution not only satisfies operational requirements but also enhances worker safety and comfort.

Finally, the proposed methodology is validated using 96 synthesized datasets and applied to benchmark datasets, producing high-quality solutions that minimize ergonomic risks and improve worker safety. Figure 3.2 illustrates the overall methodology used in this section.

3.2 Methodology of the Second Objective

The second research objective proposes a hybrid optimization model to solve the robotic assembly line design problem (RALDP), incorporating human-centric aspects such as ergonomic considerations and fatigue management. This methodology integrates both operational and ergonomic factors, focusing on optimizing task assignments while minimizing worker fatigue and overall system costs. As illustrated in Figure 3.3, the approach is structured around three main components:

1. Operational Model: The methodology begins by collecting operational data, including task execution times, load requirements, and precedence relationships among tasks. This data is gathered through direct observation, historical production records, and expert consultations to ensure accuracy. The operational constraints are then mathematically defined, considering factors such as CT, the number of workstations, and task sequencing requirements. The model incorporates constraints that ensure the technical feasibility of the solution in the first step of the optimization algorithm, providing a comprehensive representation of AL's operational dynamics.

2. Fuzzy Fatigue Model: A fuzzy inference system (FIS) integrates ergonomists' expertise and knowledge to evaluate worker fatigue at both the task and workstation levels. A novel fatigue assessment method is developed based on Potvin's initial fatigue model (Potvin, 2011), which evaluates the maximum acceptable effort (MAE) based on the duty cycle (DC), representing the task duration as a proportion of CT. Potvin's equation provides a threshold that, combined with insights from ergonomic experts, allows the development of fuzzy rules to capture the nuances of human factors in the assembly process. The fuzzy fatigue model estimates fatigue levels as fuzzy numbers for each task, accounting for uncertainties in task execution time and load. The cumulative fatigue of each workstation is then calculated by aggregating the fuzzy fatigue levels of tasks assigned to the workstation. The proposed fuzzy method provides a comprehensive view of fatigue across whole the AL. This fuzzy approach effectively handles imprecisions in fatigue evaluations, offering more realistic reflections of real-world complexities during the design phase compared to deterministic models.

   To integrate the ergonomic aspect into the initial mathematical model, scenarios are developed to impose a maximum acceptable fatigue for each workstation. This ergonomic constraint aims to balance the trade-off between fatigue costs (in the form of required recovery time) and the costs associated with SRLs that reduce fatigue level to near zero.

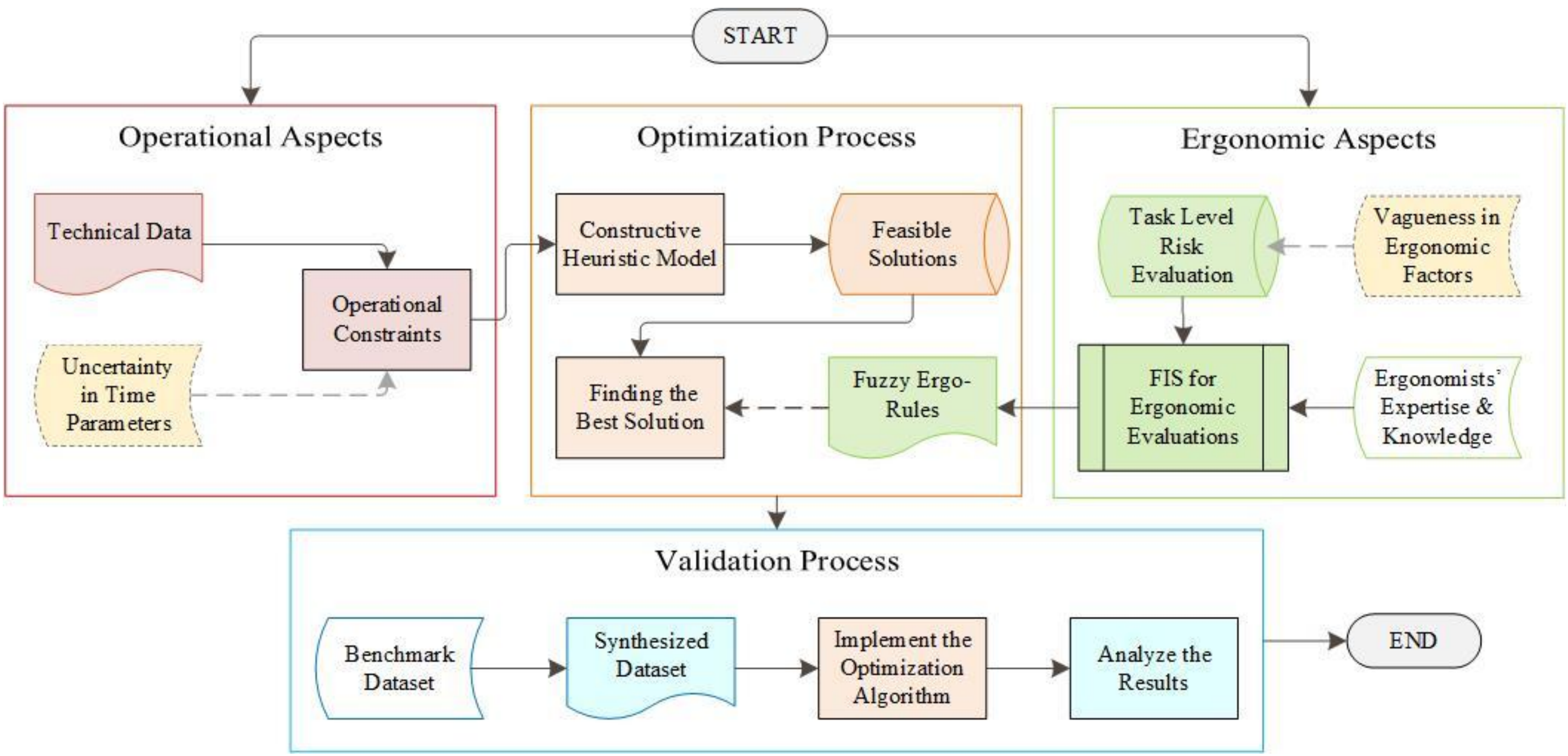

Figure 3.2 Schematic of the methodology for accomplishing the first research objective

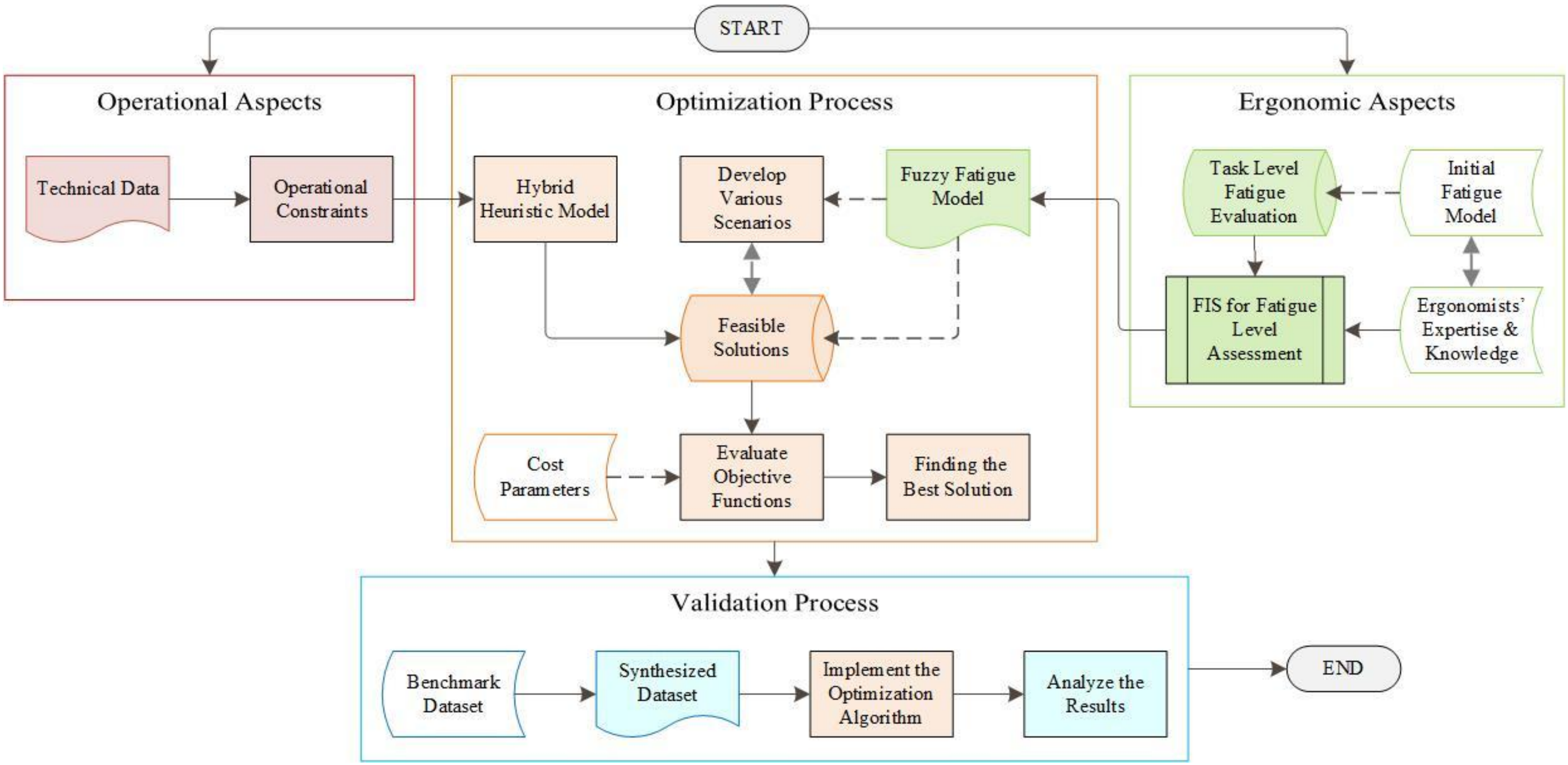

Figure 3.3 Schematic of the methodology for accomplishing the second research objective

3. Hybrid Optimization Process: A hybrid heuristic model utilizes the operational constraints defined earlier to generate FSs by randomly assigning tasks to workstations. This random selection ensures broad exploration of potential task assignments, reducing bias and increasing the likelihood of identifying near-optimal solutions. The fuzzy fatigue model is then applied to evaluate fatigue levels at each workstation, with ergonomic constraints incorporated into the model to limit fatigue based on predefined thresholds (various scenarios). When cumulative fatigue levels exceed the established limits, SRLs can be introduced to mitigate fatigue, effectively reducing the risk level to approximately zero.

   The heuristic model determines the number of SRLs required based on different fatigue scenarios, ensuring that the workstations remain within acceptable ergonomic limits. A lexicographical approach is employed to rank FSs by fatigue levels, prioritizing those that minimize fatigue across workstations. The FSs are ranked in ascending order of their maximum fatigue levels across all workstations, allowing for a clear comparison of potential solutions.

   The total system cost for each FS is calculated by summing fatigue costs (representing the need for additional recovery time) and robot costs (based on the number of SRLs deployed). The optimal solution is selected by choosing the FS that minimizes both fatigue and cost for each scenario, considering varying fatigue thresholds.

The proposed heuristic algorithm is validated using benchmark datasets and synthesized instances that emphasize fatigue levels. Empirical results confirm that the approach significantly reduces system costs and enhances ergonomic outcomes, supporting its applicability in Industry 5.0.

3.3 Methodology of the Third Objective

This study introduces Ergo4All-Pro™, an advanced ergonomic risk assessment model, suitable for DHM systems. This novel method evaluates cumulative risks in individual body parts and integrates risks in the upper limb within virtual environments. The methodology is structured into three key steps, as depicted in Figure 3.4:

1. Gap Analysis: A comprehensive analysis and integration of insights from well- established EATs such as OCRA, EAWS, OWAS, RULA, and REBA identify gaps in cumulative risk assessment across multiple body parts. This analysis aims to identify the most suitable methodologies for adaptation and enhancement, ultimately laying the foundation for

creating a comprehensive model tailored to virtual environments. The study critically evaluates the strengths and limitations of these existing tools, focusing on their applicability in dynamic ergonomic risk assessment. This step extends the basic functionality of Ergo4All™ (Bourret et al., 2021), a static tool based on standards such as ISO 11228-3 and EN 1005-3, designed for assessing individual joint risks during task performance.

2. Reverse Engineering of EATs: In this phase, cumulative risk for each body part (e.g., shoulders, elbows, wrists, neck, and back) is evaluated using a reverse engineering approach based on OCRA's methodology. This approach involves dissecting the OCRA framework to understand how it integrates time factors and assesses risks associated to different tasks. Key components contributing to cumulative risk are identified by analyzing OCRA's scoring system and simplifying assumptions where necessary. Specific attention is given to the posture and force sections of OCRA, which align with Ergo4All™ components, incorporating time considerations into risk evaluation. Through a FIS, the reverse engineering results, combined with ergonomists' knowledge, are employed to generate decision trees and rules for assessing cumulative risk levels in each body part. These fuzzy rules, developed from expert ergonomic insights, provide a more dynamic and accurate evaluation compared to conventional static methods.
3. Fuzzy Modeling: In the final phase, the cumulative risks of individual body parts are integrated to evaluate the overall ergonomic risk of the upper limb. This integration relies on tools such as RULA and REBA, which primarily assess posture-related risks. A multi-step re-engineering process, utilizing FIS, generates a final cumulative risk score for the upper limb. This process begins by assigning risk scores to each body part based on the cumulative risks identified in the previous phase. These scores are then combined using a weighted approach that accounts for the relative importance of each body part in contributing to upper limb risk. The integration also considers interactions between different body parts, ensuring that the overall risk score reflects the cumulative effects of risks across the upper limb.

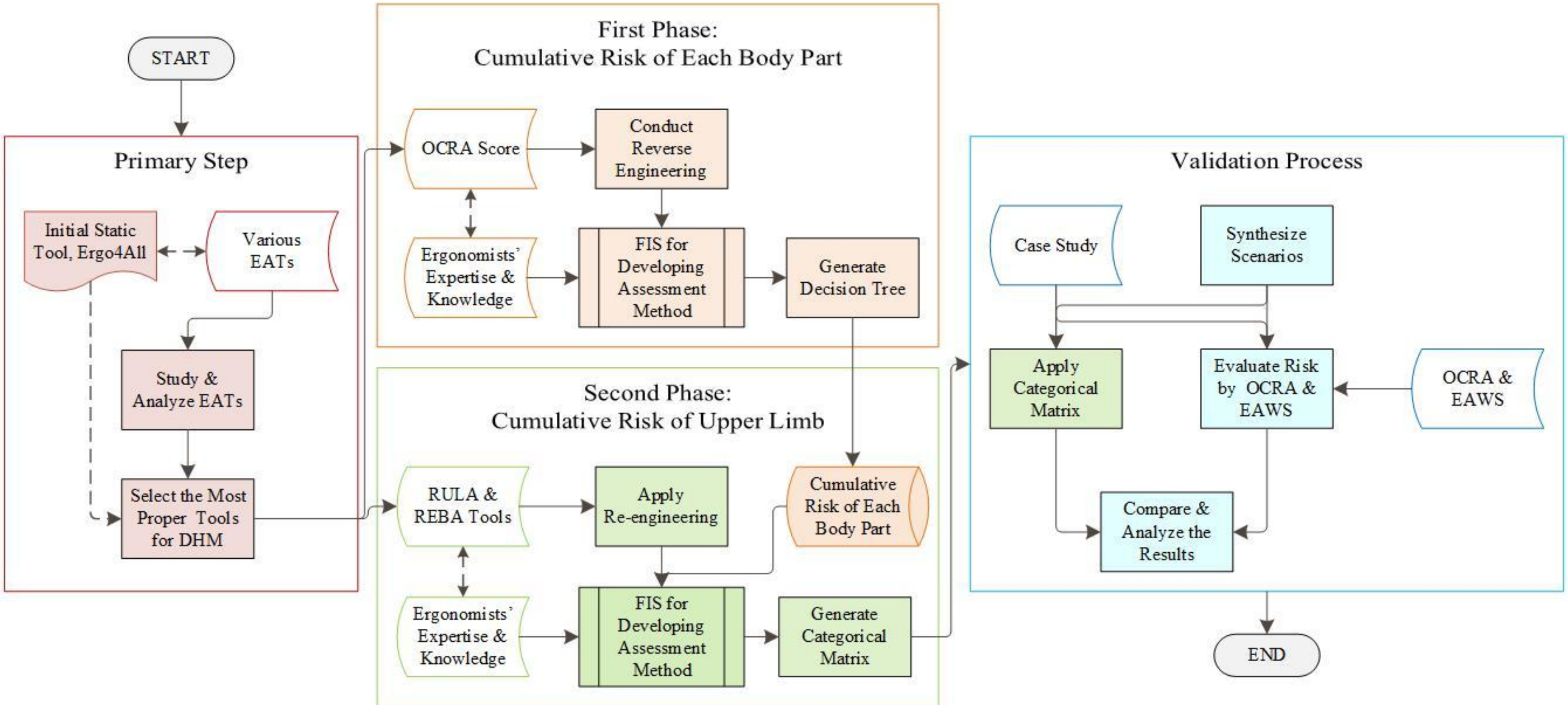

Figure 3.4 Schematic of the methodology for accomplishing the third research objective

Ergo4All-Pro™ focuses on assessing cumulative risks across workstations to optimize AL design from an ergonomic perspective. To validate the Ergo4All-Pro™ model, its risk assessments are applied to a real-world industrial workstation and several synthesized scenarios. The results are compared with benchmark methods like OCRA and EAWS, using a categorical matrix for risk scores. The model demonstrates refined and more detailed assessments, particularly in areas where conventional tools may overlook specific risks.

3.4 Synthesized and General Methodology

This research introduces a human-centric paradigm shift in AL design, focusing on ergonomic risk assessment and optimization under the principles of Industry 5.0. Across three interconnected studies, novel methodologies are developed that integrate fuzzy expert systems, ergonomic expertise, and heuristic optimization algorithms to create safer, more efficient, and human-centric work environments. These methodologies address both operational constraints and ergonomic risk management, emphasizing worker well-being and system performance. Validation of these approaches is conducted using synthesized datasets, a real case study, and scenario-based analyses. Several references were studied to select the methodologies, and nine key references supporting the choices made in the accomplishment of each research objective are presented in Figure 3.5.

The key innovation of this research lies in the application of fuzzy expert systems for ergonomic assessments. Traditional ergonomic methods often rely on deterministic models, which are insufficient for managing uncertainties in early design phases. Conventional EATs are prone to errors, time-consuming, dependent on human subjects, and influenced by observer inconsistencies (Wang et al., 2021). In contrast, the proposed fuzzy expert systems mimic the cognitive processes of ergonomic experts and utilize fuzzy logic to manage uncertainties arising from vague, incomplete, or imprecise information (Tavana & Hajipour, 2020). This approach enables more adaptable, resilient, and realistic ergonomic evaluations compared to deterministic models, which often overlook human variability in task execution and fatigue during the design phase. The proposed models are computer-based systems that guide users in integrating comprehensive methods into real or virtual systems.

Each methodology employs an FIS to handle uncertainties in ergonomic evaluations. Driven by ergonomic experts' knowledge, expressed through "If-Then" rules, the FIS assesses risks based on task duration and individual tasks risk levels. This fuzzy approach provides a more adaptable and responsive evaluation of ergonomic conditions, accommodating the complexities of worker-task interactions. The use of FIS represents a significant advancement over conventional methods, which lack the flexibility to address such complexities in dynamic, real-world settings.

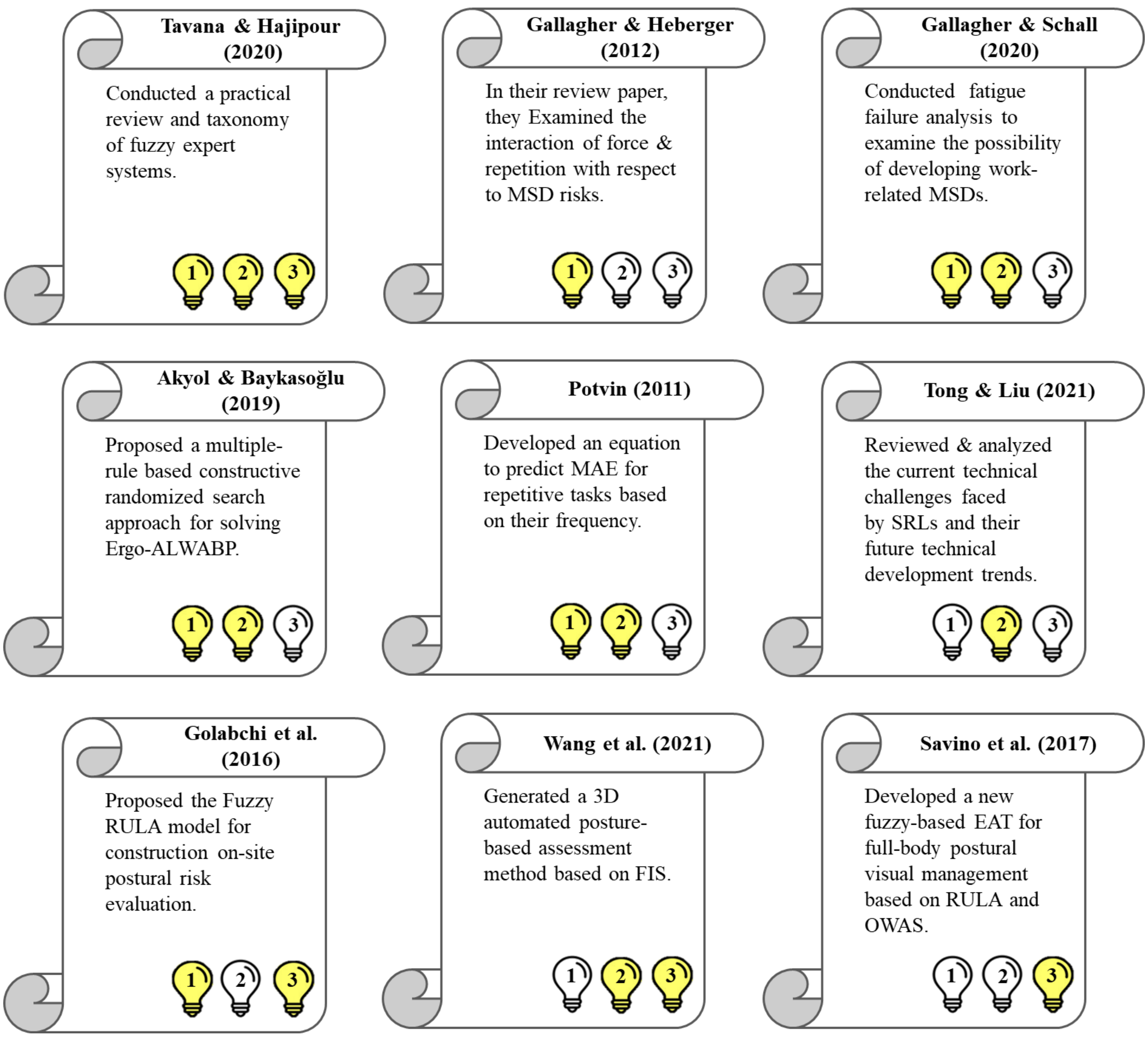

Figure 3.5 Key references for selecting the methodology of each objective

The decision to use fuzzy expert systems in this research is supported by previous studies. Golabchi et al. (2016) developed a fuzzy RULA model to reduce errors in observational ergonomic evaluations for construction activities. Savino et al. (2017) proposed an integrated postural assessment tool using FIS based on OWAS and RULA methods to minimize evaluator subjectivity. Additionally, Wang et al. (2021) advanced posture-based assessments using 3D automated tools to capture continuous human motion, addressing the limitations of traditional methods. Although these methods are posture-based, this research extends fuzzy expert systems to develop comprehensive EATs customized for the design phase, based on the insights of Tavana and Hajipour (2020).

For the first and second research objectives, the methodologies are built upon optimization frameworks that combine operational constraints and ergonomic data. These frameworks include task times, precedence relations of tasks, and worker availability, which form the foundation of the optimization models. The constructive heuristic method used for the first objective builds on the fuzzy version of the optimization algorithm developed by Akyol and Baykasoğlu (2019), incorporating fuzzy logic to handle imprecision in the early design phase. The hybrid heuristic method for the second objective explores the use of SLRs to mitigate ergonomic risk, as suggested by Tong and Liu (2021). These methods offer a comprehensive assessment of both system efficiency and worker safety, particularly in virtual environments, where traditional tools are less effective.

The optimization frameworks provide a foundation for leveraging fuzzy expert systems to address uncertainties in the design phase, integrating expert knowledge for more resilient solutions. In developing ergonomic fuzzy rules, this research draws on studies by Gallagher and Heberger (2012) and Gallagher and Schall (2020), which highlight the relationship between task repetition, time, and fatigue-related ergonomic risks. Additionally, the fatigue equation proposed by Potvin (2011) served as a basis for generating fuzzy rules, customized for the design phase and adopted to the fuzzy fatigue model.

For the third objective, the development of Ergo4All-Pro™ represents a breakthrough in DHM. The model evaluates cumulative risks for individual body parts and integrates these risks for the upper limb within virtual environments. By synthesizing insights from well-established EATs such as OCRA, RULA, and REBA, this methodology enhances traditional tools to address the complexities of virtual environments and DHM systems. The reverse-engineering and re-engineering processes applied to these EATs allow engineers to optimize AL designs from an ergonomic perspective, bridging the gap between real-world and virtual assessments.

The contributions of this research are multifaceted. It not only introduces fuzzy expert systems as a novel tool for ergonomic risk assessment but also demonstrates how these systems can be integrated into comprehensive optimization frameworks that balance both human and operational factors. This human-centric shift in AL design emphasizes adaptability, worker safety, and system resilience, departing from traditional AL models.

In conclusion, this research provides an innovative, adaptable, and comprehensive framework for designing safer and more efficient ALs. By integrating fuzzy logic, ergonomic expertise, and advanced optimization techniques, the methodologies presented here significantly improve upon traditional approaches, particularly in addressing uncertainties and complexities in both real-world and virtual environments. These methodologies underscore the importance of human-centric approaches in Industry 5.0, where worker well-being and system performance are equally prioritized.

CHAPTER 4 ARTICLE 1: ERGONOMIC ASSEMBLY LINE BALANCING PROBLEMS EVOLUTION AND FUTURE TRENDS WITH INSIGHTS INTO INDUSTRY 5.0 PARADIGM

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Abstract

This comprehensive review paper presents the state of the art on assembly line balancing problems, with a specific focus on considering ergonomics aspects (Ergo-ALBPs) and providing insights into the emerging Industry 5.0 paradigm. Traditional assembly line balancing approaches often overlook ergonomic factors, which can lead to work-related injuries and long-term expenses for manufacturing systems. However, recent advancements have seen the integration of HF/E indicators alongside operational factors in optimization problems, aiming to prevent future ergonomic-related costs. Through a systematic review of the literature published from 2011 to 2022, this study analyzes 57 selected studies, examining their content on operational and ergonomics aspects individually and concurrently. Additionally, this paper highlights the significant implications of the Industry 5.0 paradigm in Ergo-ALBPs, emphasizing the importance of human-centered design, collaboration between workers and advanced technologies, and the challenges faced during implementation. The review also identifies research trends, gaps, and opportunities through comparative content analysis, keyword frequency analysis, and co-occurrence (co-word) analysis, offering valuable insights for future research in this domain.

Keywords: Assembly line balancing problem; Ergonomic risks; Human factor; Ergonomic assessment tools; Ergo-ALBP; Industry 5.0; Worker-centric design

4.1 Introduction

ALs play a crucial role in enhancing the efficiency of mass and lean manufacturing systems by reducing per-unit costs. This pursuit of productivity gives rise to ALBPs, which involve modeling and solving optimization problems. The objective of balancing is to eliminate any unbalancing points, such as bottlenecks, which cause idle times and increase in-process inventories in other workstations. To achieve a balanced workload across workstations, assembly tasks need to be organized while considering several constraints and optimizing productivity measurements.

In the past, balancing was primarily based on the process time of tasks at different workstations to address the required production rate. While this remains a key variable, real-world manufacturing systems must also contend with market fluctuations and evolving customer needs. Consequently, ALs, as the final stage of most production systems, must be flexible. This requires the inclusion of manual tasks to accommodate the required flexibility (Vig, 2020). However, the performance of operators handling these manual operations has a direct impact on the overall system efficiency. Additionally, workers in ALs are exposed to ergonomic risks and work-related injuries due to the repetitive and prolonged nature of assembly tasks. These ergonomic issues can adversely affect line efficiency, making it crucial to prioritize the health and well-being of operators as integral components of such systems. The efficiency of manual assembly line systems relies on effectively incorporating ergonomic factors into the balancing process (Ozdemir et al., 2021), leading to the emergence of Ergo-ALBP-related research studies to address this goal.

While there have been separate review studies focusing on ALBPs (Eghtesadifard et al., 2020) and ergonomics (Joshi & Deshpande, 2019), the literature reveals a gap in systematic review studies specifically in the Ergo-ALBP field. In recent years, there has been a growing interest in exploring innovative approaches to manufacturing that prioritize not only productivity and efficiency but also the well-being and satisfaction of workers. Therefore, the present paper aims to fill this gap by conducting an in-depth analysis of research studies focused on Ergo-ALBP. This study not only helps predict future trends but also explores hot topics and identifies research gaps in this domain.

Over the past few years, the advent of Industry 5.0 has provided a new paradigm that emphasizes harmonious collaboration between human workers and advanced technologies. This paradigm shift holds immense potential for advancements in Ergo-ALBPs, where the integration of AR, VR, AI, and cobots can revolutionize the AL optimization process. By focusing on worker-centric design principles, Industry 5.0 offers opportunities to enhance worker comfort, productivity, and safety while fostering a culture of continuous improvement and learning. This paper delves into the evolution and future trends of Ergo-ALBPs within the framework of the Industry 5.0 paradigm, shedding light on the transformative potential and highlighting key aspects and challenges for successful implementation in the manufacturing industry.

The current systematic review employs explicit methods, including bibliometric and quantitative analysis, to investigate research studies published in the Ergo-ALBP field from 2011 to 2022. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method was applied to the indexed papers in the Web of Science and Engineering Village databases, resulting in the inclusion of 57 articles for a comprehensive review. This review employs knowledge mapping methodology to explore foundational knowledge, developmental trends, and future research opportunities. Furthermore, comparative content analysis, keyword frequency analysis, and co-occurrence (co-word) analysis are conducted to identify research gaps.

This manuscript is organized as follows: Section 7.2 provides a brief background on ALBPs, HF/E considerations, and the Ergo-ALBP field. Section 7.3 introduces the approach used in this study to explore the Ergo-ALBP literature, including content analysis and descriptive analysis. Section 7.4 investigates the Industry 5.0 paradigm. Section 7.5 discusses the findings of this research and highlights the research gaps that should be addressed in future studies. Finally, Section 7.6 presents the summary and concluding remarks

4.2 Principles & Literature Review

This review concentrates on the overlap of two important fields: the ALBPs and the HF/E, see Figure 4.1. In this section, first, an overview of the fundamental concepts of HF/E and ALBPs is presented. Then, a brief explanation of Ergo-ALBP is provided.

Figure 4.1 Overlap of ALBPs and HF/E fields is the focus of this review

4.2.1 Human Factor & Ergonomic (HF/E) Aspects

HF/E is a scientific discipline focused on understanding the interactions between humans and other elements of a system, such as machines or work environments, as defined by the International Ergonomics Association (IEA). The primary goal of ergonomic considerations is to adapt job activities in a way that ensures worker safety and enhances overall system performance. Worker health and safety issues are often associated with repetitive tasks, awkward postures, prolonged activities, mental stress, and job satisfaction concerns. Consequently, various methods exist for evaluating ergonomic risks in workplaces. These methods, known as EATs, include a range of techniques, from simple preliminary evaluations to more sophisticated assessments that require expertise and complex equipment (Chengalur et al., 2004).

In production systems, ergonomic risks encompass physical, cognitive, and psychosocial aspects. Physical work refers to muscular activities with or without movement, either dynamic or static. Such activities can lead to excessive fatigue, discomfort, pain, and, if not addressed adequately, MSDs. Engineers and ergonomics practitioners aim to evaluate risk factors and find ways to reduce them in the workplace. For example, frequent or prolonged static muscular effort can result in WMSD. To mitigate WMSDs, a practical approach is to design rest allowances to reduce fatigue in the relevant muscle groups (El ahrache et al., 2006).

Cognitive aspects involve the perceptual and mental abilities required to perform work tasks. The interaction between operators and their environment is crucial, as an increase in cognitive workload or an imbalance between cognitive and physical load can lead to ergonomic risks (Kong, 2019).

Psychosocial factors pertain to operators' subjective perception of various organizational aspects of work, including work-rest cycles, management style, psychological aspects of work, and workplace culture (Sekkay et al., 2018). Different methods are available for evaluating psychosocial risk factors, such as Karasek's job content questionnaire (JCQ) (Karasek et al., 1998) and the effort-reward imbalance (ERI) model (Siegrist, 1996).

Chengalur et al. (2004) categorized EATs into three main groups based on the type of data they use:

- Qualitative evaluation techniques rely on observational data and are primarily used for job monitoring. Typically, qualitative data are analyzed using checklists and job safety studies.
- Semi-quantitative assessment methods, such as REBA, RULA, OCRA, and others, combine qualitative and/or quantitative data. Through a set of decision rules, these techniques classify the occupational risks or rank job demands. They provide essential information for prioritizing interventions or allocating budgets.
- Quantitative analysis methods are data-driven approaches that facilitate continuous improvement and assess the reduction of ergonomic risks over time. These techniques can also be employed to develop guidelines and specify ergonomic interventions during the system design stage.

Li and Buckle (1999) divided EATs into four classes based on data collection methods:

- Direct (or instrumental) methods utilize specialized software and equipment to measure the PWL of a task based on physiological indicators.
- Observational methods assess the position of body parts during task performance to calculate required force and identify deviations from their neutral positions.
- Subjective methods, or self-reports, are the most commonly used techniques due to their ease of application and generally valid results.
- Other psychophysiological methods, such as electrocardiography, electromyography, and thermal imaging.

In their survey, Takala et al. (2010) compared nineteen observational EATs used in studies from 1965 to 2008 and concluded that no single measurement tool can be considered superior to others. However, most EATs include a classification of ergonomic risk levels, as illustrated in Figure 4.2.

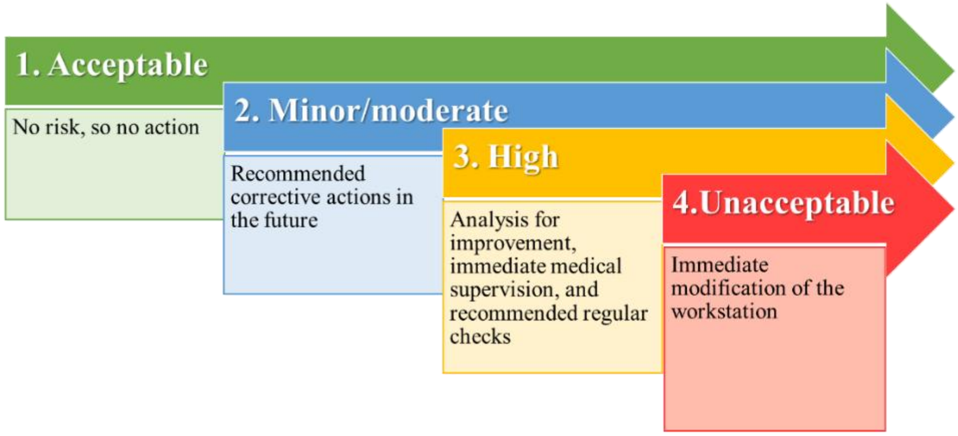


Figure 4.2 Classification of ergonomic risk levels

4.2.2 Assembly Line Balancing Problems (ALBPs)

Since Henry Ford's introduction of mass production, ALs have experienced significant improvements, transitioning from fast-paced single-model lines to more adaptable systems. Today, there are different types of ALs, and extensive studies have led to notable advancements in various aspects of their operation.

In general, ALs consist of multiple workstations arranged in a specific order to produce one or more products by following a predefined sequence of tasks. The primary objective of ALs is to efficiently produce and deliver large volumes of standardized products. Thus, ALBPs arise as optimization problems that involve assigning tasks to different workstations to achieve the required production rate while satisfying various constraints and optimizing performance measures (Becker & Scholl, 2006). These problems aim to optimize one or more objective functions, which can be broadly classified into three main groups: capacity-related objectives, cost-related objectives, and profit-related objectives (Eghtesadifard et al., 2020).

ALBPs involve the combinatorial problem of task assignment. However, when the assignment of tools or equipment to workstations is considered, ALBPs become more complex and are referred to as ALDPs (Finco et al., 2019). ALDPs encompass equipment selection and assignment in addition to task allocation to workstations.

In the literature, ALBPs are classified in various ways, but the most widely recognized classification is proposed by Baybars (1986), who divided ALBPs into two main groups: simple ALBP (SALBP) and general ALBP (GALBP).

SALBPs focus on one-sided straight ALs that mass-produce a single-type product with a predetermined operation time (deterministic CT) to optimize the desired objective while considering precedence and time cumulative constraints (Becker & Scholl, 2006). According to Rekiek et al. (2002), SALBPs can be further classified into four groups. The first type aims to minimize the number of workstations based on a given CT. Conversely, the second type considers a fixed number of workstations to minimize the CT. The other two types of SALBPs either check the feasibility of the problem with a fixed number of workstations and CT or aim to minimize both factors.

Although significant research has focused on SALBPs, there is still a need to address more complex real-world problems by concentrating on GALBPs. In the past decade, there has been a positive trend in considering additional constraints and diverse objectives to tackle more realistic scenarios. Becker and Scholl (2006) presented a comprehensive survey on GALBPs, marking a significant milestone. Figure 4.3 depicts synthesized classifications of ALBPs from various studies in this field, allowing for specific characteristics-based classification by considering each group's color in the figure.

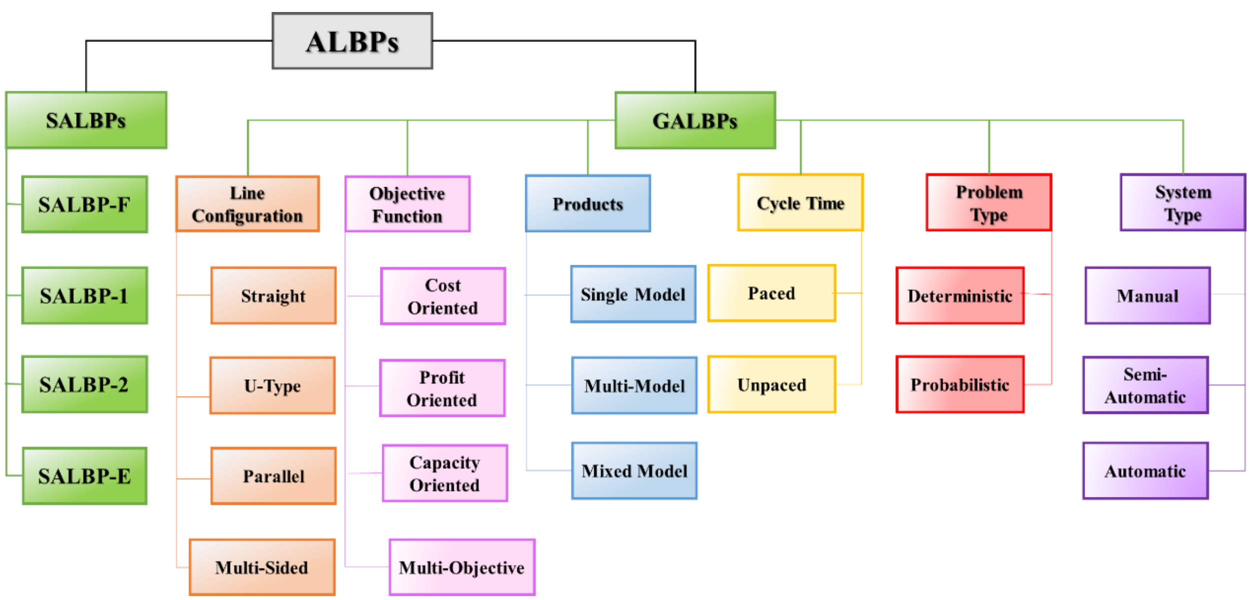


Figure 4.3 Comprehensive classification of ALBPs

In addition to Baybars (1986) classification (green category), GALBPs can be further categorized based on workstation layouts (orange category) or grouped according to their objective functions (pink category). These problems can also be categorized into three groups based on the types of products manufactured (blue category). GALBPs can be classified as "paced" and "unpaced" ALBPs (yellow category) based on the time interval for parts and materials movement between workstations. In the literature, “unpaced” and “paced” ALs are also referred to as “buffered” and “synchronous” Als, respectively (Becker & Scholl, 2006).

Although most ALBPs have focused on manual ALs, there is a growing trend towards considering the design of semi-automatic ALs and developing sustainable ALDPs. Consequently, CALBPs and RALBPs have emerged as other problem types for modeling and solving the selection and assignment of appropriate collaborative tools and instruments (Stecke & Mokhtarzadeh, 2022). Thus, based on the types of production systems, ALs can be categorized into manual, semi-automated, and automated lines (Abdous et al., 2020) (purple category).

Furthermore, ALBPs can be classified as deterministic or probabilistic models (red category) based on the nature of the task times (Cakir et al., 2011). However, in addition to stochastic operation time, other aspects of ALs can also be indeterministic, and variations may occur due to improvements in the manufacturing process and production systems (Becker & Scholl, 2006).

The ALBP was initially formulated as a LP model by Salveson (1955), and Halgeson and Birnie (1961) were the first to study these problems and propose a solution technique. However, for the first four decades, ALBPs were primarily solved using trial-and-error methods. They belong to the NP-hard class of COPs which are challenging to solve using exact methods. Therefore, solving these complex problems requires sophisticated algorithms to find an effective optimum or at least an approximation through a finite set of feasible solutions.

Various computational methods have been employed to solve ALBPs, including exact, heuristic, and metaheuristic methods. Exact methods such as dynamic programming and the branch and bound method have been used, but their efficiency is limited for NP-hard problems. Heuristic and metaheuristic approaches have been found effective in solving different ALBPs. The ranked positional weight technique (RPWT) and Kilbridge & Webster’s method are commonly used heuristic methods. Among metaheuristic algorithms, GA, PSO, and ACO have been widely utilized (Eghtesadifard et al., 2020). Hybrid algorithms, which simultaneously apply two or more heuristic and metaheuristic methods, are gaining popularity as they aim to improve solution quality by mitigating the limitations and weaknesses of each method.

4.2.3 Assembly Line Balancing Problems by Ergonomic Considerations

In contemporary manufacturing systems, manual ALs remain prevalent due to their flexibility in addressing market fluctuations and advancements (Ozdemir et al., 2021). However, assembly tasks in ALs involve prolonged repetitive activities, exposing workers to ergonomic risks. Therefore, along with other technical productivity factors, it is essential to consider HF/E indices in the optimization models of ALs to reduce ergonomic risks and enhance system efficiency (Weckenborg & Spengler, 2019).

Profit maximization is a crucial goal for companies, and traditional ALBPs primarily focus on economic parameters such as production rate, CT, and operation costs, while overlooking influential ergonomic factors. Neglecting ergonomic considerations in conventional ALBP can lead to indirect costs in the long term, such as absenteeism and medical or healthcare expenses. Additionally, Falck et al. (2010) reported that in the short term, disregarding ergonomic factors can result in costs for the car manufacturing industry, including health and safety expenses, productivity losses (e.g., line stoppages), and quality issues (e.g., scraps, reworks). Increased ergonomic risks can lead to chronic injuries, imposing significant costs on both organizations and society. Hendrick (2008) found that "good ergonomics projects typically provide a direct cost-benefit of from 1 to 2, to 1 to 10, with a typical payback period of 6–24 months."

Falck and Rosenqvist (2014) developed a model to calculate the cost of ignoring ergonomics in the design step. According to their study, the cost of corrective actions for ergonomic errors was 9.2 times higher than the cost of preventive actions taken during the design stage. Therefore, it is imperative to incorporate comprehensive ergonomic risk assessment into optimization models to achieve a more efficient and sustainable assembly system.

Gunther et al. (1983) were the first researchers to consider physical ergonomic risks in ALBPs (Otto & Battaïa, 2017). Their contribution served as a motivating starting point for subsequent discussions on ergonomics in ALBPs. Among the few studies conducted in this field, Otto and Scholl (2011) were the first to introduce an ergonomic objective. Their work marked a turning point in the literature on Ergo-ALBPs, inspiring several other studies in this area. Otto and Battaïa (2017) conducted a survey on optimization models for reducing physical ergonomic risks in ALs through line balancing and job rotation. However, to the best of the authors' knowledge, there is no systematic review of literature in the Ergo-ALBP domain. Therefore, the next section comprehensively reviews the relevant literature using content and descriptive analyses.

4.3 Systematic Review Methodology

In previous research studies conducted before 2011, ergonomic risks were rarely taken into account in the context of ALBPs. Therefore, this study focused on exploring articles published after 2011 that specifically address Ergo-ALBPs. To conduct a systematic literature review, the PRISMA method developed by Moher et al. (2010) was employed. This method consists of four main steps, as illustrated in Figure 4.4.

In the first step, “Identification”, a specific search phrase was used to query the “Web of Science” and “Engineering Village” databases, outlined in Table 4.1. Subsequently, in the second step, titles and abstracts were screened to remove duplicate papers. Following this, all the remaining articles (77 papers) underwent a thorough assessment for “Eligibility”. Ultimately, a total of 57 research papers were included for qualitative analysis.

Table 4.1 Literature search for ergonomic consideration in ALBPs

Block1	“assembly line balanc*” **OR** “assembly line”
	AND
Block2	ergonom* **OR** ergonom* risk **OR** “human factor*”

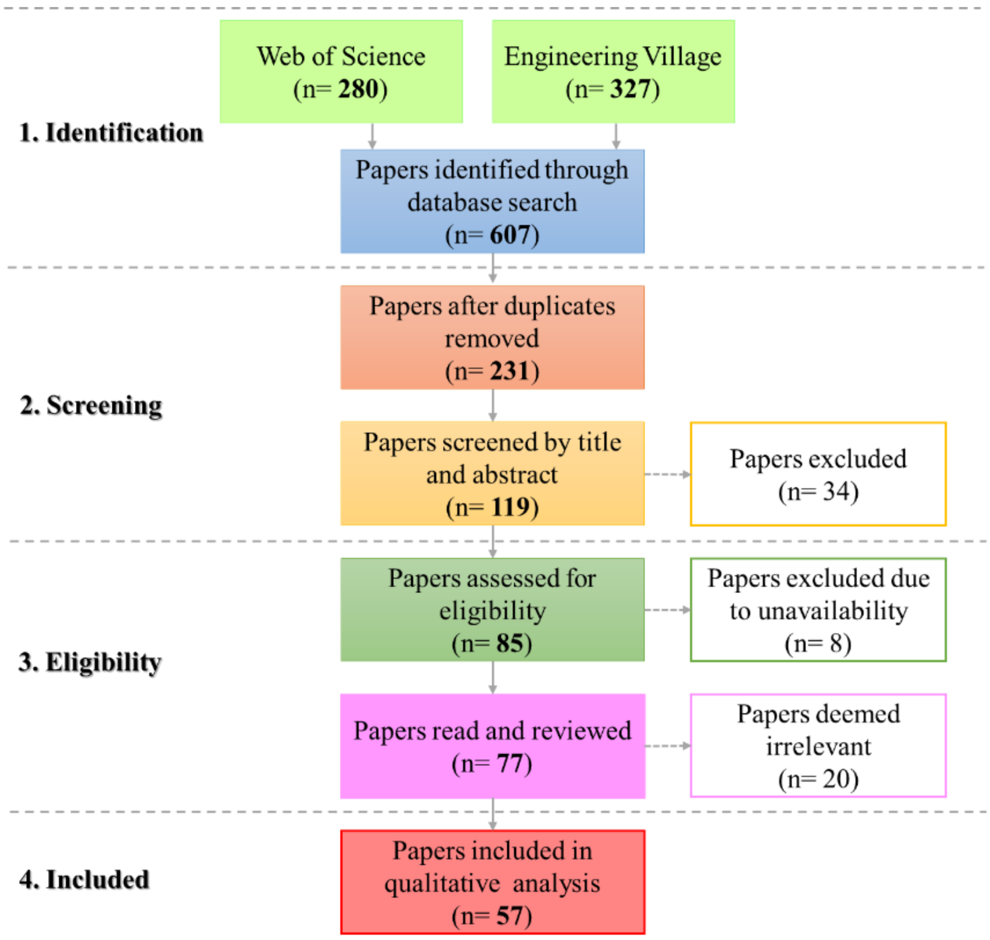


Figure 4.4 The PRISMA flowchart of the systematic literature review of this research

4.3.1 Content Analysis

In this section, the reviewed literature was analyzed from the ergonomic perspective and also from the operational perspective separately. Table 4.2 summarizes key aspects of these studies.

Table 4.2 Summary of Ergo-ALBPs papers published between 2011–2022

Authors	**Problem Type**	**Mathematic Model**	**Ergo Factor**	**EAT**	**Objective Function**	**Solution Method**	**Case Study**
(Otto & Scholl, 2011)	SALBP-1	NLP	Posture	OCRA, EAWS, NIOSH	Min (#workstations & Ergo-Risk)	two stage heuristics	
(Xu et al., 2012)	SALBP-1	MILP	Hand/Arm extremities	ACGIH* guideline	Min (#workstations & Ergo-Risk)	Exact Method (CPLEX)	x
(Mutlu & Özgörmüş, 2012)	SALBP-1	Fuzzy LP	PWL constraints	Subjective method	Min (#workstations)	Bellman-Zadeh approach	x
(Rajabalipour Cheshmehgaz et al., 2012)	SALBP-2	Fuzzy GP	Posture	OWAS	Min (CT & ARP & PWL)	GA	
(Bautista, Batalla, & Alfaro, 2013)	TSALBP-1	LP	somatic risk constraints	-	Min (#workstations & Ergo-Risk)	Exact Method (CPLEX)	x
(Bautista, Batalla, Alfaro, et al., 2013)	TSALB-1	MILP	Posture	-	Min (#workstations & Ergo-Risk)	Exact Method (CPLEX)	
(Otto, 2014)	SALBP-1	-	Posture	OCRA, EAWS	Min (#workstations & Ergo-Risk)	two stage heuristics	
(Öksüz & Satoğlu, 2014)	UALBP	-	learning effect	-	Max (competency level)	heuristic	
(Kara et al., 2014)	GALBP	MILP	Workers' skill & posture	-	Min (workers & equipment costs)	Exact Method (XPRESS Solver)	
(Battini et al., 2015)	SALBP-2	LP	Energy expenditure	(Garg et al., 1978)	Min (CT) & Max (ESI)	Pareto frontier	

Table 4.2 Summary of Ergo-ALBPs papers published between 2011–2022 (continue)

Authors	**Problem Type**	**Mathematic Model**	**Ergo Factor**	**EAT**	**Objective Function**	**Solution Method**	**Case Study**
(Bautista, Alfaro-Pozo, et al., 2016)	TSALBP	MILP	Posture	RULA, OCRA, NIOSH	Min (max Ergo-Risk)	GRASP	x
(Bautista Valhondo et al., 2015)	TSALBP	MILP	Posture	RULA, OCRA, NIOSH	Min (average Ergo-Risk)	Exact Method (CPLEX)	x
(Bautista, Batalla-García, et al., 2015)	TSALBP	MILP	Posture	RULA, OCRA, NIOSH	Min (average max Ergo-Risk)	Exact Method (CPLEX)	x
(Polat et al., 2015)	SALBP-2	GP	PWL	REBA	Min (CT & PWL deviation)	Exact Method (CPLEX)	
(Barathwaj et al., 2015)	MMALBP	MILP	ARP	RULA	Min (#workstations & Ergo-Risk)	GA	x
(Battini, Calzavara, et al., 2016)	IALBFP	MIP	Fatigue	(Garg et al., 1978)	Min (#workers)	Exact method (CPLEX)	
(Battini, Delorme, et al., 2016)	SALBP-2	MO-LP	Energy expenditure & rest allowance	PMES	Min (CT & Energy expenditure)	Pareto frontier analysis	x
(Bautista, Alfaro-Pozo, et al., 2016)	TSALBP	MILP	Posture	RULA, OCRA, NIOSH	Min (max & absolute deviation of Ergo-Risk)	GRASP	x

Table 4.2 Summary of Ergo-ALBPs papers published between 2011–2022 (continue)

Authors	**Problem Type**	**Mathematic Model**	**Ergo Factor**	**EAT**	**Objective Function**	**Solution Method**	**Case Study**
(Bautista, Batalla-García, et al., 2016)	TSALBP	MILP	Posture	semi-quantitative customized set	Min (max Ergo-Risk)	Exact method (CPLEX)	x
(Bortolini et al., 2017)	SALBP-2	MO-LP	Posture	REBA	Min (CT & Energy expenditure)	Pareto frontier	x
(Battini et al., 2017)	SALBP-2	MIP	Energy expenditure	-	Min (CT & Energy deviation)	Hierarchical planning approach	x
(Baykasoglu et al., 2017)	SALBP-1	preemptive GP	Posture	OCRA	Min (#Red Stations & OCRA index)	Constructive search algorithm	x
(Bautista-Valhondo et al., 2018)	MMALBP	MILP	Posture	-	Min (max & average absolute deviation of Ergo-Risk)	Exact method (CPLEX)	x
(Bautista-Valhondo & Alfaro-Pozo, 2018)	MMALBP	MILP	Posture	-	Min (Ergo-Risk dispersion)	GRASP	x
(Bautista Valhondo & Alfaro Pozo, 2018)	TSALB	MILP	Posture	(Bautista, Alfaro-Pozo, et al., 2016)	Min (average Ergo-Risk)	Exact method (CPLEX)	x
(Polat et al., 2018)	SALBP-2	MIP	PWL	REBA	Min (CT & PWL deviation)	Exact method (CPLEX)	
(Finco et al., 2018)	SALBP-2	-	Energy expenditure & rest allowance	(Price, 1990)	Min (CT & Energy expenditure)	Heuristic approach	

Table 4.2 Summary of Ergo-ALBPs papers published between 2011–2022 (continue)

Authors	**Problem Type**	**Mathematic Model**	**Ergo Factor**	**EAT**	**Objective Function**	**Solution Method**	**Case Study**
(Tiacci & Mimmi, 2018)	Stochastic MMALBP	NLP	Posture	OCRA	Min (Normalized design cost for corrected OCRA)	GA	x
(Abdous et al., 2018a)	SALBP-1	MO-MILP	fatigue & recovery	(Ma et al., 2009)	Min (#workstations & fatigue)	Pareto frontier & ε-constraint	
(Alghazi & Kurz, 2018)	MMALBP	IP & CP	ergonomic risk constraints	-	Min (#workers)	Branch & bound algorithm	x
(Kahya & Şahin, 2019)	SALB-1	-	Posture	REBA	Min (#workstations)	Heuristic approach	x
(Dalle Mura & Dini, 2019)	SALBP-1	-	Energy expenditure	RULA	Min (#skilled workers & cost & energy expenditure variance)	GA	x
(Weckenborg & Spengler, 2019)	CALBP	MILP	Energy expenditure	(Price, 1990)	Min (Cost per cycle)	Exact method (CPLEX)	
(Akyol & Baykasoğlu, 2019)	ALWABP	GP	Posture	OCRA	Min (Ergo-Risk)	Multi-start greedy heuristic method	
(Finco et al., 2019)	ALDP	MILP	Vibration	ISO 5349-1	Min (Design cost)	Heuristic approach	x
(Finco et al., 2020)	SALBP-2	MILP	Energy expenditure & rest allowance	OCRA	Min (Smoothness index)	Heuristic approach	
(Zhang et al., 2020)	UALWABP-2	LP	Posture	OCRA	Min (CT & Ergo-Risk)	Restarted Iterated Pareto Greedy	

Table 4.2 Summary of Ergo-ALBPs papers published between 2011–2022 (continue)

Authors	**Problem Type**	**Mathematic Model**	**Ergo Factor**	**EAT**	**Objective Function**	**Solution Method**	**Case Study**
(Abdous et al., 2020)	CALDP	MO-MINLP	fatigue & recovery	(Ma et al., 2010)	Min (Design cost) & Max (Ergonomics level)	Iterative Local Search	
(Mokhtarzadeh et al., 2021)	Parallel U-shaped MMALBP	MIP & CP	Posture	BWM	Min (#workstations & Ergo-Risk)	Heuristic approach	x
(Vollebregt, 2021)	MMALBP	MIP	Posture	REBA	Min (CT, max & sum Ergo-Risk)	GA & pareto frontier	x
(Zamzam et al., 2021)	2sided-ALBP	GP	Posture	ESI	Min (#workstations & #mated stations, ESI)	GA	
(Ozdemir et al., 2021)	SALBP-2	Fuzzy MO	Posture	DHM & ESM	Min (CT, Ergo-Risk imbalance)	Pareto frontier	x
(Bortolini et al., 2021)	SALBP-1	Tri-objective LP	Fatigue	-	Min (annual costs, time & fatigue difference)	Pareto frontier	x
(Katiraee et al., 2021)	SALBP-2	LP	Workers' diversity	(Borg, 1990)	Min (CT & max physical effort)	ε-constraint approach	x
(Finco et al., 2021)	MMALBP	LP	Fatigue and rest allowance	-	Min (CT & rest allowance)	Heuristic approach	x
(Weckenborg et al., 2022)	CALBP	MIP	Energy expenditure	Biomechanical method	Min (cost & workers' biomechanical load)	Pareto frontier	

Table 4.2 Summary of Ergo-ALBPs papers published between 2011–2022 (continue)

Authors	**Problem Type**	**Mathematic Model**	**Ergo Factor**	**EAT**	**Objective Function**	**Solution Method**	**Case Study**
(Stecke & Mokhtarzadeh, 2022)	CALBP	MILP & CP	Energy expenditure	(Garg et al., 1978)	Min (weighted sum of CT and ergonomic indicators)	Benders decomposition algorithm	
(Quenehen et al., 2023)	RALBP-2	-	fatigue	PMES	Min (CT, accumulated fatigue)	Hybridization metaheuristic (list algorithm)	x
(Chutima & Khotsaenlee, 2022)	Parallel U-shaped CALBP	MILP	Energy expenditure	PMES	Min (workload & energy expenditure variance) & Max (tax benefit & line's efficiency)	Non-dominated Sorting Teaching-Learning-Based heuristic method	
(Dalle Mura & Dini, 2022)	CALBP	CP	Energy expenditure	-	Min (cost & energy expenditure variance)	GA	x
(Tkitek & Triki, 2022)	SALBP-1	LP	Arm measurement	-	Min (#workstations)	Exact method (LINGO)	
(Abdous, Delorme, Battini, Sgarbossa, et al., 2023)	SALBP-F	ILP	Fatigue & recovery	Quantitative analytical model	Max (level of ergonomics)	Iterative Dichotomic Search Algorithm	
(Abdous, Delorme, Battini, & Berger-Douce, 2023)	CALDP	MILP	Fatigue & recovery	(Ma et al., 2010)	Min (cost & fatigue)	ε-constraint approach	x

Table 4.2 Summary of Ergo-ALBPs papers published between 2011–2022 (continue)

Authors	**Problem Type**	**Mathematic Model**	**Ergo Factor**	**EAT**	**Objective Function**	**Solution Method**	**Case Study**
(Katiraee et al., 2023)	SALBP-2	Bi-objective LP	Perceived physical effort	(Borg, 1990)	Min (CT & workload variance)	ε-constraint approach	x
(Yetkin & Kahya, 2022)	SALBP-2	Bi-objective LP	Posture	REBA	Min (CT & Ergo-Risk)	conic scalarization method	x
(Keshvarparast et al., 2022)	CALBP	MILP	Workers' diversity	(Borg, 1990)	Min (CT & workload imbalance)	ε-constraint approach	x
(Cimen et al., 2022)	ALWARBP	GP	Posture	OCRA	Min (rebalancing cost & Ergo-Risk)	Constructive rule-based heuristic method	x

4.3.1.1 Ergonomic Component of Ergo-ALBPs:

The literature review highlighted that only a limited number of EATs were predominantly used in Ergo-ALBPs studies, despite the availability of numerous ergonomic analysis techniques. While semi-quantitative and quantitative methods were suitable for task evaluations (Chengalur et al., 2004), qualitive techniques were employed in only 10% of the papers (6 cases). However, semi-quantitative approaches were utilized in more than half of the articles. Among various semi-quantitative methods, OCRA was the most popular, followed by RULA, the revised NIOSH lifting equation, and REBA, as shown in Figure 4.5.

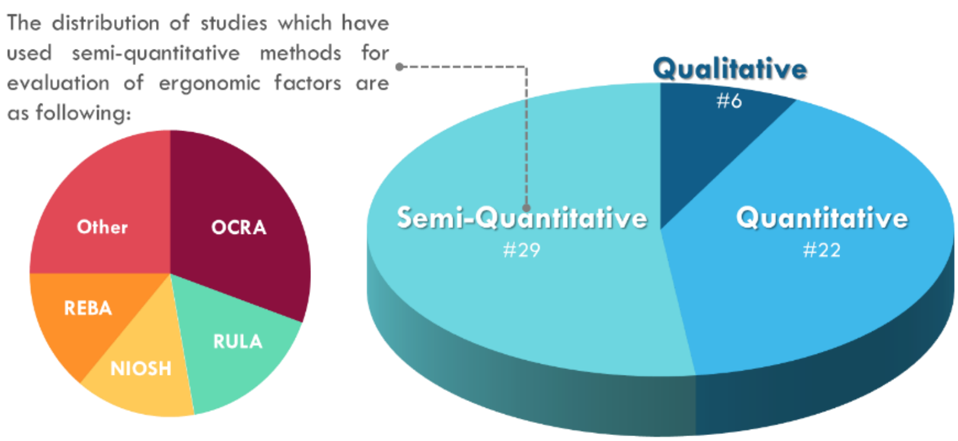


Figure 4.5 Distribution of various EATs in Ergo-ALBPs

Figure 4.6 illustrates the distribution of ergonomic factors considered in Ergo-ALBPs. The data from the studies revealed that 82% of the articles focused on posture risk factors and used semi-quantitative EATs. Quantitative methods were employed in all studies considering localized fatigue, while the rate for generalized fatigue indicators was 75%. It is important to note that fatigue can be experienced as either localized muscle fatigue (i.e., fatigue in specific muscle groups) or generalized fatigue (whole-body fatigue). To quantify generalized fatigue, the energy expenditure or metabolic rate is evaluated when the activity involves approximately 70% or more of the body's muscular mass (e.g., upper-body non-walking activity without carrying an object). For assessing localized fatigue in specific muscle groups (e.g., shoulder, arm, back), other indices and methods such as the Borg scale for different body parts should be considered.

The first study to incorporate the smoothness of ergonomic factors in ALBPs was conducted by Battini, Delorme, et al. (2016). They applied a multi-objective SALBP-2 to optimize the time and energy evenness indexes. Energy expenditure was estimated using the predetermined motion energy system (PMES), initially developed by Garg et al. (1978). The PMES includes formulations for calculating energy expenditure for each task by breaking them down into basic movements like lifting, carrying, and walking.

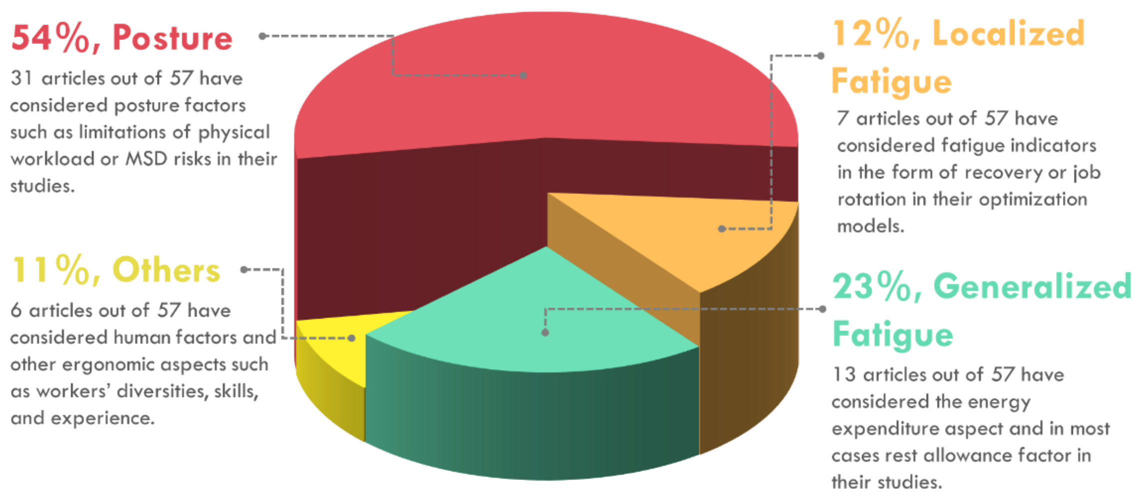


Figure 4.6 Distribution of various ergonomic aspects in Ergo-ALBPs

Different problem types in Ergo-ALBPs entail other methods and considerations. For instance, Alghazi and Kurz (2018) utilized the task difficulty indicator, which was computed based on a weighted ergonomic score and task duration. They aimed to control the cumulated difficulty of tasks assigned to each workstation using constraint programming (CP). Finco et al. (2019) sought to minimize the cost of applying automatic tools in workstations based on vibration levels compliant with ISO 5349-1. Additionally, Zamzam et al. (2021) aimed to minimize the effort smoothness index (ESI), which represented the standard deviation of the metabolic rate among workers, thereby measuring the variation in physical effort across operators.

4.3.1.2 Assembly Line Worker Assignment and Balancing Problem with Ergonomics Consideration (Ergo-ALWABP)

On the ergonomic side, individual characteristics of operators, such as gender, age, and weight, result in varying levels of energy expenditure when performing the same task (Garg et al., 1978). In the Ergo-ALBP literature, several studies have addressed these differences. For example, Öksüz and Satoğlu (2014) investigated the learning effect as a crucial human factor in balancing U-shaped assembly lines. They incorporated operators' competence levels for each task and aimed to maximize competency in their model. Dalle Mura and Dini (2019) developed an optimization algorithm to assign tasks with required skill levels to operators with diverse technical skills. They then evenly distributed energy loads to workstations based on operators' physical capabilities.

On the other hand, the ALWABP extends the SALBP when the operation time for each task varies depending on the worker performing it, resulting in the double assignment problem of tasks and workers to workstations concurrently. Introduced by Miralles et al. (2007), the ALWABP incorporates the concept of sheltered workcenter for disabled (SWD) and was initially presented through a case study in an AL with a fixed number of workstations. In contrast to the SALBP, where tasks have fixed execution times, in the ALWABP, each task's execution time varies based on the skill level of the selected worker (Katiraee et al., 2023). The primary objective of the ALWABP is to optimize the assignment of tasks and workers to workstations to enhance AL productivity. However, many studies in this field focus solely on operational aspects such as time and costs, neglecting HF/E considerations.

The first study to consider ergonomic aspects in the ALWABP was proposed by Akyol and Baykasoğlu (2019). They developed a multiple-rule-based constructive randomized search algorithm to solve ALWABP while considering ergonomic risk factors (Ergo-ALWABP). Since then, three other studies have aimed to improve the efficiency and effectiveness of Ergo-ALWABP algorithms. For example, Katiraee et al. (2021) employed the Borg scale, a subjective assessment tool, to evaluate workers' perceived physical effort and categorized tasks based on their difficulty level for individual workers. This allowed them to determine optimal worker assignments and balancing. Another study by Katiraee et al. (2023) proposed an approach to consider workers' expertise and perceived physical effort in the ALWABP. They considered workers' skill levels, experience, and physical conditions when assigning tasks and balancing the workload. Additionally, Cimen et al. (2022) presented an algorithm to rebalance an existing assembly line and assign workers to minimize ergonomic risk factors. They considered workers' physical abilities, job rotation, and workload distribution to reduce ergonomic risk factors. These studies emphasize the importance of considering ergonomic factors in the ALWABP and propose various approaches to optimize worker assignment and balancing.

4.3.1.3 Operational Component of Ergo-ALBPs

Incorporating ergonomic aspects alongside operational factors in ALBPs introduces conflicting objective functions. To address this, three papers utilized fuzzy set theory (FST). Mutlu and Özgörmüş (2012) considered the assembly task's PWL as a fuzzy set and developed a fuzzy LP model based on Bellman and Zadeh (1970) approach to solve their SALBP. Rajabalipour Cheshmehgaz et al. (2012) proposed a fuzzy goal programming (GP) method and a GA to solve the fuzzy mathematical SALBP model. They introduced a novel ergonomic factor, the accumulated risk of postures (ARP), to evaluate steady posture levels during assembly tasks, considering three conflicting objectives: CT minimization, ARP minimization, and PWL smoothness. Ozdemir et al. (2021) employed simulation software to analyze the ergonomic risk of assembly tasks and developed a fuzzy multi-objective model accordingly.

For solving NP-hard problems like ALBPs, as explained in the previous section, exact methods are not efficient enough, and it is recommended to employ heuristic and meta-heuristic approaches to find effective or near-optimal solutions. As shown in Table 2, 44% of Ergo-ALBPs have been solved by exact methods. Heuristic approaches, constituting 33% of the studies, are more popular than meta-heuristic methods (23%). Among the meta-heuristic approaches, GA is widely used individually or in combination with other methods. Innovative solution methods have also been employed in recent studies. For example, Abdous, Delorme, Battini and Berger-Douce (2023) developed an iterative dichotomic search algorithm for the feasibility study of their SALBP. Chutima and Khotsaenlee (2022) applied a non-dominated sorting teaching-learning-based optimization (NSTLBO) method to solve a parallel U-shaped ALBP (UALBP) considering the energy expenditure factor using the PMES technique.

Regarding the types of problems addressed, 47% of the studies focused on SALBPs, with an equal distribution between Type 1 (minimizing the number of workstations) and Type 2 (minimizing the cycle time), except for Abdous, Delorme, Battini, Sgarbossa, et al. (2023), who considered Type F (feasibility study), and Cimen et al. (2022), who aimed to maximize the line's efficiency (Type E). On the other hand, 53% of the papers with GALBP models tackled various types of general problems, as shown in Figure 4.7.

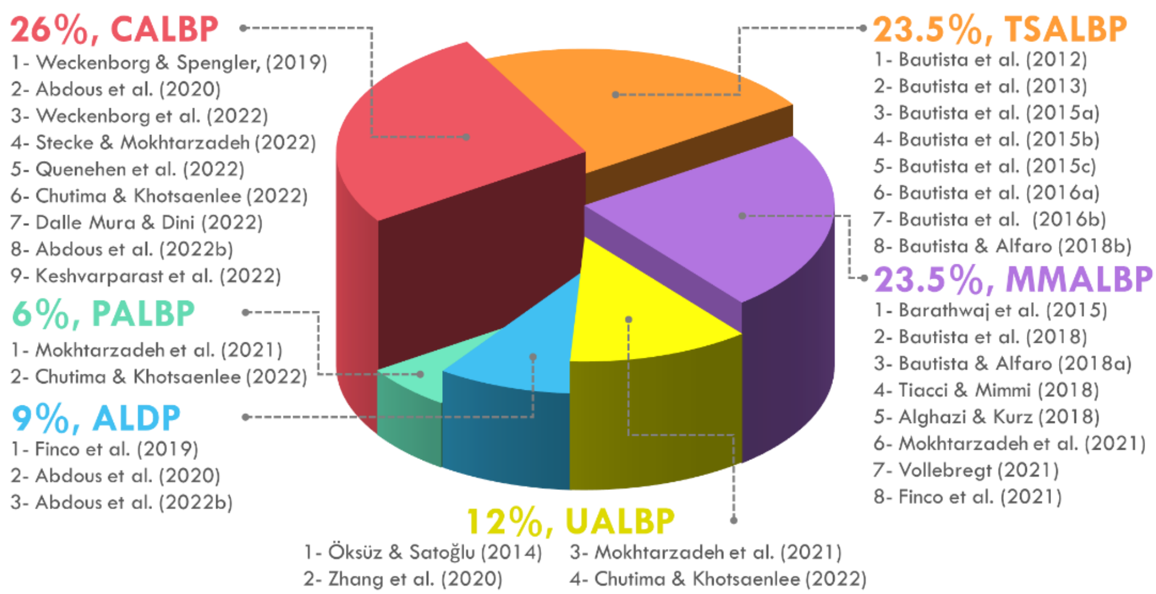


Figure 4.7 Distribution of GALBPs in ergonomic-related studies

One commonly studied problem is the TSALBP. Bautista, Batalla and Alfaro (2013) introduced TSALBP by ergonomic considerations (TSALBP-erg). They proposed a model that balances conflicting goals related to time, space, and ergonomic risks. TSALBPs are classified based on the number of workstations, CT, and available space, resulting in eight different problem models, each of which can be mono-objective or multi-objective. This research group further developed these sorts of problems and since 2015, they employed the Nissan engine company as a case study. Bautista, Alfaro-Pozo, et al. (2015) used the GRASP, a multi-start metaheuristic approach, to solve TSALBPs. In subsequent studies, they combined EATs such as RULA, OCRA, and the revised NIOSH lifting equation (Bautista, Alfaro-Pozo, et al., 2015; Bautista, Alfaro-Pozo, et al., 2016; Bautista, Batalla-García, et al., 2015; Bautista Valhondo & Alfaro Pozo, 2018; Bautista Valhondo et al., 2015).

The need for more realistic models motivated researchers to study mixed-models assembly line balancing problems (MMALBPs), which represent 26% of the papers addressing general problems (Figure 4.7). Parallel ALBPs (PALBPs) were less common, with only two hybrid models found. Chutima and Khotsaenlee (2022) investigated the Parallel U-shaped ALBP, while Mokhtarzadeh et al. (2021) considered the Parallel U-shaped mixed-model ALBP, indicating the increased use of hybrid models.

Operational aspects were incorporated in various ways in the optimization models, either as objective functions or constraints. The most frequently used operational objective functions were CT minimization (29%), number of workstations minimization (27%), and cost minimization (19%). Additionally, 25% of the articles considered operational aspects solely as constraints without an operational objective.

A small portion (7%) of the reviewed papers addressed ergonomic balancing problems in the design phase (ALDP). Baykasoglu et al. (2017) proposed a heuristic solution method for the design problem in a SALBP. Finco et al. (2019) analyzed vibration in semi-automatic ALDP and aimed to minimize design costs. Abdous et al. (2020) and Abdous, Delorme, Battini and Berger-Douce (2023) also considered ergonomic aspects in the design phase, particularly in an Industry 4.0 context.

4.3.1.4 New Trend in Industry 4.0 Era

Industry 4.0 is revolutionizing the manufacturing industry by integrating advanced technologies like cyber-physical systems, the internet of things (IoT), and big data analytics. This digital transformation and automation are also influencing ALBPs. Recent studies have highlighted the potential of Industry 4.0 in addressing ergonomic considerations in ALBPs. Collaborative robots and exoskeletons, for instance, have been employed to reduce ergonomic risks in AL tasks. Moreover, CALBPs or RALBPs can optimize CT and ergonomic risk, leading to improved economic and ergonomic performance in assembly processes.

There is a growing trend in recent years towards integrating ergonomic aspects in collaboration with robots and exoskeletons, Figure 4.7 demonstrates that out of 57 studies, nine papers focused on CALBPs, with seven published in 2022.

Weckenborg and Spengler (2019) were the first to propose a cost-oriented approach for ALBP that considers collaborative robots and ergonomics. Their approach aims to reduce workers' PWL, balance energy expenditure, and increase productivity by incorporating collaborative robots.

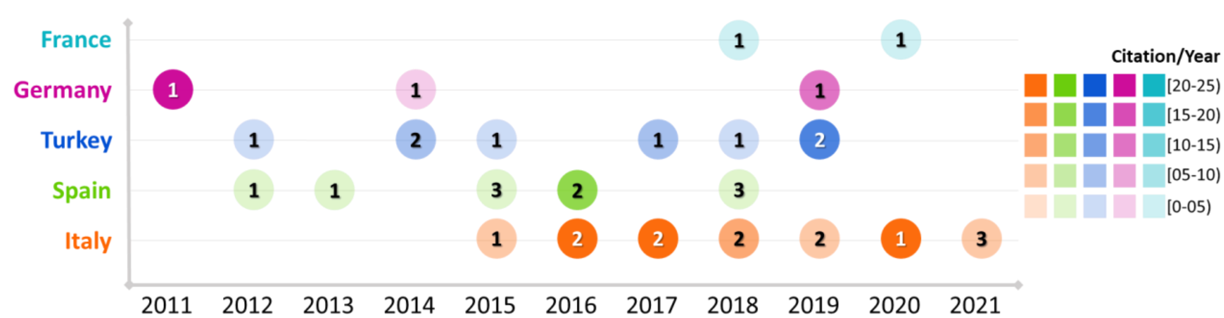
Abdous et al. (2020) subsequently investigated the collaborative problem in the design phase (CALDP) to minimize the design cost of ALs while also reducing the ergonomic risk level. They assessed dynamic muscle fatigue based on the formula proposed by Ma et al. (2009) for assigned tasks at each workstation. Two years later, Abdous, Delorme, Battini and Berger-Douce (2023) proposed a multi-objective approach to CALDP, optimizing ergonomic criteria such as workload, body posture, and repetitive motions, as well as economic factors like production cost, equipment cost, and space utilization.

Weckenborg et al. (2022) and Stecke and Mokhtarzadeh (2022) incorporated the energy expenditure factor in their semi-automatic ALs. They solved their model using exact methods and tested them on numerical examples. Quenehen et al. (2023), on the other hand, employed the PMES to measure fatigue in the RALBPs and solved the problem using a hybrid metaheuristic approach (list algorithm), considering a specific case study.

4.3.2 Descriptive Analysis

This section presents the findings from the quantitative data analysis using bibliometric approaches. These findings, along with those from the content analysis approach (Section 4.3.1), were utilized to identify research gaps and main trends in the field of study.

The review of 57 Ergo-ALBP papers revealed that 79% of the studies were conducted in five countries: Italy, Spain, Turkey, France, and Germany, with 16, 10, 10, 5, and 4 articles, respectively. Figure 4.8 visually illustrates the distribution of articles from these countries based on their citation rate (i.e., number of citations per year). The citation rates were collected up until October 2022, so publications from 2022 were not considered for a fair analysis.



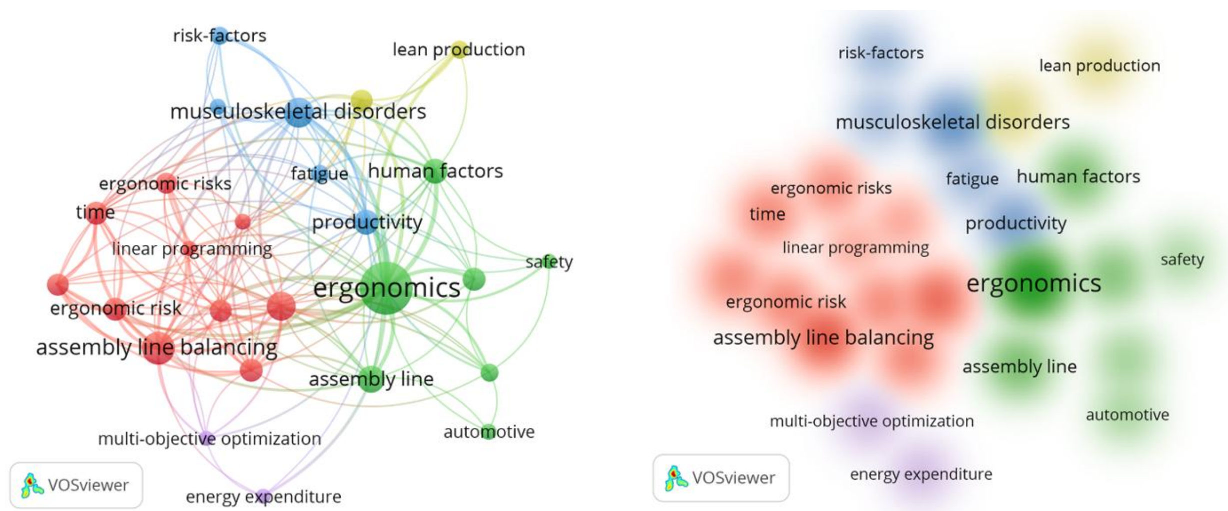
Note: The numbers in circles identify the number of studies at the same point and the citation rate is cumulative.

Figure 4.8 Research contributions of the top five pioneer countries in the field of Ergo-ALBPs

Furthermore, nearly 60% of the reviewed papers (34 articles) included a case study in their research, while the remaining studies employed numerical examples to validate their models.

Automotive manufacturers accounted for more than half of the case studies in the literature (19 articles), with Bautista's research group utilizing the Nissan engine plant in nine of their studies. Additionally, four studies focused on electronic appliance assembly lines (Bortolini et al., 2017; Kahya & Şahin, 2019; Ozdemir et al., 2021; Xu et al., 2012). Among all the reviewed articles, 63% were journal papers, 35% were conference papers, and one article was a thesis.

Finally, the VOSviewer software was used to conduct co-occurrence (co-word) analysis and identify trends in the studies. This analysis employs statistical methods to cluster main keywords based on the strength of their relationships in the literature. Figure 4.9 displays the keyword co-occurrence network as an output of VOSviewer.



(a) Co-occurrence map of the keywords (b) Cluster density of the keywords

Figure 4.9 The map of connections between the keywords within 2011–2022

The analysis of the information in the co-word map provides insights into research gaps and future trends, which will be discussed in the following sections.

4.4 Industry 5.0 Paradigm

Industry 5.0 represents a significant transformation in manufacturing, emphasizing collaboration between human workers and advanced technologies to achieve improved productivity, efficiency, and innovation. Unlike Industry 4.0, which focused on automation, Industry 5.0 places greater emphasis on mass customization and recognizes the importance of human intelligence and creativity in manufacturing processes (Baicun et al., 2020). By integrating advanced technologies like AR, VR, AI, and collaborative robots, Industry 5.0 has the potential to assist workers in performing complex tasks, reducing ergonomic risks, and optimizing AL performance.

Within the context of Ergo-ALBPs, Industry 5.0 offers several potential benefits. Firstly, it acknowledges the importance of worker well-being and safety, aiming to incorporate ergonomic design principles into ALBPs. This can lead to improvements in worker comfort, productivity, and job satisfaction. Secondly, Industry 5.0 solutions incorporate human feedback and input into the ALBPs, enabling a more flexible and adaptive production environment that can better accommodate variations in worker behavior and physical abilities. Thirdly, Industry 5.0 facilitates the integration of advanced technologies, such as wearables and AR, which can enhance worker performance and reduce the risk of injuries. Lastly, Industry 5.0 promotes a culture of continuous learning and improvement, encouraging workers and organizations to adopt a growth mindset and explore new ways to optimize the ALBPs.

The core values of Industry 5.0 can be categorized into three main aspects: human-centricity, resilience, and sustainability (Xu et al., 2021). Furthermore, Leng et al. (2022) discussed relevant concepts related to Industry 5.0, including Industry 4.0, Operator 5.0, and Society 5.0. However, there are commonalities between the main aspects of Industry 5.0 and its related concepts.

The following subsections provide an explanation of the related concepts and aspects of Industry 5.0 and demonstrate their potential future impacts on Ergo-ALBPs, as briefly depicted in Figure 4.10.

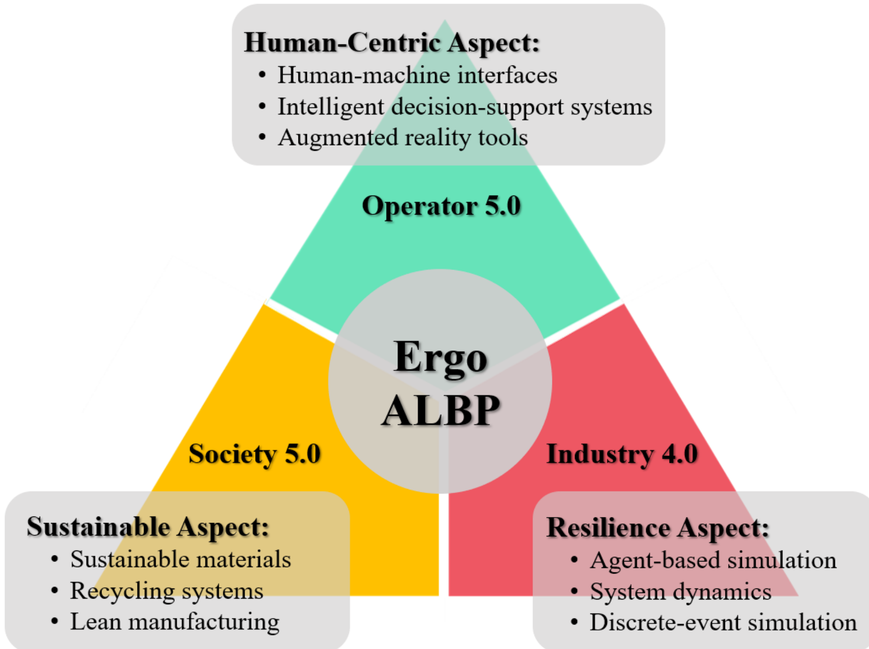


Figure 4.10 Concepts related to Industry 5.0 and their applications in Ergo-ALBPs

4.4.1 Paradigm Shift from Industry 4.0

As mentioned earlier, Industry 4.0 is a manufacturing paradigm that relies on interconnected machines, data analytics, and AI to create a highly efficient and automated production environment. While Industry 4.0 has revolutionized many aspects of manufacturing, it has limitations when it comes to addressing Ergo-ALBPs. For example, Industry 4.0 tends to focus primarily on optimizing production throughput and minimizing costs, often neglecting worker well-being. It treats workers as passive participants in the production process, rather than recognizing them as active agents capable of contributing to the overall efficiency and ergonomics of the assembly line. Furthermore, Industry 4.0 solutions often fail to consider the variability in human behavior and physical abilities, resulting in potential safety hazards and reduced worker productivity. Therefore, there is a need to explore new manufacturing paradigms, such as Industry 5.0, that can address these limitations and incorporate worker-centered design principles into ALBP.

Industry 5.0 represents a new paradigm that builds upon the strengths of Industry 4.0 while placing a greater emphasis on human-centered design and collaboration between workers and machines (Leng et al., 2022). Industry 4.0 is closely linked to the resilience aspect of Industry 5.0, which establishes the technical foundations for leveraging digital technologies to enhance the flexibility and agility of manufacturing processes (Zizic et al., 2022).

In the context of Ergo-ALBPs, the resilience aspect of Industry 5.0 can involve the use of simulation tools to optimize the AL and proactively identify potential issues. Various simulation approaches, including discrete-event simulation, agent-based simulation, and system dynamics, can be employed. Additionally, Industry 4.0 offers technologies that assist companies in adapting to changes and disruptions, such as predictive maintenance systems or adaptive manufacturing systems.

4.4.2 Operator 5.0

Operator 5.0 is a concept that describes a new generation of workers who are empowered by advanced technologies and trained to collaborate with machines to optimize production processes. Operator 5.0 signifies a transition towards a more collaborative and team-based production environment, where workers are trained to work alongside machines as partners rather than mere operators. This concept highlights the crucial role of human skills, creativity, and problem-solving abilities in the manufacturing process, with advanced technologies supporting operators to achieve higher levels of productivity, quality, and flexibility.

In the context of Ergo-ALBPs, Operator 5.0 represents a paradigm shift from the traditional view of workers as passive participants in the production process to active agents who contribute to the optimization of the AL. The concept of Operator 5.0 aligns with the human-centric aspect of Industry 5.0, which emphasizes placing human needs and values at the core of manufacturing processes. One key characteristic of Operator 5.0 is the use of wearable technology and sensors to monitor worker behavior and physical capabilities. This data can be utilized to optimize ALB and reduce the risk of injuries or MSDs. For instance, wearables can track worker posture and movements, identifying potential ergonomic hazards and providing real-time feedback to help workers adjust their posture or movements. Wearables can also monitor worker fatigue and issue alerts when workers need to take breaks or switch tasks to prevent injuries.

Moreover, Operator 5.0 entails the adoption of human-machine interfaces, AR and VR technologies, and intelligent decision-support systems. These technologies offer workers real-time information on ALB and guide them through complex tasks. For example, AR can overlay instructions or images onto physical objects, enabling workers to precisely place components or perform specific tasks. VR can simulate various balancing scenarios, providing workers with virtual training and feedback on their performance. An operator wearing an AR headset can receive real-time feedback on assembly tasks and receive suggestions for optimal work postures to prevent ergonomic injuries. Additionally, there are advancements in the development of intelligent exoskeletons that enhance the strength and endurance of workers involved in physically demanding tasks, such as lifting heavy objects or working in awkward postures.

These technologies possess the potential to enhance the cognitive and physical abilities of human operators, enabling them to perform their tasks more efficiently, safely, and comfortably. As a result, they can improve the overall ergonomics of assembly processes and enhance the well-being and job satisfaction of workers (Gervasi et al., 2023).

4.4.3 Society 5.0

Society 5.0 represents a shift towards a more inclusive and diverse production environment that benefits all members of society. This concept emphasizes integrating advanced technologies with societal needs and values to create a sustainable future. It requires organizations to adopt a holistic and human-centric approach to production that considers the diverse needs and perspectives of workers, customers, and other stakeholders. By promoting diversity and inclusion, organizations can enhance creativity, innovation, and collaboration, while ensuring that their products and services meet the needs of a diverse customer base. Society 5.0 envisions a production system that balances economic, social, and environmental considerations to create value for all stakeholders. This concept aligns closely with the sustainable aspect of Industry 5.0, which emphasizes the importance of creating an environmentally and socially responsible manufacturing industry.

In the context of Ergo-ALBPs, Society 5.0 can be applied to create ALs that are not only efficient but also sustainable and human-centered. For example, advanced sensors and AI algorithms can monitor workers' physical and mental states and adjust the AL to reduce physical strain and improve workers' well-being. Integrating social values and ethics ensures that the AL is designed to meet the needs of workers, customers, and society as a whole. The principles of Society 5.0 can involve using sustainable materials and processes, such as biodegradable materials, closed-loop systems, and lean manufacturing principles, to reduce waste and minimize the environmental impact of manufacturing.

Therefore, in Ergo-ALBPs, it is important to consider technologies that support sustainable manufacturing practices, such as employing renewable energy sources or implementing recycling systems. Additionally, efforts can be made to prevent the environmental impact of production in the design phase by incorporating eco-design principles or closed-loop manufacturing. These actions align with the principles of Society 5.0 and contribute to the creation of a more sustainable and socially responsible manufacturing industry.

4.4.4 Potential Challenges of Industry 5.0 in Ergo-ALBPs

While Industry 5.0 holds great potential for revolutionizing Ergo-ALBPs, there are several challenges that organizations may encounter during its implementation. One key challenge is the investment required in new technologies and training programs to support worker-centered design and collaboration. This entails upfront costs and a shift in organizational culture and mindset. Resistance from workers who may be apprehensive about new technologies or fear job loss due to automation is another challenge to address (Zizic et al., 2022). Involving workers in the planning and implementation process and giving them a voice in decision-making can help reduce these concerns. Additionally, regulatory and legal barriers may obstruct the adoption of Industry 5.0 solutions, particularly in industries with strict safety and health regulations. Moreover, organizations need to develop new performance metrics and evaluation frameworks to effectively measure the impact of Industry 5.0 on improving Ergo-ALBPs. Despite these challenges, the potential benefits of Industry 5.0 in creating a more efficient, safe, and worker-centered production environment make it an area of significant interest and investment for many organizations.

To address the challenges posed by Industry 5.0, Baicun et al. (2020) suggest focusing education and training programs on enhancing workers' interdisciplinary skills, such as engineering, information technology, and psychology, to meet the demands of human-centered intelligent manufacturing. Additionally, Industry 5.0 requires a new organizational structure that prioritizes collaboration, communication, and flexibility to adapt to evolving customer needs and technological advancements.

4.5 Findings & Discussion

The content and quantitative analysis of this literature review yielded several trends in Ergo-ALBP research studies, shedding light on the current research gaps in this field. The systematic review identified the following research gaps and future study trends:

- In recent years, studies have explored the ALBP with human-machine or human-robot collaboration within the context of Industry 4.0. However, this is a newly emerged field in the Ergo-ALBP domain, which requires further investigation and offers numerous research opportunities. Cyber-physical systems, such as sensors and robots, can provide real-time data on AL processes, enabling better decision-making and optimization. AR and VR technologies can enhance the design and planning phases by enabling workers to visualize and test different scenarios. The integration of AI and machine learning algorithms can automate ALB processes and improve efficiency over time. These opportunities have the potential to significantly improve productivity, quality, and worker safety in manufacturing.
- The integration of HF/E considerations with practical aspects represents a major trend in Ergo-ALBP research (Boysen et al., 2007). While many studies have focused on TSALBP or MMALBPs, there is a new trend of studying ergonomic factors in more complex ALs, such as parallel U-shape mixed-model (Mokhtarzadeh et al., 2021) and Parallel U-shape (Chutima & Khotsaenlee, 2022) ALBPs. Although progress has been made in incorporating task features, performance indicators, restrictions, and objective functions in ALBPs, there remains a gap between real-world problems and mathematical models.
- While heuristic and meta-heuristic approaches have been commonly used to solve Ergo-ALBPs and find near-optimum solutions, there is a growing interest in applying hybrid methods and machine learning techniques. Hybrid methods, as demonstrated in recent studies such as Chutima and Khotsaenlee (2022) and Quenehen et al. (2023), can lead to more effective solutions. Learning techniques, such as neural networks, have been used to model ergonomic factors and incorporate them into optimization algorithms. These new optimization methods hold promise in achieving better assembly line balancing considering ergonomic factors, leading to improved worker health and productivity.
- Uncertainty in Ergo-ALBPs can be classified as environmental and system uncertainty (Ho, 1989). Environmental uncertainty relates to market variations and customer behavior, while

system uncertainty includes uncertainties within the production process, including human aspects. Moreover, the findings of some studies (Golabchi et al., 2017; Golabchi et al., 2016) proved the imprecision of inputs in EATs which significantly affects the results. Stochastic programming models can incorporate variability by treating certain parameters as stochastic values. However, only one study in the Ergo-ALBP domain (Tiacci & Mimmi, 2018) has included stochastic task times in their model. Fuzzy programming models, employing fuzzy numbers, can be useful when historical data is insufficient. Additionally, a small number of studies have applied fuzzy set theory to handle conflicting objectives (Mutlu & Özgörmüş, 2012; Ozdemir et al., 2021; Rajabalipour Cheshmehgaz et al., 2012). Future research should explore the application of stochastic and fuzzy programming models to address the uncertain nature of Ergo-ALBPs.

- The robustness of solutions in Ergo-ALBPs, considering indeterministic factors, is an important aspect to measure and evaluate. No research has explored robustness objectives in this area. A robust configuration of ALs, considering both ergonomic and operational aspects, can ensure long-term efficiency.
- The integration of lean tools in ALBPs can simplify computational optimization models and improve results (Qattawi & Chalil Madathil, 2019). Several studies have recommended incorporating ergonomic indicators in lean production methods to enhance production system efficiency (Oliveira et al., 2018). However, none of the Ergo-ALBP studies reviewed in this research have incorporated the lean approach, presenting an opportunity for future investigation.
- The design phase is critical for considering ergonomic aspects to prevent health-related issues and minimize the need for corrective actions. While most reviewed articles focus on existing ALs, there are only a few studies that consider ergonomic factors in the design phase such as Baykasoglu et al. (2017), Finco et al. (2019) and (Abdous et al., 2020) . Thus, further research is needed in the area of Ergo-ALDP.
- More research is needed to examine the range of available methods for addressing ergonomic factors in optimization problems in production industries. The methods used in the reviewed papers are very few compared to the large range of available methods (ex., Takala et al. (2010)). One research opportunity is investigating newer methods and

evaluating their effectiveness in optimization problems that can contribute to the advancement of Ergo-ALBP.

- The advent of Industry 5.0 as a value-driven concept represents a paradigm shift towards resilient, sustainable, and human-centric systems (Leng et al., 2022). While Industry 4.0 focuses on technology-driven solutions, Industry 5.0 integrates human-centric initiatives. Ergo-ALBP is expected to become a popular research domain in the context of Industry 5.0. Further research is needed to explore the full potential of Industry 5.0 in coping with Ergo-ALBPs and other manufacturing challenges.

In conclusion, the main future trend in Ergo-ALBPs is to develop more realistic models and propose efficient solutions. Considering the variability and uncertainty of environmental aspects, finding sustainable solutions that remain efficient in the long term is essential. Exploring the implications of emerging paradigms such as Industry 4.0 and Industry 5.0 can further improve Ergo-ALBPs.

4.6 Conclusions

Given the significant role of efficiency in ALs and the crucial importance of HF/E in optimizing ALBPs, this paper provides a comprehensive literature review of Ergo-ALBPs. This review aims to benefit process engineers, ergonomic practitioners, and researchers interested in simultaneously addressing operational and ergonomic considerations for achieving optimal AL balancing and design. Utilizing the PRISMA methodology, a total of 57 research articles published after 2011 were analyzed.

The analysis of the literature revealed notable trends in Ergo-ALBPs. While early studies primarily focused on simple ALBPs, current studies have expanded to investigate more complex problems. For instance, there are investigations into collaborative ALs and mathematical aspects such as balancing parallel U-shape mixed-model assembly lines. Additionally, hybrid algorithms have been employed in solution methodologies to improve the efficiency of finding optimal solutions.

Several research gaps were identified, indicating potential future research directions. There is a growing emphasis on modeling more realistic problems by addressing indeterministic parameters and handling uncertainties in the environment and system using stochastic or fuzzy programming approaches. Furthermore, considering the dynamic nature of markets and industry conditions, ensuring the robustness of optimal solutions poses a new challenge for researchers. The importance of incorporating HF/E aspects in the design stage presents a motivating factor for further exploration of Ergo-ALDP. Integrating lean tools into Ergo-ALBPs is another promising area to simultaneously enhance ergonomic and operational aspects.

The advent of Industry 4.0 and Industry 5.0 has the potential to revolutionize Ergo-ALBPs. Industry 4.0, characterized by automation and advanced technologies, has already shown promise in addressing ergonomic concerns in AL tasks. However, there is still ample room for exploration, with cyber-physical systems, AR, and AI offering further improvements to ALBPs. Industry 5.0, with its human-centered approach and emphasis on collaboration between humans and machines, can further enhance Ergo-ALBPs by utilizing advanced technologies to assist workers in complex tasks and mitigate ergonomic risks. Addressing challenges such as skills training and organizational restructuring will be pivotal in harnessing the benefits of Industry 5.0.

In conclusion, future research should continue to investigate the impact of Industry 4.0 and 5.0 on worker well-being and organizational performance. It is essential to develop innovative solutions that promote human-centered intelligent manufacturing. By leveraging advanced technologies and promoting collaboration between humans and machines, the manufacturing industry can achieve greater efficiency, productivity, and worker safety in Ergo-ALBPs.

CHAPTER 5 ARTICLE 2: FUZZY EXPERT SYSTEM FOR ERGONOMICS ASSEMBLY LINE WORKER ASSIGNMENT AND BALANCING PROBLEM UNDER UNCERTAINTY

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Abstract

In the era of Industry 5.0, there is a significant gap in addressing ergonomic risks and imprecise task times in manufacturing systems. This study aims to fill this gap by extending the ergonomic assembly line balancing problem with worker assignment. It employs a novel two-phase framework combining a constructive heuristic for feasibility with a unique ergonomic assessment method developed through a fuzzy expert system. Validated using 96 synthesized numerical instances, the proposed method addresses the scarcity of fuzzy and ergonomic-oriented data in benchmarks. Then computational results are thoroughly analyzed to evaluate the method's performance and identify potential areas for further research. The proposed optimization method provided high-quality solutions with a majority demonstrating low ergonomic risk and high worker safety, contributing to an overall improvement in ergonomic conditions. The integration of fuzzy expert system and advanced optimization techniques yields a robust framework for achieving a safer and more efficient manufacturing environment.

Keywords: Assembly line balancing problem; Ergonomic risks; Fuzzy expert system; Line balancing; Worker assignment

5.1 Introduction

ALs play a vital role in manufacturing industries, enabling efficient and large-scale production of goods. These systems offer several advantages, including increased productivity, standardized processes, reduced production durations, and cost-effectiveness. However, to fully take advantage of ALs, it is crucial to optimize their operations. This optimization process is commonly referred to as ALBPs. These problems involve the allocation of tasks to workstations and ensuring workload equilibrium to achieve maximum efficiency. ALBPs are significant as they minimize idle time, enhance worker utilization, improve overall productivity, and maintain a balanced workflow (Ghorbani et al., 2023).

Most ALs incorporate manual or semi-automatic operations for increased flexibility. Consequently, human operators are integral to the efficiency and productivity of these lines. However, the repetitive and prolonged nature of assembly tasks can lead to WMSDs and ergonomic issues for operators (Cimen et al., 2022). WMSDs refer to conditions that gradually develop due to excessive use and are either caused or worsened by operators' occupation or the conditions within their workplace and affect their muscles, joints, tendons, nerves, and circulatory system (Sekkay et al., 2018). According to the Association of Workers' Compensation Boards of Canada (AWCBC), manufacturing sector report a significant number of work-related MSDs. For instance, in 2021, WMSDs represented 23% of the total claims in manufacturing industries (2,278 cases out of 9,960), and in 2022, they accounted for 23.6% (2,414 cases out of 10,211), emphasizing the prevalence and severity of such injuries (Association of Workers’ Compensation Boards of Canada, 2024). This data underscores the critical need for ergonomic improvements in manufacturing environments, especially ALs, to mitigate the risk of MSDs among workers.

While traditional ALBPs have been extensively studied since their introduction in 1955, the majority of literature overlooks the impact of HF/E aspects in their optimization models. To address this gap, the Ergo-ALBP was developed, which extends the traditional balancing problems to incorporate HF/E parameters (Ghorbani et al., 2024e). Another limitation of traditional ALBP is the assumption of fixed operation times for each task. In real-life manufacturing systems, workers possess diverse characteristics, skills, experience, and abilities, resulting in varying task execution times. This variability is particularly evident in labor-intensive ALs. To bridge the gap between conventional ALBPs and actual AL scenarios, the ALWABP was introduced. ALWABP optimizes

ALs by considering both task allocation and worker assignment based on their differences (Miralles et al., 2007).

Enhancing ALWABPs holds significant importance within the manufacturing sector, particularly in addressing the complexities posed by heterogeneous workforces. These challenges encompass the strategic allocation of tasks to stations and workers to optimize overall efficiency and productivity, while accounting for various factors such as worker disabilities, absenteeism rates, and the potential need for temporary workers (Liu et al., 2022). Improving ALWABPs is imperative for achieving a balanced workload distribution across stations, optimizing worker assignments based on their individual capabilities, and accommodating real-world constraints such as divergent worker profiles, ergonomic considerations, and environmental factors (Yener & Can, 2023).

In ALBP, workload is computed based on station times, assuming that workers with equal station times have the same workload. However, even if two tasks have the same operation times, the required effort and force for executing them may differ, resulting in workers being exposed to various loads (Katiraee et al., 2023). This oversimplification can lead to suboptimal task allocations and increased ergonomic risks in real-world ALs. Ergo-ALWABP addresses this issue by optimizing both task and worker assignments while considering ergonomic risk factors within the working environment (Zhang et al., 2020). This holistic approach not only minimizes ergonomic risks but also enhances productivity, worker satisfaction, and overall operational efficiency by aligning tasks with individual skills and physical capacities. Furthermore, addressing uncertainty is another crucial aspect of ALWABPs. Uncertainty in ALs can stem from environmental factors, such as market fluctuations and consumer behavior, as well as system aspects, including unreliable production processes and unpredictable failures (Ho, 1989). To find robust and sustainable solutions, it is necessary to account for these uncertainties.

Fuzzy expert systems have proven to be invaluable tools in addressing complex problems under uncertainty. By leveraging fuzzy logic to handle uncertainties arising from imprecise information and incomplete data, these systems can effectively model the logical processes of human experts in specialized domains (Tavana & Hajipour, 2020). In the context of ALWABP, the application of a fuzzy expert system offers a systematic approach to optimizing worker assignments and balancing tasks on assembly lines, taking into account the ambiguous nature of ergonomic factors and varying workloads. By incorporating fuzzy inference systems and expert knowledge, this research can benefit from the ability of fuzzy expert systems to manage uncertainty and provide valuable insights for enhancing the efficiency and effectiveness of ergonomic practices in AL environments.

In recent years, the concept of Industry 5.0 has emerged, signifying a notable shift towards collaboration between human workers and advanced technologies. Unlike its predecessor, Industry 4.0, which focused on automation, Industry 5.0 underscores the importance of mass customization and the pivotal role of human intelligence and creativity in manufacturing processes (Baicun et al., 2020). This paradigm shift has profound implications for optimizing ALs with ergonomic considerations, leveraging AR, VR, AI, and cobots (Zizic et al., 2022). By prioritizing worker-centric design principles, Industry 5.0 enhances worker comfort, productivity, and safety, promoting continuous improvement and learning (Ghorbani et al., 2023). The contributions of this study support the ongoing progress toward human-centric design in ALs, accommodating heterogeneous workers, and navigating uncertainty conditions.

Aiming to contribute to the relevant literature and address identified research gaps, this study introduces four key contributions across three main parts: problem modeling, ergonomic evaluation method, solution approach, and validation and verification processes. As Figure 5.1 illustrates, these contributions are as follows:

- Firstly, this research develops a new extension of the Ergo-ALWABP under uncertainty, considering the imprecision and vagueness of parameters related to task execution times and ergonomic risk levels. Fuzzy set logic is applied to address these uncertainties, modeling the variation in task times using TFNs, and extracting fuzzy ergonomic rules through expert systems to evaluate ergonomic risk levels.
- Secondly, a comprehensive fuzzy risk assessment framework is developed for ergonomic evaluation, analyzing ergonomic risk aspects at the task level, worker level, and AL level. At the task level, the output of fatigue models is categorized into three risk levels, similar to a traffic light, and integrated into the AL optimization model, enabling the application of various fatigue models in the optimization design processes. At the worker level, a customized fuzzy EAT is developed by employing experiments and the knowledge of ergonomic experts to evaluate cumulative ergonomic risk levels based on task duration in

each CT through a fuzzy rule-based approach. Then the fuzzy ergonomic score for all fuzzy sets is evaluated to find the optimal solution(s).

- Thirdly, for solving the proposed fuzzy Ergo-ALWABP-F (Type F, feasibility), a two-phase framework integrates a constructive heuristic approach into a fuzzy knowledge-based system. In the proposed heuristic algorithm, the multiple rules based constructive randomized search (MRBCRS) algorithm proposed by Akyol and Baykasoğlu (2019) are customized to be applicable to the fuzzy optimization problem under study.
- Finally, the proposed solution method is applied to solve benchmark dataset of ALWABP (A. Chaves et al., 2007) for validation and verification purpose. However, those numerical instances are neither fuzzy nor ergonomic-oriented, 96 numerical instances are synthesized based on the original 320 samples. The results demonstrate that the proposed solution method can find high-quality optimum solutions in a reasonable time.

This paper is organized as follows: Section 7.2 provides a literature review on ALWABPs, focusing on existing studies in the Ergo-ALWABP field. Section 7.3 introduces the mathematical optimization problem, while Section 7.4 presents the proposed heuristic solution approach. The computational results of implementing the proposed algorithm on benchmark instances are discussed in Section 7.5. Section 7.6 analyses the findings of this research, and Section 7.6 concludes the paper by summarizing the key points, presenting concluding remarks, and identifying research gaps that should be addressed in future studies.

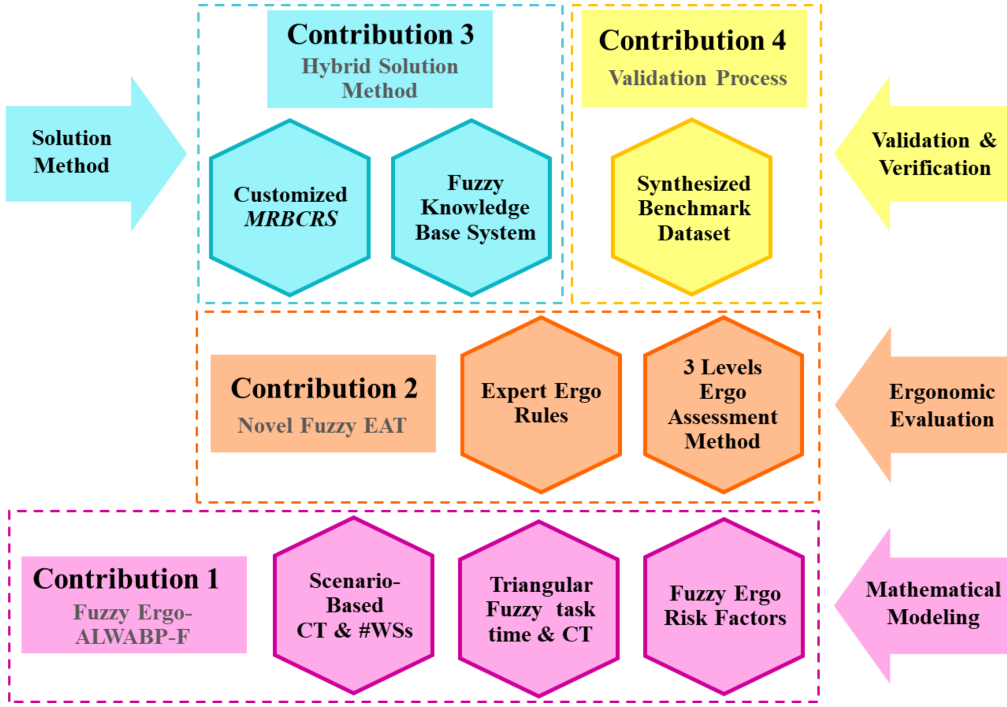


Figure 5.1 Contributions of the present study

5.2 Literature Review

This study concentrates on the overlap of four main fields: AL optimization problems, worker assignment in balancing models, uncertainty considerations in these models, and ergonomics aspects of these problems. The following subsections present a brief review of these four areas.

5.2.1 Assembly Line Optimization Problems

ALBPs constitute a vital aspect of optimizing ALs, aiming to mitigate imbalances that can lead to bottlenecks and diminish efficiency, thereby affecting KPIs (Hazır et al., 2015). The origins of ALBPs trace back to Salveson's pioneering work in 1955 (Salveson, 1955), with the formulation of LP models for ALs in 1961 (Halgeson & Birnie, 1961). Recognized as NP-hard COPs, trial-and-error methodologies predominated the resolution of ALBPs for many years and ALBPs involve identifying the optimal solution from a finite set of feasible solutions (FSs) (Ghorbani et al., 2024e).

ALBPs are typically categorized into two main classes: simple (SALBPs) and general (GALBPs) problems, each addressing different complexities and objectives. SALBPs focus on single-sided linear ALs with fixed operation times and usually target the optimization of one or two objectives. They are further classified into four types: Type 1 minimizes the number of workstations for a predetermined CT, Type 2 aims to minimize the CT with a fixed number of workstations, Type F evaluates the feasibility of a given combination of workstations and CT, and Type E endeavors to minimize both CT and the number of workstations simultaneously. On the other hand, GALBPs encompass more intricate configurations, including MMALBP, PALBPs, and UALBPs, presenting a broader array of challenges (Ghorbani et al., 2023).

5.2.2 Worker Assignment in Balancing Models

For the first time, Miralles et al. (2007) introduced ALWABP to optimize an AL in a Spanish sheltered work center for the disabled workers. However, the application of these problems not only for considering disabled operators but also for assessing the impact of heterogenous workers on the systems caught the attention of researchers in this field. ALWABPs are under the umbrella of the classic ALBPs, thus, they inherit some characteristics of the broader ALBP. Same as SALBP, this problem is categorized into four types of optimization problems: ALWABP-1 minimizes the number of workstations with a given CT, ALWABP-2 minimizes the CT with a fixed number of workstations, ALWABP-E finds the most efficient combination of workstations' number and CT, and ALWABP-F checks the feasibility of any combination of workstations' number and CT (Borba & Ritt, 2013).

The pioneers of ALWABP (Miralles et al., 2007) considered type 2 of these problems that tries to minimize the CT by considering fixed numbers of workstations. Then in 2008 the same research group (Miralles et al., 2008) solve this problem by an exact method based on the branch-and-bound approach. Since then, extensive studies were done on ALWABP-2 and several heuristic and meta-heuristic methods were proposed to solve these NP-hard problems including tabu-search approach (Moreira & Costa, 2009), beam search (BS) method (Blum & Miralles, 2011), and genetic algorithm (GA) (Mutlu et al., 2013). There have been several hybrid methods for solving ALWABP-2 as well such as clustering-based heuristic approach (A. A. Chaves et al., 2007), hybrid clustering algorithm and iterated local search (ILS) (Chaves et al., 2009), constructive heuristic approach via GA (Moreira et al., 2012), and two-phase variable neighborhood search (VNS) algorithm (Polat et al., 2016).

Although most of the studies in this field tried to develop solution method for ALWABP-2 instead of developing the problem model, a few authors are concerned with other types of ALs (Yener, 2022). Oksuz et al. (Oksuz et al., 2017), for example, tried to maximize the efficiency of a U-shaped line and employed an artificial bee colony (ABC) algorithm and GA to solve it. Ramezanian and Ezzatpanah (2015) considered a mix-model ALWABP-2 and solved it by GP and imperialist competitive algorithm (ICA). Moreover, 2-sided ALWABP was studied in Janardhanan et al. (2019) and a migrating birds optimization (MBO) algorithm was developed to solve the mixed-integer programming model. Some studies included another objective function in addition to minimizing CT like minimizing operation costs (Ramezanian & Ezzatpanah, 2015), labor costs (Yılmaz, 2022), and smoothness index (Zacharia & Nearchou, 2016, 2020, 2021). Furthermore, Yilmaz (2021) considered variation of setup times in Als and applied SA to solve this version of ALWABP-2.

5.2.3 Uncertainty Considerations in ALWABPs

Although considering uncertainty in these problems can offer potential solutions to enhance the efficiency and flexibility of AL operations in the face of unpredictable workforce conditions, limited numbers of studies in the field of ALWABP have considered uncertain conditions in their models. Ritt et al. (2016) considered ALWABP-2 with stochastic worker availability and tried to minimize the CT through a local search (LS) heuristics algorithm based on SA. Liu, Liu, et al. (2019) tried to optimize the same problem as Ritt et al. (2016) but for solving this problem, they considered the probability of insufficient available operators due to workforces' absenteeism. For solving this problem, they proposed a two-stage stochastic model to minimize the weighted sum of CT and penalty cost of various scenarios of insufficient operators. Liu, Liang, et al. (2019) considered stochastic task time times and developed a risk-averse ALWABP-2. They employed risk measures in the objective function and tried to minimize risk aspects in addition to minimizing CT through a sample average approximate algorithm. In their next study (Liu et al., 2022), they considered a new risk-averse problem by incorporating temporary and moving workers. They developed a two-stage stochastic programming model and solved it via a combination of GA, K-means clustering method and variable neighborhood search.

All mentioned studies applied stochastic approach to address uncertainty and assumed that probability distribution is known. However, in the real world, most of the time probability distributions are unknown, and it is hard or impossible to find and define the probability of uncertain parameters. Thus, fuzzy logic is proper approximation to employ possibility functions instead of probability distributions in these cases. For the first time, Zacharia and Nearchou (2020) considered ALWABP-2 in a fuzzy environment to minimize both fuzzy CT and fuzzy smoothness index. They employed TFNs to define the uncertainty in task times and solved it by the fuzzy multi-objective GA. Once again, in their next study (Zacharia & Nearchou, 2021), they applied fuzzy concept to manage uncertain task times in fuzzy ALWABP-2 to optimize the same objectives. However, they utilized a Pareto-based approach, and a weighted-sum based approach simultaneously to facilitate effective trade-off decision-making.

5.2.4 Ergonomics Aspects in ALWABPs

While ALWABPs are introduced to consider the differences among workforces, these variations limited to task execution time. Most of the studies in this field have tried to optimize the problem and balance the workload by considering the variation of task performing times. However, workloads are not just dependent on the time and various operators can experience different workloads for doing the same task as they have diverse physical and psychological characteristics (Ghorbani et al., 2023). Therefore, considering HF/E aspects in ALWABPs is vital, and Akyol and Baykasoğlu (2019) were the first researchers to introduce Ergo-ALWABP. They added ergonomic risk parameters to the Type2 of these problems (Ergo-ALWABP-2). Then, the proposed model was solved by integrating OCRA method to the MRBCRS algorithm (Akyol & Baykasoğlu, 2019).

After that there have been limited number of studies on this area, Ergo-ALWABP. Zhang et al. (2020) developed a U-shape Ergo-ALWABP-2 and applied restarted iterated pareto greedy algorithm (RIPGA) besides OCRA to minimize the CT and total ergonomic risks. Katiraee et al. (2021) and Katiraee et al. (2023) utilized the Borg scale, a subjective evaluation method, to classify tasks according to the perceived difficulty level for each operator based on their experience and physical effort. They applied ε-constraint approach to solve the bi-objective problem that minimized CT in addition to maximized physical effort (Katiraee et al., 2021) and minimized workload variance (Katiraee et al., 2023). Furthermore, Cimen et al. (2022) applied ergonomic consideration in the rebalancing of these problems. They proposed a goal programming based on MRBCRS approach for optimizing different objectives including minimizing rebalancing total cost, smoothness index, the ergonomic risks evaluated by OCRA, the changes in tasks, and maximizing similarity of employed workers in rebalanced line to initial line and the efficiency of the line.

ALs, positioned at the end of production processes, require flexibility to meet dynamic market requirements that are often achieved through manual tasks. Yet, these repetitive and prolonged manual tasks can result in muscle fatigue accumulation, raising concerns about WMSDs. The inclusion of fatigue and recovery models in the optimization model of these problems is crucial for understanding and mitigating muscle fatigue, thereby reducing the ergonomic risk for assembly operators, promoting their well-being, and enhancing AL efficiency in alignment with ergonomics and occupational safety principles. Katiraee et al. (2023) and Katiraee et al. (2021) were the only research group that applied the Borg scale, a subjective assessment tool for categorizing fatigue level, to evaluate operators perceived physical effort in Ergo-ALWABP literature. However, there are various applicable fatigue models that can be used in these optimization problems such as Potvin (2011), Ma et al. (2009), and so on.

5.2.5 Research Gaps in Literature

In summary, the literature review has identified several key research gaps within the field of ALWABP. This study aims to contribute to the existing body of knowledge by addressing these research gaps as follows:

- As illustrated in Table 5.1, only a limited number of studies on ALWABPs addressed uncertainty in their models (six studies out of 29 articles). Most of these (four out of six) employed stochastic programming to handle imprecise and vague parameters. However, historical data is not always available in certain cases, such as design problems. In such contexts, fuzzy programming is recognized as a beneficial alternative approach (Ghorbani et al., 2023). To the best of our knowledge, only Zacharia and Nearchou (2020) have addressed uncertainty by considering fuzzy task times. Additionally, imprecision in the inputs of EATs has been identified as influencing the results (Golabchi et al., 2016). Therefore, it is crucial to not only consider uncertainty in task execution time but also address imprecision in the outputs of EATs.

Table 5.1 Summary of previous research contributions in the ALWABP

Ref	**Problem Variant**	**Solution Approach**	**Uncertainty**	**Ergonomics**
(Miralles et al., 2007)	Type 2	Exact-IP	-	-
(A. A. Chaves et al., 2007)	Type 2	Clustering	-	-
(Miralles et al., 2008)	Type 2	B&B	-	-
(Chaves et al., 2009)	Type 2	Clustering & ILS	-	-
(Costa & Miralles, 2009)	Job rotation	MILP & heuristic	-	-
(Moreira & Costa, 2009)	Type 2	Tabu search	-	-
(Blum & Miralles, 2011)	Type 2	BS	-	-
(Moreira et al., 2012)	Type 2	GA & heuristic	-	-
(Mutlu et al., 2013)	Type 2	Iterated GA	-	-
(Borba & Ritt, 2014)	Type 2	B&B & probabilistic BS	-	-
(Vilà & Pereira, 2014)	Type F	B&B & recall algorithm	-	-
(Ramezanian & Ezzatpanah, 2015)	Mixed model Type 2	GP & ICA	-	-
(Polat et al., 2016)	Type 2	VNS	-	-
(Ritt et al., 2016)	Stochastic Type 2	MIP & SA	Worker availability	-
(Zacharia & Nearchou, 2016)	Bi-objective	GA	-	-
(Oksuz et al., 2017)	U-shape Type E	GA & ABC	-	-
(Pereira, 2018)	Robust Type 2	Exact & heuristic	Time intervals	-
(Janardhanan et al., 2019)	2sided Type 2	MBO	-	-

Table 5.1 Summary of previous research contributions in the ALWABP (continue)

Ref	**Problem Variant**	**Solution Approach**	**Uncertainty**	**Ergonomics**
(Akyol & Baykasoğlu, 2019)	Ergo Type 2	MRBCRS	-	OCRA
(Liu, Liu, et al., 2019)	Stochastic Type 2	MIP	Absenteeism risk	-
(Liu, Liang, et al., 2019)	Stochastic Type 2	MIP	Stochastic task time	-
(Zacharia & Nearchou, 2020)	Fuzzy Bi-objective	GA	Fuzzy time	-
(Zhang et al., 2020)	U-shape Ergo Type 2	RIPGA	-	OCRA
(Katiraee et al., 2021)	Bi-objective Ergo Type 2	ε-constraint	-	Borg scale
(Liu et al., 2022)	Stochastic Type 2	MIP & GA	Temporary workers	-
(Katiraee et al., 2023)	Bi-objective Ergo Type 2	ε-constraint	-	Borg scale
(Cimen et al., 2022)	Rebalancing	MRBCRS	-	OCRA
(Yener & Can, 2023)	Ergo Type 2	CPLEX	-	REBA, light, noise
This Study	Ergo Type F	Customized MRBCRS	Fuzzy time & ergo	Expert ergo rules

- A limited number of studies (six out of 29 articles) incorporated HF/E aspects into their models, as shown in Table 5.1. All existing studies on Ergo-ALWABPs employed EATs in existing lines, with approaches that are not applicable under uncertainty or during the design phase. To address the imprecision and vagueness in ergonomic aspects during the design phase, a customized EAT needs to be developed
- Although heuristic and meta-heuristic methods are commonly used to solve these optimization problems and identify near-optimum solutions, there is growing interest in hybrid approaches to achieve more effective solutions (Ghorbani et al., 2023). During the design stage, various potential scenarios can lead to different FSs. Consequently, a critical research gap exists in developing a comprehensive optimization framework that assesses trade-offs between FSs under different scenarios and provides decision-makers with the necessary data to select the most efficient solution.
- For the validation and verification of the proposed solution methods, the conventional dataset (A. Chaves et al., 2007), commonly utilized in most studies in this field, has not considered ergonomic aspects. Thus, to utilize this benchmark dataset, there is a need for synthesized data that can be applied to the validation process of Ergo-ALWABPs studies.

This paper contributes to the existing literature by addressing these research gaps. It extends the field of Ergo-ALWABP by considering uncertainty and applying fuzzy set logic to model task execution times and fatigue risk levels. A comprehensive fuzzy risk assessment method is developed, analyzing ergonomic risk aspects at the task, worker, and AL levels. The study also proposes a two-phase framework that integrates a constructive heuristic approach into a fuzzy knowledge-based system to solve the fuzzy Ergo-ALWABP-F. Furthermore, the proposed solution method is validated using benchmark datasets, demonstrating its capability to find high-quality optimum solutions within a reasonable CPU time.

5.3 Problem Formulation

This study presents the development of an Ergo-ALWABP in uncertain environments, addressing imprecise and vague data using the fuzzy logic method. The problem can be viewed as an extension of SALBP- F, aiming to find an optimal or near-optimal solution based on feasible solutions with a specific CT and a predetermined number of operators. As Table 5.1 shows, Vilà and Pereira (2014) were the only researchers who addressed Type-F of ALWABP and employed iterative partitioning of the search space into smaller subproblems and systematically exploring the solution space to identify promising solutions. However, this study specifically aims to help manufacturing systems by identifying the most ergonomically friendly solution while ensuring operational feasibility. The subsequent subsections provide a detailed explanation of the fuzzy Ergo-ALWABP- F.

5.3.1 Problem Assumptions

The following assumptions are considered to develop the desired mathematical model of the optimization problem:

- Although initial ALWABP evolved to consider disabled workers in workplaces, in some studies (Yener & Can, 2023; Zacharia & Nearchou, 2021), the presence of heterogeneous operators has been considered. In this study, it is assumed that each worker can do all tasks but with different performance levels. Hence, the task execution times are related to their skill, experiment and various personal aspects that cause vague task times in the system. To address these differences, three levels of capability are considered that results in three level of task times, like as TFNs (Zacharia & Nearchou, 2020). Therefore, each task has three different possible execution times: minimum, average, and maximum time.
- In this problem, there are several scenarios for planning AL based on market conditions and demand variations. Thus, in each scenario, there are specific number of workers and an acceptable fuzzy CT. These two parameters act as constraints in the developed optimization model with the objective of finding the maximum ergonomic score while minimizing the total ergonomic risk level.
- Initially, each task has a specific ergonomic risk level, defined as task level risks. However, at worker level, risks depend on the worker who performs the set of tasks. Since the duration of executing the task can vary for various operators, they might experience diverse levels of fatigue and as a result, they can be exposed to different levels of ergonomic risks. To address the vagueness and imprecise ergonomic risks in worker level, fuzzy rules are extracted through a knowledge-based system.

5.3.2 Problem Notations

Sets & Indexes:

N Set of tasks

  i,j Indices for tasks: $i,j \in \{1, \ldots, n\}$

W Set of works

  k,l Indices for workstations: $k,l \in \{1, \ldots, m\}$

IP_i Set of immediate predecessors of task i

P_i Set of predecessors of task i

IF_i Set of immediate successors of task i

F_i Set of successors of task i

Parameters:

n Number of tasks

m Number of workstations (workers)

t_{ki} Task time when worker k executes task i

r_{ki} Ergonomic risk factor of task i when worker k executes it

CT Cycle time

Decision variables:

x_{ki} Binary variable, if task i is assigned to worker k, it will be equal to 1 otherwise 0

y_{kl} Binary variable, if worker k must precede worker l, it will be equal to 1 otherwise 0

Miralles et al. (2008) initially formulated the mathematical model for ALWABP-2. Their primary model, like many others in the field, considers the sequential assignment of tasks to workstations and the allocation of workers to those workstations. Borba and Ritt (2014) later proposed a MIP model for the same problem, directly assigning tasks to workers. Their MIP model mitigated the complexity of the problem hugely, and more efficient solutions were found through it.

While the literature review emphasizes type 2 balancing models in ALWABPs, aiming to minimize the CT while considering a fixed number of workers, this research focuses on minimizing ergonomic risks based on a determined CT and a fixed number of workers. Consequently, the problem model in this study is an Ergo-ALWABP-F that aims to determine the best task assignment while minimizing ergonomic risk. The proposed model's constraints align with the model developed in Borba and Ritt (2014) since workers under uncertain conditions can be treated as workstations. Thus, the initial optimization model of this paper is as follows:

$$Min \sum_{i \in N} x_{ki} \,.\, r_{ki} \tag{5.1}$$

Subject to:

$$\sum_{k \in W} x_{ki} = 1 \qquad \forall i \in N \tag{5.2}$$

$$y_{kl} \geq x_{ki} + x_{lj} - 1 \qquad \forall\, i \in P_j | k, l \in W \tag{5.3}$$

$$y_{kq} \geq y_{kl} + y_{lq} - 1 \qquad \forall\, k, l, q \in W, |\{k, l, q\}| = 3 \tag{5.4}$$

$$y_{kl} + y_{lk} \leq 1 \qquad \forall\, k \in W, l \in W \backslash \{k\} \tag{5.5}$$

$$\sum_{i \in N} x_{ki} . t_{ki} \leq CT \qquad \forall\, k \in W \tag{5.6}$$

$$x_{ki} \in \{0,1\} \quad \forall\, k \in W;\ \forall\, i \in N \tag{5.7}$$

$$y_{kl} \in \{0,1\} \quad \forall\, k \in W, l \in W \backslash \{k\} \tag{5.8}$$

$$t_{ki} \geq 0 \quad\ r_{ki} \geq 0 \qquad \forall\, i, k \in N \tag{5.9}$$

In equation (5.1), the objective function minimizes the total ergonomic risks to which the workers are exposed. Constraint (5.2) ensures that each task i is assigned to only one operator. Equation (5.3) defines dependencies between operators based on the precedence relations between tasks. Constraints (5.4) and (5.5) ensure that operator dependencies adhere to the principles of transitivity and anti-symmetry, resulting in operators being allocated in a linear order within every feasible solution. Equation (5.6) verifies that the total workers' operation time does not exceed the CT. Equations (5.7) and (5.8) indicate that decision variables x_{ki} and y_{kl} are binary variables. Finally, the last equation states that task time and ergonomic risk are positive numbers.

5.3.3 Fuzzy Problem Definition

This study considers a set of workers with diverse characteristics (heterogeneous workers) such as gender, physical capabilities, expertise, age, etc. However, during the design stage, these differences are unspecified, and the operators to be allocated to the assigned tasks are unknown. This imprecise and uncertain condition influences task execution times and the ergonomic risks faced by each worker. To handle the uncertainty in both aspects, fuzzy logic is employed. Thus, the task time (t_{ki}) and ergonomic risk parameters (r_{ki}) can be defined as fuzzy numbers and presented as $\tilde{t}_i$ and $\tilde{r}_i$, respectively. As a result, Equation 1 and 6 are changed and would be written as Equation (5.10) and (5.11).

$$\text{Min} \sum_{i \in N} x_{ki} \, . \, \tilde{r}_i \tag{5.10}$$

$$\sum_{i \in N} x_{ki} . \, \tilde{t}_i \leq \widetilde{CT} \quad \forall \, k \in W \tag{5.11}$$

Consequently, Equation (5.9) which defines these two fuzzy parameters is eliminated and they are explained in the subsequent subsections.

5.3.3.1 Fuzzy Task Time

By considering three skill levels for workers (high, average, and low skilled), the execution time for each task can be defined as a triplet: (t_{min}, t_{avg}, t_{max}). Consequently, the fuzziness of task times is represented by TFNs. Equation (5.12) and Figure 5.2 illustrate the membership function of task time.

$$\tilde{t} = \begin{cases} \dfrac{t - t_{min}}{t_{avg} - t_{min}} & if \ t_{min} < t \leq t_{avg} \\ \dfrac{t_{max} - t}{t_{max} - t_{avg}} & if \ t_{avg} < t \leq t_{max} \\ 0 & if \ t < t_{min} \ or \ t_{max} < t \end{cases} \tag{5.12}$$

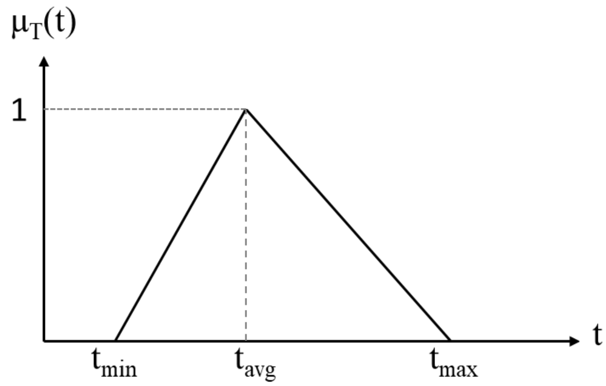


Figure 5.2 The membership function of each task execution time

5.3.3.2 Fuzzy Ergonomic Aspects

In manufacturing systems, particularly those that rely heavily on human operators, it is common to allocate different operators to various operations. As previously mentioned, it is worth noting that even when workers are performing the same task, the ergonomic risks they face can differ due to variations in their individual characteristics. This imprecision in the inputs of EATs can impact the obtained results (Ghorbani et al., 2024e). In this study, the uncertainty in EAT results is addressed by employing fuzzy rules generated through a fuzzy expert system. In this paper, ergonomic aspects are assessed in three levels:

Task level: In this phase, it is assumed that each task is evaluated using a fatigue model among all available fatigue and recovery models in ergonomics literature. Then the output of the selected fatigue model is categorized into three risk levels like a traffic light system. Green represents low risk, yellow indicates medium risk, and red signifies high risk.

- Worker level: in the second step, ergonomic risk is evaluated by considering the cumulative risk of several tasks assigned to each operator. Due to the variability of task times which results in uncertainty regarding accurate risk levels, four levels of risk: low, minor, medium, and high are proposed. It should be noted that these ergonomic risk levels are determined based on the ergonomic interventions necessary to mitigate the risk of MSD occurrence. Consequently, assignments with high-risk levels require more substantial investments of time and resources to implement ergonomic interventions (preventive actions or redesign process) that effectively mitigate the associate risks compared to assignments with medium or minor risk levels. Similarly, assignments with medium-risk levels require more investment than those with minor-risk levels for implementing appropriate ergonomic interventions.

- AL level: In the final part of considering ergonomics in the optimization problem, the aim is to rank various operationally feasible assignments to identify the combination of assignments that result in the minimum ergonomic risks, thus requiring the least number of ergonomic interventions.

To address the uncertain conditions in ergonomic aspects, fuzzy logic through a fuzzy knowledge-based system is utilized. The subsequent section provides a detailed explanation of the algorithm used to solve this optimization problem.

5.4 Proposed Solution Algorithm

This section explains the algorithm for solving the fuzzy Ergo-ALWABP-F problem discussed in the previous section. To enhance comprehension, the solution methodology is explained in two parts in the following subsections. The first part focuses on generating feasible solutions (FSs) based on operational considerations such as desired takt time, the number of operators, and precedence relationships between tasks. Subsequently, the ergonomics aspects of these solutions are evaluated using a set of fuzzy rules developed by ergonomic experts and practitioners. The detailed flowchart of the proposed solution method is depicted in Figure 5.3.

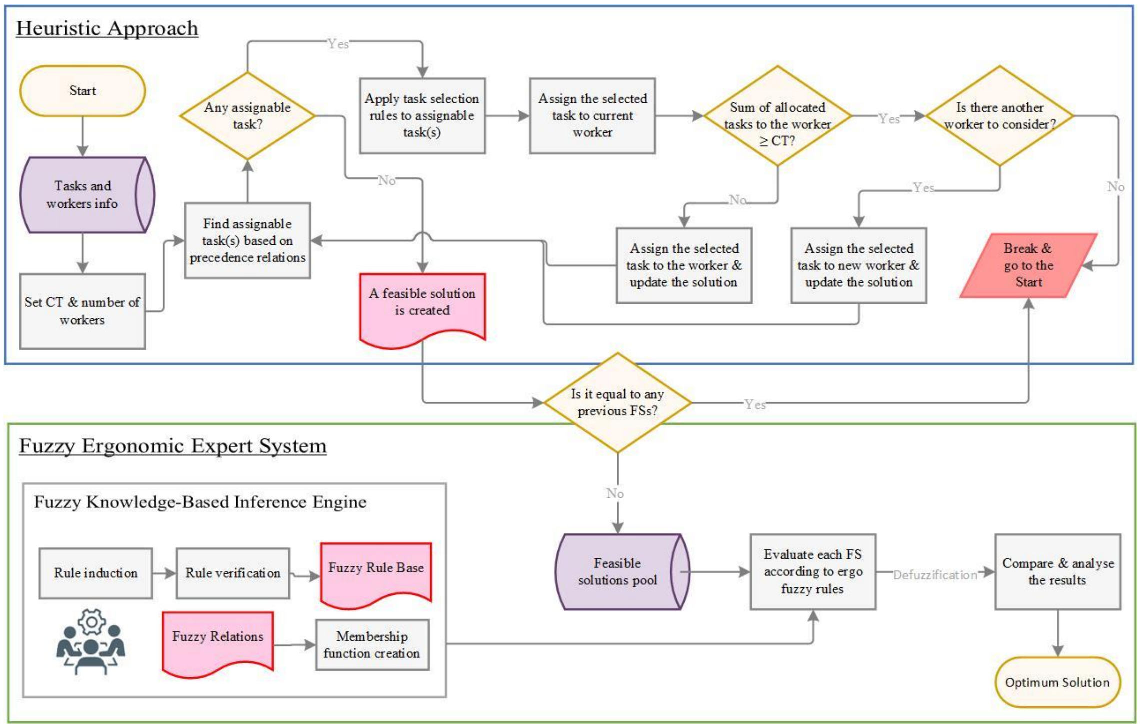


Figure 5.3 Flowchart of the proposed solution for fuzzy Ergo-ALWABP-F

5.4.1 Feasible Solutions (FSs)

In the initial stage of the solution, the aim is to identify feasible task assignments by accounting for operational constraints and considerations. As stated in the mathematical model, the constraints in the optimization problem consist of the precedence relationships between tasks, the number of workers, and the desired CT. To explore and test all possible task assignment sequences, various task priority rules (selected from rules proposed in Akyol and Baykasoğlu (2019)) are employed, as shown in Table 5.2. However, since the task times are represented as TFNs, some adjustments are necessary to compare different assignable tasks:

- For rules that involve t_i in their formulas (rule No.1-10 in Table 5.2), minimum, average, and maximum task times are considered separately in iterations.
- Additionally, the fuzzy task times are defuzzified using the centroid method ($C(\tilde{t}) = 1/3(t_{min}+t_{avg}+t_{max})$) and the distance method ($D(\tilde{t}) = 1/4(t_{min}+2t_{avg}+t_{max})$) (Yao & Chiang, 2003). These two defuzzified values are then employed in other iterations to apply all rules that include t_i in their formulas, allowing exploration of potential new solutions.

- For setting the desired CT at the start of the solution approach, the centroid method is employed, as it is sufficient for most applications (MathWorks, 2023). Thus, the initial point is the ideal CT (CT*), calculated using Equation (5.13). By incrementing α in CT = CT*+ α through trial and error, the desired CT can be determined.

$$CT^* = \left\lceil \sum_{i \in N} C(\tilde{t}_i)/n \right\rceil \tag{5.13}$$

- To assure that there is no more FS, rule No.14 is run 1000 times in order to find any other different FS.

Table 5.2 Task priority rules for task selection step in feasible solution searching process

No.	**Rules**	**Formulas**
1	Longest processing time	Max t_i
2	Shortest processing time	Min t_i
3	Greatest ranked positional weight	Max $(t_i + \sum_{j \in IF_i} t_j)$
4	Greatest average ranked positional weight	Max $(t_i + \sum_{j \in IF_i} t_j)/(\lvert IF_i \rvert + 1)$
5	Smallest bound	Min $(t_i + \sum_{j \in IF_i} t_j)/CT$
6	Greatest bound	Max $(t_i + \sum_{j \in IF_i} t_j)/CT$
7	Smallest bound divided by #successors	Min $((t_i + \sum_{j \in IF_i} t_j)/CT)/(\lvert IF_i \rvert + 1)$
8	Greatest bound divided by #successors	Max $((t_i + \sum_{j \in IF_i} t_j)/CT)/(\lvert IF_i \rvert + 1)$
9	Smallest processing time divided by the bound	Min $t_i/((t_i + \sum_{j \in F_i} t_j)/CT)$
10	Greatest processing time divided by the bound	Max $t_i/((t_i + \sum_{j \in F_i} t_j)/CT)$
11	Smallest task number	Min i
12	Greatest number of immediate successors	Max $\lvert IF_i \rvert$
13	Greatest number of immediate predecessors	Max $\lvert IP_i \rvert$
14	Random priority	-

The pseudo-code for this stage of the proposed solution approach is presented in Figure 5.4. Once several FSs are obtained based on operational aspects such as takt time, the number of workers, and precedence relations, ergonomic assessment rules need to be generated to identify the best solution that minimizes the ergonomic risk throughout the AL.

```
Procedure: Rule-based task assignment method
Input: The set of tasks and workers
Output: Feasible solutions
BEGIN
Create a list of "unassigned tasks" and a list of "unassigned workers"
Create two empty lists: "assigned tasks" and "assigned workers"
Set CT = CT* + α (start with α=0)
FOR each rule in the set of "task assignment rules":
    WHILE list of unassigned tasks ≠ Ø:
        Create an "assignable tasks" list by considering precedence relations
        Select a task from the "assignable tasks" list by applying the current rule
        FOR each worker in the "unassigned workers" list:
            IF the total execution time of assigned tasks to this worker + selected task's time ≥ CT:
                Remove this worker from the "unassigned workers" list & Add it to the "assigned workers" list
            ELSE:
                Assign the selected task to the current worker & Update the "assigned tasks" and "unassigned tasks" lists
                BREAK (exit the FOR loop)
        IF the selected task is still in the "unassigned tasks" list:
            Print: "The current rule cannot find any feasible solution with this CT"
    CONTINUE (continue the FOR loop)
    END WHILE
```

Figure 5.4 Pseudo code of the rule-based task assignment algorithm

5.4.2 Ergonomic Evaluation of Solutions

In this phase, an expert system was utilized to generate fuzzy rules based on the knowledge of ergonomic experts to interpret the possible cumulative ergonomic risks for each worker. Fuzzy rules are "If…, Then…" statements that evaluate specific conditions to derive conclusions using fuzzy logic. To interpret the potential risk at the worker level, the current analysis considered the accumulation of fatigue, focusing on the interplay between the task's risk level and the duty cycle, which represents the proportion of time allocated to each task within a given CT. This approach provides valuable insights for interpreting assembly tasks that involve repetitive and prolonged activities.

Given that different workers may perform the same tasks for varying durations (referred to as fuzzy task times), leading to diverse fatigue levels, a methodology was developed to evaluate risk based on the set of tasks assigned to each worker. Consequently, fatigue levels are estimated through fuzzy logic for each task set. As a result, a set of fuzzy rules was devised to compare each task against all the tasks an operator must undertake in each CT. This methodology dictates that within each cycle, a worker should allocate a limited percentage of time to executing high-risk tasks to prevent excessive fatigue exposure. Conversely, tasks with lower fatigue levels, considered low risk, can help mitigate cumulative risk levels. To operationalize this logic, five time-based fuzzy rules were established, drawing upon the collective ergonomic expertise of a panel of experts, to comprehensively interpret and assess cumulative ergonomic risks at the worker level.

In this fuzzy expert system, the identification of primary thresholds is crucial and relies on the valuable insights contributed by ergonomist experts. These thresholds serve as the foundation for formulating appropriate fuzzy rules, allowing us to predict potential ergonomic risk levels among workers. Consequently, the two primary thresholds are presented as follows:

- X= Minimum percentage of operation time allocated to low-risk tasks that can mitigate the risk.
- Y = Maximum acceptable percentage of a CT devoted to executing high-risk tasks.

Based on these assumptions, the following fuzzy rules are employed for each worker to predict their possible ergonomic risk level:

- Rule1: If there are no high-risk tasks among the assigned tasks, and the cumulative execution time of medium-risk tasks exceeds X% of the CT, then the worker is exposed to medium risk (orange).
- Rule2: If there are no high-risk tasks among the assigned tasks, and the cumulative execution times of low-risk tasks exceed X% of the operation time, then the worker is exposed to low risk (green).
- Rule3: If the cumulative execution time of high-risk tasks exceeds Y% of the CT, then the worker is exposed to high risk (red).
- Rule4: If the cumulative execution time of high-risk tasks falls between 0 and Y% of the CT, and the cumulative execution time of low-risk tasks exceeds X% of the operation time, then the worker is exposed to minor risk (yellow).
- Rule5: If the cumulative execution time of high-risk tasks falls between 0 and Y% of the CT, but the cumulative execution time of low-risk tasks is less than X% of each operation time, then the worker is exposed to medium risk (orange).

In these fuzzy rules, the percentage of low-risk task times in the worker's operation time is considered, while accounting for the percentage of medium-risk and high-risk tasks in each CT.

This approach is chosen because the operation time is always equal to or less than the CT. When a worker's operation time is less than the CT, it means that they have some time to rest in each cycle, which can be considered a zero-risk task.

As previously mentioned, this study assesses workers' risk levels by considering the ergonomic interventions required to mitigate potential risks of MSDs and future possible injuries. Therefore, in the final ergonomic evaluation of AL, assignments resulting in low risk at the worker level are deemed the most desirable (score of 1), while assignments exposing workers to high risk are considered the least desirable (score of 0). Minor-risk and medium-risk assignments can receive scores of MI and ME, respectively. MI and ME are values ranging from zero and one that represent the partial desirability of minor-risk and medium-risk assignments in each FS. Equation (5.14) is employed to calculate the final ergonomic score for each FS:

$$ErgoScore = \frac{(\#low \times 1) + (\#minor \times MI) + (\#medium \times ME) + (\#high \times 0)}{\#workers} \tag{5.14}$$

Figure 5.5 outlines the pseudo-code for applying the fuzzy rules to FSs and identifying the optimal solution with the highest ergonomic score. In the next section, computational experiments will be conducted to evaluate the proposed solution method using a set of well-known benchmark instances.

```
Procedure: Fuzzy rule-based method for ergonomic evaluation
Input: Feasible solutions
Output: Optimum solution
BEGIN
Take a list of feasible solutions
FOR each feasible solution:
    FOR each worker in this feasible solution:
        Calculate the percentage of time for doing tasks in each CT
        Calculate the cumulative percentage of time for tasks in each risk level (t_low, t_medium, t_high)
        IF t_high = 0 & t_medium > X% of CT:
            The worker risk level = "Medium"
        ELIF t_high = 0 & t_medium < X% of CT & t_low ≥ X% of operation time:
            The worker risk level = "Low"
        ELIF t_high > Y% of CT:
            The worker risk level = "High"
        ELIF 0 < t_high < Y% of CT & t_low ≥ X% of operation time:
            The worker risk level = "Minor"
        ELIF 0 < t_high < Y% of CT & t_low < X% of operation time:
            The worker risk level = "Medium"
        Add the worker risk level to the set of "FS workers risk"
    Calculate the Ergo-Score for each FS and select the maximum as the best solution
END FOR
```

Figure 5.5 Pseudo-code of the fitness evaluation by fuzzy expert system

5.5 Numerical Experiments

In light of the discussions presented earlier, insights obtained from prior research studies, and the valuable contributions of ergonomist experts, specific thresholds and parameters have been assumed for the solution algorithm applied to numerical instances: X=50%, Y=20%, MI=0.6, and ME=0.3. Hence, the decision tree related to the fuzzy ergonomic rules at all levels can be visualized in Figure 5.6. Before delving into the implementation of the proposed algorithm on benchmark dataset, an illustrative small-scale numerical example is provided to effectively explain the solution approach.

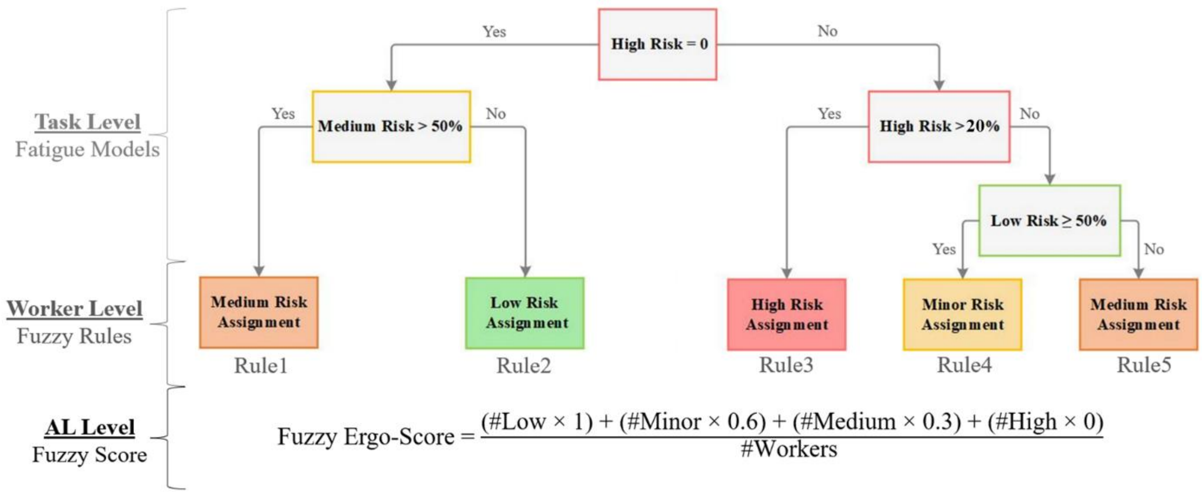


Figure 5.6 Decision tree of the proposed fuzzy knowledge-based system for ergonomic evaluation

5.5.1 Small-scale Numerical Example

To provide further explanation on the proposed solution method, consider the following small-scale numerical example. As depicted in Figure 5.7, this sample is an AL consisting of 10 tasks represented as nodes, with their precedence relationships illustrated as arcs. Additionally, fuzzy execution times are indicated either above or below the nodes, while task risk levels are denoted by three colors: green, yellow, and red which correspond to low, medium, and high risks, respectively.

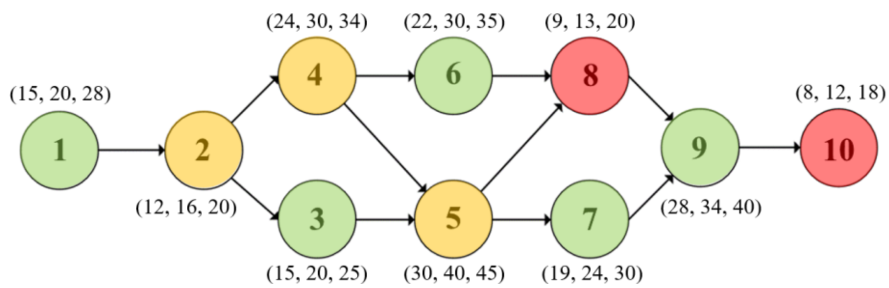


Figure 5.7 Precedence network of a sample assembly tasks

In this problem, the desired fuzzy CT is set as (48, 70, 84), and there are four workers to allocate to the workstations. If there are two feasible solutions, as outlined in Table 5.3, the risk level for each worker can be determined based on the fuzzy rules presented in the decision tree in Figure 5.6. To calculate the percentage of the time the worker executes each task in one cycle, centroid method could be employed to defuzzify the task time and final CT of each solution.

For example, in the first solution, for worker 1, there are no high-risk tasks, and the worker allocates less than 50% of the CT to medium-risk tasks. Consequently, based on the second fuzzy rule, the worker's risk level is classified as low. Conversely, in the second solution, for worker 1, the cumulative execution time of medium-risk tasks surpasses 50% of the CT, leading to a medium risk classification in accordance with the first fuzzy rule.

Table 5.3 Comparison of two feasible solutions based on fuzzy assessment method

Workers	**Solution1**	**Risk Level**	**Solution2**	**Risk Level**
W1	Tasks 1,2,3	R2: Low	Tasks 1,2,4	R1: Medium
W2	Tasks 4,6	R2: Low	Tasks 3,6	R2: Low
W3	Tasks 5,8	R5: Medium	Tasks 5,7	R1: Medium
W4	Tasks 7,9,10	R4: Minor	Tasks 8,9,10	R3: High
Fuzzy Ergo-Score		0.725		0.4

After finding the risk level for each worker based on the fuzzy rules, the fuzzy Ergo-Score of each FS can be calculated to compare them and identify the more desirable solution. For solution1, the Ergo-Score is computed as follows: $((2\times1) + (1\times0.6) + (1\times0.3))/4 = 0.725$, whereas for solution2, it is calculated as $((1\times1) + (2\times0.3) + (1\times0))/4 = 0.4$. As a result, solution1 exhibits a superior ergonomics level compared to solution2. Even in this small-scale problem, there is a noticeable variation between feasible balancing solutions. Thus, it becomes evident that applying this fuzzy approach can be instrumental in identifying superior ergonomic solutions across all practically feasible options.

5.5.2 Benchmark Testing Dataset

In this study, several experiments were conducted using the well-known ALWABP benchmark dataset (A. Chaves et al., 2007). Akyol and Baykasoğlu (2019) were the first researchers to consider ergonomic aspects in this dataset. They randomly selected three of 27 samples of ergonomic parameters that were proposed in (Otto & Scholl, 2011) for SALBP-1 dataset and used the OCRA score to evaluate ALWABP-2. In comparison to their study, the present research contributes by considering ALWABP-F under uncertainty and employing a knowledge-based system to generate fuzzy rules that can be applied to the output of any fatigue model with converting their results into three risk levels like a traffic light indicator.

To the best of our knowledge, there is no existing research that has specifically synthesized ergonomic parameters for the ALWABP benchmarks proposed in (A. Chaves et al., 2007). Therefore, in this study, ergonomic risks in task level are synthesized to enable the evaluation of proposed model on instance problems. To prepare the dataset and implement the proposed solution algorithm to find optimum solutions, some modifications were made. The original ALWABP benchmark dataset contains four families of instances, each with a constant number of tasks (#tasks) and predetermined precedence relations between them. Each family contains eight groups of numerical examples, with each group including 10 samples with varying task times. As a result, the original dataset comprises 320 test instances (4 families × 8 groups × 10 samples). The following adjustments are considered to prepare the dataset for implementing the solution method on it:

- Task times: Although task times vary between groups, the range of task times within each group is mostly uniform. Therefore, in this implementation, each group is considered as a unique sample and determines fuzzy task times by considering the time variability for each task. Thus, for each task in each group, the fuzzy task time ($\tilde{t}_i$) is represented as ($t_{i\text{-min}}$, $t_{i\text{-avg}}$, $t_{i\text{-max}}$), as explained in section 5.3.3.1.
- Number of workers: Another characteristic of this dataset is the number of workers (#workers). In each family of problems, the first half of the groups have a different and lower number of workers compared to the last four groups of the same family. To account for and test the impact of these variations, three different numbers of workers are considered as different scenarios within each family. This variation allows us to evaluate the proposed solution algorithm for ALWABP-F in different combinations of determined CT and number of workers. Table 5.4 presents the customized dataset.
- Ergonomic factor: For synthesizing ergonomic parameters for benchmark instances, a normal distribution was employed to generate numbers in the range of [0,100] for all tasks in each group. Tasks with a number lower than 50 are considered low risk (green), those in the range of 50 to 80 are considered medium risk (yellow), and those above 80 are considered high risk (red).

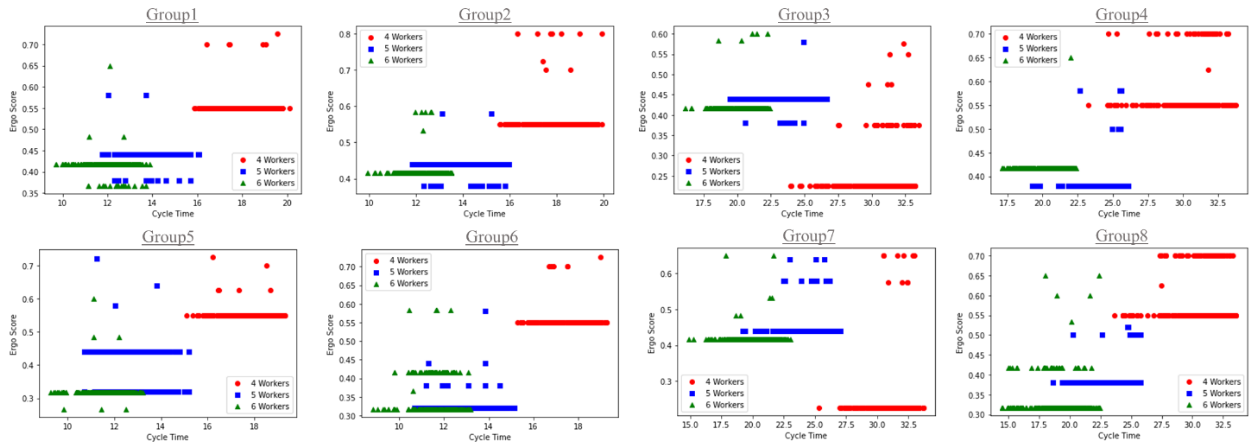
After preparing the dataset, the solution method is implemented to solve all 96 sample problems (4 families × 8 groups × 3 scenarios). The proposed heuristic algorithm was coded using Python version 3.10. Then synthesized numerical experiments were conducted on a Core i3 3.00 GHz CPU and 20 GB RAM, with the Windows 11 OS. Figure 5.8 illustrates the output of all iterations for comparison purposes. In the next section, the results are discussed to validate the solution method.

Table 5.4 Characteristics of ALWABP benchmark dataset

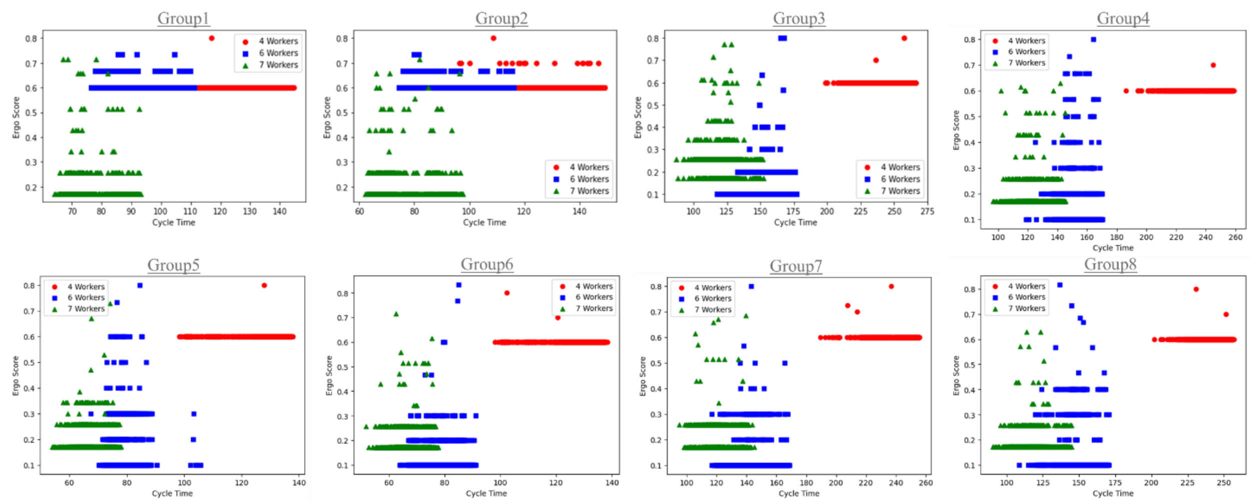
Family	**#tasks**	**#workers** (initial)	**#workers** (scenarios)
Roszieg	25	4 or 6	4, 5, and 6
Heskia	28	4 or 7	4, 6, and 7
Tonge	70	10 or 17	10, 13, and 17
Wee-Mag	75	11 or 19	11, 15, and 19

5.6 Results & Discussion

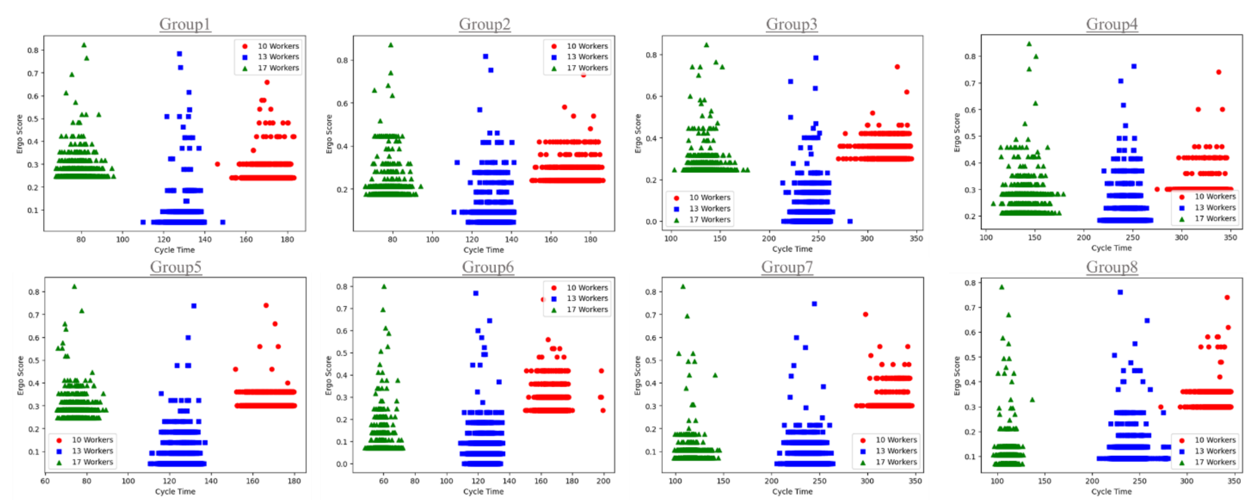
All 96 synthesized benchmark numerical examples were run on a reasonable CPU time, minimum average 55 seconds for the smallest problems (first scenarios of the Roszieg family) and maximum average 250 seconds for the biggest problems (third scenarios of the Wee Mag family). Table 5.5 presents the optimum results obtained by the proposed solution method. In the next subsections the results are analyzed and discussed.



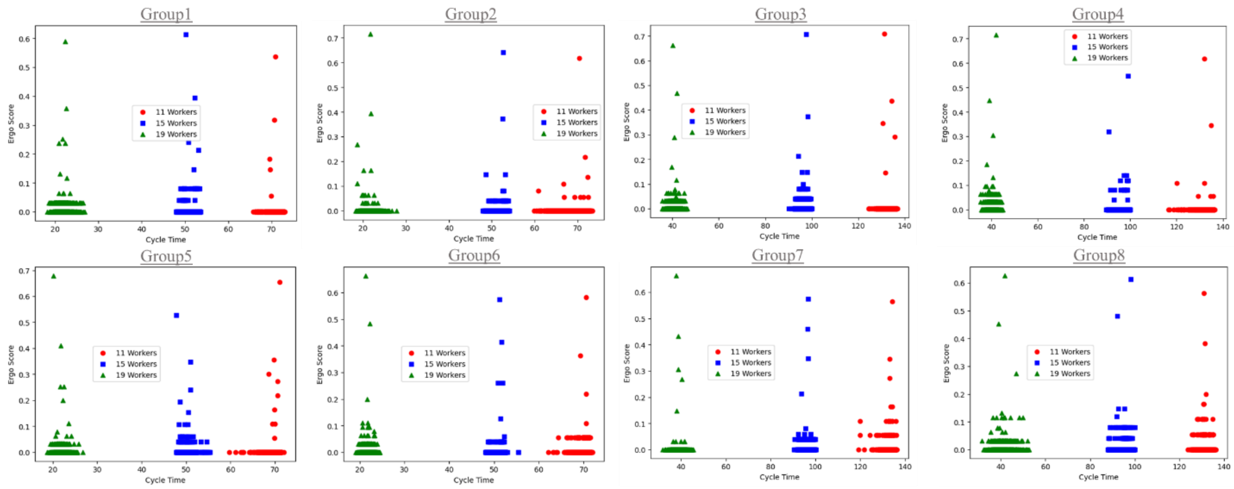
(a) Roszieg family instances



(b) Heskia family instances



(c) Tonge family instances



(d) Wee-Mag family instances

Figure 5.8 The output of optimization algorithm on synthesized ALWABP benchmark instances

5.6.1 Result Discussion

Results obtained from the numerical experiments show the high quality of solutions. For analyzing the final outputs of the optimization method, several key performance indicators (KPIs) are defined including percentage of low-risk and high-risk assignments in each optimum solution, and ergonomic scores of them. Then following results are the conclusion of measuring these KPIs:

- 75% of optimum solutions (72 out of 96 samples) includes less than 20% of high-risk assignments.
- 60% of optimum solutions (58 out of 96 samples) includes more than 50% of low-risk assignments.
- While ergonomic scores of all optimum solutions are more than 50%, 57% of them are greater than 70%.
- On average 50% of each optimum solution consists of low-risk assignments, and 13% of them includes high-risk assignments.

Figure 5.9 illustrates the distribution of various risk levels in the optimum solutions of each family, and Table 5.6 presents the comparison of various KPIs for all families.

Table 5.5 Results of proposed heuristic model for fuzzy Ergo-ALWABP instances

Family	Group	#worker	$CT_{centroid}$	$CT_{distance}$	#Low	#Minor	#Medium	#High	ErgoScore
Roszieg	1	4	19.57	20.19	2	1	1	0	0.725
		5	13.72	14.82	2	1	1	1	0.58
		6	12.11	12.75	3	1	1	1	0.65
	2	4	18.97	19.81	2	2	0	0	0.8
		5	13.09	14.47	2	1	1	1	0.58
		6	12.22	12.86	2	2	1	1	0.58
	3	4	32.38	32.35	2	0	1	1	0.575
		5	24.94	25.23	2	1	1	1	0.58
		6	21.09	21.22	3	0	2	1	0.6
	4	4	30.24	30.19	1	3	0	0	0.7
		5	25.53	25.62	2	1	1	1	0.58
		6	21.99	21.83	3	1	1	1	0.65
	5	4	16.21	17.56	2	1	1	0	0.725
		5	11.23	13.23	3	1	0	1	0.72
		6	11.11	11.88	3	0	2	1	0.6
	6	4	18.99	19.46	2	1	1	0	0.725
		5	13.86	14.61	2	1	1	1	0.58
		6	11.69	12.22	2	2	1	1	0.58
	7	4	32.12	31.98	2	1	0	1	0.65
		5	22.99	23.19	2	2	0	1	0.64
		6	17.85	18.61	3	1	1	1	0.65
	8	4	30.58	30.50	1	3	0	0	0.7
		5	24.70	24.83	2	0	2	1	0.52
		6	18.01	19.10	3	1	1	1	0.65

Table 5.5 Results of proposed heuristic model for fuzzy Ergo-ALWABP instances (continue)

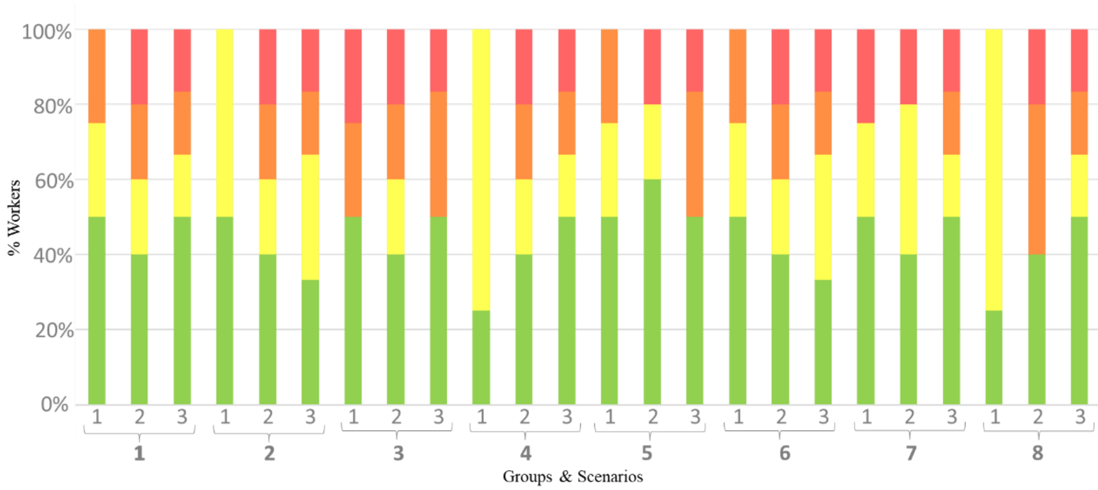
Family	Group	#worker	$CT_{centroid}$	$CT_{distance}$	#Low	#Minor	#Medium	#High	ErgoScore
Heskia	1	4	116.92	129.85	2	2	0	0	0.8
		6	86.96	94.21	2	4	0	0	0.73
		7	68.62	76.18	2	5	0	0	0.71
	2	4	108.73	126.93	2	2	0	0	0.8
		6	79.78	90.23	2	4	0	0	0.73
		7	81.89	86.36	2	5	0	0	0.71
	3	4	257.21	257.74	2	2	0	0	0.8
		6	165.33	167.69	3	3	0	0	0.79
		7	122.70	125.39	3	4	0	0	0.77
	4	4	244.78	248.26	1	3	0	0	0.7
		6	164.09	165.9	3	3	0	0	0.79
		7	142.04	143.10	2	3	2	0	0.63
	5	4	127.75	132.89	2	2	0	0	0.8
		6	84.54	86.42	3	3	0	0	0.79
		7	74.02	76.54	3	3	1	0	0.73
	6	4	102.24	115.36	2	2	0	0	0.8
		6	88.32	88.32	5	0	0	1	0.8
		7	62.57	67.36	2	5	0	0	0.71
	7	4	236.71	235.62	2	2	0	0	0.8
		6	143.11	147.66	3	3	0	0	0.79
		7	139.44	140.59	3	2	2	0	0.68
	8	4	230.64	231.99	2	2	0	0	0.8
		6	136.80	139.95	4	1	1	0	0.82
		7	123.46	126.42	2	4	0	1	0.63

Table 5.5 Results of proposed heuristic model for fuzzy Ergo-ALWABP instances (continue)

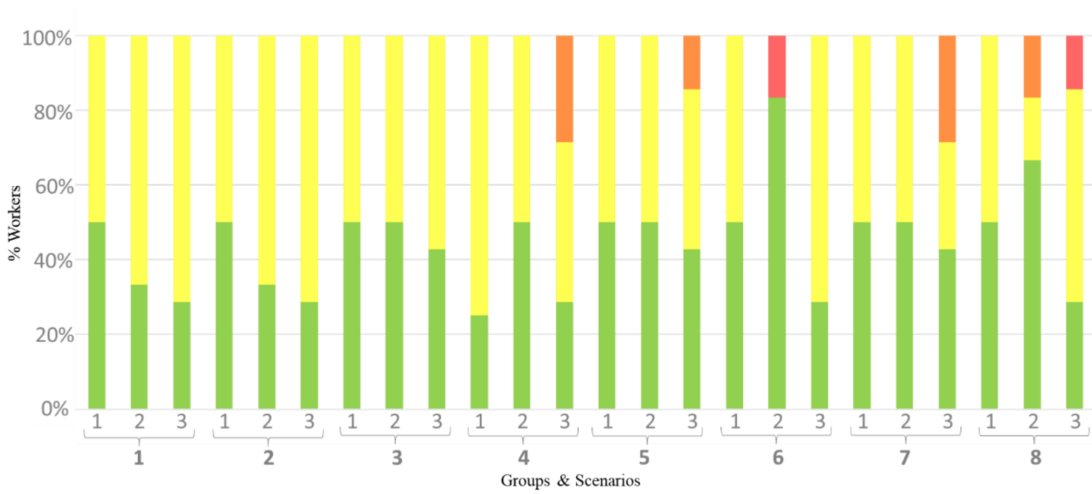
Family	Group	#worker	$CT_{centroid}$	$CT_{distance}$	#Low	#Minor	#Medium	#High	ErgoScore
Tonge	1	10	170.04	172.48	3	6	0	1	0.66
		13	127.66	132.66	6	7	0	0	0.78
		17	81.34	81.54	11	5	0	1	0.82
	2	10	176.38	179.54	4	5	1	0	0.73
		13	126.93	130.61	7	6	0	0	0.82
		17	78.87	80.57	13	3	0	1	0.87
	3	10	329.97	331.30	5	4	0	1	0.74
		13	247.24	250.63	6	7	0	0	0.78
		17	136.08	133.79	12	4	0	1	0.85
	4	10	337.76	339.03	5	4	0	1	0.74
		13	250.97	255.00	6	6	1	0	0.76
		17	143.78	141.94	12	4	0	1	0.847
	5	10	166.26	168.20	5	4	0	1	0.74
		13	131.61	133.53	6	6	0	1	0.74
		17	74.02	73.52	11	5	0	1	0.82
	6	10	161.47	168.59	5	4	0	1	0.74
		13	118.65	123.35	7	5	0	1	0.77
		17	60.18	60.37	10	6	0	1	0.79
	7	10	297.82	300.45	4	5	0	1	0.7
		13	244.48	244.60	7	4	1	1	0.75
		17	107.56	109.56	11	5	0	1	0.82
	8	10	341.89	340.44	5	4	0	1	0.74
		13	229.31	237.14	6	6	1	0	0.76
		17	104.26	106.22	10	5	1	1	0.78

Table 5.5 Results of proposed heuristic model for fuzzy Ergo-ALWABP instances (continue)

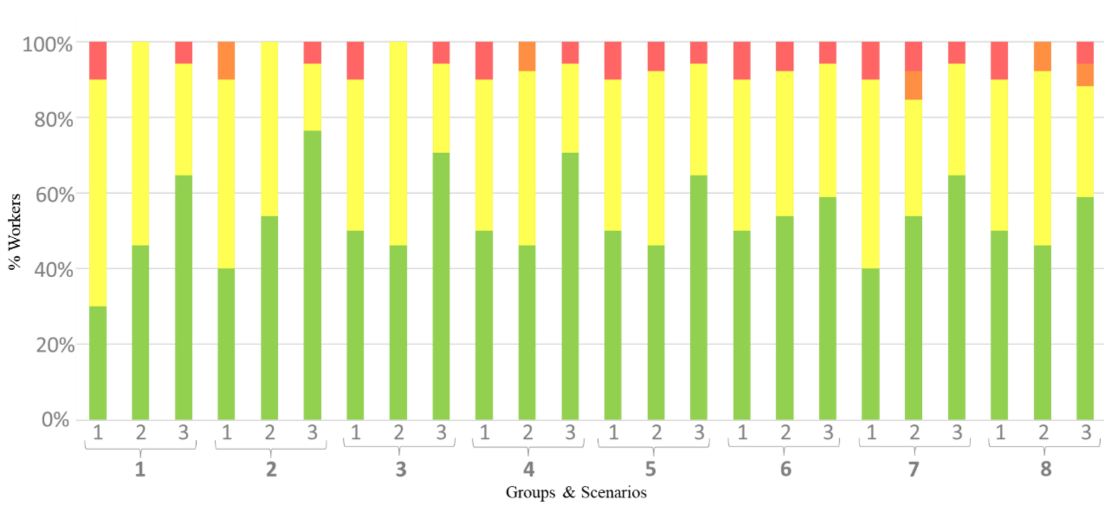
Family	Group	#worker	$CT_{centroid}$	$CT_{distance}$	#Low	#Minor	#Medium	#High	ErgoScore
Wee-Mag	1	11	70.82	71.71	5	1	1	4	0.54
		15	50.17	51.27	8	1	2	4	0.61
		19	22.33	22.47	10	1	2	6	0.59
	2	11	70.40	72.06	5	3	0	3	0.62
		15	52.58	53.19	9	1	0	4	0.64
		19	21.69	21.64	13	1	0	5	0.72
	3	11	131.33	131.13	6	3	0	2	0.71
		15	97.60	97.16	10	1	0	4	0.71
		19	40.09	40.51	12	1	0	6	0.66
	4	11	132.04	131.84	5	3	3	0	0.62
		15	98.96	98.34	7	2	0	6	0.55
		19	41.89	41.10	13	1	0	5	0.72
	5	11	71.04	71.23	6	2	0	3	0.65
		15	47.79	49.35	7	1	1	6	0.53
		19	20.18	21.16	12	1	1	5	0.68
	6	11	70.54	70.75	4	4	0	3	0.58
		15	51.25	51.84	8	1	0	6	0.57
		19	21.38	22.28	12	1	0	6	0.66
	7	11	134.18	133.70	5	2	0	4	0.56
		15	96.68	96.29	8	1	0	6	0.57
		19	37.88	38.52	12	0	2	5	0.66
	8	11	130.98	130.19	5	2	0	4	0.56
		15	98.12	97.85	8	2	0	5	0.61
		19	41.71	42.01	11	1	1	6	0.63



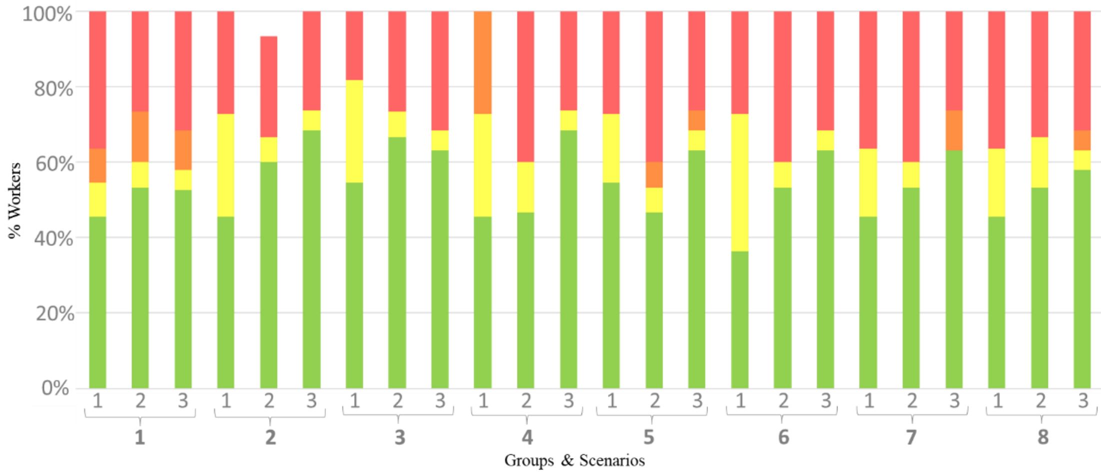
(a) Roszieg family



(b) Heskia family



(c) Tonge family



(d) Wee-Mag family

Figure 5.9 Distribution of workers' risk level in optimum solutions of each group and scenarios of synthesized ALWABP benchmark instances

If the percentage of high-risk assignments is considered as an indicator for identifying the undesirability rate of solutions, percentage of low-risk assignments can be considered as an indicator for desirability rate of them. However, Wee Mag family in both factors has the highest rate. Thus, a new index is introduced called the solution quality index which is the difference between desirability and undesirability rates. Consequently, optimum solutions of Tonge family problems have the best quality and Heskia, Roszieg, and Wee Mag are after it, respectively.

Table 5.6 Comparison of various KPIs

Family	**%Low Risk**	**%High Risk**	**Avg Ergo Score**
Roszieg	44	14	0.64
Heskia	44	1	0.75
Tonge	53	6	0.77
Wee Mag	54	30	0.62

5.6.2 Validation & Verification

The pioneers in introducing the Ergo-ALWABP were Akyol and Baykasoğlu (2019), considering the OCRA score in their model. To validate their proposed solution approach, they incorporated the ergonomic factors generated by Otto and Scholl (2011) into the SALBP-1 dataset and integrated them into the ALWABP benchmark dataset (A. Chaves et al., 2007). However, since then, no customized ergonomic factor consideration has been given to the well-known and popular ALWABP benchmark instances.

In addition, Zacharia and Nearchou (2020) and Zacharia and Nearchou (2021) were the first and only researchers to consider the uncertainty and variability of time in ALWABP-2. They fuzzified all task times by considering α as the original task processing time in the benchmark dataset and defined TFNs as a triplet: (0.85α, α, 1.3α). In this paper, the subproblems of each group were approached as a single unique problem with three scenarios of the number of available workers. Fuzzy task times were defined based on task time variety, and TFNs were generated using the minimum, average and maximum task execution times. This assumption was made based on the similarity of the distribution of variable times within each group. Consequently, 96 numerical examples (4 families × 8 groups × 3 scenarios) were generated from the original dataset.

To verify the robustness of the fuzzy CTs and ensure validity, two different defuzzification methods, centroid and distance, were used. The average difference between these defuzzified CTs was 2.14 seconds, confirming the accuracy and reliability of the final CTs in the optimum solutions. Furthermore, as the proposed optimization model considered the output of any fatigue model and converted it as an ergonomic risk in three levels, similar to a traffic light, random numbers were generated to synthesize the risk levels for each task. For reasonable analysis of the final optimum solutions, one set of risk levels was generated for each family of instances.

The results of the validation process demonstrate the consistent ability of the proposed solution approach to produce accurate solutions, as evidenced by various KPIs. It is important to note that as this paper is the first study on fuzzy Ergo-ALWABP-F, the results cannot be directly compared to previous research in this field. Additionally, the synthesized data in the ergonomic part can influence the optimum results in either a favorable or unfavorable manner. However, this study represents the first attempt to generate customized ergonomic factors for the conventional

ALWABP benchmark dataset, and future studies could include sensitivity analysis when adding ergonomic data to this well-known dataset.

5.6.3 Theoretical Implementations

To the best of our knowledge, this paper represents the first study on Ergo-ALWABP in a fuzzy environment, offering several applications for the proposed model in academic settings. This research addresses significant gaps identified in the literature, such as the integration of HF/E into ALWABPs and the handling of uncertainty through fuzzy expert systems.

Firstly, the application of fuzzy expert systems to ALWABP provides a novel approach to managing uncertainties arising from imprecise task time data and ergonomic risk levels. Future research can explore other types of fuzzy numbers, such as Gaussian or Trapezoidal, instead of TFNs used in the present study. Conducting a sensitivity analysis on these different fuzzy methods would help determine the most suitable approach for accurately capturing the vagueness of the problem and generating reliable solutions.

Secondly, the model's ergonomic component, which incorporates three levels of risk assessment (task, worker, and AL levels), presents opportunities for further contributions in future studies. At the task level, various fatigue models with customized outputs (e.g., traffic light: low, medium, and high risk) can be utilized and compared. The thresholds defined in this paper based on expert knowledge can be modified and further analyzed to establish improved fuzzy rules. The decision tree shown in Figure 5.6 can be explored using alternative expert systems and adjusted based on different methodologies for diverse applications.

Thirdly, while a constructive heuristic solution method was developed to solve the proposed problem, alternative metaheuristic or hybrid methods can be investigated to compare results and potentially enhance solution efficiency. For example, GA, SA, or particle swarm optimization (PSO) could be applied to the fuzzy Ergo-ALWABP to identify improvements in solution quality and computational efficiency.

Finally, in evaluating all FSs in the final step of the proposed solution approach, an ergonomic score was employed for each FS to find the optimum solution with the maximum ergonomic score. However, other evaluation approaches can be explored. For example, solutions could be optimized by focusing on better and best-case scenarios, omitting the worse-case scenarios. Various analysis approaches can be applied to FSs to determine the solution that closely approximates the optimum, thereby enhancing the robustness and applicability of the model.

This research offers numerous potential contributions to the academic community. The novelty of the problem and the proposed solution method can stimulate further studies in academic scenarios, fostering advancements and innovative approaches in the field. By addressing the complexities posed by heterogeneous workforces and incorporating ergonomic considerations and uncertainty, this study supports ongoing progress toward human-centric design in ALs, aligning with the principles of Industry 5.0.

5.6.4 Practical Implications

The present paper holds significant potential implications and benefits for industrial applications. The implementation of the proposed solution method in real-world industrial settings allows for the incorporation and integration of managerial insights and the knowledge of ergonomic experts into the optimization process. The proposed ergonomic evaluation approach, comprising task level, worker level and AL level assessments, can be easily customized at each level to enhance the model's applicability in industrial contexts. At the task level, the utilization of the output of any fatigue model, which is categorized in three general risk levels, make it easy to integrate and apply any method and compare the results. Additionally, the fuzzy rules for evaluating ergonomic risk factors at the worker level can be adopted based on some ergonomic models and industry requirements.

Furthermore, since the proposed model aims to find an optimum solution based on ergonomic score, this score can be defined in alternative ways to assess other desired concepts, such as recovery requirements, worker satisfaction, and overall operational performance. Although this study primarily focused on the feasibility type of ALWABP, which includes constraints related to task precedence, CT, and the number of workers, the optimization model is adaptable and can be adjusted to incorporate additional constraints and limitations that address the preference and requirements of specific production systems.

Consequently, the proposed framework offers applicability in addressing challenges faced by manufacturing industries in ALWABP by providing customization options based on the characteristic of assembly tasks and line features. By addressing uncertain and imprecise data through the application of fuzzy logic, engineers and ergonomic practitioners can discover more reliable and robust solutions, handling the variability of parameters in a more effective manner. These advancements contribute to planners' ability to achieve a more productive and efficient AL.

5.6.5 Limitations

In this study, several limitations are acknowledged that may affect the validity and reliability of the findings:

- Data quality and quantity: The quality and quantity of the synthesized data could influence the robustness of the results. While diligent efforts were made to gather comprehensive data and synthesize TFNs across the entire benchmark dataset, and generate ergonomic parameters, these factors may limit the generalizability of the conclusions.
- Evaluator expertise: The expertise of the evaluators, while generally adequate, varied to some extent, potentially introducing subjectivity into the assessments. These limitations were mitigated by employing standardized assessment tools, which helped maintain consistency to a certain extent.
- Solution framework: The solution framework offers valuable insights into ALWABPs. However, it may not guarantee the identification of optimal or Pareto optimal solutions, especially when dealing with large-scale instances of the problem. The complexity and size of the problem can influence the effectiveness of the framework in finding the best solutions. For problems with significant scalability challenges, alternative approaches, such as metaheuristics, may prove more effective in achieving superior solutions. Future research could explore the integration of metaheuristic techniques to enhance solution quality.
- Ergonomic evaluation method: In the proposed approach, the output of fatigue models, used to assess ergonomic risks, primarily focuses on analyzing the frequency and duration of repetitive actions. However, it does not encompass other critical ergonomic factors, including posture, load, vibration, and environmental conditions. Consequently, the ergonomic assessment may not provide a comprehensive view of workplace ergonomics. To attain a more thorough understanding and effective mitigation of ergonomic risks, future research should aim to develop a more encompassing ergonomic assessment method that considers these additional factors.

- Fuzzy task times: The proposed fuzzy ALWABP considers worker capability using only three levels represented by TFNs. This simplification may not accurately represent the diversity and heterogeneity of the workforce. Future research could explore the application of other types of fuzzy numbers, such as trapezoidal or Gaussian fuzzy numbers, to account for worker differences and model imprecise task execution times more accurately.
- Optimization model: In the optimization model, the objective function seeks to minimize the sum of the ergonomic risk factors for tasks assigned to each worker. However, other objective functions, such as minimizing the maximum ergonomic risk factor among all workers, minimizing the weighted sum of ergonomic risk factors based on task position in the sequence, or minimizing the deviation of ergonomic risk levels among workers, can be considered. Additionally, the model was constrained with worker and cycle time limits due to the feasibility type of optimization problems studied. Future research could explore the minimization of the number of workers (Type 1) or CT (Type 2) or consider new objective functions to address balancing workload, maximizing throughput, or other aspects, potentially leading to multi-objective mathematical models.

These limitations should be considered when interpreting the study's results and implications. They also highlight potential directions for future research in the field of Ergo-ALWABPs.

5.7 Conclusions

In the era of Industry 5.0, with a growing emphasis on human-centric approaches, the significance of prioritizing ergonomics in manufacturing systems cannot be overstated. This study introduced a new extension of the Ergo-ALWABP, incorporating fuzzy set logic to effectively handle imprecise task execution times and ergonomic risk levels. The primary objective was to address the critical intersection of ergonomics, uncertainty, and AL optimization, providing valuable insights for creating safer and more efficient manufacturing environments.

To address the challenges posed by uncertainty in terms of imprecise task execution times and vague ergonomic risk levels, the power of fuzzy set logic was utilized. TFNs were employed to model task time variations caused by the presence of heterogeneous operators in the AL. Moreover, a comprehensive framework was developed for ergonomic evaluation in the fuzzy environment, enabling the evaluation of ergonomic risks at the task, worker, and AL levels. This framework can integrate existing assessment methods and models to address ergonomic risk aspects. By considering fuzzy task times and tasks' risk level, the proposed model strived to effectively assess cumulative ergonomic risk levels. Moreover, the proposed two-phase framework effectively combined a constructive heuristic approach with a fuzzy knowledge-based system to solve the developed fuzzy Ergo-ALWABP-F (feasibility) with remarkable adaptability and efficiency.

The academic and industrial implementations of the proposed model offer extensive potential theoretical and practical contributions and significant implications for various fields. In theoretical section, researchers can explore alternative fuzzy number types and conduct sensitivity analyses to refine the modelling of imprecise task time data, yielding even more reliable solutions. Additionally, the integration of different EATs and the customization of ergonomic rules at various levels open doors for diverse methodological approaches. Furthermore, investigating alternative solution methods, such as metaheuristics and hybrid techniques, presents exciting opportunities to compare and enhance solution efficiency. In the industrial and practical setting, the proposed approach integrates managerial insights and ergonomic expertise into the optimization process. The model's adaptability ensures effortless customization to various industrial contexts, while considering multiple ergonomic risk factors to prioritize worker safety, satisfaction, and operational performance. Effectively addressing manufacturing challenges, the proposed framework offers practical solutions that significantly boost productivity and efficiency in real-world operations.

Considering the limitations identified in this study, several avenues for future research are evident. First, enhancing the data quality and quantity, particularly by incorporating more comprehensive and diverse datasets, could improve the robustness and generalizability of the findings. Second, addressing the variability in evaluator expertise by developing more standardized and automated assessment tools could reduce subjectivity in ergonomic evaluations. Third, exploring the integration of metaheuristic techniques into the solution framework may offer more effective approaches for solving large-scale instances of the problem and achieving optimal solutions. Additionally, developing a more comprehensive ergonomic evaluation method that includes factors such as posture, load, vibration, and environmental conditions would provide a more holistic view of workplace ergonomics. Future research could also investigate the use of alternative fuzzy numbers, such as trapezoidal or Gaussian fuzzy numbers, to better represent worker diversity and task execution times. Finally, expanding the optimization model to include various objective functions, such as minimizing the maximum ergonomic risk factor or balancing workload among workers, and considering multi-objective mathematical models, could yield more effective solutions. These directions will help advance the field of Ergo-ALWABPs and address the current study's limitations.

In conclusion, the integration of fuzzy set logic, advanced optimization techniques, and customized ergonomic considerations has resulted in a robust framework for achieving optimal solutions in manufacturing systems. The results of the computational experiments, validation process, and comprehensive discussions highlighted the effectiveness and diverse applications of the proposed approach in both academic and industrial settings. This research has paved the way for further exploration and advancements in the field, fostering the development of safer and more efficient manufacturing environments in the dynamic era of Industry 5.0 era. The contributions of this study provide a strong foundation for future research endeavors, driving continuous progress and innovation in the pursuit of human-centric manufacturing excellence.

CHAPTER 6 ARTICLE 3: Human-Centric Robotic Assembly Line Design: A Fuzzy Inference System Approach for Adaptive Workload Management

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Abstract

In the transition from Industry 4.0 to Industry 5.0, the integration of human-centric considerations into manufacturing processes becomes vital. This study advances beyond conventional Industry 4.0 frameworks by introducing a novel fatigue model that emphasizes ergonomic risk management during the design phase of robotic assembly lines. Utilizing a hybrid model that employs a fuzzy inference system based on ergonomist knowledge, this fuzzy approach manages the imprecise nature of ergonomic optimization more accurately than deterministic models and effectively reflects real-world complexities. By evaluating fatigue at both task and worker levels, this fuzzy inference mechanisms addresses technical aspects through feasibility studies and significantly improves ergonomic outcomes. The integration of supportive robots is explored through scenario-based analysis, highlighting productivity enhancements and substantial ergonomic benefits in line with Industry 5.0's focus on enhancing worker well-being and operational resilience. The proposed heuristic algorithm enables decision-makers to identify the most efficient solutions tailored to individual preferences, showcasing flexibility and real-world applicability. Empirical validation, enriched with synthesized ergonomic-oriented instances, confirms the superiority of this approach in creating more sustainable and ergonomically optimized assembly lines. Implementing this approach is predicted to decrease system costs by up to 47%, particularly advantageous during human resources crises, by reducing ergonomic risk, recovery needs, and additional capacity requirements for fatigue mitigation. This study contributes to the discourse on the practical implications of Industry 5.0 and demonstrates its applicability in designing ergonomically optimized assembly lines that prioritize long-term productivity and worker satisfaction

Keywords: Assembly line design problem; Ergonomic risks; Fatigue and recovery model; Fuzzy expert system; Industry 5.0; Supportive robots

6.1 Introduction

ALs are essential components of most production systems, responsible for producing vast quantities of both general and customized products. They play a critical role in manufacturing by enhancing productivity and efficiency. The primary objective of planning ALs is to optimize these factors through ALBPs, which aim to distribute tasks evenly across workstations to avoid bottlenecks and overloading, thereby maximizing productivity and minimizing operational costs. However, as the final stage in production and the closest link to the market, ALs are particularly vulnerable to market fluctuations and evolving customer demands. These factors introduce uncertainty, necessitating adaptable production systems. While manual tasks within ALs can improve flexibility, they also introduce ergonomic and productivity risks (Ghorbani et al., 2023).

Traditional ALBPs often neglect the ergonomic risks linked to prolonged and repetitive tasks, which can lead to increased rates of MSDs, errors, and absenteeism, ultimately decreasing productivity. To address this, Ergo-ALBPs have been developed, integrating HF/E into the optimization process to consider both operational efficiency and ergonomic well-being. Although failure to address ergonomic aspects during the design phase can lead to costly corrective actions in the future (Falck & Rosenqvist, 2014), only a limited number of studies have considered ergonomic aspects in the design phase of these optimization problems, referred to as Ergo-ALDPs (Ghorbani et al., 2023). These problems represent strategic planning that can prevent future costs associated with redesigning and implementing corrective measures to resolve ergonomics issues.

Optimization problems in the design phase encompass vague and imprecise aspects, such as future demand rates and diverse worker characteristics, which can affect desired takt times and ergonomic risk levels. Thus, the design optimization model should address these uncertain conditions to find more robust and applicable solutions. Workload calculation in conventional ALBPs relies on station times, assuming workers at stations with equal operation times encounter identical workloads. However, even tasks with equivalent operation times may require different levels of effort, resulting in diverse degrees of fatigue among workers (Katiraee et al., 2023). This can lead to muscle fatigue and MSDs, raising significant concerns. Among the limited studies in Ergo-ALBPs, many used semi-quantitative EATs to evaluate posture risk factors. Therefore, integrating fatigue and recovery models into these optimization problems is crucial to improve operator well-being and efficiency. Selecting and customizing a suitable fatigue/recovery model for use in the design phase under uncertainty is a critical challenge in this research.

This study contributes to the literature on Ergo-ALBPs by introducing several novel contributions. Firstly, it integrates a novel fatigue model into the design optimization process, effectively managing uncertainties related to ergonomic fatigue risks and their associated costs. Unlike existing deterministic models, this approach employs fuzzy logic to interpret and evaluate potential fatigue levels, thereby minimizing ergonomic risks across the assembly line with predetermined cycle times and a fixed number of workstations (feasibility study). Additionally, the proposed model uniquely accounts for muscular fatigue and evaluates fatigue rates under uncertain conditions, leveraging the expertise of ergonomists through a FIS. This facilitates decision-makers in identifying the most desirable solutions at both task and worker levels (Ghorbani et al., 2023).

Furthermore, this study addresses the challenge of incorporating recovery time into AL planning. To mitigate fatigue levels, it is crucial to integrate sufficient recovery time into the planning process, ensuring the final CT accounts for both operation time and necessary recovery periods while aligning with the defined takt time (the rate at which demand is received). Additional capacity may be introduced by incorporating extra working shifts or adding workstations, but these options require increased human resources. Given the global worker shortage, alternative strategies are essential. One viable approach is the integration of supportive robots, which can alleviate fatigue in specific areas of the body and offer a promising solution to workforce limitations. This study considers the application of supportive robots, specifically supernumerary robotic limbs (SRLs), to assist workers in performing complex and fatigue-prone tasks, thereby improving productivity and efficiency (Tong & Liu, 2021). Despite the benefits of SRLs, such as productivity enhancement, physical strain reduction, and safety improvements, their cost compared to traditional options remains a challenge. Therefore, this study considers different scenarios to compare the investment levels required for each solution, helping decision-makers to find the best option through a managerial dashboard.

Lastly, the optimization procedure in this study presents a hybrid modeling approach that combines the feasibility study of balancing problems with a FIS, developing a heuristic solution method to minimize both the system's fatigue level and the over-cost of the AL. This hybrid optimization model evaluates several future scenarios, providing decision-makers with sufficient information to make the best choices based on operational and ergonomic aspects during the design phase.

The novelties of this work lie in the integration of fuzzy logic to manage uncertainty and vagueness in modeling complex systems where precise mathematical relationships are unavailable. These contributions collectively advance the field by providing a comprehensive framework for ergonomic risk management in robotic assembly line design. This study is among the first to integrate fuzzy logic theory and supportive robots into Ergo-ALDPs, providing a novel framework for designing ALs that can cope with uncertainty, variability, and human factors. The proposed solution method is validated and verified by applying it to benchmark problem samples from the SALBP dataset (Otto et al., 2013). Although these instances are not originally ergonomic-oriented, 60 numerical instances are synthesized based on the original samples to test the efficacy of the solution method.

This manuscript is organized as follows: Section 7.2 reviews the literature on Ergo-ALBPs, focusing on studies incorporating fatigue and recovery methods. Section 7.3 introduces the optimization model and the new fuzzy fatigue model. Section 7.4 details a hybrid heuristic method designed to solve the problem. Section 7.5 outlines the implementation of the proposed solution algorithm on numerical samples, and Section 7.5 discusses the research findings. Finally, Section 7.6 presents the concluding remarks and potential avenues for future research.

6.2 Literature Review

The inception of Ford's automobile production facilities in the early 20th century marked a pivotal moment in applying ALs within mass production. Since then, this cornerstone of both mass and lean production systems has undergone significant evolution, transitioning into a more flexible and adaptive system. The optimization of ALs has been a focal point of scholarly research, aiming to balance processes and eliminate inefficiencies hindering their smooth operation. Since ALs represent the terminal phase of most production systems and are proximal to the final market, they are inherently sensitive to market fluctuations, which can critically impact their performance (Ghorbani et al., 2024e). Consequently, optimizing ALs presents a complex and multifaceted challenge that has been the subject of numerous studies. The subsequent subsections provide a comprehensive review of the literature related to the principal dimensions of these optimization problems.

6.2.1 Assembly Line Balancing Problems (ALBPs)

The optimization of ALs primarily aims to address imbalances that can lead to bottlenecks, reducing efficiency and negatively impacting key performance metrics. Balancing these lines enhances performance by maximizing productivity and efficiency (Ghorbani et al., 2024a). The concept of ALBPs traces back to Salveson's work in 1955 (Salveson, 1955). Although a solution method was proposed in 1961 (Halgeson & Birnie, 1961), trial-and-error methodologies dominated the resolution of ALBPs for many subsequent years.

ALBPs are recognized as NP-hard combinatorial optimization problems (COPs), involving identifying the optimal solution from a finite set of possible configurations known as feasible solutions (FSs). There are two primary classifications of ALBPs: simple (SALBP) and general (GALBP) problems.

SALBPs refer to single-sided linear ALs with fixed operation times and usually target the optimization of one or two objectives. They are further categorized into four types: Type 1 focuses on minimizing the number of workstations for a predetermined CT; Type 2 aims to minimize the cycle time with a fixed number of workstations; Type F evaluates the feasibility of a given combination of workstations and CT; and Type E endeavors to minimize both CT and the number of workstations simultaneously.

On the other hand, GALBPs address more complex configurations, including mixed-model product types (MMALBP), parallel ALs (PALBPs), and U-shaped lines (UALBPs), presenting a broader array of challenges (Ghorbani et al., 2023).

6.2.2 Ergonomics Considerations in Assembly Lines

Ergonomic considerations are critical in ALBPs due to the high risk of MSDs that workers may develop from repetitive and prolonged assembly activities. Integrating HF/E with operational parameters is vital not only for enhancing the efficiency of ALs but also for reducing and preventing potential ergonomic risks. The influential work of Gunther et al. (1983) initiated the integration of ergonomic risks into ALBPs. However, significant progress in this area was relatively modest until the pivotal study by Otto and Scholl (2011), which incorporated an ergonomic objective into the optimization model of ALBPs, thereby triggering further research into Ergo-ALBPs. Despite extensive studies on various ALBPs, the research on Ergo-ALBPs especially during the design phase, known as Ergo-ALDPs- remains comparatively limited (Ghorbani et al., 2024a).

Several EATs have been applied to evaluate ergonomic risks associated with ALBPs (Ghorbani et al., 2023). Most EATs, such as the OCRA, RULA, and REBA, produce an index applied as an interval scale to rate ergonomic risks on a scale ranging from low to high. While each tool offers a distinct approach to risk assessment, there is no consensus on a universally preferred tool for all contexts (Takala et al., 2010).

6.2.3 Fatigue Models in Balancing Problems

In the manufacturing realm, ergonomic risks include physical, cognitive, and psychosocial factors. Physical tasks involving dynamic or static muscle efforts can lead to fatigue and pain, potentially resulting in MSDs if not managed effectively. Ergonomists try to identify these risks and develop strategies to mitigate them in the workplace (Sekkay et al., 2018). For example, prolonged static muscle exertion may lead to work-related MSDs, and a common mitigation strategy is to introduce recovery breaks to alleviate muscle fatigue. Fatigue is categorized as localized, affecting specific muscle groups, or generalized, affecting the entire body. Generalized fatigue is often measured by EE or metabolic rate (MR), particularly in activities engaging a significant portion of muscle mass (approximately 70% or more). Localized muscle fatigue, on the other hand, is evaluated using methods like EMG, blood lactate concentration, or the Borg scales, adapted for different body parts such as the shoulder, arm, or back.

Ghorbani et al. (2023) found in their review that 35% of studies on Ergo-ALBP from 2011 to 2022 incorporated fatigue considerations into their models. Table 6.1 presents a summary of these studies, along with recent research in this area, demonstrating that a limited number of fatigue assessment methods have been applied to ALBPs. Typical EATs for fatigue evaluation include:

- Price (1990): Rohmert (1973) pioneered the development of models assessing rest allowance (RA) as the time required for adequate rest following static or dynamic exertion. Building upon Rohmert's work, Price (1990) formulated a model to calculate RA concerning the maximum acceptable energy expenditure (MAEE), presumed to be 4.3 kcal/min.
- Garg et al. (1978): The Garg model estimates the total average metabolic consumption in a manual handling task by summing EE for activities and posture maintenance, averaged over

the job's duration. This assumes tasks can be broken down into simpler activities, each with a calculable metabolic cost and affected by factors such as gender, body weight, load weight, lifting/lowering heights, lateral arm movements, walking speed with load, postures, and job duration.

- Borg (1990): The Borg scales offer a psychophysical method to gauge perceived exertion during physical activities, providing a subjective evaluation of how workers feel while performing tasks.
- Ma et al. (2009) and Ma et al. (2010): The model introduced by this research group presents a new, straightforward dynamic muscle fatigue model that offers a quantitative analytical method for assessing muscular fatigue and required recovery of assembly workers.
- PMES: Battini, Delorme, et al. (2016) developed a technique known as the predetermined motion energy system (PMES), which builds on the EE formulations by Garg et al. (1978). It includes tables for the rapid estimation of task-related EE, similar to traditional predetermined time motion systems (PTMS).

6.2.4 Ergonomic Assessment in the Design of Assembly Lines

Neglecting ergonomic aspects during the design stages of ALs can lead to a spectrum of long-term issues, ranging from health-related absenteeism to irreversible disabilities. Corrective measures implemented post-design can cost significantly more -up to 9.2 times- than preventive actions taken during the design stage (Falck & Rosenqvist, 2014). While research on optimizing ALs by considering HF/E is limited, most studies have focused on existing lines, underscoring the need for extensive research into ergonomic integration within the ALDP to address the complexities of real-world design challenges (Ghorbani et al., 2023).

Baykasoglu et al. (2017) pioneered this field by addressing the design of a simple assembly line using a heuristic approach. Finco et al. (2019) optimized the design of a semi-automatic AL by minimizing design costs and ergonomic risks associated with the vibration of automatic hand-held tools. Recently, the application of robots in ALs has evolved design problems in new directions, particularly through the use of cobots (Ghorbani et al., 2024e).

Table 6.1 Summary of related research contributions in Ergo-ALBP with a fatigue model

Authors	**Problem Type**	**Opt Model**	**Ergo Factor**	**EAT**	**Objective Function**	**Solution Approach**
(Battini et al., 2015)	SALBP-2	LP	EE	(Garg et al.)	Min (CT) & Max (ESI)	Pareto Optimality
(Battini, Calzavara, et al., 2016)	IALBFP	MIP	EE	(Garg et al.)	Min (#workers)	Exact Method (CPLEX)
(Battini, Delorme, et al., 2016)	SALBP-2	MO-LP	EE & RA	PMES	Min (CT & EE)	Pareto Optimality
(Battini et al., 2017)	SALBP-2	MIP	EE	(Price)	Min (CT & Energy Dev)	Hierarchical Planning
(Finco et al., 2018)	SALBP-2	MO-MILP	EE & RA	(Price)	Min (CT & EE)	Heuristic Approach
(Abdous et al., 2018a)	SALBP-1	MO-MILP	fatigue & recovery	(Ma et al.)	Min (#Stations & fatigue)	Pareto & ε-constraint
(Dalle Mura & Dini, 2019)	SALBP-1	-	EE	(Garg et al.)	Min (#Skilled Workers, Cost, EE Var)	GA
(Weckenborg & Spengler, 2019)	CALBP	MILP	EE	(Price)	Min (Cost per Cycle)	Exact method (CPLEX)
(Finco et al., 2020)	SALBP-2	MILP	EE & RA	(Price)	Min (SI)	Heuristic Approach
(Abdous et al., 2020)	CALDP	MO-MINLP	Fatigue & Recovery	(Ma et al.)	Min (Cost) & Max (Ergo level)	Iterative Local Search
(Finco et al., 2021)	MMALBP	LP	EE & RA	(Price)	Min (CT & RA)	Heuristic Approach

Table 6.1 Summary of related research contributions in Ergo-ALBP with a fatigue model (Continue)

Authors	**Problem Type**	**Opt Model**	**Ergo Factor**	**EAT**	**Objective Function**	**Solution Approach**
(Chutima & Khotsaenlee, 2022)	PUCALBP	MILP	EE & RA	PMES	Max (efficiency& tax benefit) Min (EE & Var)	NSTLBO
(Weckenborg et al., 2022)	CALBP	MIP	EE	Biomechanical	Min (Cost & Biomechanical Load)	Pareto Optimality
(Stecke & Mokhtarzadeh, 2022)	CALBP	MILP	EE	(Garg et al.)	Min Weighted Sum (CT & Ergo)	Benders Decomposition
(Quenehen et al., 2023)	CALBP-2	-	EE	PMES	Min (CT & Fatigue)	Hybrid Metaheuristic
(Dalle Mura & Dini, 2022)	CALBP	CP	EE	(Garg et al.)	Min (cost & EE Var)	GA
(Katiraee et al., 2023)	ALWABP-2	Bi-Obj LP	Perceived Physical Effort	(Borg)	Min (CT & Workload Var)	ε-Constraint
(Keshvarparast et al., 2022)	CALBP	MILP	Workers' Diversity	(Borg)	Min (CT & Workload Var)	ε-Constraint
(Abdous, Delorme, Battini, Sgarbossa, et al., 2023)	SALBP-F	ILP	Fatigue & Recovery	(Ma et al.)	Max (Ergo Level)	Iterative Dichotomic SA
(Abdous, Delorme, Battini, & Berger-Douce, 2023)	CALDP	MILP	Fatigue & Recovery	(Ma et al.)	Min (Cost & Fatigue)	ε-Constraint
This Study	RALDP	MILP	Fatigue & Recovery	Fuzzy Model	Min (Fatigue & Over Cost)	Hybrid Heuristic

6.2.5 Optimization of Assembly Lines in the Industry 4.0 Era

While most Ergo-ALBPs have concentrated on manual ALs, there is an increasing trend towards incorporating Industry 4.0 technologies. This trend is driven by the need for flexible and adaptive production systems capable of meeting the demands of mass customization in the Industry 4.0 era. Recent studies have begun to focus on robot-assisted ALBPs (RALBPs). The introduction of robots into ALs brings both advantages and challenges related to task allocation, line balancing, and scheduling decisions (Kheirabadi et al., 2023). These challenges underscore the need to not only optimize technical processes but also to prioritize the ergonomic well-being of the workforce.

Industry 5.0 further evolves these concepts by emphasizing a more human-centric automation approach. It seeks to harmonize the efficiency of robotic precision with human intelligence, thereby enhancing workforce well-being while maintaining high operational efficiency. This paradigm shift is evident in recent Ergo-ALBPs, which now increasingly focus on CALBPs that promote sustainable and resilient manufacturing ecosystems (Ghorbani et al., 2023).

The interaction between humans and robots in manufacturing systems has been typologically categorized into coexistence, interaction, cooperation, and collaboration (Wang et al., 2020). Each category reflects varying degrees of human-robot synergy, from independent operation in the same environment to direct collaborative task completion. The literature shows that ergonomic considerations are increasingly integrated into these interactions, particularly in collaborative settings, where both humans and robots share tasks and spaces. This integration addresses significant ergonomic challenges and enhances both the efficiency and safety of assembly lines. However, among the limited number of Ergo-ALBPs that considered fatigue/recovery models in their studies (as shown in Table 6.1), around half of them focused on collaborative problems (nine out of 20 articles). Of these, most (seven papers) concentrated on balancing problems in existing ALs while only two papers (Abdous et al., 2020; Abdous, Delorme, Battini, & Berger-Douce, 2023) studied the design of these cobotic lines.

Pioneering research like Weckenborg and Spengler (2019) has demonstrated the value of incorporating ergonomic aspects into cost-oriented approaches for CALBP, using models such as Price (1990) to balance EE and reduce physical workload. Subsequent studies by Stecke and Mokhtarzadeh et al. (2021) and Weckenborg et al. (2022) have further explored the EE factor, employing the Garg et al. (1978) model and a biomechanical approach, respectively. They solved the MIP models using exact methods. Alternatively, Chutima and Khotsaenlee (2022) and Quenehen et al. (2023) measured EE in their proposed CALBP applying the PMES approach and solved it with a hybrid metaheuristic approach.

Furthermore, Dalle Mura and Dini (2022) applied GA to solve the job rotation problem in collaborative Als, aiming to minimize the cost of allocating workers with varying skill levels and installing different equipment, including cobots. They also tried to minimize the variation of EE among workstations based on the Garg et al. (1978) model, considering workers' movements, physiological characteristics, the degree of collaboration with robots, and job rotations. Keshvarparast et al. (2022) proposed a bi-objective optimization model for CALBP to minimize CT and workers perceived physical workload, evaluated using the Borg scales approach. They applied a Pareto front to solve the developed model.

Abdous et al. (2020) introduced an optimization model in a CALDP context that aimed to minimize both equipment costs and ergonomic risk. This model assessed dynamic muscle fatigue using the formula proposed by Ma et al. (2009) for tasks assigned to each workstation. Building on this, Abdous, Delorme, Battini and Berger-Douce (2023) formulated a multi-objective problem to optimize CALDP across various criteria, including equipment and production costs, space utilization, and fatigue risk factors, utilizing the model proposed by Ma et al. (2010).

6.2.6 Addressing Uncertainty in Optimization Problems

As discussed, there is a scarcity of studies integrating ergonomic considerations into ALBPs, especially during the design phase, referred to as Ergo-ALDP. Moreover, much of the existing research has concentrated on deterministic scenarios. However, during the design phase, it is crucial to account for two primary types of uncertainty: environmental and system uncertainty (Ho, 1989). Environmental uncertainty in the current context includes demand variability due to market fluctuations, while system uncertainty arises from imprecisions within the production process. These system uncertainties encompass human-related aspects such as variability in system reliability, task durations, and the workforce's physical abilities (Ghorbani et al., 2024e). Additionally, the imprecision inherent in the inputs of EATs can significantly influence the results (Golabchi et al., 2016). To manage these uncertainties, stochastic programming models are often employed when historical data is available to estimate the probability distributions of uncertain factors. Without such historical data, fuzzy programming is recognized as a beneficial alternative approach (Ghorbani et al., 2024c).

To the best of authors knowledge, Tiacci and Mimmi (2018) are the only researchers who have incorporated uncertainty into their optimization problem. They tackled this by factoring in stochastic task durations and imposing penalties for violations of ergonomic constraints or deviations from projected cycle times. For ergonomic factor evaluation, they utilized the OCRA method and applied a GA to optimize cost.

Moreover, ergonomics considerations and operational aspects within assembly line optimization problems often present conflicting objectives. Some research has utilized fuzzy goal programming to tackle the inherent ambiguity in multi-objective models that integrate ergonomics with operational functions (Ozdemir et al., 2021; Rajabalipour Cheshmehgaz et al., 2012). While numerous ALBP-related studies have employed FST to manage uncertain and imprecise conditions, only Mutlu and Özgörmüş (2012) have considered ergonomics risks in the form of fuzzy numbers within the Ergo-ALBP. They employed Bellman and Zadeh (1970)'s approach to minimize the number of workstations and the perceived workload.

6.2.7 2.7. Research Gaps in the Literature

In summary, the literature review has identified several key research gaps within the field of Ergo-ALBP. This study aims to contribute to the existing body of knowledge by addressing these research gaps as shown in Figure 6.1.

Contributions:

Gap 1	**Limited consideration of fatigue parameters during the design phase, leading to future redesign expenses.**	Integrate a novel fatigue model into the design optimization of the assembly line to effectively manage uncertainties related to ergonomic risks in the fatigue form and associated costs.
Gap 2	**Existing studies employ deterministic models, ignoring the imprecision and variability of critical factors during the design phase.**	Apply fuzzy logic to interpret and evaluate potential fatigue levels, thereby minimizing ergonomic risks across the assembly line with predetermined CT and a fixed number of workstations (feasibility study). This approach also aims to minimize the potential over-cost of the design.
Gap 3	**Existing fatigue models do not account for muscular fatigue and fail to evaluate fatigue rates under uncertain conditions in the design phase.**	Develop a novel fatigue model based on the knowledge of ergonomic experts and utilize a fuzzy inference system to analyze fatigue levels at both task and worker levels. This makes it easier for decision-makers to identify the most desirable solution.
Gap 4	**The supportive role of robots has not been adequately considered, and collaborative robots are primarily applied to minimize economic aspects.**	Consider the utilization of supportive robots to reduce fatigue levels and, consequently, minimize overall costs. This will be based on different scenarios to help decision-makers analyze and interpret all possible solutions, thereby finding the optimal (near optimal) solution.
Gap 5	**Lack of hybrid decision-making integration, combining ALBP with other decision problems during the design stage.**	Present a hybrid modeling approach that includes a feasibility type of balancing problem and a fuzzy inference system. Develop a heuristic solution method to minimize both the fatigue level of the system and the over-cost of the AL based on different scenarios.

Figure 6.1 Research gaps in the literature and contributions of this paper to bridge these gaps

As Figure 6.1 presents, this study makes several key contributions to address the research gaps. The principal contribution is the integration of a fuzzy knowledge-based fatigue model into the ALDP, enhancing the existing framework with a fuzzy extension of Potvin's fatigue model (Potvin, 2011) to effectively manage uncertainties related to fatigue levels. To address ergonomic concerns, the customized fatigue model based on the FIS is integrated into the AL optimization process, assessing the cumulative fatigue levels at each workstation and across the entire line (Ghorbani et al., 2024c).

Moreover, hybrid heuristic solution approach presented in this paper first identifies FSs meeting operational constraints and calculates fatigue levels through FIS. Then the best solution is verified using a lexicographic method based on a conventional recovery model. Furthermore, the integration of supportive robots, in the form of SRLs, is examined through scenario-based analysis to find the best combination of robots and workers, aiming to minimize the total cost, including fatigue and robot expenses.

Recognizing that various potential scenarios can yield different FSs during the design stage, this study proposes a comprehensive optimization framework equipped with a visual dashboard. This decision tool aids decision-makers in assessing trade-offs between FSs under different scenarios and selecting the most appropriate solutions based on current conditions. To the best of our knowledge, no previous research has explored these optimization problems from this perspective.

6.3 Problem Definition

This research develops an optimization model for the ergonomic design of an AL by integrating supportive robots in uncertain environments, that is a sort of Ergo-RALDP. This problem extends the SALBP-F with the objective of identifying the optimal (or near optimal) AL configuration that adheres to a predetermined CT and a specified number of workstations. Previous studies, as indicated in Table 6.1, have often overlooked the inherent vagueness and imprecision in evaluating fatigue levels and recovery times in ALBPs. This study seeks to identify the most ergonomically sound solution without compromising operational efficiency under uncertain conditions. The following subsections elaborate on the proposed fuzzy fatigue model tailored for the optimization problem. Table 6.2 illustrates all notations used in this study and Figure 6.2 presents all components of the model in a schematic framework.

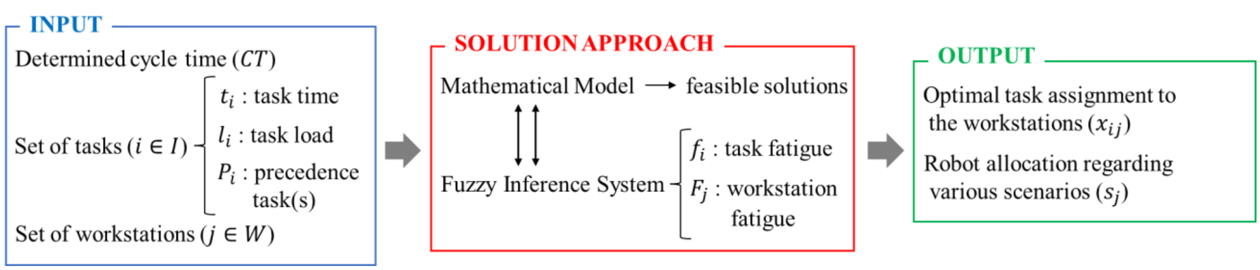


Figure 6.2 Illustration of model components

Table 6.2 Notations of the optimization model

Sets & Indexes	
I	{1, …, i, …, n}: Set of assembly tasks
W	{1, …, j, …, m}: Set of workstations
P_i	Set of immediate predecessors of task i (i'∈ P_i if task i' precedes task i)
Parameters	
t_i	Execution time of task I (seconds)
l_i	Load of task i (% of MAE)
f_i	Fatigue level of task i (ranging from 0 and 1 based on Potvin's model)
CT	Desired cycle time of the AL (seconds)
c	Cost of each supportive robot (% of worker cost per shift)
Decision Variables	
$x_{ij} = \begin{cases} 1, & \text{if task i is assigned to station j} \\ 0, & \text{otherwise} \end{cases}$	
$y_j = \begin{cases} 1, & \text{if workstation j is opend} \\ 0, & \text{otherwise} \end{cases}$	
$s_j = \begin{cases} 1, & \text{if a supportive robot is allocated to workstation j} \\ 0, & \text{otherwise} \end{cases}$	

6.3.1 Initial Fatigue Model

Muscle fatigue is a significant contributor to MSDs, especially in physical work (Ma et al., 2010). Therefore, assessing muscle fatigue is crucial for establishing effective recovery schedules to minimize MSD risks (El ahrache et al., 2006). Among limited number of fatigue models that assess muscular fatigue, this study selects Potvin (2011) equation for evaluating localized fatigue in the upper limbs due to its suitability for analysis under uncertainty and fuzzy logic. Potvin's model delineates the relationship between the maximum acceptable effort (MAE) and the duty cycle (DC), which is the proportion of time spent exerting effort within each CT. This insight is crucial for analyzing repetitive and extended assembly tasks, focusing on the ergonomic risks they pose to the upper body (Ghorbani et al., 2024c). Equation 1 shows the original formula of this model, which is applied to calculate fatigue level or recovery time, and Figure 6.3 illustrates the related curve of this model:

$$MAE = 1 - \left[DC - \frac{1}{28800}\right]^{0.24} \qquad (6.1)$$

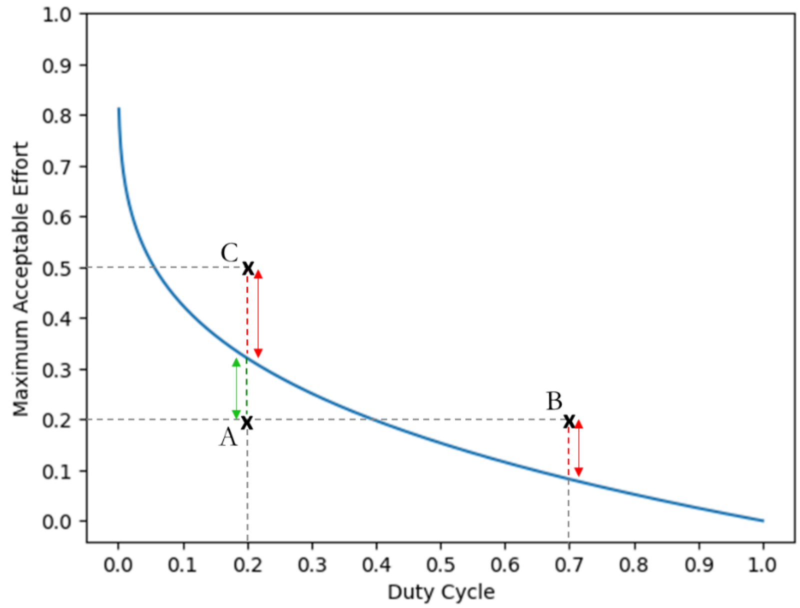


Figure 6.3 Potvin's proposed equation with some samples

Potvin developed this equation to estimate acceptable forces for repetitive tasks (Potvin, 2011). This model categorizes tasks into two groups: hazardous (points above the curve, indicating positive fatigue or insufficient rest within the cycle) or safe (points below the curve, indicating sufficient rest time within the cycle). Figure 6.3 depicts the generally inverse correlation between MAE and DC. The fatigue level is influenced by the duration of the task relative to the CT (t_i/CT) and the load of the task based on MAE (l_i).

For instance, in Figure 6.3, consider tasks A and B, both with a load representing 20% of the MAE. Task A, with a DC of 20%, falls below the threshold, avoiding excess fatigue. In contrast, task B, with a DC of 70%, results in increased fatigue for the worker. Similarly, tasks A and C share a DC of 20%, but task C induces more fatigue due to its load being 50% of the MAE. To prevent excessive fatigue in C, the DC must be kept below 10%.

Although fatigue level depends on the proportion of task time (t_i) in each CT (DC) and task load (l_i) based on MAE, the uncertainty and vagueness of these influential parameters in the design phase make fatigue calculation complex for the following reasons:

- Unknown rate of demand: The exact rate of demand is unknown, making takt time (available production time divided by demand) imprecise. Therefore, the desired CT, calculated based on takt time, is also inexact.
- Variability of task time: Task time can vary based on the worker's experience, skill, and other characteristic. Moreover, in the design stage, information about the workers who will work on each workstation is unspecific. Thus, task times are not exact parameters, and in most cases, the most possible values are considered as task times.
- Imprecise task load: Task load, like task time, depends on the characteristics of the operator. Additionally, the estimation of load levels in the design phase contains some degree of error and approximation, making the task load ambiguous.

The vagueness and imprecision in time parameters such as takt time, CT, and task time, along with imprecision in load, result in inaccurate fatigue and recovery assessments. To address uncertainties in the environment and system and to model more realistic optimization problems, these imprecise and vague parameters are managed using stochastic or fuzzy approaches. Stochastic programming requires historical data to develop a proper plan based on the probability of various scenarios. However, in the design phase, sufficient historical data is generally unavailable. Therefore, this paper adopts fuzzy set logic for fatigue/recovery calculation, a promising method to address these challenges.

6.3.2 Fuzzy Fatigue Model

In the face of uncertainty, it is necessary to adapt and analyze Potvin's model to address all vague and imprecise factors. Potvin's equation is instrumental at the worker level for calculating the necessary recovery time within a work cycle, preventing the accumulation of residual fatigue from repetitive tasks. While Potvin's fatigue model provides a threshold for evaluating each task based on the MAE, it does not quantify the magnitude of fatigue in terms of categorical ergonomic risk or as the cumulative risk of multiple tasks.

To address these gaps, a fuzzy fatigue model is developed using an expert system based on a FIS informed by the collective expertise of selected ergonomic specialists. The selection of these experts was based on a set of criteria including their published work, practical experience in ergonomics, and previous involvement in developing ergonomic assessment tools. Expert opinions are crucial in developing FIS models, and selecting the right experts is the first step in creating an effective FIS-based approach (Keivanpour, 2022).

The knowledge extraction process involved structured interviews followed by multiple feedback sessions to iteratively refine the fuzzy rules, ensuring their alignment with both empirical data and theoretical ergonomic principles. The development of the FIS, outlined in Figure 6.4, begins with input from the Potvin fatigue equation, which is essential for quantifying necessary recovery times. This input undergoes 'Fuzzification' converting precise data into fuzzy values that can better handle uncertainties in ergonomic assessments. Our system includes a comprehensive 'Knowledge Base,' consisting of a 'Rule Base' with fuzzy logic rules derived from expert insights, which help interpret varying fatigue levels. Defining fuzzy rules is crucial in developing a fuzzy expert system, with the number of rules dependent on the input variables and the membership functions used (Keivanpour, 2022). These rules are processed in the 'Inference Engine,' which applies logical operations to generate fuzzy conclusions. Finally, the 'Defuzzification' process converts these fuzzy conclusions back into precise outputs, resulting in the fuzzy fatigue model that provides actionable insights for ergonomic risk management.

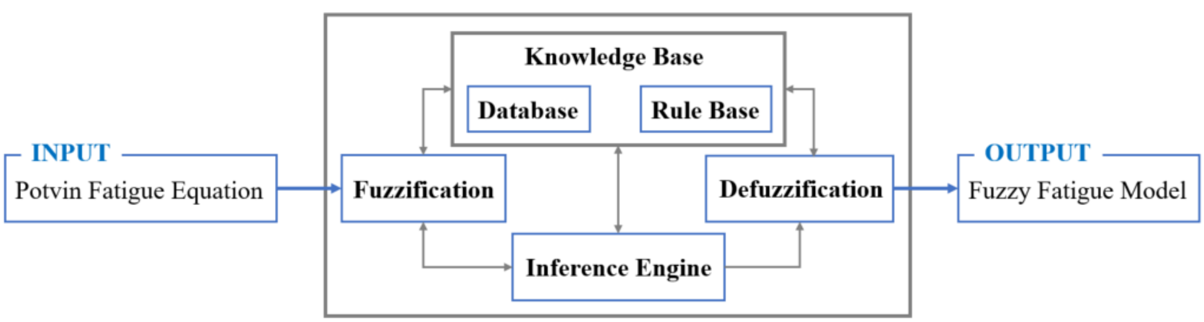
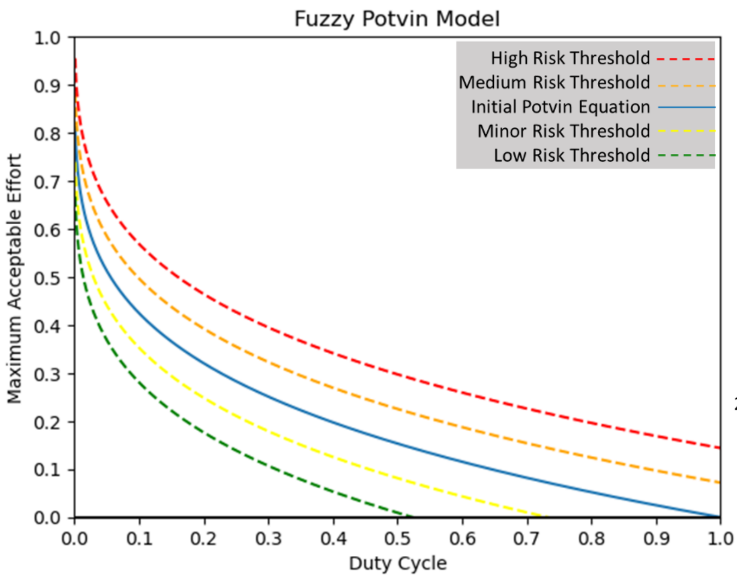


Figure 6.4 Fuzzy inference system to develop a fuzzy fatigue model (generated from Tavana and Hajipour (2020))

Therefore, this model accounts for variability in task time and load by applying fuzzy logic, allowing for the assessment of fatigue risk levels with a degree of uncertainty during the design stage through possibility sets. The proposed fatigue model relies on a set of fuzzy rules derived from ergonomic specialists' insights. These rules evaluate potential ergonomic risks of localized fatigue in the upper limbs associated with each task, incorporating Potvin's equation.

Fuzzy rules are "If…, Then…" statements that evaluate specific conditions to derive conclusions using fuzzy logic. Potvin’s model has an accuracy with a root mean square (RMS) error of 7.2% of MAE. Therefore, to create fuzzy rules, we consider a 7.2% MAE margin and divide the entire potential area around the initial curve into six risk zones and a fatigue level (f_i) is assigned to each risk level that presents the ergonomic risk related to the fatigue magnitude. As illustrated in Figure 6.5, fuzzy rules are based on the distance of each point from the initial curve (D_i) and can be demonstrated as follows:

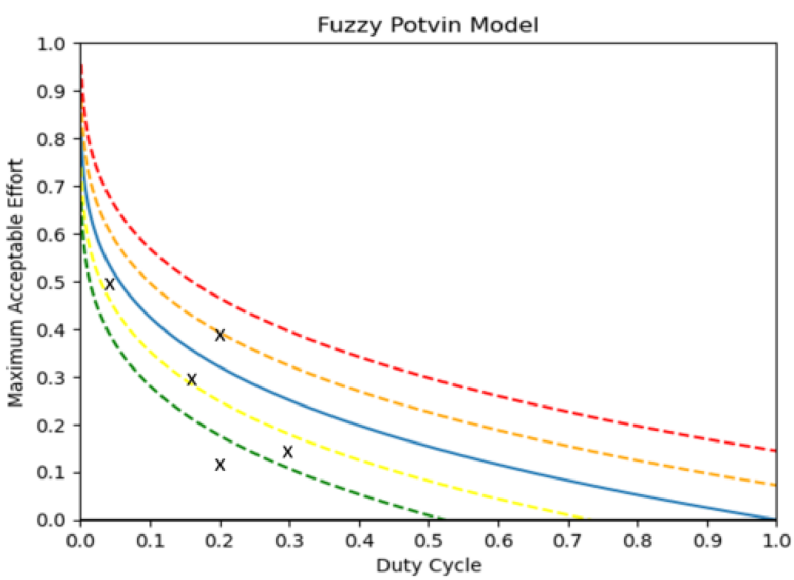
- If $D_i \leq -14.4\%\ MAE$, then the task imposes no risk, and f_i is equal to 0.
- If $-14.4\%\ MAE\ < D_i \leq -7.2\%\ MAE$, then the task imposes low risk, and f_i is equal to 0.25.
- If $-7.2\%\ MAE\ < D_i \leq 0\%\ MAE$, then the task imposes minor risk, and f_i is equal to 0.4.
- If $0\%\ MAE\ < D_i \leq 7.2\%\ MAE$, then the task imposes moderate risk, and f_i is equal to 0.6.
- If $7.2\%\ MAE\ < D_i \leq 14.4\%\ MAE$, then the task imposes medium risk, and f_i is equal to 0.75.
- If $14.4\%\ MAE\ < D_i$, then the task imposes high risk, and f_i is equal to 1.



Distance from Potvin's Equation	Fatigue Level (f_i)	Ergo Risk
2 × 0.072 < **D**	1	High Risk
0.072 < **D** ≤ 2 × 0.072	0.75	Medium Risk
0 < **D** ≤ 0.072	0.6	Moderate Risk
- 0.072 < **D** ≤ 0	0.4	Minor Risk
2 × (- 0.072) < **D** ≤ - 0.072	0.25	Low Risk
D ≤ 2 × (- 0.072)	0	No Risk

Figure 6.5 Fuzzy fatigue model derived from FIS of an expert system

To explain this method numerically, consider a sample workstation depicted in Figure 6.6. Five tasks are assigned to workstation j, and task times and loads (t_i and l_i) are specified based on their most possible values during the design phase. The DC_i is then calculated assuming a CT of 60 seconds.



Tasks (i)	t_i	DC_i	l_i	f_i
1	11	18%	30%	**0.4**
2	12	20%	12%	**0**
3	18	30%	15%	**0.25**
4	3	5%	50%	**0.4**
5	12	20%	40%	**0.6**

Figure 6.6 Evaluation of a sample workstation with five tasks based on the proposed model

As shown in Figure 6.6, the fatigue level of each task can be evaluated based on its location on the fuzzy Potvin model, considering the distance of the point to the initial curve.

6.3.3 Cumulative Fatigue & Ergonomic Risk Mitigation

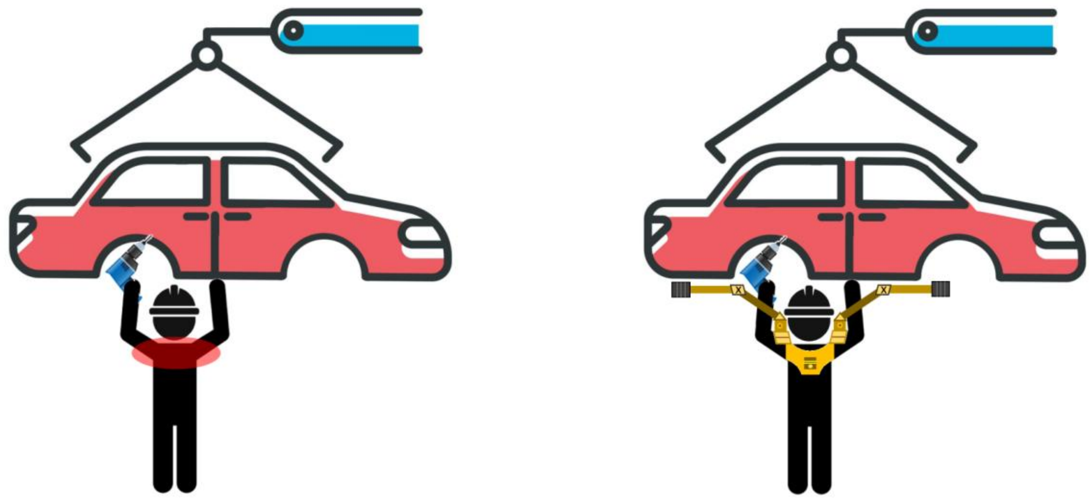
The proposed approach evaluates cumulative fatigue in each workstation (F_j) by summing the fatigue levels of all assigned tasks. This is calculated using the following equation:

$$F_j = \sum_{i \in I} x_{ij} . f_i \tag{6.2}$$

For instance, in the sample workstation illustrated in Figure 6.6, the cumulative fatigue is 1.65. This means that the magnitude of fatigue necessitates assigning an additional 1.65 shifts to a worker. In other words, the current CT does not meet adequate recovery and must be adjusted to achieve an ergonomic, human-centric design.

To mitigate fatigue levels at each workstation and reduce ergonomic risk on the AL, sufficient recovery time must be integrated into the planning process. In manual AL settings, this implies adjusting the CT to include the required recovery time based on the fatigue model. However, during the design phase, the CT is presumed to be predetermined based on takt time to meet potential future demand rates. Thus, an alternative to adjusting the CT is adding extra capacity by employing more workers and covering the associated costs. Given the workforce scarcity in many industries, a viable solution is to utilize supportive robots to assist workers with complex and fatigue-inducing tasks (Tong & Liu, 2021).

In manufacturing systems, human-robot interaction during task executing can be categorized into four roles: inactive (resting), active (leading), supportive (following), and adaptive (where the robot dynamically adjusts its role) or intuitive (role determined by human decision) (Wang et al., 2020). This study emphasizes the supportive role of robots in the form of SRLs. These robots are additional robotic appendages designed to augment human capabilities in industrial settings like assembly lines and help mitigate fatigue without impacting task execution time. Figure 6.7 shows an example of an SRL that supports the shoulders to reduce ergonomic risks by lessening the load on them.



(a) A worker performing high-risk tasks affecting the shoulders (b) The same worker with SRL support

Figure 6.7 A sample of supernumerary robotic limb (SRL) for shoulder support

Thus, in this paper, we focus on the supportive role of these robots in assisting human workers in handling complex or physically demanding tasks. This support helps decrease fatigue levels while allowing workers to maintain their active roles, with no changes to task execution time.

6.3.4 Mathematical Optimization Problem

The proposed mathematical model in this study falls under Type F (feasibility programming) optimization, which is a decision problem aimed at finding the most effective (either maximum or minimum) solution among all FSs that satisfy the constraints of the problem (Abdous, Delorme, Battini, & Berger-Douce, 2023). The initial model, applicable to manual AL, seeks to identify all possible FSs, adhering to the following constraints (Equations 6.3 to 6.6):

$$\sum_{j \in W} x_{ij} = 1 \qquad \forall i \in I \tag{6.3}$$

$$\sum_{j \in W} y_j = m \tag{6.4}$$

$$\sum_{j \in W} j x_{i'j} \leq \sum_{j \in W} j x_{ij} \qquad \forall\, i' \in P_i, \qquad i' \in I \backslash \{i\} \tag{6.5}$$

$$\sum_{i \in I} x_{ij}.t_i \leq CT.y_j \qquad \forall\, j \in W \tag{6.6}$$

Equation 6.3 ensures that each task i is assigned to only one workstation. Equation 6.4 verifies the fixed number of available workstations. Constraint 6.5 defines the sequence of workstations based on the precedence relations between tasks. Constraint 6.6 ensures that the total operation time in any open workstation does not exceed the CT. Decision variables x_{ij} and y_j are binary, as defined in Table 6.2.

These four constraints form the foundational step in developing the mathematical model. To address ergonomic risk and alleviate fatigue using SRLs, a threshold F_{max} is set as the maximum accepted fatigue level in each workstation. Based on Equation 6.2 the cumulative fatigue in workstation j (F_j) is summation of fatigue of all assigned tasks to that workstation. Therefore, Equation 6.7 ensures that the cumulative fatigue level in any workstation does not exceed F_{max}, and if it does, an SRL must be allocated to that workstation:

$$F_j - s_j . F_{max} \leq F_{max} \qquad \forall\, j \in W \tag{6.7}$$

The problem model aims to optimize two criteria: the fatigue level and the overall cost of the AL. Among all possible FSs, the model strives to find the best solution based on two objective functions. The first objective (Equation 6.8) is to minimize the maximum ergonomic risk (fatigue level) across the entire AL:

$$\text{Obj1 : Min}\left(\text{Max}_{j\in W}\left\{\sum_{i\in I} x_{ij} . f_i\right\}\right) = \text{Min}\ (\text{Max}_{j\in W}\{F_j\}) \tag{6.8}$$

The second objective is to minimize the additional costs of the AL, which comprise fatigue costs and robot costs. In this study fatigue cost represents the need for additional recovery time, reflecting the over cost of providing workers per shift to mitigate the impact of fatigue on productivity. For calculating the fatigue cost (Equation 6.9), it is assumed that the magnitude of additional recovery time to eliminate ergonomic risk in each workstation is equal to its fatigue level. It means that if cumulative fatigue level of a workstation is equal to 1 (high risk level) a recovery time equal to one working shift should be considered to eliminate the risk. If an SRL is assigned to a workstation, its fatigue level is considered zero. Therefore, the fatigue cost for each FS (the entire AL) is the sum of this cost for all workstations:

$$\text{Fatigue Cost} = \sum_{j\in W}(1 - s_j)\sum_{i\in I} x_{ij} . f_i \ = \sum_{j\in W}(1 - s_j)F_j \tag{6.9}$$

Each unit of cost represents a unit of capacity required to meet necessary recovery time, implying that an additional cost of “1” corresponds to one unit of capacity (a workstation with a worker for one shift) needed for addressing required recovery. For simplicity, only one type of SRL (e.g., a supportive robot for shoulders, as shown in Figure 6.7) is considered. Thus, the robot cost is calculated as a fixed percentage of the fatigue cost (cost of adding each unit of capacity, worker cost per shift):

$$\text{Robot Cost} = \mathrm{c} \sum_{j \in W} s_j \tag{6.10}$$

Therefore, the second objective is to minimize the total over cost of the AL, which is the sum of fatigue and robot costs, the summation of Equations 6.9 and 6.10 as follows:

$$\text{Obj2}: \text{Min} \left(\sum_{j \in W} (1 - s_j) F_j + \mathrm{c} \sum_{j \in W} s_j \right) \tag{6.11}$$

6.3.5 Problem Assumptions

To develop a robust solution approach for the optimization problem, the following assumptions are considered:

- Work Shifts: According to Potvin (2011), work shifts are considered as standard eight hours without any job rotations.
- Task Load and Time: Initially, the load and time for each task are assumed to be equal to their most possible values. However, the fatigue level, which is related to both load and time, is evaluated through an FIS to accommodate the uncertainty inherent in the problem.
- Scenario Planning: The problem entails several scenarios for planning ALs based on the maximum allowed fatigue level at each workstation. Although numerical instances in this paper consider only three different fatigue levels, the proposed solution method can be adopted for any predefined levels.
- Cost Considerations: This study considers only the costs associated with fatigue and robot deployment. Other relevant costs, such as equipment maintenance, training, and potential productivity gains from robot utilization, are not included. Fatigue costs encompass factors such as reduced productivity, increased error rates, and absenteeism. These costs are evaluated based on the cumulative fatigue level at each workstation (F_j) and are equated to

the overtime cost required to mitigate them. To simplify the model, robot costs are expressed in terms of additional work shifts as well.

- Supportive Robots: Although, there are different sorts of SRLs for supporting various parts of body (Tong & Liu, 2021), for simplicity and avoid model complicity, only one type of them is considered in this study.
- Impact of SRLs: When an SRL is allocated to a workstation, it does not affect the execution time of tasks. It is assumed that assigning a robot to a workstation reduces the fatigue level at that workstation to zero.

6.4 Proposed Solution Algorithm

To address the problem outlined in the previous section, an optimization algorithm is proposed, as illustrated in Figure 6.8. The initial stage of the algorithm involves finding multiple FSs while considering all constraints, including precedence relationships between tasks, the defined CT, and the limited number of workstations. An appropriate number of iterations (based on the size of problem) are performed to explore a wider range of potential solutions, thereby increasing the chances of finding the optimal or near-optimal solution. In the solution algorithm, tasks are selected randomly from the “assignable tasks” list. This approach was chosen to ensure a broad exploration of possible task assignments, which can help in identifying diverse solutions and avoiding local optima. While priority rules based on fatigue level, task load, or other criteria can be beneficial, random selection allows for a more unbiased exploration of the solution space. Subsequently, for each FS, the fatigue level of each workstation, F_j (Equation 6.2), is calculated. Based on different scenarios involving various F_{max}, the number of required SRLs (Equation 6.7) is determined.

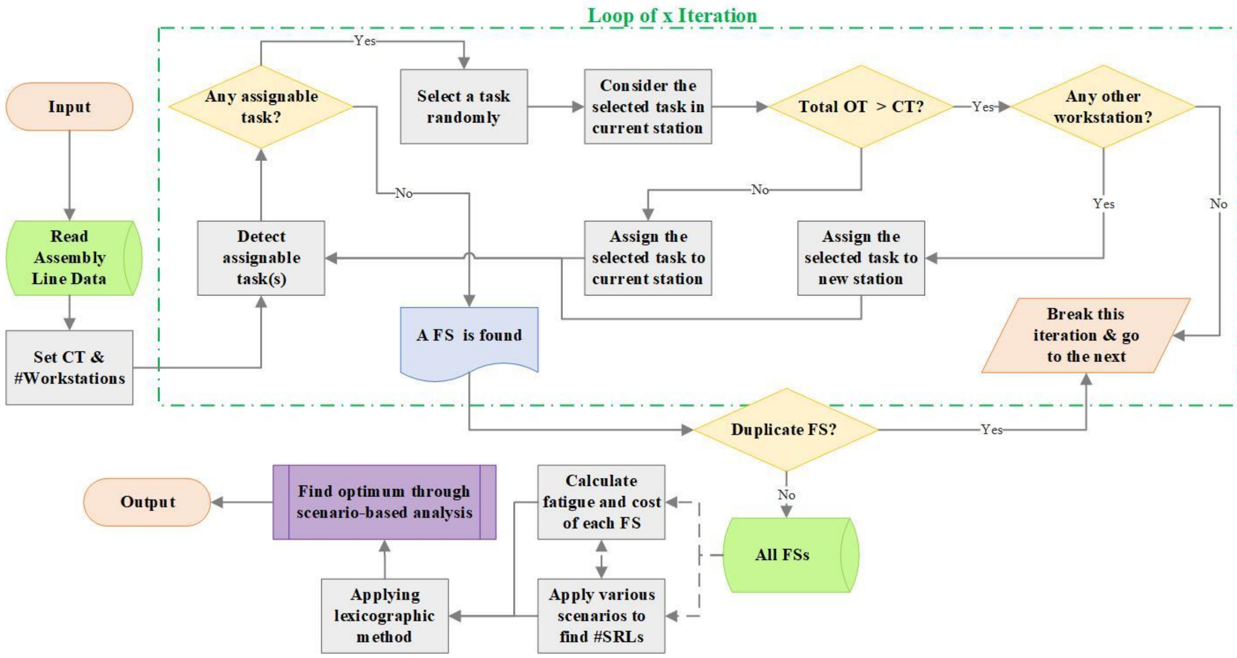


Figure 6.8 Flowchart of the proposed solution for Ergo-RALDP under uncertainty

The primary objective is to identify an FS with the minimum fatigue level across workstations (Equation 6.8), ensuring that all workers experience the lowest level of pressure, resulting in minimal fatigue and reduced recovery times. To facilitate lexicographical programming, all FSs are sorted in ascending order based on their fatigue levels (the value of the first objective).

The second objective, as expressed in Equation 6.11, seeks to minimize the system's overall cost associated with alleviating the fatigue level of the AL. Considering different scenarios based on various thresholds, as outlined in Equation 6.7, can lead to different combinations of fatigue cost (Equation 6.9) and robot cost (Equation 6.10). Using a lexicographical approach, the best solution with the minimum overall cost from the top of the sorted list is identified as the best (optimal or near optimal) solution. The pseudo-code for the proposed solution approach is presented in Figure 6.9.

```
Procedure: Heuristic algorithm for solving fatigue optimization of RALDP
Input: Information on assembly tasks (time, load, precedence relations), #workstations, and #available SRLs
Output: Optimal solution
Read dataset.
FOR x iterations:
    Create two empty lists: "assigned tasks" and "assigned workstations."
    Set initial CT and calculate fatigue for each task.
    WHILE the list of assigned tasks ≠ total #tasks:
        Create an "assignable tasks" list by considering precedence relations.
        Randomly select a task from the "assignable tasks" list
        FOR each workstation in the set of workstations in sequence:
            IF the workstation is not in the list of "assigned workstations':
                IF the total operation time of assigned tasks to this workstation + the selected task's time
                    ≤ CT:
                        Add the selected task to the current workstation & update the sets.
                ELSE:
                        Add the current workstation to the "assigned workstations" list.
                        Continue the FOR loop.
        IF there is no workstation for assigning the selected task:
            Reset all lists & break the WHILE loop.
    Generate an FS for this iteration that contains workstations & their assigned tasks.
    IF the generated FS is not in the "FS Pool":
        Calculate the fatigue level (Fj) of each workstation.
        Calculate the #SRLs needed for different scenarios (various Fmax) and their relative over costs.
END FOR
Apply the lexicographical method to find the best solution with minimum cost (objective 2) through FSs with
the minimum fatigue level (objective1).
```

Figure 6.9 Pseudo code for optimizing the fatigue model for RALDP under various scenarios.

6.4.1 Small-scale Numerical Example

In this part, an illustrative small-scale numerical example is provided to elucidate the proposed solution approach. For an instance, consider an AL comprising 15 tasks. Figure 6.10 visually represents assembly tasks labelled from A to O, with arrows indicating their precedence relationships. Table 6.3 details various data for each assembly task. Initial task data, including "Time", t_i, and "Load", l_i, is presented in the and related columns. The DC is calculated by dividing task time by the CT, with the desired CT set to 60 seconds in this problem. MAE is determined using Equation 1 to establish the initial threshold for Potvin's model. Additionally, the "Distance" column illustrates the gap between MAE and task load, helping in determining the fatigue level according to Figure 6.5.

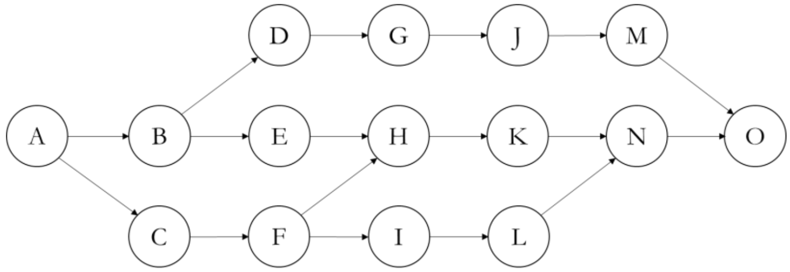


Figure 6.10 Precedence network of a sample assembly line

Table 6.3 Notations of the optimization model

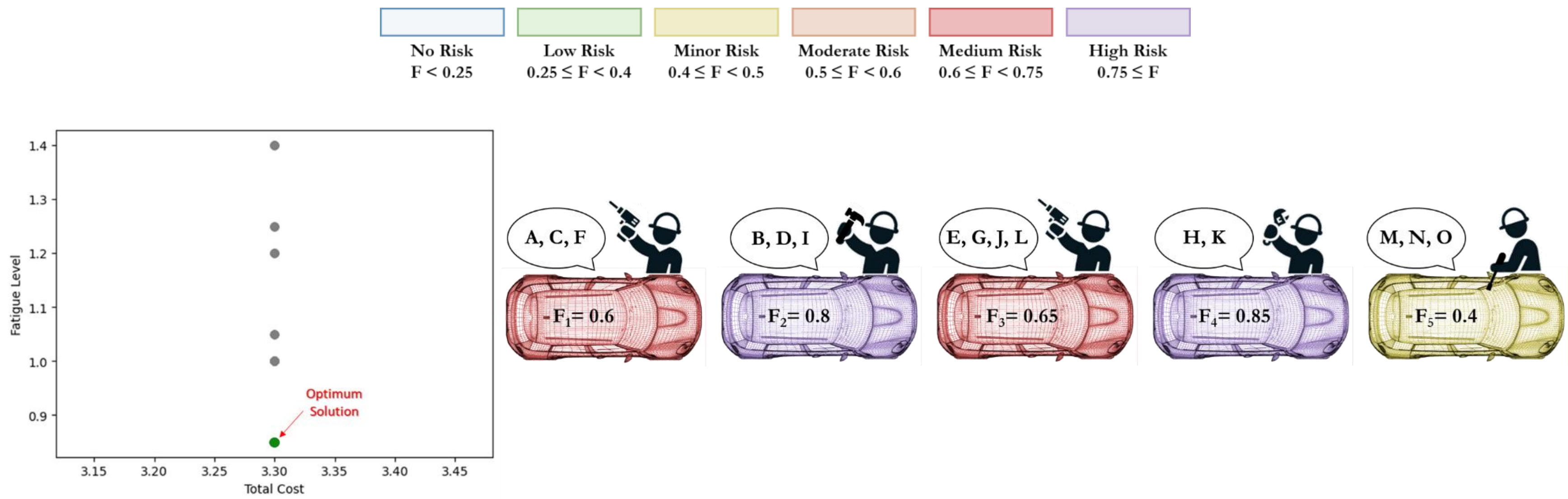
Tasks	**Time**	**Load**	**DC**	**MAE**	**Distance**	**Fatigue**
A	15	0.1	0.25	0.28	-0.18	0
B	20	0.08	0.33	0.23	-0.15	0
C	10	0.13	0.17	0.35	-0.22	0
D	25	0.15	0.42	0.19	-0.04	0.4
E	15	0.14	0.25	0.28	-0.14	0.25
F	20	0.27	0.33	0.23	0.04	0.6
G	10	0.2	0.17	0.35	-0.15	0
H	30	0.19	0.50	0.15	0.04	0.6
I	15	0.23	0.25	0.28	-0.05	0.4
J	10	0.15	0.17	0.35	-0.2	0
K	25	0.1	0.42	0.19	-0.09	0.25
L	20	0.17	0.33	0.23	-0.06	0.4
M	15	0.28	0.25	0.28	-0.003	0.4
N	20	0.05	0.33	0.23	-0.18	0
O	10	0.16	0.17	0.35	-0.19	0

By considering five workstations to assign the tasks, this problem is solved using the coded heuristic algorithm in Python version 3.10. For the second objective of minimizing the over cost, three scenarios are considered in this problem: F_{max} = 0.5, 0.75 or 1. Four parts of Figure 6.11

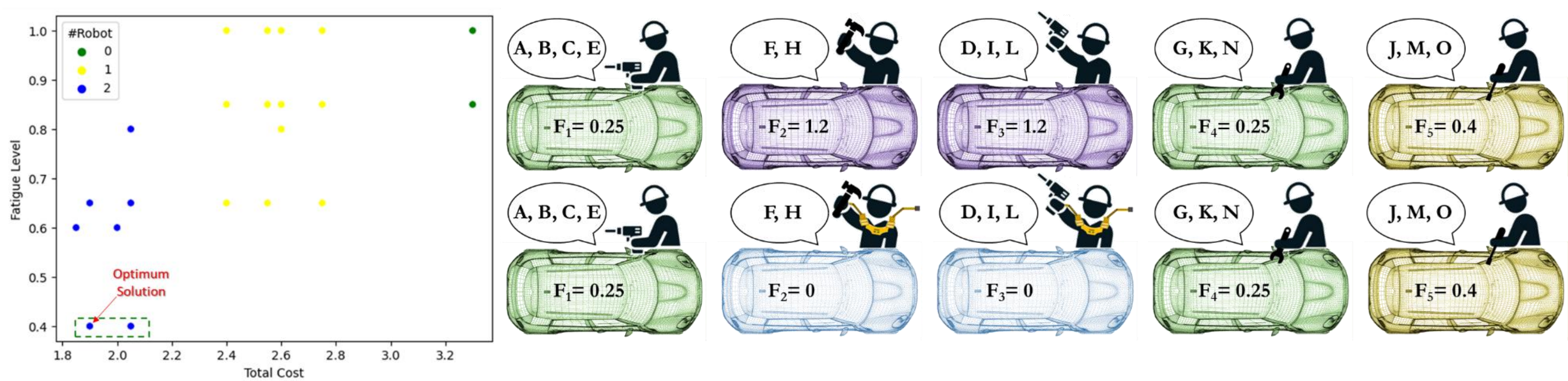
displays FSs and optimum solution in each scenario in addition to considering manual AL option and comparing the optimum solution in each case with manual option.

The left-side plots in Figure 6.11 demonstrate the lexicographic approach, illustrating that the best solution based on the minimum cost is within the group of FSs with the minimum fatigue level. The right-side schematic images present the optimum solution in each scenario while comparing them with the manual option. As Figure 6.11 illustrates, applying tighter thresholds results in lower fatigue level, while leading to more need for SRL and consequently increase the robot cost. Thus, for decision making by considering all pros and cons, one useful factor can be saving amount. If the robot cost in the current example is considered equal to 0.5 unit, meaning equal to 50% of worker cost, the optimum cost and saving for optimum solutions in different scenarios can be shown in Figure 6.12.

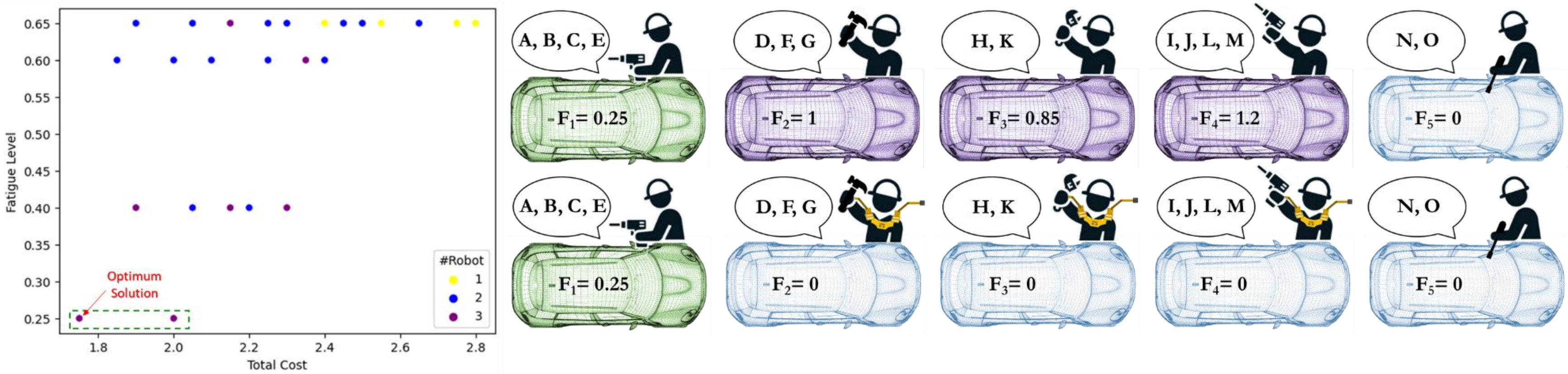
In Figure 6.12, cost components are indicated separately, fatigue cost and robot cost, in addition to total cost to make it easier for analyzing. For instance, the cost of the optimum solution in the second scenario (F_{max} = 0.75) is equal to 1.75 units, which includes one worker who should do over time work for 25% of a shift (fatigue cost = 0.25), and the AL applies three SRLs in workstations 2, 3, and 4 (Figure 6.11c) with the cost of 1.5 units (robot cost = 3×0.5). Based on this diagram, the desirability of the optimum solution in each scenario can be compared to others by considering the area associated to its color. By considering this rule, while the optimum solution of three fatigue-based scenarios has approximately the same desirability, the fatigue level and its cost are decreased as much as the thresholds get tighter. Thus, in scenario 3 (F_{max} = 0.5) fatigue level and its related cost are zero that means no ergonomic risk in the design phase.



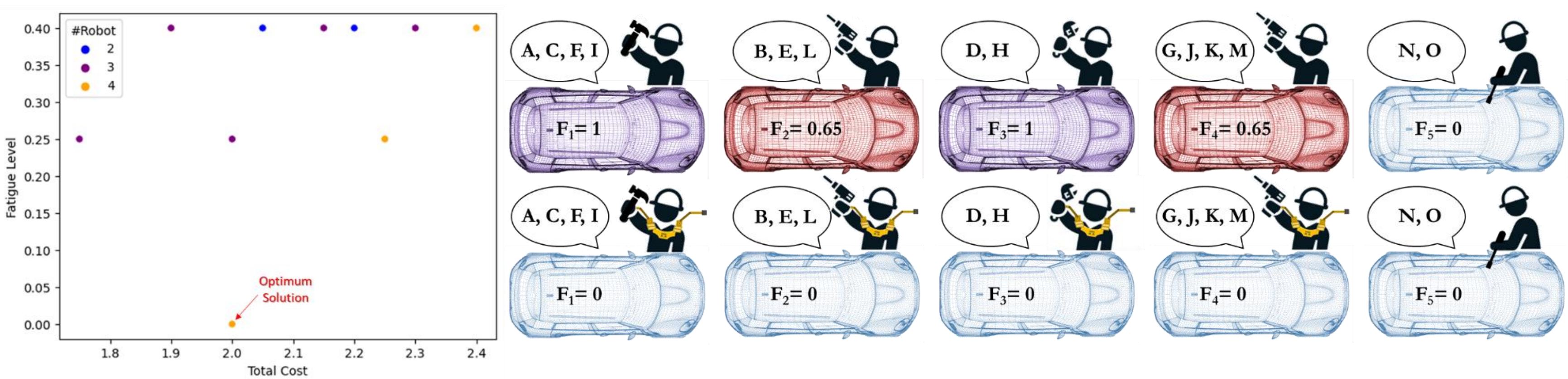
(a) Manual AL without considering fatigue constraint (left: all FSs based on two objectives; right: optimum solution)



(b) Fist scenario: $F_{max} = 1$ (left: all FSs based on two objectives; right: comparing optimum solution with manual AL)



(c) Second scenario: F_{max} = 0.75 (left: all FSs based on two objectives; right: comparing optimum solution with manual AL)



(d) Third scenario: F_{max} = 0.5 (left: all FSs based on two objectives; right: comparing optimum solution with manual AL)

Figure 6.11 Comparison of FSs and optimum (near optimum) solution based on different scenarios

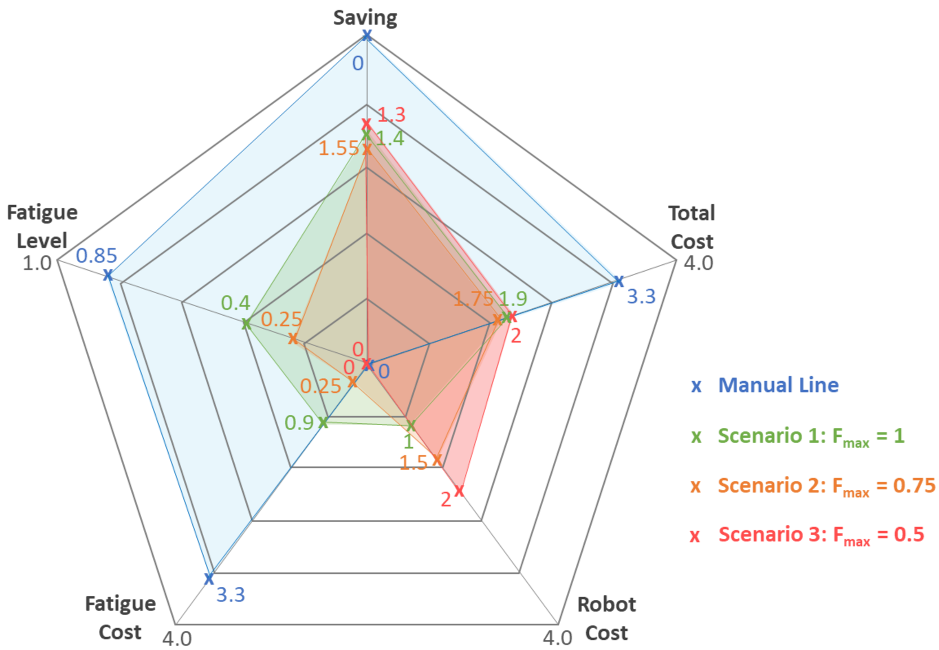


Figure 6.12 Comparison the optimum solution in different scenarios

6.5 Numerical Experiments

This study delves into the implementation of the proposed solution algorithm on a benchmark dataset. In this section, 60 synthesized numerical examples are conducted on a Core i3 3.00 GHz CPU with 20 GB RAM, running Windows 11 OS.

6.5.1 Characteristics of Dataset & Data Preparation

In this step, several experiments were conducted using the well-known SALBP benchmark dataset proposed by Otto et al. (2013). To prepare the dataset and implement the proposed solution algorithm, some modifications were made. The original benchmark dataset contains four groups of instances, each group contains 525 numerical examples with a constant number of tasks (n) but different number of workstations (m) and precedence relations between tasks. The following adjustments were considered to prepare the dataset for implementing the solution method on it:

- Sample selection: Four groups of this dataset have been defined based on the number of tasks in each group. Thus, the problem size identifies the groups like “Small” group (n=20), “Medium” group (n=50), “Large” group (n=100), and “Very Large” group (n=1000). Due to the complex nature of large and very large numerical examples and the extensive computational effort required to solve them, this study focused on small and medium-sized problems. Hence, 30 sample problems were selected from each category to have a sufficient and balanced sample size for the implementation of the solution method. It was ensured the randomness and representativeness of the selection by using a random number generator to pick the sample problems from the original dataset. The distribution and characteristics of the selected sample problems were also checked to make sure that they were similar to the original dataset.

- Time adjustments: Although CT is constant and predetermined in all groups and it is equal to 1000 seconds, from an ergonomic perspective, it is not logical to have such a long CT, and it is too long and unrealistic for most ALs. Therefore, the CT was changed to 60 seconds that is a typical CT in most automotive manufacturing industry. A long CT would increase the ergonomic risk and fatigue level of the workers, as they would have to perform the same tasks for a longer duration without sufficient breaks. A shorter CT would reduce the ergonomic impact and improve the productivity and quality of the AL. Consequently, all task times (t_i) were adjusted by multiplying them by 0.06.
- Number of workstations: This dataset is for solving SALBP-Type 1 which tries to find the minimum number of workstations by considering predetermined CT. Then, for each sample problem, the minimum number of workstations was identified in specific number of iterations (Otto et al., 2013). In the implementation of the proposed algorithm, it was tried to consider the minimum number of workstations suggested in the reference paper.
- Ergonomic parameter: To the best of authors knowledge, there is no existing research specifically synthesizing load parameters for fatigue calculation in available benchmark datasets. Therefore, in this study, load parameter was synthesized through a beta distribution to enable the evaluation of the proposed model on instance problems. The parameters of the beta distribution for the load parameters were determined based on some assumptions and expert opinions. It was assumed that the load parameters are in the range of [2%, 40%] of the MAE. Beta distribution was used to generate the load parameters because it is a flexible and bounded distribution that can model various shapes and behaviors. The parameters of the beta distribution were chosen: $\alpha = 1$ and $\beta = 2$ to generate more numbers near the lower end of the range, as it was expected that most tasks would have a low to moderate load (Abdous, Delorme, Battini, Sgarbossa, et al., 2023). The

assumptions and parameters were also validated by consulting some experts in the field of AL design and ergonomics.

After preparing the dataset, the solution method was implemented to solve all 60 sample problems (2 groups × 30 samples). Moreover, the assumptions for the implementation of the solution algorithm on these samples were the same as what considered in the small-scale numerical example in subsection (6.4.1). As a result, three scenarios were considered including F_{max} equal to 1, 0.75, and 0.5; and the cost of allocating each unit of the robot was considered 0.5 unit of capacity.

6.5.2 Numerical Results

Tables 6.4 and 6.5 present the output of three scenarios, alongside the initial optimum solution for each case, representing the manual AL. For each scenario, in addition to the values of first and second objectives (fatigue level (Obj1) and total cost (Obj2), respectively), the number of SRL(s) and cost saving amount are presented to make the analysis process easier.

Table 6.4 The output of optimization algorithm on synthesized small-size instances (n=20)

No.	**m**	**Manual AL**		**S1 (F_{max}=1)**				**S2 (F_{max}=0.75)**				**S3 (F_{max}=0.5)**			
		Obj1	**Obj2**	**Obj1**	**#SRL**	**Obj2**	**Save**	**Obj1**	**#SRL**	**Obj2**	**Save**	**Obj1**	**#SRL**	**Obj2**	**Save**
3	3	0.4	0.65	0.4	0	0.65	0	0.4	0	0.65	0	0	1	0.5	0.15
5	3	0.6	1.7	0.25	1	0.75	0.95	0	2	1	0.7	0	2	1	0.7
18	11	1.25	8.7	0.8	3	6.1	2.6	0.65	5	5.5	3.2	0.25	6	4	4.7
41	6	0.85	3.55	0.6	2	2.1	1.45	0.25	3	1.75	1.8	0	4	2	1.55
43	5	0.85	2.9	0.65	1	1.8	1.1	0	3	1.5	1.4	0	3	1.5	1.4
50	4	1.0	2.9	0.25	2	1.25	1.65	0.25	2	1.25	1.65	0	3	1.5	1.4
90	3	0.4	0.9	0.4	0	0.9	0	0	1	0.5	0.4	0	1	0.5	0.4
120	6	1.0	3.7	0.8	1	2.6	1.1	0.25	4	2.25	1.45	0.25	4	2.25	1.45
132	4	0.75	2.3	0.4	1	1.4	0.9	0.25	2	1.25	1.05	0	3	1.5	0.8
135	6	0.65	3.25	0.6	1	2.55	0.7	0.25	3	1.75	1.5	0.25	3	1.75	1.5
143	3	0.75	1.25	0	1	0.5	0.75	0	1	0.5	0.75	0	1	0.5	0.75

Table 6.4 The output of optimization algorithm on synthesized small-size instances (n=20) (continue)

No.	m	Manual AL		S1 (F_{max}=1)				S2 (F_{max}=0.75)				S3 (F_{max}=0.5)			
		Obj1	Obj2	Obj1	#SRL	Obj2	Save	Obj1	#SRL	Obj2	Save	Obj1	#SRL	Obj2	Save
145	3	0.75	1.9	0.5	1	1.25	0.65	0.5	1	1.25	0.65	0.25	2	1.25	0.65
164	4	0.65	2.4	0.25	2	1.25	1.15	0.25	2	1.25	1.15	0	3	1.5	0.9
171	13	1.25	9.3	0.85	2	7.65	1.65	0.75	5	6.55	2.75	0.4	10	5.9	3.4
193	5	0.65	2.75	0.4	1	1.4	1.35	0.4	1	1.4	1.35	0	3	1.5	1.25
215	5	1.0	3.4	0.65	1	2.3	1.1	0.65	2	1.9	1.5	0.25	3	1.75	1.65
225	3	0.4	0.65	0.4	0	0.65	0	0.4	0	0.65	0	0.4	0	0.65	0
243	10	1.25	8.0	0.85	3	5.95	2.05	0.5	7	4.25	3.75	0.25	8	4.5	3.5
282	4	0.6	1.65	0.6	0	1.65	0	0	2	1	0.65	0	2	1	0.65
289	5	0.75	2.55	0.5	1	1.9	0.65	0.5	1	1.9	0.65	0.25	3	1.75	0.8
313	3	0.65	1.05	0.65	0	1.05	0	0.65	0	1.05	0	0.4	1	0.9	0.15
347	6	0.85	4.35	0.65	3	2.4	1.95	0.25	4	2.25	2.1	0	5	2.5	1.85
355	5	1.0	2.85	0.6	1	1.75	1.1	0.6	2	1.6	1.25	0.0	3	1.5	1.35
356	5	0.75	3.05	0.65	1	2.3	0.75	0.5	2	2.15	0.9	0.25	3	2.0	1.05
387	3	0.65	1.9	0.4	1	1.15	0.75	0	2	1.0	0.9	0	2	1	0.9
400	12	1.25	9.75	1	2	7.15	2.6	0.75	5	6.25	3.5	0.5	9	5.5	4.25
462	3	0.8	1.45	0.8	0	1.45	0	0.4	1	1.15	0.3	0.4	1	1.15	0.3
481	13	1.25	9.0	0.8	3	6.4	2.6	0.75	5	6.25	2.75	0.25	10	5.75	3.25
489	12	1.15	8.7	1	3	6.75	1.95	0.6	6	5.55	3.15	0.5	7	5.45	3.25
510	5	1.0	3.15	0.4	2	1.65	1.5	0.4	2	1.65	1.5	0.25	3	1.75	1.4

Table 6.5 The output of optimization algorithm on synthesized medium-size instances (n=50)

No.	**m**	**Manual AL**		**S1 (F_{max}=1)**				**S2 (F_{max}=0.75)**				**S3 (F_{max}=0.5)**			
		Obj1	**Obj2**	**Obj1**	**#SRL**	**Obj2**	**Save**	**Obj1**	**#SRL**	**Obj2**	**Save**	**Obj1**	**#SRL**	**Obj2**	**Save**
4	7	0.65	3.10	0.5	2	2	1.1	0.5	2	2	1.1	0.25	3	2	1.1
12	7	0.4	1.15	0.4	0	1.15	0	0.25	1	0.75	0.4	0.25	1	0.75	0.4
53	13	1.15	6.1	0.75	1	5.35	0.75	0.6	3	4.65	1.45	0.4	6	4.55	1.55
81	7	0.5	2.2	0.4	1	1.4	0.8	0.4	1	1.4	0.8	0	3	1.5	0.7
82	6	0.4	1.55	0.25	1	1	0.55	0.25	1	1	0.55	0.25	1	1	0.55
94	7	0.6	2.15	0.6	0	2.15	0	0.4	1	1.8	0.35	0.25	2	1.75	0.4
96	7	0.75	3.6	0.65	1	2.9	0.7	0.5	2	2.5	1.1	0.25	3	2.5	1.1
100	7	0.75	3.2	0.5	1	2.15	1.05	0.4	2	2.15	1.05	0.25	3	2	1.2
139	12	0.8	6.35	0.8	1	5.6	0.75	0.6	5	4	2.35	0.4	6	3.9	2.45
152	7	0.4	1.9	0.25	1	1.25	0.65	0.25	1	1.25	0.65	0.25	1	1.25	0.65
173	8	0.4	2.15	0.25	1	1.5	0.65	0.25	1	1.5	0.65	0.25	2	1.5	0.65
174	7	0.4	1.8	0.4	0	1.8	0	0.4	1	1.4	0.4	0.25	2	1.25	0.55
201	13	1.35	8.2	1.0	1	7.35	0.85	0.75	4	6.1	2.1	0.4	9	5.4	2.8
206	12	0.9	6.85	0.75	2	5.1	1.75	0.6	4	4.5	2.35	0.5	5	4.4	2.45
238	7	0.5	2.3	0.5	0	2.3	0	0.25	2	1.5	0.8	0.25	2	1.5	0.8
277	14	1.0	7.9	0.85	2	6.25	1.65	0.65	5	5.15	2.75	0.4	7	5.05	2.85
285	14	0.8	6.55	0.65	2	5.1	1.45	0.65	2	5.1	1.45	0.5	4	4.8	1.75
300	13	0.65	6.0	0.6	2	4.7	1.3	0.25	5	3.75	2.25	0.25	5	3.75	2.25
325	7	0.5	2.55	0.5	1	2	0.55	0.5	1	2	0.55	0.25	3	2	0.55
351	13	0.8	7.0	0.8	2	5.5	1.5	0.75	3	5.2	1.8	0.4	7	4.65	2.35
353	14	0.75	6.2	0.75	2	4.8	1.4	0.65	4	4.35	1.85	0.25	7	4	2.2
367	12	1.35	7.65	1	1	6.8	0.85	0.75	4	5.65	2.0	0.5	8	5.25	2.4

Table 6.5 The output of optimization algorithm on synthesized medium-size instances (n=50) (continue)

No.	m	Manual AL		S1 (F_{max}=1)				S2 (F_{max}=0.75)				S3 (F_{max}=0.5)			
		Obj1	Obj2	Obj1	#SRL	Obj2	Save	Obj1	#SRL	Obj2	Save	Obj1	#SRL	Obj2	Save
372	11	0.9	5.25	0.65	1	4.35	0.9	0.4	5	3.4	1.85	0.4	6	3.4	1.85
388	7	0.6	1.1	0.6	0	1.1	0	0.25	1	0.75	0.35	0.25	1	0.75	0.35
434	12	0.8	6.35	0.8	1	5.5	0.85	0.75	4	4.55	1.8	0.4	6	4.15	2.2
452	8	0.65	3.3	0.6	1	2.6	0.7	0.6	1	2.6	0.7	0.5	3	2.5	0.8
453	7	0.5	2.3	0.5	0	2.3	0	0.4	1	1.9	0.4	0.25	2	1.75	0.55
463	8	0.75	3.55	0.75	0	3.55	0	0.5	2	2.8	0.75	0	5	2.5	1.05
501	12	1.1	8.6	1	1	7.6	1	0.75	2	7.1	1.5	0.5	4	6	2.6
517	14	0.75	7.0	0.65	2	5.1	1.9	0.65	3	5.1	1.9	0.5	4	4.95	2.05

6.5.3 Results Analysis

The results from the numerical experiments highlight the high quality of solutions achieved. To analyze the final outputs of the optimization method comprehensively, several key indicators have been defined to compare the optimum solution in each scenario with the initial optimum answer for the manual AL. These indicators include:

- Reduction in fatigue level: $\frac{Fatigue_{manual} - Fatigue_{scenario\ x}}{Fatigue_{manual}}$
- Reduction in total cost: $\frac{Cost_{manual} - Cost_{scenario\ x}}{Cost_{manual}}$
- Saving per capacity: $\frac{Saving_{scenario\ x}}{\#Workstation}$

The comparison of the average results of measuring these indicators across 30 numerical samples of both small and medium groups is presented in Table 6.6. The “Ineffective” parameter in this table indicates the number and percentage of samples that the optimum solutions in them in each scenario did not change the benefit (saving) in comparison to previous scenario. For example:

- In small-size samples, the first scenario (F_{max} = 1) in six samples (20% of all samples) did not show any improvement in comparison to the manual option. Based on these parameters, it is obvious that the second and third scenarios have the same desirability in economic perspective as they both have the same cost reduction factor. However, the third scenario has more fatigue reduction that means it has better performance in ergonomics aspect.

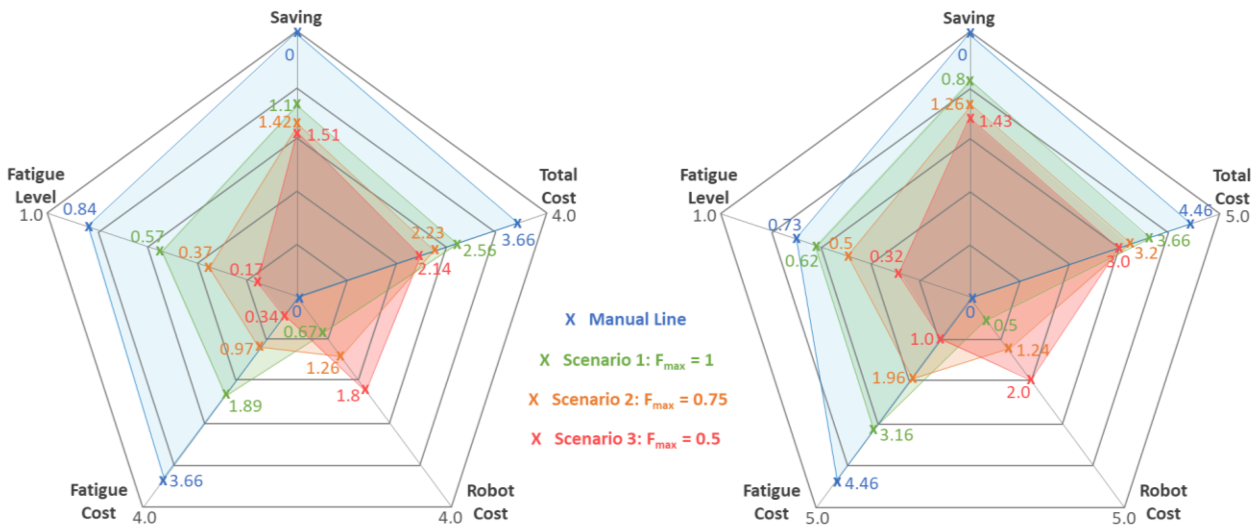
- In medium-size samples, the third scenario shows less impact as around 37% of samples do not show any improvement in comparison to the second scenario. However, in the other samples the improvements are significant and compensate for the ineffective samples.

Therefore, different scenarios, various thresholds, might have diverse impacts on problems based on their characteristics, constraints, and limitations.

Table 6.6 Comparison of several indicators in different scenarios

Category	**Scenarios**	**Fatigue Reduction**	**Cost Reduction**	**Saving per Capacity**	**Ineffective**
Smal	S1: F_{max} = 1	30%	34%	32%	6 (20%)
	S2: F_{max} = 0.75	52%	47%	44%	10 (33%)
	S3: F_{max} = 0.5	81%	47%	44%	10 (33%)
Medium	S1: F_{max} = 1	16%	15%	12%	7 (23%)
	S2: F_{max} = 0.75	30%	28%	22%	9 (30%)
	S3: F_{max} = 0.5	55%	37%	29%	11 (37%)

Although, the application of each scenario is dependent on the characteristics of the AL, comparing the value of important factors in various scenarios can give some idea about defining the best effective threshold (F_{max}) for fatigue reduction and robot assignment. Figure 6.13 illustrates the comparison between the average of some important factors in different scenarios for small and medium-size samples.



(a) Small-size instances (b) Medium-size instances

Figure 6.13 Comparison the average values of optimum solutions in different scenarios

6.6 Discussion

Subsequent subsections will delve into detailed analysis and discussion of the results of implementing the model on sample dataset.

6.6.1 Validation & Verification

This study represents a pioneering effort in incorporating fuzzy fatigue models into the realm of RALDPs. While previous studies in Ergo-ALBP have considered fatigue and/or recovery models, none have addressed the uncertain conditions of these problems in the design phase. By employing the fatigue model proposed by Potvin (2011), this research has developed a novel fatigue model through a fuzzy expert system and applied it to ALDPs.

Moreover, recognizing the prevailing human resource shortage crisis in many industries and countries, this study incorporated the application of robots, specifically SRLs, to alleviate operators' fatigue and reduce required recovery times. By considering these factors, several scenarios were developed to optimize RALDPs and minimize the total over costs of the system, encompassing fatigue and robot costs allocations for equipping workstations with SRLs.

Given the novelty of incorporating fuzzy fatigue model in RALDP, direct comparisons with previous research are limited. Additionally, synthesized data in ergonomic and technical aspects may influence optimum results favorably or unfavorably. Nevertheless, to compare the performance of the proposed approach with alternative methods or benchmark datasets, statistical significance testing was conducted using the ANOVA approach. Table 6.7 reports the statistical significance of the differences in fatigue levels (objective 1) and overall costs (objective 2) between the optimized solutions of different scenarios.

Table 6.7 ANOVA test results ($\alpha = 0.05$)

Category	Test Type		F-statistic	P-value	F-critical
Small	One-way ANOVA (Obj1)		45.18	2.04×10^{-19}	2.68
	One-way ANOVA (Obj2)		3.05	0.031	2.68
	Two-way ANOVA	Sample Effect	5.83	0.0007	2.64
		Scenario Effect	116.31	3.03×10^{-22}	3.88
		Interaction Effect	1.22	0.30	2.64
Medium	One-way ANOVA (Obj1)		22.65	1.29×10^{-11}	2.68
	One-way ANOVA (Obj2)		3.11	0.029	2.68
	Two-way ANOVA	Sample Effect	4.86	0.0027	2.64
		Scenario Effect	275.91	2.37×10^{-41}	3.88
		Interaction Effect	1.75	0.156	2.64

Overall analysis of the results shows the approximately same results for both small and medium instances. One-factor ANOVA analysis reveals significant differences in the first objective function between the four scenarios. The high F-statistic and the very low P-value indicate that the differences between the groups are not due to random chance, and the scenario choice significantly impacts the first objective function. For the second objective, the differences between various scenarios are noticeable, as the P-value is less than 0.05 and the F-statistic is greater than F-critical; however, the impact of scenario choice on the second objective is less pronounced than on the first one.

Two-factor ANOVA analysis also presents consistent results across both instance types. Both the sample effect and the scenario effect are statistically significant, indicating that both the choice of sample and the choice of scenario significantly affect the objective functions. The scenario effect is particularly strong, as indicated by the very high F-statistic and extremely small P-value. However, the interaction effect between sample and scenario is not statistically significant. This means that the effect of the scenario on the objective functions does not depend significantly on the sample chosen.

Therefore, the results of the validation process demonstrate the consistent ability of the proposed solution approach to produce accurate solutions in terms of minimizing fatigue levels and overall costs. This study represents the first attempt to generate customized fuzzy fatigue factors for the conventional ALBP benchmark dataset, paving the way for future sensitivity analyses when incorporating fatigue data into such datasets.

6.6.2 Academic Implementation

The present research introduces a novel approach to fatigue consideration in RALDPs under uncertainty, offering potential applications in academic settings. Firstly, by employing three levels of thresholds as scenarios for decision-making and finding optimum solutions with minimum ergonomic and operational cost, this study lays the groundwork for conducting sensitivity analyses to determine the most suitable scenario for capturing the possibility of future conditions accurately.

Secondly, the thresholds defined in this study based on the expert knowledge can be further explored and analyzed to establish improved fit fuzzy rules. Alternative expert systems can be employed to adjust or modify fuzzy rules based on different methodologies, and various statistical analyses can be applied to different case studies to identify optimal thresholds for fatigue risk evaluation.

Thirdly, the novelty of FIS application in developing the fatigue model presents opportunities for further contributions in future studies. Alternative fatigue and recovery methods can be fuzzified, and the solution approach can be implemented on them for comparative analysis. Furthermore, the model can be applied to other problem types such as assembly line worker assignment and balancing problems (ALWABPs), disassembly cells considering collaborative robots, or rebalancing problems with different scenarios and possibilities. Therefore, this research offers numerous potential contributions to the academic community, stimulating further studies in academic scenarios and fostering advancements and innovative approaches in the field.

6.6.3 Industrial Implementation

The proposed solution method carries significant implications and potential benefits for industrial applications, particularly within the framework of Industry 4.0. This era of manufacturing is characterized by increased automation and a growing emphasis on human-robot collaboration, where the implementation in real-world industrial settings allows for the integration of managerial insights and ergonomic expertise during the optimization process becomes crucial. By applying the fuzzy fatigue evaluation approach during the design phase, the model's applicability in industrial contexts can be enhanced, influencing by Industry 4.0 innovations. At the task level, the output from this fuzzy fatigue model aids in work cell planning by categorizing possible results into approximate fatigue levels, facilitating a more robust approach to human-robot interaction.

Moreover, the flexibility of the proposed fuzzy rules allows for customization to meet specific industry requirements, such as the integration of supportive robots, cobots, or specialized equipment designed to mitigate potential fatigue levels. This adaptability is particularly relevant in the context of Industry 4.0, where the blend of technical optimization and human-centric considerations is paramount. The proposed hybrid model also addresses the economic aspects of Industry 4.0 by optimizing based on fatigue levels and total system cost. This cost metric can be varied to include different types of SRLs with varying costs or to ensure the smoothness of risk levels across the AL, thus impacting support levels and overall operational performance.

While the focus of this study has primarily been on the feasibility aspect of ALDPs, the optimization model is highly adaptable, able to incorporate additional constraints and limitations to suit specific production system preferences within Industry 4.0 frameworks. By tackling uncertain and imprecise data through fuzzy logic, engineers and ergonomic practitioners can derive more reliable and robust solutions, effectively managing parameter variability. These advancements contribute to planners' achieving higher productivity and efficiency in automated and human-interactive AL, aligning with the strategic goals of Industry 4.0 and paving the way for the smooth integration of Industry 5.0's human-centric values. This study not only supports the operational efficiencies desired in Industry 4.0 but also anticipates the ergonomic and collaborative advancements introduced by Industry 5.0, demonstrating a progressive alignment with the evolving needs of modern manufacturing industries.

6.6.4 Limitations

In this study, several limitations are acknowledged that may affect the validity and reliability of the findings:

- Data quality and quantity: Despite our efforts to compile comprehensive data and establish logical time parameters and generate ergonomic factors across the benchmark dataset, the quality and quantity of synthesized data could impact the robustness of our findings, potentially limiting their generalizability.
- Evaluator expertise: While our evaluators possessed adequate expertise, there was some variation, introducing potential subjectivity into the assessments. To mitigate this, we utilized standardized assessment tools to maintain consistency to a certain extent.
- Solution framework: Our solution framework offers valuable insights into ALDPs; however, it may not guarantee the identification of optimal or Pareto optimal solutions, especially for large-scale instances of the problem. The complexity and size of the problem can affect the efficacy of our framework in uncovering the best solutions. For instances with significant scalability challenges, alternative methods such as metaheuristics might offer greater effectiveness in attaining superior solutions. Future research could explore integrating metaheuristic techniques to enhance solution quality.
- Ergonomic assessment approach: While we employed the fatigue model developed by Potvin (2011) to assess fatigue risk levels, this marks the first instance of using such a distinguished fatigue model for developing fuzzy rules to model uncertainty in the system. Consequently, there might be bugs and weaknesses in our proposed ergonomic evaluation method, potentially hindering a comprehensive view of workplace ergonomics. Future studies should analyze the approach through real-world case studies to gain a thorough understanding and effective mitigation of ergonomic risks.
- Optimization model: In our optimization model, we aimed to minimize the maximum fatigue level among all workstations and the overall cost of the system. However, other objective functions, such as minimizing cumulative fatigue on various body parts or minimizing the deviation of fatigue levels among workstations, could be considered. Furthermore, our model was constrained with predetermined CT and workstation number limits due to the Type F optimization problems we studied. Future research avenues could

explore minimizing the number of workstations (Type 1) or CT (Type 2) or consider new objective functions to address workload balancing, maximizing throughput, or other aspects, potentially leading to the development of alternative multi-objective mathematical models.

These limitations underscore the importance of considering various factors when interpreting our study's results and implications. They also suggest promising directions for future research in the field of Ergo-RALDPs.

6.7 Conclusions

In this study, the challenges of optimizing RALDPs were addressed by introducing a novel solution framework that incorporates fuzzy fatigue evaluation and robotic support. Present research aimed to minimize operator fatigue levels and reduce overall system costs in AL environments, directly aligning with the strategic goals of Industry 4.0, which advocates for increased automation and smarter integration of human-robot collaboration.

The modeling part of this paper identified the key challenges faced in RALDPs, including the need to minimize operator fatigue and optimize system costs while considering all constraints. These challenges emphasized the importance of developing a comprehensive solution framework to address the complexities of AL optimization within an Industry 4.0 framework. This approach bridges significant gaps identified in the existing literature, particularly in integrating ergonomic considerations that have often been overlooked in traditional optimization efforts.

The solution approach presented in this research utilized an innovative optimization method, leveraging a heuristic algorithm to generate multiple FSs while addressing task precedence and timing considerations. By incorporating fuzzy fatigue evaluation and robotic support, proposed algorithm aimed to minimize operator fatigue levels and optimize system costs through a heuristic method that incorporates several scenarios in order to facilitate decision-making process. This approach exemplifies the transition from Industry 4.0 to Industry 5.0 by emphasizing a human-centric automation strategy, thereby enhancing worker well-being alongside operational efficiency.

The results of the numerical experiments validated the effectiveness of the solution approach, demonstrating significant reductions in operator fatigue and system costs across various scenarios. Through comparative analysis and rigorous validation efforts, the consistency and reliability of the solution approach in optimizing RALDPs were established, showcasing its practical applicability in real-world industrial settings.

In conclusion, this study contributes significantly to the field of AL optimization by addressing the dual challenges of operator fatigue/recovery management and system cost reduction within the Industry 4.0 paradigm. By integrating fuzzy fatigue evaluation and robotic support into the optimization process, this research offers a practical and effective framework for enhancing productivity, efficiency, and worker well-being in industrial AL environments. This study not only supports the operational efficiencies desired in Industry 4.0 but also anticipates the ergonomic and collaborative advancements introduced by Industry 5.0, demonstrating a progressive alignment with the evolving needs of modern manufacturing industries.

Moving forward, further research can explore additional optimization objectives, incorporate real-world case studies, and refine the solution framework to address evolving challenges and requirements in AL design and operation. By continuing to innovate and refine this approach, it can contribute to the advancement of AL optimization practices and facilitate the transition towards more efficient and ergonomic AL systems.

CHAPTER 7 ARTICLE 4: ERGO4ALL-PRO: EMPOWERING HUMAN-CENTRIC DESIGN IN THE VIRTUAL ERA

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Abstract

As industries transition towards Industry 5.0, which emphasizes human-centric values and well-being, the importance of ergonomic risk assessment in workplace design has never been more critical. Traditional ergonomic assessment tools have played a crucial role in evaluating and identifying potential risks; however, their limitations, particularly in virtual environments and digital human modeling systems, highlight the need for more comprehensive and adaptable methodologies. This paper introduces Ergo4All-Pro™, a novel ergonomic risk assessment model designed to enhance existing virtual systems by providing a detailed evaluation of cumulative and integrated risks across various body parts. Building upon the foundational Ergo4All™ model, Ergo4All-Pro™ incorporates insights from well-established methods such as OCRA, RULA, and REBA, while addressing challenges in assessing risks related to individual body parts of upper limb. The model leverages a fuzzy knowledge-based expert system to generate rules for predicting ergonomic risks, offering both categorical and score-based assessments. To validate its effectiveness, Ergo4All-Pro™ was applied to real-world industrial workstation and synthesized scenarios, with results compared to benchmark tools, including EAWS and OCRA. The findings demonstrate that Ergo4All-Pro™ not only aligns well with these benchmarks but also provides a more refined assessment of ergonomic risks, particularly in areas that conventional tools may overlook. The model's ability to evaluate cumulative risks in individual body parts, help to optimize assembly lines in the design phase, and reduce subjective biases inherent in traditional assessments underscores its potential for both academic and industrial applications. Ergo4All-Pro™ represents a significant advancement in ergonomic risk assessment, paving the way for safer, more efficient workplace designs in the era of Industry 5.0.

Keywords: Assembly workstation; Digital human modeling; Disassembly cell; Ergonomic risks; Expert system; Industry 5.0; Virtual reality

7.1 Introduction

The increasing complexity of modern industrial environments, driven by advancements in automation and human-robot collaboration, has intensified the need for robust ergonomic risk assessment methodologies in workplace design. As industries transition toward Industry 5.0, which emphasizes human-centric values, well-being, and sustainability, there is a growing demand for advanced tools that can proactively assess and mitigate ergonomic risks (Ghorbani et al., 2023). Despite the availability of traditional EATs, these tools often fall short in dynamic and virtual environments (Da Silva et al., 2022). This is particularly evident in DHM systems, where complex work tasks and interactions between humans and their environments necessitate more adaptive approaches (Chaffin, 2005; De Magistris et al., 2013). Integrating HF/E early in the design phase is essential to ensure that ergonomic considerations are central to design and assembly planning (Ahmed et al., 2021).

The limitations of conventional EATs are well-documented. Traditional tools often focus on static assessments of body parts, overlooking cumulative ergonomic risks over time, an issue particularly relevant in repetitive tasks (Li et al., 2019). Furthermore, many of tools rely heavily on subjective evaluations, such as checklists, which introduce variability and inconsistency in risk assessments (Dahibhate et al., 2023). These challenges are exacerbated in virtual environments, where spatial and environmental factors are more difficult to assess (Poirson & Delangle, 2013). Additionally, conventional EATs are prone to errors, time-consuming processes, and observer inconsistencies (Wang et al., 2021).These challenges underscore the need for more comprehensive and adaptable ergonomic assessment methodologies that integrate time-based factors and provide detailed evaluations across different body parts.

This research addresses these gaps by introducing a novel ergonomic assessment framework that integrates cumulative risk evaluation into DHM systems. Unlike traditional EATs, which primarily focus on static postures, the proposed model incorporates dynamic simulation capabilities using virtual environments to enhance ergonomic risk assessments. This model integrates insights from established methods such as OCRA (occupational repetitive action) index (Occhipinti, 1998) and adopts a fuzzy knowledge-based expert system approach. This enables a comprehensive assessment of cumulative risks, particularly in individual body parts of the upper limb, using a reverse engineering approach to incorporate time factors based on OCRA's logic.

To further enhance the model, methodologies from the RULA (rapid upper limb assessment) (McAtamney & Nigel Corlett, 1993) and REBA (rapid entire body assessment) (Hignett & McAtamney, 2000) are incorporated, facilitating comparisons with other EATs and generating a unique risk factor for the upper limb. The proposed model, Ergo4All-Pro™, enhances existing DHM systems by providing detailed evaluations of cumulative and integrated risks across various body parts.

In addition to addressing broader scientific challenges, this research bridges the gap between academic research and industrial application. Therefore, the proposed methodology is implemented specifically in ergonomic workplace design (EWD), developed by Dassault Systèmes, which helps engineers design safer and more efficient workplaces by applying DHM to avoid MSDs and their associated costs. EWD applies the Ergo4All™ methodology, which leverages existing standards to assess ergonomic risks in each body part for static tasks (Dassault Systèmes, 2024). Building upon this foundation, Ergo4All-Pro™ is introduced, which incorporates insights from OCRA, RULA, and REBA, while addressing gaps in traditional methods. This comprehensive model uses a fuzzy knowledge-based expert system to generate rules for predicting ergonomic risks, offering both categorical and score-based assessments.

The model offers several key capabilities that enhance ergonomic assessments within DHM systems:

- Elimination of subjectivity: The model significantly reduces the subjective variability inherent in conventional EATs. By using static evaluation methods that assess posture and force risks in upper limb joints, the model employs a dynamic simulation-based expert system to determine the cumulated risk for each body part individually, as well as the overall upper limb. With inputs based on the Ergo4All™ method, adhering to biomechanical evaluation and various standards such as EN1005-2, EN1005-3, EN1005-4, ISO 14738, ISO 11226, and ISO 11228-3 (Bourret et al., 2021), the model provides more objective and reliable ergonomic risk assessments.
- Individual body part risk assessment: The model enables ergonomic-oriented job rotation in ALBPs by detecting cumulative risks for each body part individually. It also supports decision-makers in assigning collaborative robots (cobots) and supportive robots based on identified risk points (Tong & Liu, 2021).

- Adaptability: The model is designed to integrate with a range of static EATs, allowing for dynamic simulation of risk evaluations. This adaptability allows engineers to assess cumulative ergonomic risks early in the design process, facilitating the optimization of workstations for safety and efficiency across different industrial environments.
- Optimization of assembly/disassembly lines: As a virtual assessment tool, Ergo4All-Pro™ allows for the optimization of workstations and entire ALs during the design phase, preventing future ergonomic issues and associated costs.

The primary objective of this study is to validate the effectiveness of Ergo4All-Pro™ through its application in real-world industrial workstations and simulated scenarios. By comparing the model's performance with benchmark EATs such as the EAWS and OCRA, this research demonstrates the model's potential to significantly enhance DHM systems, offering both academic insights and practical solutions to ergonomic challenges.

This chapter is structured as follows: after reviewing the relevant literature in Section 7.2, the methodology underlying the development of Ergo4All-Pro™ is presented in Section 7.3. Subsequently, Section 7.4 details the model's implementation, followed by a discussion of the results in Section 7.5, including validation efforts and potential academic and industrial applications. Finally, Section 7.6 presents the concluding remarks and suggests directions for future research.

7.2 Literature Review

The field of ergonomic risk analysis has significantly evolved with the integration of advanced technologies, including DHM, VR, and automation tools. The application of EATs within DHM systems for the design of assembly/disassembly workstations has attracted growing interest, particularly in the contexts of Industry 4.0 and the emerging Industry 5.0. This trend reflects the need to mitigate the risks of WMSDs and enhance worker safety and productivity through innovative technologies. Recent studies have highlighted the evolution and application of various digital and virtual tools in ergonomic risk analysis, emphasizing the importance of precise posture analysis, real-time feedback, and the integration of human factors in the design process. This section reviews the relevant literature, focusing on key developments in ergonomic workstation design, the application of DHM systems, and novel methodologies that enhance the assessment of ergonomic risks.

7.2.1 Traditional Ergonomic Assessment Tools (EATs)

Traditional EATs, such as the RULA (McAtamney & Nigel Corlett, 1993), REBA (Hignett & McAtamney, 2000), and the OWAS (Karhu et al., 1977), have been widely used for decades. These tools have played a critical role in identifying and mitigating ergonomic risks, particularly in industrial and manual work environments. Despite their effectiveness in general risk identification, these methods often rely on manual observation and qualitative assessments, which can introduce subjectivity and reduce accuracy.

Conventional tools remain relevant in environments where digital tools are not yet fully integrated. However, their role is particularly important for providing baseline assessments, which can be augmented by modern technologies such as DHM. For instance, RULA and REBA are still utilized in digital environments like DHM systems to quantify postural risks before more advanced modeling takes place (Sardar et al., 2024). By integrating traditional and modern techniques, a more comprehensive ergonomic assessment can be achieved, combining the strengths of both approaches.

7.2.2 Emerging Trends in Ergonomic Risk Assessment

In recent years, there has been a shift toward the integration of emerging technologies such as artificial intelligence (AI), machine learning (ML), and big data analytics in ergonomic risk assessment. These technologies allow for more sophisticated analyses of large datasets, uncovering patterns and trends in worker posture and behavior that were previously undetectable. AI-driven ergonomic tools can continuously monitor worker movements in real-time, providing instant feedback and recommendations for risk mitigation (Hamilton et al., 2023).

AI-powered vision systems, such as 3D human pose estimation frameworks (Paudel et al., 2022), have become essential for real-time posture analysis, increasing accuracy and reducing the need for manual observation. Additionally, ML algorithms can predict the likelihood of WMSDs by analyzing historical ergonomic data, offering a proactive approach to risk management (MassirisFernández et al., 2020). For instance, these algorithms have the capability to classify safe and unsafe postures during weight-lifting tasks, utilizing inertial sensor data to automatically differentiate between these postures. A recent study applied ML algorithms to time and frequency domain features derived from inertial signals, achieving accuracy rates as high as 96% in predicting unsafe postures (Prisco et al., 2024). This use of AI enables continuous monitoring of physical activities, which can aid in reducing WMSDs.

In addition to AI and ML, big data analytics plays a pivotal role by aggregating and analyzing data across multiple worksites (Walker & Strathie, 2016), allowing for a comprehensive risk assessment that is both predictive and adaptive to specific worker populations. The integration of these advanced technologies is crucial for identifying systemic risks and developing targeted interventions. These technologies are transforming traditional risk assessments into proactive, real-time systems that can personalize recommendations for worker safety.

7.2.3 Technological Innovations in Ergonomic Risk Assessment

Recent advancements in ergonomic risk assessment tools have seen a significant shift towards integrating digital technologies to enhance accuracy, efficiency, and user-friendliness. The integration of digital tools has been significantly boosted by advancements in VR and DHM technologies. Da Silva et al. (2022) conducted a comprehensive review of patents and literature, emphasizing how VR combined with DHM can improve ergonomic assessments during industrial product development. Their findings suggest that the integration of these technologies provides a more immersive and accurate analysis of ergonomic risks, supporting a more effective design process aligned with Industry 4.0 and Industry 5.0 principles.

One notable innovation is the development of integrated solutions that combine wearable sensors with digital posture assessment methodologies, such as the time-based assessment computerized (TACOs) method. As detailed by Khamaisi et al. (2024), this approach allows for reliable postural assessments even by non-experts, accelerating analysis and providing enhanced qualitative data compared to traditional methods. The TACOs setup, which includes a wearable suit and proprietary software, has been tested in controlled industrial environments, demonstrating its potential to improve ergonomic evaluations in line with Industry 5.0 objectives.

Additionally, Emir et al. (2022) emphasized the significance of computer-assisted tool that specifically analyses working postures causing strain. Their research focuses on the identification of high-risk postures through computational methods, emphasizing the need for ergonomic tools that can swiftly evaluate posture-related risks in various occupational settings.

7.2.3.1 Digital Human Modeling & Ergonomic Assessment

DHM systems play a critical role in optimizing workstation design and reducing ergonomic risks. Chaffin (2005) emphasized the proactive application of DHM tools to address ergonomic concerns during the design phase, minimizing the risk of WMSDs before physical prototypes are developed. More recent contributions by De Magistris et al. (2013) focused on enhancing real-time ergonomic assessments through dynamic control of DHM. By simulating human motion with greater accuracy, DHM systems allow for early detection of posture-related risks in dynamic work environments.

The integration of DHMs into assembly process planning and ergonomic design has gained significant attention, reflecting the growing need to optimize human-machine interactions and ensure worker safety and productivity. Ahmed et al. (2021) explored the benefits of integrating human factors early in the design process using DHM and surrogate modeling. Their research demonstrates that early consideration of ergonomic factors through DHM significantly improves design outcome, reducing the need for later-stage modifications and ensuring that ergonomic principles are embedded throughout the product lifecycle.

This approach aligns with Yin and Li (2023) findings, which highlight the critical role of DHMs in simulating human tasks, evaluating ergonomic risks, and optimizing workstation layouts. Their review underscores the versatility of DHMs in predicting potential ergonomic issues early in the design process, reducing the need for costly modifications during later stages of product development. Additionally, DHMs enable detailed analysis of human movements and postures, which is crucial for improving assembly efficiency and minimizing the risk of WMSDs.

These systems offer substantial benefits by providing a virtual environment where human interactions with workstations, tools, and tasks can be simulated and analyzed without the need for costly physical prototypes and supports iterative testing and optimization. For instance, Paudel et al. (2022) introduced a 3D human pose estimation framework for real-time postures analysis, which integrates traditional tools like OWAS, REBA, and RULA to accurately assess postural risks and prevent injuries in industrial settings. Dahibhate et al. (2023) further explored the use of DHM systems in designing products and work environments that accommodate diverse workforce by simulating different body types and postures, enhancing both safety and comfort.

Poirson and Delangle (2013) conducted a comparative analysis of human modeling tools, providing insights into their strengths and weaknesses. Their work, alongside Dahibhate et al. (2023), guides decision-making regarding the most appropriate DHM tools for specific applications. Based on Poirson and Delangle (2013) and Dahibhate et al. (2023), the four most popular DHM systems for ergonomic assessments are CATIA-DELMIA, Jack, RAMSIS, and AnyBody.

7.2.3.2 Virtual Reality & Automation in Ergonomic Design

The ErgoVR tool, developed by Manghisi et al. (2022), offers a VR-based approach to ergonomic design, allowing for both real-time and offline evaluation during the workstation design phase. This tool highlights the advantages of immersive, user-centered design processes in enhancing workstation ergonomics, providing designers with a more interactive and realistic platform for assessing ergonomic risks.

Moreover, the integration of automated design processes, as demonstrated by Beuss et al. (2023), shows promise in streamlining the ergonomic design of workstations through CAD models and human-in-the-loop decision-making. Their approach integrates real-time human feedback within the design process, dynamically adjusting workstation parameters to ensure alignment with ergonomic standards and individual worker requirements.

7.2.4 Human-Centricity and Sustainability in Ergonomic Design

The technologies and methods discussed above contribute to the overall goals of human-centricity and sustainability in ergonomic design. By leveraging DHM, VR, and AI, designers can create workstations optimized not only for efficiency but also for worker safety and well-being. This aligns with Industry 5.0’s vision of balancing productivity with human-centric design. These technologies enable the creation of adaptive, worker-friendly environments that account for individual differences in body types, postures, and ergonomic needs, fostering inclusivity and safety (Agote-Garrido et al., 2023).

Furthermore, the use of digital tools like DHM and VR supports sustainability by reducing reliance on physical prototypes and enabling virtual simulations. This reduction in resource consumption, combined with the ability to create long-lasting ergonomic designs that prevent WMSDs, underscores the sustainable impact of these tools in the design process. Dynamic DHM systems contribute to both human-centric and sustainable designs by enabling early and iterative risk assessment (De Magistris et al., 2013).

7.2.5 Contributions to the Literature

The reviewed literature illustrates the significant progress in ergonomic risk analysis, particularly through the integration of digital technologies and human-centered design principles. While traditional EATs continue to serve as foundational tools, emerging technologies such as AI, ML, and big data analytics are paving the way for more precise, adaptive, and real-time ergonomic assessments.

The studies underscore the importance of developing tools that are not only technologically advanced but also capable of providing holistic ergonomic assessments. However, key research gaps remain, particularly in developing holistic ergonomic assessment methods that address both human-centric and environmental concerns. This research aims to contribute to this evolving field by introducing a novel ergonomic assessment tool designed for use within DHM systems, addressing existing gaps and offering new possibilities for ergonomic workstation design. Thus, this research aligns with the broader industry movement towards more sophisticated, technology-driven ergonomic risk assessment methods, which enhance both the precision and reliability of evaluations. This novel EAT emphasizes inclusivity, real-time feedback, and proactive risk mitigation, addressing both human and environmental concerns. By doing so, it contributes to the broader goals of human-centric, sustainable design in the workplace, aligning with the principles of Industry 5.0.

7.3 Methodology

7.3.1 Problem Description

This study focuses on evaluating cumulative ergonomic risk in individual body parts as well as the integrated cumulative risk in upper limb within a virtual environment using a DHM system. To achieve this, well-known EATs are applied as benchmarks to enhance the primary method, Ergo4All™. Ergo4All™ is based on several standards and methods for assessing individual tasks. It is important to note that the definition of “task” in Ergo4All™ differs from other EATs like OCRA. In this research, tasks are defined as the smallest units of activity requiring force, taking a specific amount of time, and identifiable based on a defined posture. As shown in Figure 7.1, each workstation in an assembly line contains several tasks, which can be categorized into operations based on their purpose and goal. For example, workstation A in the sample assembly line in Figure 7.1 includes three operations, each containing a varying number of tasks.

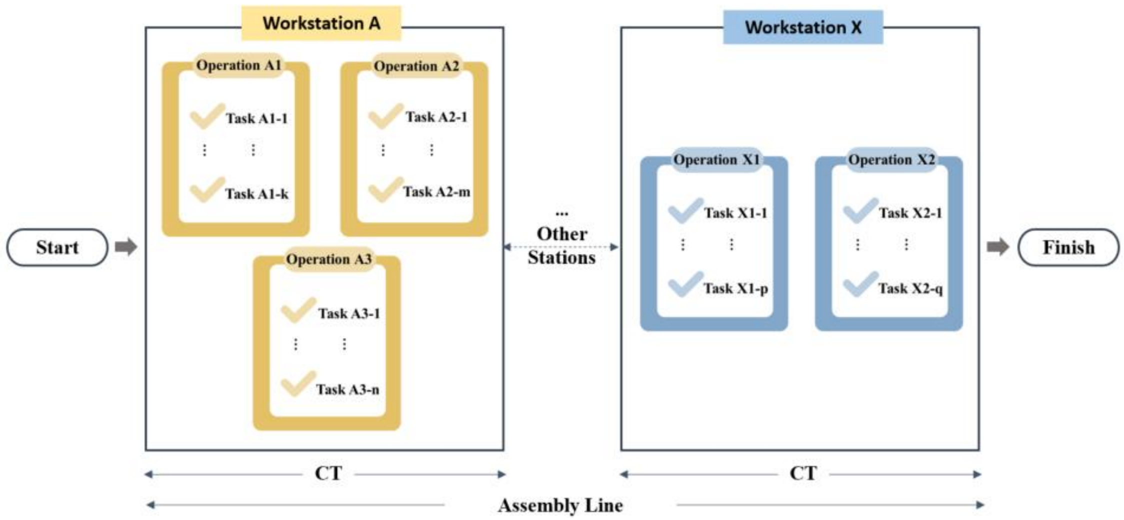


Figure 7.1 Sample assembly line with several workstations

While Ergo4All™ evaluates the risk of each task, while the proposed model in this research, Ergo4All-Pro™, aims to assess the cumulative risk at each workstation. The proposed model enhances the original method by incorporating insights from benchmark methods, including OCRA, RULA and REBA. The initial stage of this project involves a detailed study of OCRA to identify key sections that incorporate time factors, enabling the development of an assessment tool capable of evaluating cumulative ergonomic risk in each body part. Subsequently, based on RULA and REBA methodologies, the research seeks to develop a method for evaluating the cumulative integrated ergonomic risk of the upper limb.

7.3.2 Proposed Framework

The central component of the proposed model is a fuzzy expert system, developed using a fuzzy inference system (FIS). This system contains the collective expertise of ergonomic specialists and incorporates conventional EATs through a set of fuzzy rules. The selection of these tools is guided by key ergonomic criteria, including load, posture, and time considerations.

The knowledge extraction process is structured in two phases: reverse-engineering and re-engineering of the selected EATs. This process is further refined through multiple feedback sessions with ergonomic experts to iteratively adjust and fine-tune the fuzzy rules. The goal is to ensure alignment with both empirical data and theoretical ergonomic principles. The development of this approach, illustrated in Figure 7.2, begins by selecting appropriate traditional EATs to extract the initial logic and foundational knowledge.

Once the initial input is gathered, it undergoes a 'Fuzzification' process, converting precise quantitative data into fuzzy values. This transformation allows for better handling of uncertainties inherent in ergonomic assessments. In the first phase of the proposed approach, reverse-engineering is applied to identify the logic for evaluating the cumulative risk of each body part based on the OCRA index. In the second phase, the re-engineering of RULA and REBA tools is employed to assess a unique, integrated risk score for the upper limb.

This methodology includes the development of a comprehensive 'Knowledge Base,' which consists of a 'Rule Base' of fuzzy logic rules. These rules, derived from expert insights, serve to evaluate ergonomic risk levels within virtual environments. The proposed framework emphasizes the flexible application of fuzzy logic, ensuring that ergonomic risk evaluations account for both static and dynamic elements in different task contexts.

As described earlier, this study focuses specifically on developing a customized method for the EWD software. However, the proposed framework is applicable to other DHM systems using different static assessment tools at the task level. Ergo4All™ is a static tool that assesses ergonomic risk levels for individual joints during a task, based on multiple standards including EN1005-2, EN1005-3, EN1005-4, ISO 14738, ISO 11226, and ISO 11228-3 (Bourret et al., 2021). This study aims to enhance the capabilities of Ergo4All™ by proposing a dynamic tool, Ergo4All-Pro™, which evaluates not only the cumulative risk in each joint but also the overall risk for the upper limb.

Figure 7.2 outlines the three steps of the proposed framework in detail. The following subsections will explain the step-by-step approach to developing Ergo4All-Pro™.

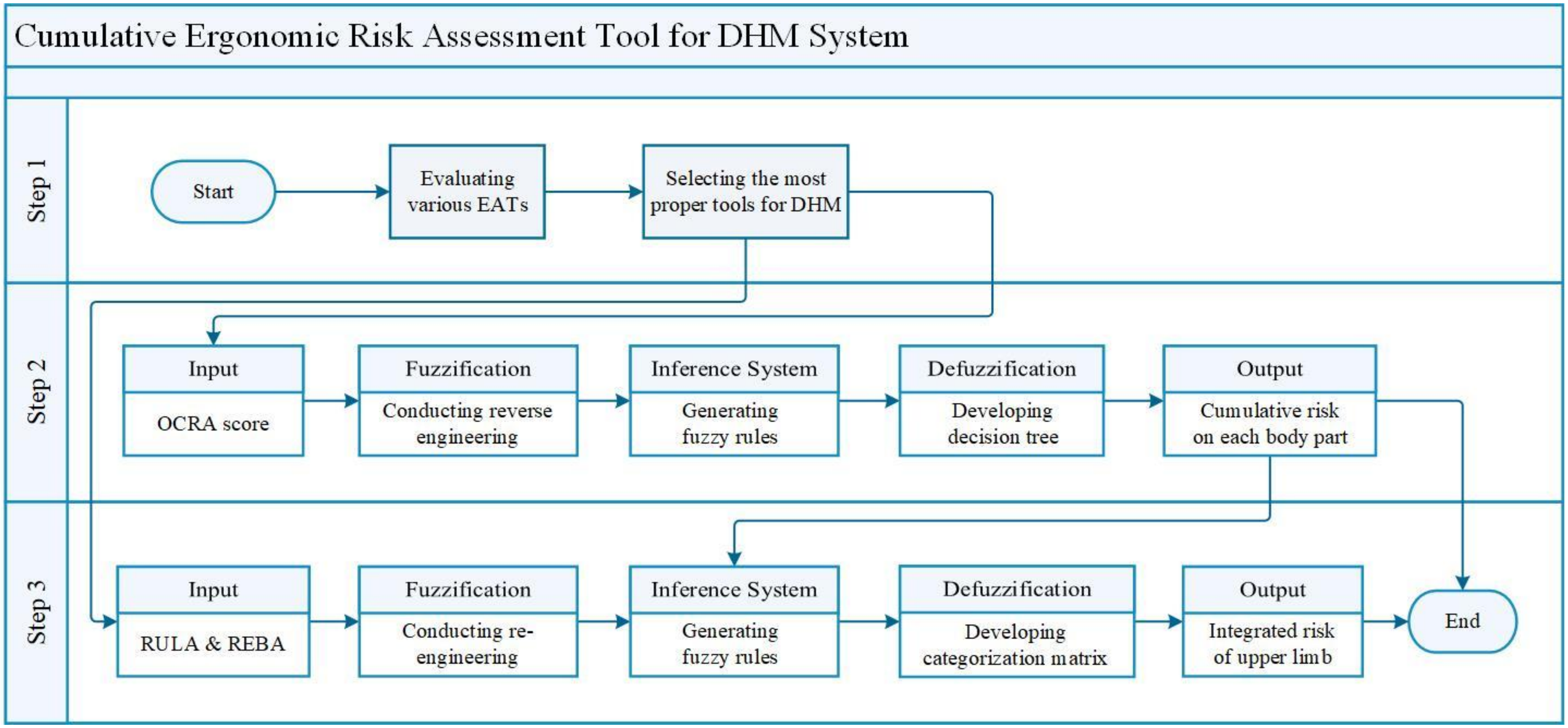


Figure 7.2 Flowchart of expert system for developing Ergo4All-Pro^{TM} model

7.3.3 Step 1: Evaluating Ergonomics Assessment Tools

Ergo4All™ categorizes the risk level of each joint per task into three levels, low (green), medium (yellow), and high (red). To enhance this method, the study integrates elements from two widely used EATs: OCRA and EAWS. OCRA's scoring system is used as the primary reference due to its transparency and established structure, while EAWS is considered for supplementary insights. Based on the task and operation-level evaluations in OCRA, fuzzy rules are formulated to assess cumulative ergonomic risks, enabling their integration into the Ergo4All™ framework.

In the next step, it is necessary to select benchmark EATs that typically integrate the risk of individual body parts to generate a unique risk level for the upper limb. Finding this integrated risk will enable the proposed methodology to be validated against existing assessment tools like OCRA or EAWS. Figure 7.3 presents the components of the proposed framework based on initial EATs.

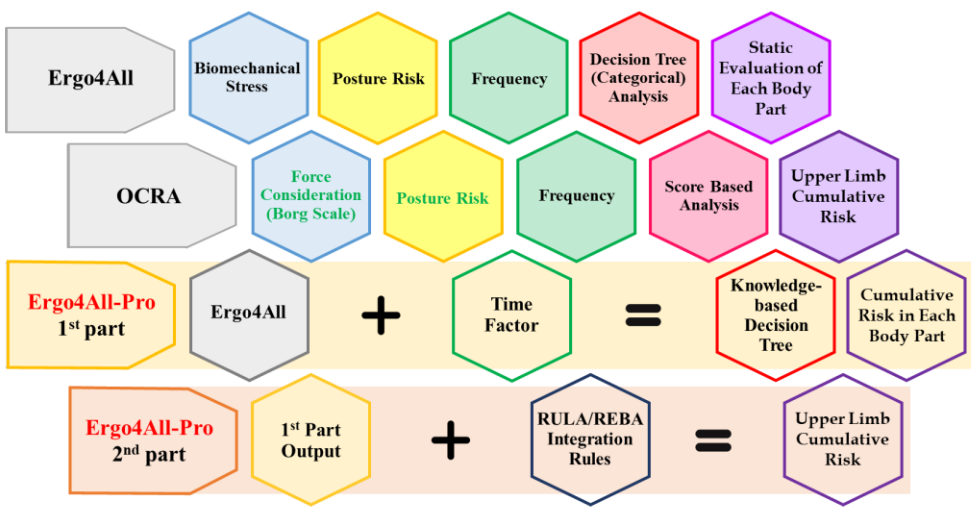


Figure 7.3 Features of Ergo4All-Pro™ model derived from an expert system

7.3.4 Step 2: Detecting Cumulative Risk in Each Body Part

While Ergo4All-Pro™ integrates time considerations post-assessment of posture and biomechanical risks, OCRA integrates time during the risk evaluation process. Thus, interpreting the rules, weights, and processes involving time factor consideration in this model requires ergonomics professionals' expertise to ensure mathematical validity and acceptability. As presented in Figure 7.4, OCRA integrates time factors into four sections of its scoring system. This paper focuses on analyzing and simulating the posture section's scoring method to adapt it for the dynamic framework. This approach is applicable due to the shared consideration of specific body parts, such as the shoulder, elbow, and wrist, in both methods. By understanding the logic behind scoring risk factors for these body parts in OCRA, this study aims to generalize it for Ergo4All™ based on time considerations. This multi-step methodology is delineated in this subsection.

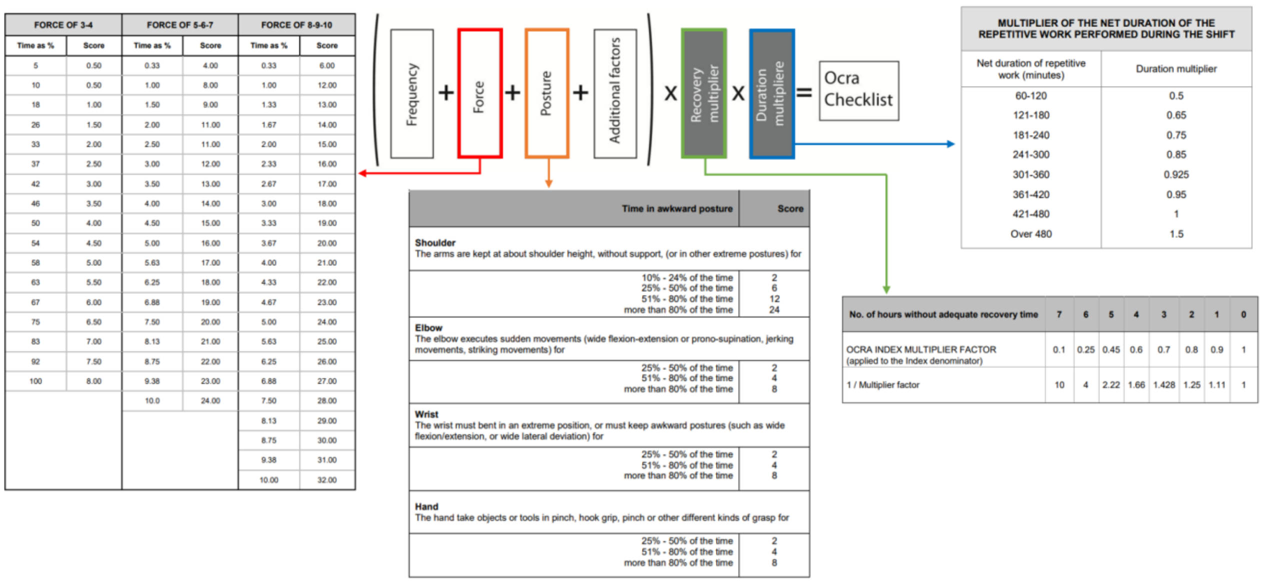


Figure 7.4 Time considerations in the OCRA (based on Colombini et al. (2013))

7.3.4.1 Model Assumptions

As illustrated in Figure 7.4, four sections of the OCRA method account for the time factor in accumulating ergonomic risk scores. Although the foundation of Ergo4All-Pro™ is based on the "Posture" analysis of OCRA, several assumptions must be considered in developing this method to prevent potential discrepancies, as shown in Figure 7.5.

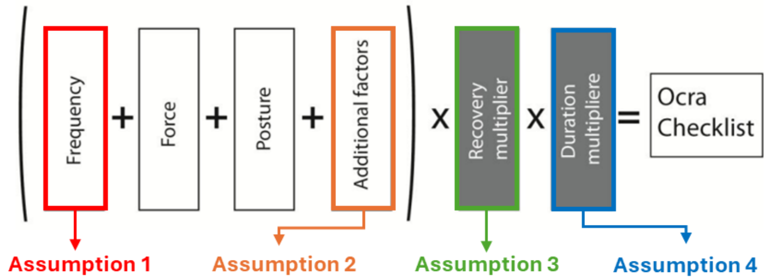


Figure 7.5 Assumptions of OCRA reverse engineering process

The assumptions presented in Figure 7.5 are as follows:

- Assumption 1: In the "frequency" section of OCRA, the frequency of technical actions is evaluated based on the number of actions per minute. In Ergo4All-Pro™, it is assumed that this parameter is less than 32.4, resulting in a risk score of 0, 0.5 or 1, which can be ignored in the reverse engineering process due to its negligible impact on the final risk score.
- Assumption 2: The "additional factors" section of OCRA includes nine conditions for assessing physio-mechanical factors and two conditions for socio-organizational factors. In Ergo4All-Pro™, it is assumed that none of these conditions are applicable.
- Assumption 3: The "recovery multiplier" presents the number of hours without adequate recovery time. In this study, it is assumed that there is sufficient recovery time, so no hours are without adequate recovery.
- Assumption 4: The "duration multiplier" presents the net duration of repetitive work performed during a shift. It is assumed that this duration is equivalent to an 8-hour shift (421-480 minutes). This assumption ensures that the duration factor is not applied twice in the cumulative model, as Ergo4All™ already considers this factor in joint load assessments.

These assumptions allow the elimination of environmental and situational factors impact when analyzing OCRA and focusing on the primary ergonomic factors: "Posture" and "Force".

7.3.4.2 Force Considerations in OCRA Index

To calculate the force multiplier in the OCRA model, the Borg CR-10 scale (Borg, 1990) is used by interviewing workers and asking them to subjectively describe their perceived effort during repetitive tasks. This subjective tool is not suitable for Ergo4All-Pro™, which is designed for a DHM system. To understand the logic behind OCRA's scoring system, explanations in the OCRA index, as detailed in ISO 11228-3, were considered. According to this standard, the force multiplier in OCRA based on the Borg scale is comparable with the force level (F_B) in EN 1005-3, which is the basis for joint load consideration in Ergo4All™. Therefore, it can be assumed that both evaluations will result in approximately the same output for force evaluation. Figure 7.6 presents the accordance of both models, OCRA and Ergo4All™, based on ISO 11228-3 considerations.

As Figure 7.6 shows, while there are some differences between OCRA's force considerations and Ergo4All™'s joint load evaluations, they are compatible with each other. It is worth noting that force evaluation in OCRA is an input for the final formula to calculate the risk score, but in Ergo4All™, force in each joint is evaluated based on EN 1005-3 and EN 1005-4 to find the final risk level of each task. Therefore, the evaluation in Figure 7.6 is a mid-process evaluation in OCRA and whole force consideration in Ergo4All™.

In Figure 7.6, the comparison between these two methods is explained in three parts, highlighted by numbers on the figure:

- In both OCRA index and Ergo4All™, F_M and F_B, respectively, are multipliers in the denominator of the formula for calculating the risk. In the first step, all optimal conditions that prevent increasing the risk level are considered as the optimum value equal to 1. These conditions are highlighted in color in Figure 7.6. As mentioned in ISO 11228-3, all the optimal conditions are based on the EN 1005-3 standard, making both OCRA index and Ergo4All™ compatible under these conditions.
- In Ergo4All™, the load on each joint is evaluated separately from posture risk, with all effective factors such as the duration, frequency, or speed of tasks considered in this part to assess the risk multiplier (m_r), which ranges from 0 to 1, and the joint load result is reported directly. In OCRA, if one or some of the optimal conditions are not met, the force multiplier (F_M) is determined by applying the average level of force as a function of time.
- The minimum value of the F_M in OCRA is equal to 0.01 when the required force for executing a task exceeds 50% of maximum voluntary contraction (MVC) or is greater than 5 on the Borg scale and is applied for more than 10% of the CT.
- Although the OCRA index clearly explains the minimum and maximum values of F_M as a percentage of time that force is applied during each CT, other values in this range are not detailed. However, as the grey-highlighted parts in Figure 7.6 show, the duration multiplier in EN 1005-4 specifies three levels for different task durations as a percentage of CT.

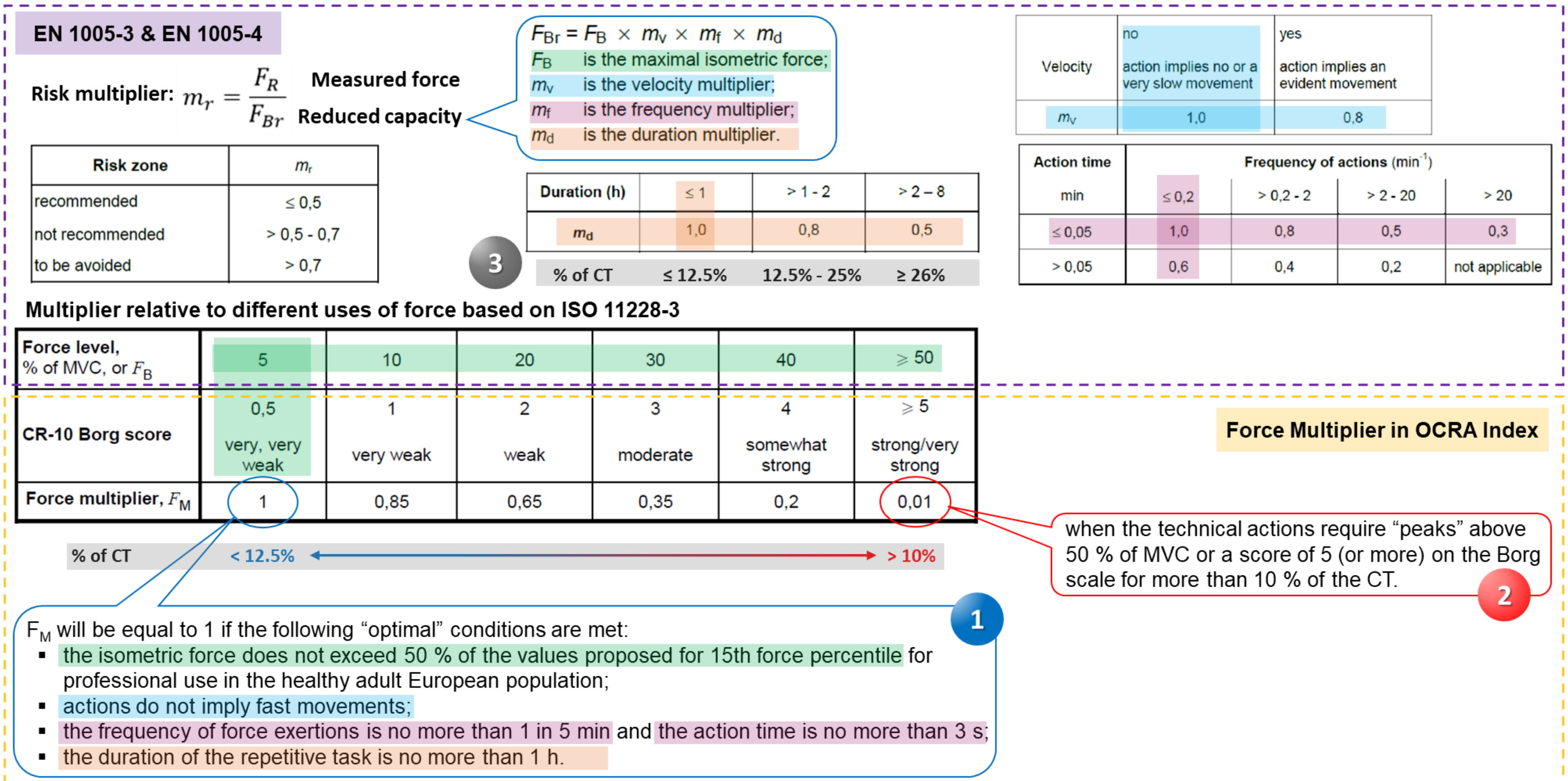


Figure 7.6 Comparing force consideration in OCRA (based on Borg scales) with Ergo4All™ (based on EN 1005-3) according to ISO 11228-3

These three points in Figure 7.6 demonstrate that, despite some differences in the process of evaluating the force factor in Ergo4All™ and the OCRA index, both yields approximately the same output. While in Ergo4All™, parameters such as frequency and duration are considered in the joint load evaluation phase of each task, in OCRA, these factors are incorporated into the formula for cumulative risk of the upper limb.

7.3.4.3 Posture Risk in OCRA Checklist

As previously discussed, all considerations in force evaluation in the final OCRA formula have been employed in the joint load evaluation of Ergo4All™. To better apply the reverse engineering approach in analyzing OCRA's risk assessment methodology, this section focuses on posture risk evaluation, aiming to incorporate time factors to develop cumulative risk for each body part.

7.3.4.3.1 Normalization of Scores

Unlike OCRA's scoring approach, Ergo4All™ employs a categorical method. Therefore, normalization of scores is necessary to establish consistent risk levels across different body parts. Table 7.1 facilitates this normalization by scaling OCRA checklist indices between 0 and 1 for uniform interpretation.

Table 7.1 Normalized OCRA checklist scores in the range 0 to 1

Risk Level	Risk Category	OCRA Score	Norm Score
Green	Acceptable	< 7.5	0 - 0.25
Yellow	Very low	7.6 - 11.0	0.26 – 0.36
Light red	Medium-low	11.1 - 14.0	0.37 – 0.46
Dark red	Medium	14.1 - 22.5	0.47 – 0.75
Purple	High	≥ 22.6	0.76 - 1

7.3.4.3.2 Integration of Time-Based Rules in Ergo4All™

While OCRA focuses solely on awkward postures in the posture section, Ergo4All™ identifies medium and high-risk tasks by considering additional factors beyond time. Consequently, time-based rules derived from OCRA are selectively applied to medium and high-risk tasks in Ergo4All™ through a reverse engineering approach.

In the OCRA checklist, for evaluating awkward postures of each body part, including shoulder, elbow, wrist and hand, the percentage of time in each CT that those postures occurred is calculated, and specific scores are assigned based on the time percentage range. Therefore, for each body part, T(x) is calculated based on the percentage of cumulative time of awkward posture (medium risk, T_m, or high risk, T_h), as per the following equations:

$$T(x) = \frac{\sum t_{awkward}}{CT} \tag{7.1}$$

$$T_m = \frac{\sum t_{medium\ risk}}{CT} \tag{7.2}$$

$$T_h = \frac{\sum t_{high\ risk}}{CT} \tag{7.3}$$

7.3.4.3.3 Differentiation between Medium-risk and High-risk Tasks

To align with OCRA's posture evaluation, it is necessary to interpret awkward postures in a way to include both medium-risk and high-risk tasks in Ergo4All™. Using the shoulder as an example (Table 7.2), medium-risk tasks are evaluated based on normalized scores categorization. Subsequently, risk levels for medium-risk tasks are adjusted to reflect the comprehensive evaluation conducted by Ergo4All™. Differentiation between medium-risk and high-risk tasks is achieved by imposing stricter criteria for the percentage of cumulative time to determine cumulative risk levels. For instance, if the cumulative time of medium-risk level tasks (T_m) contains 25% to 50% of the CT, the risk level will be "very low", but if the same amount of time occurs for high-risk tasks (T_h), the cumulative risk level will be "medium-low".

Table 7.2 Cumulative risk of the shoulder based on normalized OCRA scores

T(x)	OCRA Score	Norm Score	Initial Risk ($M_{Ergo4All}$)	Adjusted Risk ($M_{Ergo4All}$)	Concluded Risk ($H_{Ergo4All}$)
T ≤ 10%	0	0	No Risk	No Risk	Acceptable
10% < T ≤ 25%	2	0.07	Acceptable	Acceptable	Very low
25% < T ≤ 50%	6	0.2	Acceptable	Very low	Medium-low
50% < T ≤ 80%	12	0.4	Medium-low	Medium-low	Medium
80% < T	24	0.8	High	High	High

This methodology can be applied to the elbow and wrist, as shown in Table 7.3. However, it appears that the OCRA scoring system for wrist and elbow posture risk evaluation reflects their less importance compared to the shoulders in the final evaluation. Since the primary goal in developing Ergo4All-Pro™ is to evaluate the cumulative risk in each body part, it is important to consider the time factor in greater detail. Therefore, the time consideration in shoulder posture (Table 7.2) is applied as a baseline for other body parts, including the neck, elbow, wrist, and back. Additionally, OCRA primarily addresses awkward postures in specific body parts, such as the shoulder, elbow, wrist and hand. Based on the high correlation between OCRA and EAWS4 (Lavatelli et al., 2012), insights obtained from OCRA's methodology can be generalized to body parts not explicitly considered, such as the back and neck. This extension ensures a holistic approach to ergonomic risk assessment within Ergo4All™. Thus, in the initial step of the proposed model, the time consideration for the shoulder is applied to other body parts, including the neck, elbow, wrist, and back.

Table 7.3 Cumulative risk of elbow and wrist based on normalized OCRA scores

T (x)	**OCRA Score**	**Norm Score**	**Risk ($M_{Ergo4All}$)**	**Risk ($H_{Ergo4All}$)**
$T \leq 25\%$	0	0	No Risk	Acceptable
$25\% < T \leq 50\%$	2	0.2	Acceptable	Medium-low
$50\% < T \leq 80\%$	4	0.4	Medium-low	Medium
$80\% < T$	8	0.8	High	High

7.3.4.4 Ergo4All-Pro™ Decision Tree for Various Scenarios

While Tables 7.2 and 7.3 present a limited number of scenarios focusing on medium-risk or high-risk tasks, real-world scenarios often entail diverse combinations of task assignments. Hence, Table 7.4 can be generated to encompass various combinations of medium and high-risk tasks at a single workstation.

Table 7.4 Different scenarios of cumulative risk for each body part

		Time Zone	1	2	3	4	5
T(x)	**Time Zone**	$H_{Ergo4All}$ / $M_{Ergo4All}$	A	VL	ML	M	H
$T \leq 10\%$	1	NR	A	VL	ML	M	H
$10\% < T \leq 25\%$	2	A	A	VL	ML	M	H
$25\% < T \leq 50\%$	3	VL	VL	ML	M	H	H
$50\% < T \leq 80\%$	4	ML	ML	M	H	I	I
$80\% < T$	5	H	H	H	H	I	I

Note: NR: No Risk, A: Acceptable, VL: Very Low, ML: Medium Low, M: Medium, H: High, I: Impossible

In the Fuzzy Inference Systems (FISs) presented in Figure 7.2, ergonomic experts' knowledge was utilized to interpret possible cumulative ergonomic risks for each worker and generate fuzzy rules. These fuzzy rules are "If…, Then…" statements that evaluate specific conditions to derive conclusions using fuzzy logic (Ghorbani et al., 2024b). Table 7.5 presents the information from Table 7.4 in the form of fuzzy rules.

Table 7.5 Fuzzy rules for interpreting cumulative risk in each body part

	1st Condition		**2nd Condition**		**Cumulative Risk**
If	$T_h \leq 10\%$	&	$T_m \leq 25\%$	Then	Acceptable
			$25\% < T_m \leq 50\%$		Very Low
			$50\% < T_m \leq 80\%$		Medium Low
			$80\% < T_m$		High
If	$10\% < T_h \leq 25\%$	&	$T_m \leq 25\%$	Then	Very Low
			$25\% < T_m \leq 50\%$		Medium Low
			$50\% < T_m \leq 80\%$		Medium
			$80\% < T_m$		High
If	$25\% < T_h \leq 50\%$	&	$T_m \leq 25\%$	Then	Medium Low
			$25\% < T_m \leq 50\%$		Medium
			$50\% < T_m$		High
If	$50\% < T_h \leq 80\%$	&	$T_m \leq 25\%$	Then	Medium
			$25\% < T_m$		High
If	$80\% < T_h$	-	-	Then	High

To visualize the complexity of cumulative risks across different body parts and task combinations, the decision tree depicted in Figure 7.7 serves as a practical tool. This decision tree facilitates the assessment and management of ergonomic risks in real-world scenarios, offering clarity amidst complexity.

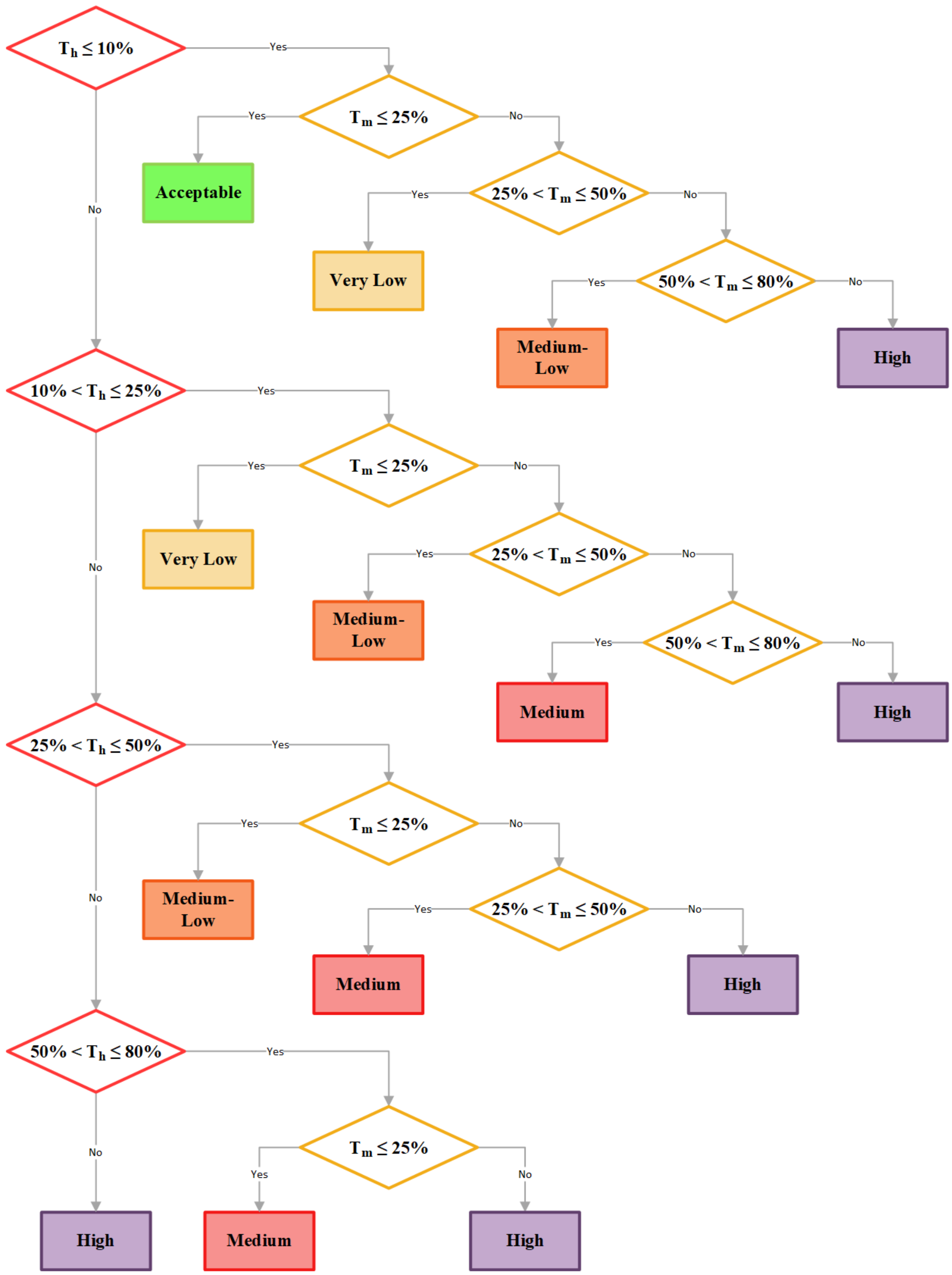


Figure 7.7 Decision tree illustration for the initial step of the proposed Ergo4All-Pro™

7.3.5 Step 3: Identifying Upper Limb Ergonomic Risk

Evaluating the cumulative risk in each body part is the main novelty of the proposed model, Ergo4All-Pro^{TM}. However, besides the aforementioned process, it is essential to develop a comprehensive cumulative risk assessment for the upper limb to validate the proposed methodology by comparing its output with the results of other methods like OCRA, EAWS, etc. This step integrates the risk scores of various body parts in the upper limb based on the RULA and REBA models. To explore the rules for these integrations, a reverse engineering approach was conducted, and fuzzy rules were generated based on ergonomic experts' knowledge and presented in matrix form, as shown in Figure 7.8 to 7.10. The process of developing an integrated risk score for evaluating the overall risk of the upper limb begins with assigning risk scores from 1 to 5 to each risk level, from "acceptable" to "high", respectively. Then the following three steps should be conducted:

- Total Risk Score of Arm: The first step involves integrating risk scores for the entire arm, including wrist, elbow and shoulder. Figure 7.8 presents this evaluation in detail. According to RULA and REBA, in arm evaluation, shoulders take precedence over wrist and elbow. Thus, as shown in Figure 7.8a, the risk scores for the wrist and elbow are combined and converted into a 1 to 5 scale (instead of 1 to 10) to focus on the shoulder in this phase. Figure 7.8b illustrates the details of assessing these three body joints together. Finally, Figure 7.8c presents the final matrix of integrated risk scores for the whole arm.
- Total Risk Score of Trunk: The second step integrates the risk scores of the neck and back to produce a 10-point score for the trunk (Figure 7.9). Since RULA and REBA also consider the legs in the posture risk evaluation for the trunk and use different score ranges for the back and neck, each method is evaluated separately and covered in our scale, as shown in Figure 7.9a. Therefore, the final matrix of integrated risk scores for the trunk (Figure 7.9b) is evaluated based on ergonomists' knowledge to address the differences between the final proposed model and RULA or REBA, which evaluate posture risk in an integrated manner.
- Final Risk Score of Upper Limb: In the final step, by comparing the 10- point scores for the arm and trunk, the final upper limb risk matrix is obtained. As shown in Figure 7.10, the final result is a 10-point risk score, which can be categorized into five risk levels similar to OCRA.

If $\sum$ *risk score of wrist & elbow =* x *then cumulative risk score will be …*

x		Cumulative risk score
2 or 3	→	1
4 or 5	→	2
6 or 7	→	3
8 or 9	→	4
10	→	5

(a) Integrated risk of elbow and wrist

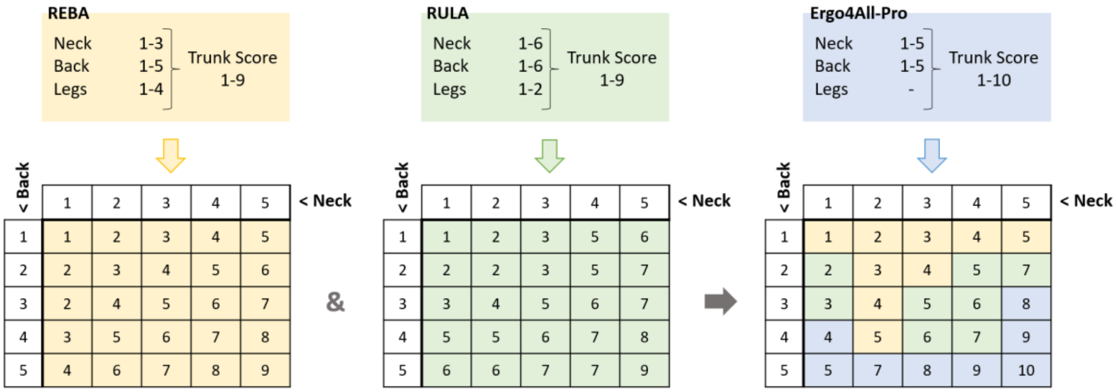
< Elbow	1					2					3					4					5				
< Wrist	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
< Elbow & Wrist	**1**		**2**		**3**	**1**	**2**		**3**		**2**		**3**		**4**	**2**	**3**		**4**		**3**		**4**		**5**
< Shoulder 1	1	1	2	2	3	1	2	2	3	3	2	2	3	3	4	2	3	3	4	4	3	3	4	4	6
2	1	1	3	3	4	1	3	3	4	4	3	3	4	4	5	3	4	4	5	5	4	4	5	5	7
3	3	3	4	4	5	3	5	5	5	5	4	4	5	5	6	4	5	5	6	6	5	5	6	6	8
4	4	4	5	5	7	4	5	5	7	7	5	5	7	7	8	5	7	7	8	8	7	7	8	8	9
5	6	6	7	7	8	6	7	7	8	8	7	7	8	8	9	7	8	8	9	9	8	8	9	9	10

(b) Process of investigating the integrated risk of arm based on RULA and REBA

Elbow		1					2					3					4					5				
Wrist		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Shoulder	1	1	1	2	2	3	1	2	2	3	3	2	2	3	3	4	2	3	3	4	4	3	3	4	4	6
	2	1	1	3	3	4	1	3	3	4	4	3	3	4	4	5	3	4	4	5	5	4	4	5	5	7
	3	3	3	4	4	5	3	5	5	5	5	4	4	5	5	6	4	5	5	6	6	5	5	6	6	8
	4	4	4	5	5	7	4	5	5	7	7	5	5	7	7	8	5	7	7	8	8	7	7	8	8	9
	5	6	6	7	7	8	6	7	7	8	8	7	7	8	8	9	7	8	8	9	9	8	8	9	9	10

(c) Final matrix for integrated risk of arm

Figure 7.8 Integrated risk of the arm



REBA

< Back \ < Neck	1	2	3	4	5
1	1	2	3	4	5
2	2	3	4	5	6
3	2	4	5	6	7
4	3	5	6	7	8
5	4	6	7	8	9

RULA

< Back \ < Neck	1	2	3	4	5
1	1	2	3	5	6
2	2	2	3	5	7
3	3	4	5	6	7
4	5	5	6	7	8
5	6	6	7	7	9

Ergo4All-Pro

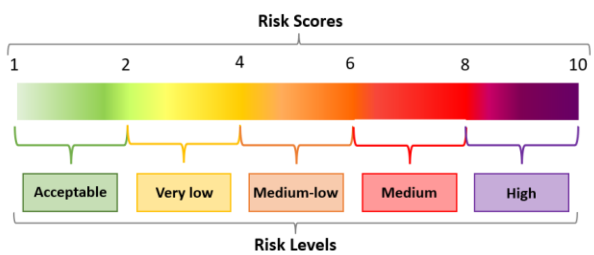
< Back \ < Neck	1	2	3	4	5
1	1	2	3	4	5
2	2	3	4	5	7
3	3	4	5	6	8
4	4	5	6	7	9
5	5	7	8	9	10

(a) Process of investigating the integrated risk of trunk based on RULA and REBA

	Neck	1	2	3	4	5
Back	1	1	2	3	4	5
	2	2	3	4	5	7
	3	3	4	5	6	8
	4	4	5	6	7	9
	5	5	7	8	9	10

(b) Final matrix for integrated risk of trunk

Figure 7.9 Integrated risk of the trunk



	Arm	1	2	3	4	5	6	7	8	9	10
Trunk	1	1	1	2	3	3	4	5	5	6	6
	2	1	2	3	4	4	5	5	5	6	7
	3	2	3	4	4	4	5	6	7	7	7
	4	3	3	4	4	5	6	7	7	8	8
	5	5	5	6	6	6	7	7	8	8	8
	6	6	6	6	7	7	8	8	9	9	9
	7	7	7	7	8	8	8	9	9	9	9
	8	8	8	8	9	9	9	10	10	10	10
	9	9	9	9	9	10	10	10	10	10	10
	10	10	10	10	10	10	10	10	10	10	10

Figure 7.10 Final matrix of integrated risk of upper limb

Although the proposed model has several considerable differences compared to conventional methods, the result is now comparable to several methods that provide an integrated risk level for the upper limb or the whole body, such as EAWS, OCRA, etc.

7.4 Model Implementation

To validate the Ergo4All-Pro^{TM} model, a real sample workstation is evaluated, and the results are compared with benchmark EATs. Additionally, the model is applied to several synthesized scenarios, and the results are discussed to validate the proposed method.

Implementing the proposed model on a real case study and several synthesized scenarios demonstrates its ability to investigate potential risks in various upper limb body parts, both individually and in an integrated manner. Although this new feature is crucial for enhancing DHM systems and the ergonomic design of workplaces in virtual environments, the validation process requires certain considerations. As explained in previous sections, to compare the results of Ergo4All-Pro^{TM} with other benchmark EATs, a scoring system was implemented to incorporate RULA and REBA methodologies in assessing the integrated risk of the upper limb. While the base of the proposed model, Ergo4All^{TM}, is a categorical tool, and the evaluation of cumulative risk in each body part is also categorical, the final output of Ergo4All-Pro^{TM} for upper limb risk includes both categorical and score-based assessments. However, each category in the upper limb results contains just two scores, simplifying the evaluation of the model's convergence with benchmarks. These two scores are sufficient to show the approximate alignment of the integrated upper limb risk with traditional EATs, given the various imprecisions inherent in the virtual design phase compared to real workplaces.

7.4.1 A Real Case Study

In this section, a real assembly workstation from a car manufacturer is evaluated using OCRA, EAWS, EAWS4, and Ergo4All-Pro^{TM}. The results are then compared to determine if the proposed model is validated. Table 7.6 presents the operations, tasks, and execution time of each task in this workstation. In addition, based on a video of this sample, the risk level in various body parts is evaluated using Ergo4All^{TM}, as shown in the columns of Table 7.6. In this case study, the CT is equal to 60 seconds. Therefore, the cumulative time of medium and high-risk tasks in each CT, Tm and Th, can be calculated using equations 2 and 3, respectively. Then, according to the decision tree in Figure 7.7, the cumulative risk in each joint is assessed, and the results are presented in Table 7.7.

Table 7.6 Detailed information of the sample workstation with ergonomic assessment of each task through Ergo4All™

Operations Tasks	**Time**	**Back**	**Neck**	**Shoulder**		**Elbow**		**Wrist**	
				Right	**Left**	**Right**	**Left**	**Right**	**Left**
1. Prepare component A									
1.1. Retrieve component A	2	L	L	L	H	L	L	L	L
1.2. Align component A on surface	2	L	H	L	L	L	L	L	L
1.3. Position face up on fixture	1	L	H	L	L	L	L	L	L
2. Install component B to A									
2.1. Retrieve component B	1	L	L	L	L	L	L	L	L
2.2. Align component B to A	3	L	H	L	L	L	L	L	L
2.3. Attach component B to A	2	L	H	L	L	L	L	L	L
3. Secure component B to A with screws									
3.1. Collect screws and load tool	2	L	H	L	L	L	L	L	L
3.2. Fasten top left screw	3	L	H	H	L	M	L	L	L
3.3. Fasten top right screw	3	L	H	L	L	L	L	L	L
3.4. Fasten bottom left screw	2	L	H	L	L	L	L	L	L
3.5. Fasten bottom right screw	2	L	H	L	L	L	L	L	L
3.6. Fasten top middle screw	3	L	L	L	L	L	M	L	L
3.7 Fasten bottom middle screw	2	L	H	L	L	L	L	L	L
4. Verify documentation									
4.1. Verify assembly document	1	L	H	L	L	M	L	L	L
5. Verify component B barcode									
5.1. Scan component B barcode & confirm	2	L	L	L	L	L	L	L	L
6. Connect coupler to component B									
6.1. Position coupler near opening	3	L	H	L	L	L	L	L	M
6.2. Align coupler with B	1	L	H	L	L	L	M	L	L
6.3. Connect coupler securely	1	L	H	H	L	L	L	L	L
7. Route harness through component A									
7.1. Route harness through opening	1	L	H	L	L	L	L	L	L
8. Route branch through frame & component A									
8.1. Route branch through frame to front	2	L	H	L	L	L	L	L	L
9. Install component A to frame									
9.1. Align component A to frame	2	L	L	L	L	L	L	L	L
9.2. Secure right side	1	L	H	L	L	L	L	L	M
9.3. Secure left side	4	L	L	L	L	M	L	L	L
9.4. Secure middle area	4	L	L	L	L	L	L	L	M
9.5. Secure above component downward	3	L	L	L	H	L	L	L	L
9.6. Secure above component upward	1	L	L	L	L	L	L	L	L

Table 7.7 Results of cumulative risk in each body part based on Ergo4All-Pro™

Cumulative Time of Risky Tasks (% of CT)	Back	Neck	Shoulder		Elbow		Wrist	
			Right	Left	Right	Left	Right	Left
T_m	0	0	0	0	14	7	0	14
T_h	0	53	7	8	0	0	0	0
Cumulative Risk	A	M	A	A	A	A	A	A

Note: A: Acceptable; M: Medium.

The cumulative risk for the upper limb of the worker in this workstation, based on Ergo4All-Pro™ and the explanation in section 7.3.5, is very low, with a risk score of 3. Figure 7.11 provides more details. Furthermore, the ergonomic risk of this sample workstation was evaluated using three different EATs: EAWS, EAWS4, and OCRA, and their procedures are presented in Figure 7.12.

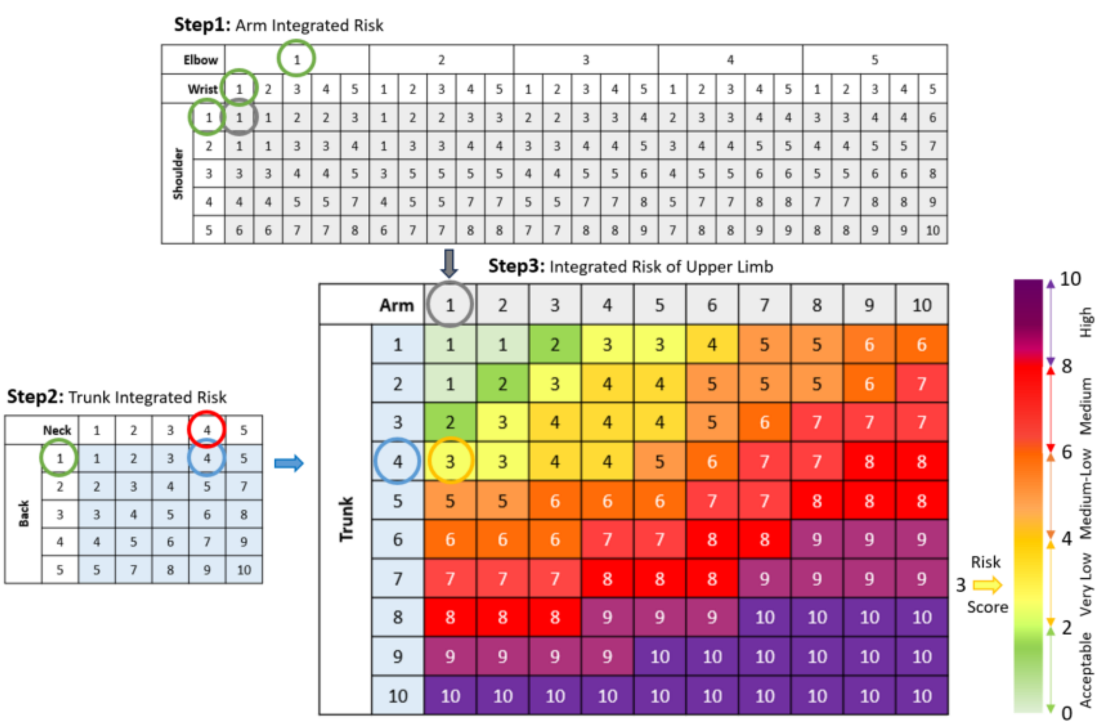


Figure 7.11 Details of integrated upper limb risk evaluation of the sample workstation

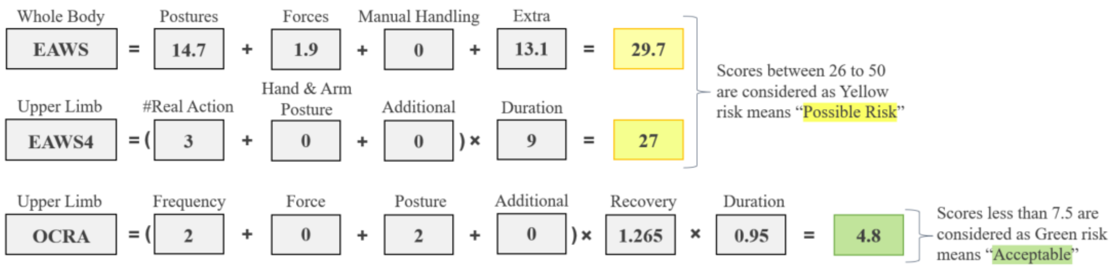


Figure 7.12 The risk evaluation of the sample workstation in different benchmark tools

By comparing the results of various EATs in Figure 7.12 with the evaluation results from Ergo4All-Pro™ in Figure 7.11, it can be concluded that the proposed method aligns more closely with EAWS4. The results from EAWS differ slightly because it considers the entire body, whereas the proposed model focuses only on the upper limb. The differences between OCRA and Ergo4All-Pro™ in this specific sample are due to the neck risk, which is not considered in the OCRA checklist.

7.4.2 Scenario-based Analysis

In the previous section, it was demonstrated that the results of Ergo4All-Pro™ are consistent with EAWS4 and more precise than OCRA, as it accounts for neck risk in addition to other body parts. To further compare the results of these methods with the proposed approach and to better analyze their differences, weaknesses, and strengths, several scenarios are developed in this section. Furthermore, the results of implementing Ergo4All-Pro™ are compared with EAWS4 and OCRA as upper limb EATs.

Figure 7.13 presents nine scenarios that specifically focus on the back and shoulder. In all these scenarios, the same number of tasks and task times as in the sample workstation from the previous subsection are considered. However, it is assumed that the worker in this workstation spends 50% of the CT on tasks with no risk and the other 50% exposed to high risks in the shoulders, back, or both. As the proposed methodology, based on Ergo4All™, focuses on posture and force, the scenarios generated consider the risk to shoulders and back in these two forms. The coding system in Figure 7.13 indicates the type of risk in each body part. For instance, scenario 01-B is a sample where the worker is exposed to a high-risk level of force in the back for half of the CT.

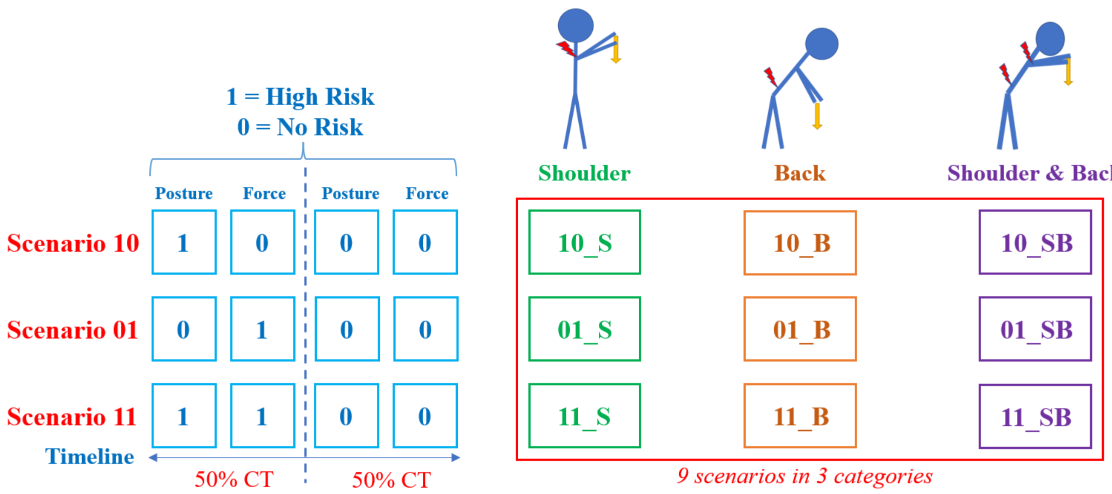
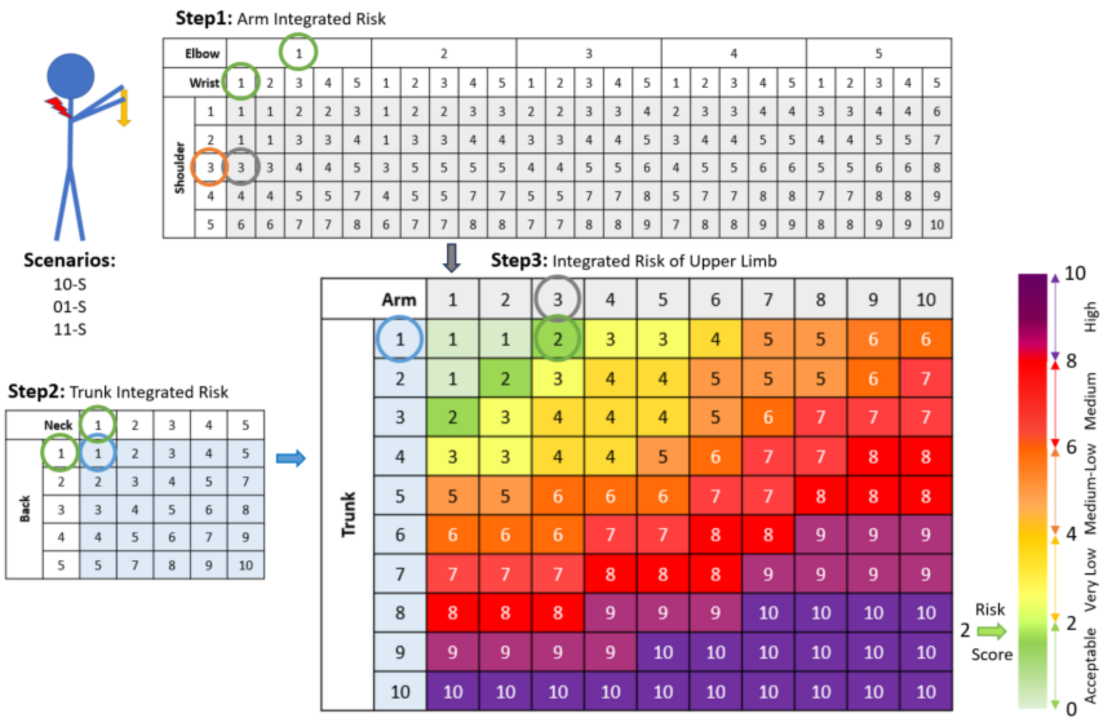


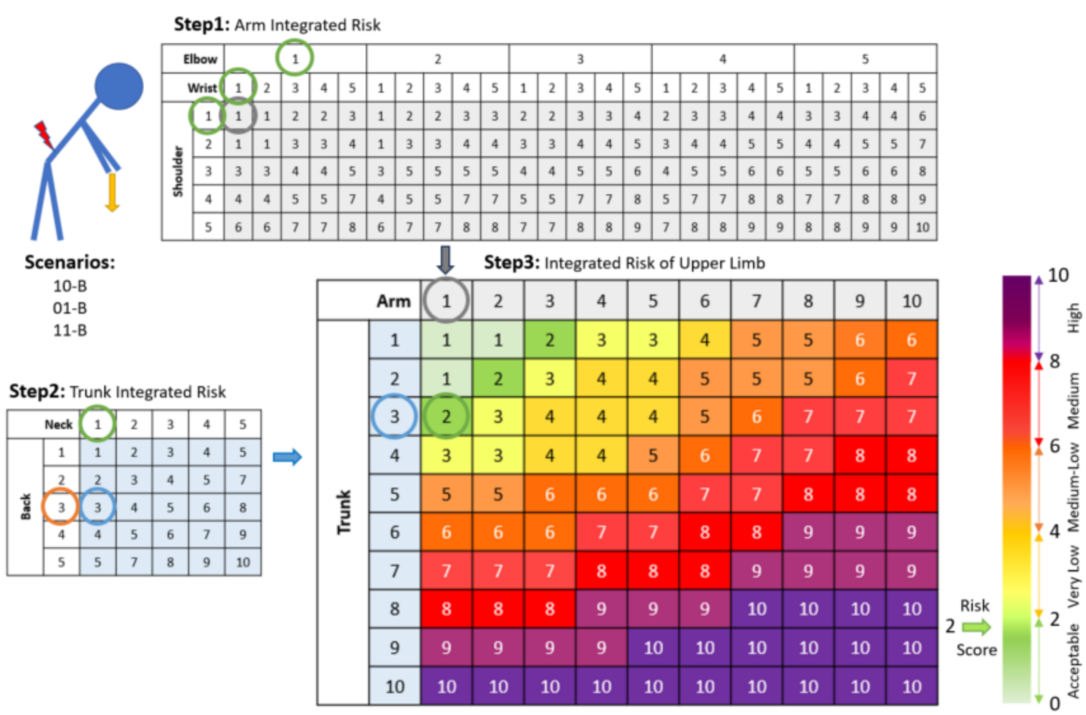
Figure 7.13 Developing nine scenarios to examine posture and force considerations in different methods

Based on Figure 7.7, the cumulative risk for the joint(s) under the risk of posture and/or force will be medium-low (T_h = 50%). Therefore, in each group of scenarios related to the shoulders, back, or both, there will be no difference between the cumulative risk of the joint under the risk of posture, force, or both. This is because in Ergo4All™, the results are based on the worst-case. Thus, whether the risk is caused by poor posture, high load, or both, the result for the task will be "High". As a result, it is only necessary to evaluate the integrated risk of the upper limb for each of the three groups of scenarios based on the procedure explained in section 3.5. Figure 7.14 illustrates the evaluation process of Ergo4All-Pro™ for each group of scenarios in detail to assess the integrated risk in the upper limb.

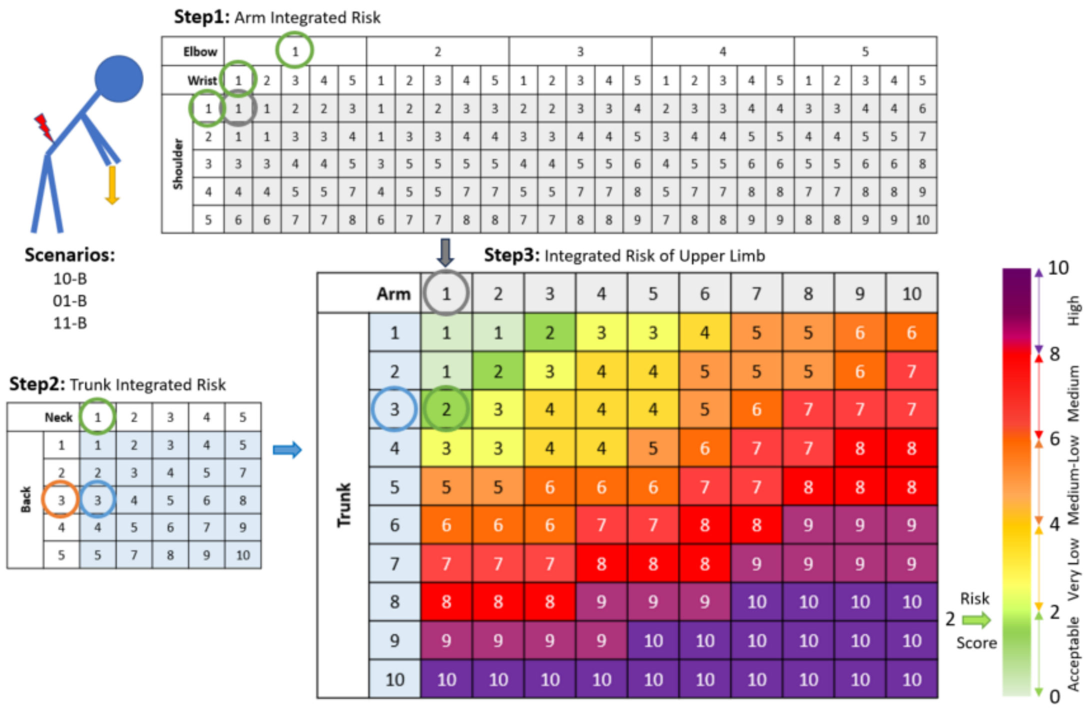
Figure 7.14 shows that in the first two groups of scenarios, where there is a medium-low level of risk to the shoulder or back, the integrated risk to the upper limb is at an acceptable level (green category) with a risk score of "2". Furthermore, when there are medium-low risks to both the shoulder and back, the integrated risk to the upper limb is very low (yellow category) with a risk score of 4. It is worth noting that Ergo4All-Pro™ is primarily a categorical assessment tool in the first step for cumulative risk in each body part, and in the second step, it provides a risk score to evaluate the integrated risk of the upper limb.



(a) Upper limb risk for the first group of scenarios related to risk on shoulder



(b) Upper limb risk for the second group of scenarios related to risk on back



(c) Upper limb risk for the third group of scenarios related to risk on both shoulder and back

Figure 7.14 Details of integrated upper limb risk evaluation of scenarios

However, as the proposed method is intended for DHM systems and workplace design, categorical assessments are better suited to identify the possibility of risk, as it is challenging to evaluate the exact risk score in the design phase. Therefore, in the integrated risk of the upper limb, the proposed model can provide scores that are a kind of categorized risk with two scores in each category. For example, when the risk score in the third group of scenarios (risk on both shoulder and back) is “4”, it means that the risk level is “very-low” but closer to “medium-low” than “acceptable”. With this in mind, it is easier to understand how the proposed model can be compared to other score-based methods like EAWS4 and OCRA. Table 7.8 presents the results of the evaluation of all nine scenarios using the proposed model and the two benchmark methods, OCRA and EAWS4.

Table 7.8 Results of integrated risk of upper limb in benchmark EATs and Ergo4All-Pro™

Scenario		**Shoulder (S)**			**Back (B)**			**Shoulder & Back (SB)**		
Posture	**Force**	**OCRA**	**Ergo4 All-Pro**	**EAWS4**	**OCRA**	**Ergo4 All-Pro**	**EAWS4**	**OCRA**	**Ergo4 All-Pro**	**EAWS4**
1	0	7.6	2	25	0	2	5	7.6	4	25
0	1	5.1	2	10	5.1	2	10	5.1	4	10
1	1	12.7	2	30	5.1	2	10	12.7	4	30

By visualizing the results from EAWS4, OCRA and Ergo4All-Pro™ in Figure 7.15, it becomes easier to explain and analyze the differences. Comparing the outcomes of these three assessment tools yields the following findings:

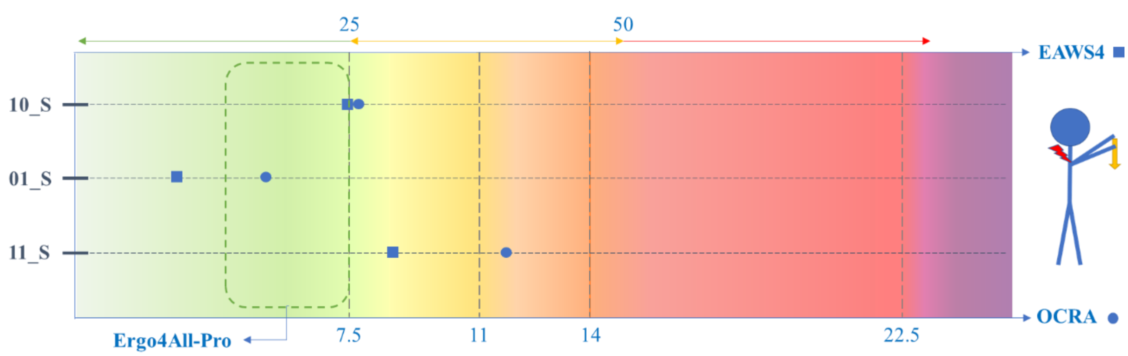
- As shown in Figure 7.15a and 7.15c, related to shoulder and combined shoulder and back scenarios, the same results are observed in EAWS4 and OCRA. This indicates that these two methods may overlook the risk of the back while overestimating the risk to the shoulder. This result is expected from OCRA as it does not consider back risk, focusing instead on the shoulder, elbow, wrist and hand. Therefore, if there is any risk in one of those parts, the integrated risk to the upper limb may be slightly exaggerated. Although OCRA is sensitive to these body parts, in Ergo4All-Pro™, these parts are included in the integrated risk of the arm and then combined with the trunk risk, which includes the back and neck. As a result, the final upper limb risk evaluated by the proposed method is moderated when the risk is present in either the shoulder or back, compared to OCRA and EAWS4. However, in the third group of scenarios where both shoulder and back are at risk, Ergo4All-Pro™ provides a different evaluation compared to the first two groups, which seems more logical given the higher risk when both parts are involved.
- Although Ergo4All-Pro™ is not sensitive to the type of risk, whether posture or force, it does account for the force risk in all scenarios. However, in "01" scenarios where the risk source is force, EAWS4 and OCRA identify the same risk level across all groups, indicating they may not properly assess force risk.
- It should be noted that the proposed model in this research is a categorical method, and its results can be evaluated to determine if they are approximately aligned with the other two

benchmark tools. Based on the explanations, in all three groups of scenarios, Ergo4All-Pro™ yields reasonable results:

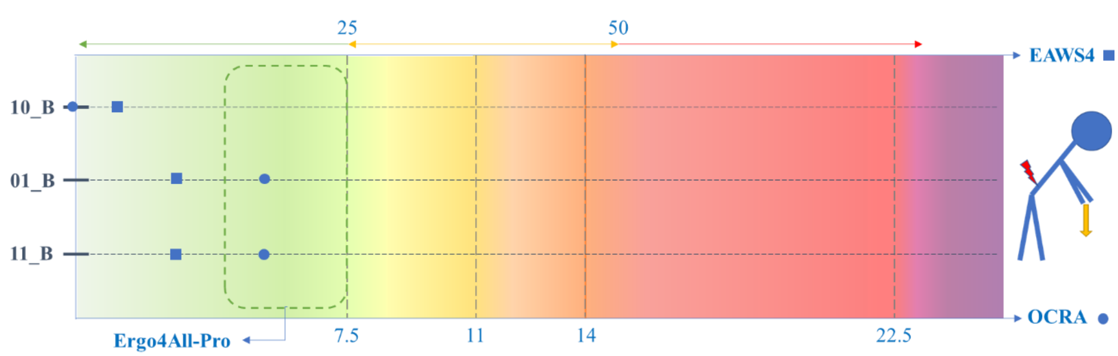
✓ In the first group of scenarios (Figure 7.15a), the proposed model provides an appropriate evaluation whether the risk source is posture or force, and when both exist, the evaluated risk is not exaggerated.

✓ In the second group of scenarios (Figure 7.15b), the model can approximately identify the risk to the back, while the other two methods, compared to the shoulder, tend to ignore the risk to the back, especially when the risk source is posture or both posture and force.

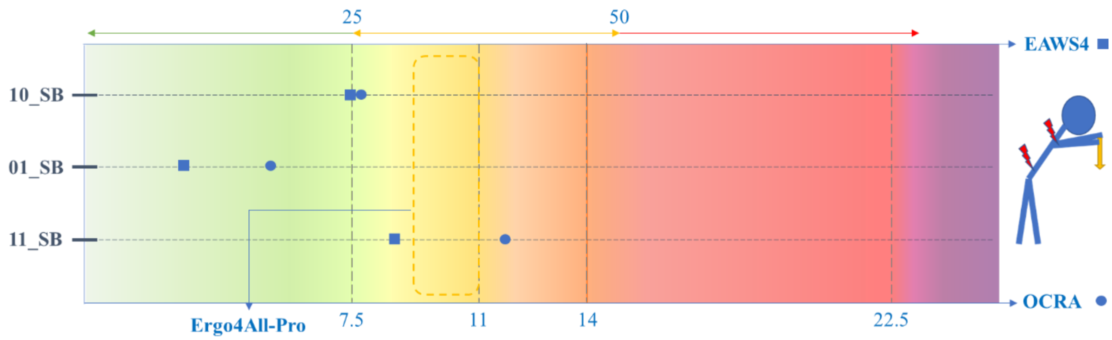
✓ The main strength of the proposed model is evident in the third group of scenarios (Figure 7.15c), where there is a risk to both shoulder and back. In these cases, Ergo4All-Pro™ not only properly considers the risk to the back but also accounts for the risk resulting from force.



(a) Results of evaluation for the first group of scenarios related to risk on shoulder



(b) Results of evaluation for the second group of scenarios related to risk on back



(c) Results of evaluation for the third group of scenarios related to risk on both shoulder and back

Figure 7.15 Comparison of scenario evaluations in two benchmark EATs

7.5 Discussion

While the novel comprehensive model proposed in this study has some limitations and assumptions that makes it challenging to be validated based on conventional methods, its various potential implementations and contributions in academic and industrial environment is invaluable. Subsequent subsections will delve into detailed analysis and discussion of the results obtained from implementing the model on a sample example and scenarios.

7.5.1 Validation & Verification

The validation and verification of the Ergo4All-Pro™ model are essential to ensure the model's reliability and accuracy in assessing ergonomic risks. This subsection focuses on the methods used to validate and verify the model, emphasizing its alignment with established EATs and its performance across different scenarios.

To validate the accuracy of Ergo4All-Pro™, a real assembly workstation from a car manufacturer was evaluated. The model's outputs were compared with those obtained from three benchmark ergonomic assessment tools: EAWS, EAWS4, and OCRA. As detailed in Tables 7.6 and 7.7 and Figures 7.10 and 7.11, Ergo4All-Pro™ provides a more refined evaluation of ergonomic risks, particularly in considering risk factors for the neck and upper limbs. This validation confirms that Ergo4All-Pro™ aligns well with EAWS4, offering a comparable or even more precise risk assessment, especially in areas that other tools may overlook.

Further validation was performed using several synthesized scenarios designed to test Ergo4All-Pro™ under different ergonomic conditions. These scenarios focused on varying levels of risk exposure to the shoulder and back, as illustrated in Figure 7.13. The model's performance was compared with EAWS4 and OCRA, and the results are summarized in Figure 7.15. The scenario-based analysis demonstrated that Ergo4All-Pro™ consistently provides reasonable and accurate risk assessments, particularly when evaluating complex scenarios involving multiple body parts. The model's ability to assess both posture and force risks across different scenarios underscores its robustness and applicability in diverse ergonomic contexts.

The validation efforts demonstrate that Ergo4All-Pro™ is a reliable and valid tool for ergonomic risk assessment. Its results are consistent with established EATs, and it shows particular strength in evaluating risks that may be overlooked by other tools. These findings validate the model's capability to provide accurate ergonomic assessments in both real-world and synthesized scenarios.

7.5.2 Academic Implementation

This research introduces a comprehensive approach to ergonomic risk evaluation in virtual environments, with the capability to assess cumulative risk in each body part, offering significant potential for academic applications. First, the study presents a novel expert system infrastructure that utilizes reverse engineering to develop fuzzy rules based on ergonomists' knowledge and expertise. This approach is a substantial academic contribution, enabling sensitivity analyses to identify the most appropriate rules for accurately predicting future ergonomic risks. The study also establishes thresholds based on expert knowledge, providing a foundation for further exploration. These thresholds can be analyzed to refine fuzzy rules, and alternative expert systems could be employed to adjust these rules using different methodologies, leading to more precise risk evaluations.

Second, the application of expert systems in ergonomic risk assessment presents numerous opportunities for future academic research. For instance, the methodology could be applied to other EATs for comparative analysis, offering valuable insights into their relative effectiveness. Moreover, the Ergo4All-Pro™ model could be used to address various optimization problems, such as ALBPs (Ghorbani et al., 2024e), ALWABPs (Ghorbani et al., 2024b), disassembly cells involving collaborative robots, or rebalancing tasks. These applications could yield valuable data, enhancing the model and bridging the gap between theoretical research and real-world scenarios.

Furthermore, this research has the potential to stimulate further studies in academic environments, encouraging the development of new approaches to ergonomic risk assessment. By providing a comprehensive model applicable across various contexts, this study lays the groundwork for future academic contributions, fostering innovation and advancing the field of ergonomics.

7.5.3 Industrial Implementation

The proposed solution method carries significant implications and potential benefits for industrial applications. Its implementation in real-world industrial settings allows for the integration of managerial insights and ergonomic expertise into the design process. As industries increasingly move towards automation and human-robot collaboration, ergonomic considerations become crucial. The proposed ergonomic methodology, based on a fuzzy knowledge-based expert system, aligns with the human-centric values of Industry 5.0, representing a shift from the purely technical focus often seen in Industry 4.0 literature. This approach emphasizes the well-being of workers as a priority.

The Ergo4All-Pro™ model addresses gaps in the Industry 4.0 framework by integrating ergonomic expertise into the design phase of workplaces, ensuring that worker safety and comfort are considered from the outset. This proactive approach not only optimizes immediate productivity but also contributes to the long-term sustainability and resilience of the workforce.

Ergo4All-Pro™ exemplifies this shift towards prioritizing worker well-being and personalized solutions. It offers a unique feature that allows for the evaluation of cumulative and integrated ergonomic risks across four categories of potential workers, including different percentiles of female and male operators (5th percentile of female, 50th percentile of female or male, and 95th percentile of male). This capability makes the model highly adaptable to specific industry requirements, such as the integration of supportive robots, cobots, or specialized equipment designed to mitigate potential risks. By customizing the ergonomic assessments based on the physical characteristics of different worker groups, industries can optimize workplaces for all employees, reducing injury risks and improving overall efficiency.

Unlike existing models, which evaluate the integrated risk of the upper limb or the whole body, Ergo4All-Pro™ offers a comprehensive assessment across all body parts individually in virtual environments. This study represents a pioneering effort in developing an EAT specifically suited for DHM systems. Thus, the ability to evaluate cumulative risk in each body part opens new possibilities for industrial applications, such as assigning appropriate supportive robots to workstations or implementing more effective ergonomic-based job rotation strategies in assembly and disassembly lines. This approach not only enhances worker safety but also contributes to the overall productivity and sustainability of industrial operations.

7.5.4 Limitations

This study acknowledges several assumptions and limitations that may impact the validity and reliability of the findings:

- Assumptions and Constraints: Despite efforts to conduct a comprehensive analysis, establish logical parameters, and consider ergonomic factors throughout the model's development, certain assumptions were necessary during the reverse engineering process for the sake of simplicity. These assumptions may affect the robustness of our investigations, potentially limiting the generalizability of the results.
- Evaluator expertise: While the evaluators had sufficient expertise, variations in their experience could introduce subjectivity into the assessments. To mitigate this, standardized assessment tools were utilized to maintain consistency to a reasonable extent, though some degree of evaluator bias may still be present.
- Proposed framework: The proposed framework offers valuable insights into ergonomic risk consideration; however, it may not always guarantee the precise identification of risks. Nevertheless, it is highly capable of predicting and effectively estimating potential future risks, as demonstrated by the implementation results discussed in section 4. The complexity of the problem arises from the uncertainty and vagueness inherent in future scenarios. During the design phase, precise data about the worker who will eventually occupy the developed workstation is not available, and certain ergonomic aspects may be affected during the implementation phase. Future research could explore integrating additional techniques to enhance the quality and accuracy of the results.
- Selected EATs: While three different EATs -OCRA, RULA, and REBA- were employed in developing Ergo4All-Pro™ from its foundational method, Ergo4All™, the inclusion of other tools might provide a more precise evaluation. As a result, there may be limitations and potential weaknesses in the proposed ergonomic evaluation method, which could hinder a comprehensive understanding of workplace ergonomics. Future studies should analyze this approach through real-world case studies to gain a more thorough understanding and effectively mitigate ergonomic risks.

These limitations highlight the need to consider various factors when interpreting the study's results and implications. They also suggest promising directions for future research in ergonomic assessment methodology, particularly in virtual environments and DHM systems.

7.6 Conclusions

This study presents a comprehensive and innovative ergonomic risk assessment model designed to address the challenges and limitations of traditional EATs within the context of DHM systems. By integrating insights from established tools like OCRA, RULA, and REBA, the proposed framework offers a refined approach to assessing cumulative and integrated ergonomic risks across various body parts of the upper limb. The model's validation through real-world and synthesized scenarios demonstrates its reliability and alignment with benchmark EATs, highlighting its potential to provide more precise and holistic ergonomic evaluations.

This approach contributes significantly to both academic research and industrial practice. Academically, it introduces a robust expert system infrastructure that facilitates the development of fuzzy rules based on ergonomic expertise, paving the way for future studies to refine and optimize ergonomic risk assessments. In industrial settings, the model's ability to assess cumulative risks across diverse worker groups supports the design of safer, more efficient workplaces, aligning with the human-centric values of Industry 5.0. By prioritizing worker well-being and integrating ergonomic considerations into the early stages of workplace design, Ergo4All-Pro™ not only enhances productivity but also promotes long-term sustainability and workforce resilience.

While Dassault Systèmes' Ergo4All™ methodology forms the foundation for this work, the focus is on advancing scientific knowledge in the domain of ergonomic risk assessment rather than solely fulfilling the specific needs of a company. The proposed framework is designed to be widely applicable across various industrial environments. Thus, the multifaceted expert system developed in this manuscript can be applied to simulate dynamic evaluation based on other static EAT, enabling engineers and decision-makers to design safer and more efficient workstations by integrating cumulative ergonomic risk factors early in the design process.

Despite its strengths, the study acknowledges certain limitations, including the assumptions made during the model's development and the need for further validation through additional case studies and the inclusion of other EATs. These limitations highlight the ongoing challenges in ergonomic risk assessment, particularly in virtual environments, and underscore the importance of continued research in this field.

In conclusion, Ergo4All-Pro™ represents a significant advancement in ergonomic risk assessment, offering a versatile and adaptable tool for both academic exploration and industrial application. By bridging the gap between theoretical research and practical implementation, this model sets the stage for future innovations in ergonomic design and assessment, contributing to safer and more sustainable industrial practices.

CHAPTER 8 GENERAL DISCUSSION

This chapter synthesizes the findings from the three research objectives that form the foundation of this Ph.D. thesis. These objectives were addressed through three articles, presented in Chapter 5 to 7 (Articles 2, 3, and 4). The research advances knowledge in the integration of ergonomic principles and fuzzy expert systems into ALBPs during the design phase, contributing to the growing body of literature on human-centric design in manufacturing systems.

This research contributes to the broader discourse on Industry 5.0, emphasizing the shift from technology-centric approaches in Industry 4.0 to human-centric values. By integrating ergonomic risk management into AL optimization, this thesis addresses critical gaps in the literature, particularly regarding the humanization of manufacturing systems.

Each objective prioritizes worker well-being as a central element of AL design, aligning with the principles of Industry 5.0. Articles 2 and 3 demonstrate how ergonomic considerations at the task, worker, and system levels improve both safety and efficiency. Article 4 further advances this by incorporating virtual ergonomics into DHM systems.

A common theme across all three articles is the emphasis on fuzzy expert systems as a tool to manage uncertainties in ergonomic assessments and decision-making processes in AL optimization. Each study demonstrates how fuzzy logic can address the imprecision of real-world data, particularly with respect to task times and ergonomic risks. Article 2 (first objective, Chapter 5) leverages fuzzy expert systems to handle the uncertainty and variability in task performance and worker conditions. Article 3 (second objective, Chapter 6) applies a FIS to develop a novel fuzzy fatigue model, focusing on growing role of cobots and supportive robotic systems in enhancing human-centric design. Article 4 (third objective, Chapter 7), while focused on virtual ergonomic assessments, uses a similar fuzzy logic approach in conjunction with reverse- and re-engineering of traditional EATs to generate rules based on expert knowledge. This demonstrates the versatility and robustness of fuzzy systems in various manufacturing contexts.

The studies contribute to the growing body of research on ergonomics in AL optimization by introducing novel fuzzy-based frameworks. While previous literature has focused on deterministic methods for assessing ergonomic risks, this work shows that fuzzy logic better reflects the imprecise nature of ergonomic data, offering more robust solutions.

By highlighting the potential of robots to reduce fatigue and enhance worker well-being (as demonstrated in Articles 3), this research aligns with current trends in the literature, which emphasize human-robot collaboration as a key driver of sustainable and efficient manufacturing. Furthermore, Article 4's focus on virtual environments contributes to the emerging field of digital ergonomics, particularly the use of DHM systems for ergonomic risk assessment. This work extends existing literature by offering a comprehensive tool that evaluates cumulative risks across body parts, filling a gap left by traditional ergonomic tools.

The key implications from academic and industrial perspectives, as well as the limitations and future research directions, are detailed in the following sections.

8.1 Implications and Significance

This thesis provides substantial theoretical and practical contributions grounded in the development of fuzzy expert systems and ergonomic assessments for AL optimization in both physical and virtual environments. These contributions align with the goals of Industry 5.0, where human-centric design and worker well-being are prioritized in manufacturing innovation.

8.1.1 Theoretical Contributions

The academic implications of this thesis revolve around the application of fuzzy expert systems to ALBPs and ergonomic risk assessments, addressing critical gaps in the literature on uncertainty management, human factors, and the integration of human-robot collaboration (HRC).

- Advancing Fuzzy Logic Applications in ALWABPs and RALDPs: The introduction of fuzzy expert systems to handle uncertainty in task time data and ergonomic risk levels represents a novel contribution to ALWABPs. This thesis pioneers the application of fuzzy logic in managing vagueness and imprecision in ergonomic assessments, resulting in a more robust and adaptable optimization framework. Experimental results (Zacharia & Nearchou, 2020) indicate that the fuzzy logic approach outperforms traditional deterministic methods on benchmark test problems. The flexibility of fuzzy logic allows for better handling of real-world complexities, leading to improved solution quality in terms of KPIs in ALs. However, in future research, comparative studies can be conducted between fuzzy logic and deterministic methods to highlight the advantages and limitations of each approach in handling uncertainties in AL optimization.

- Multi-Level Ergonomic Risk Assessment Frameworks: Across all three articles, this thesis introduces a multi-level ergonomic risk assessment model that evaluates risks at the task, worker, and AL levels. This holistic framework provides a comprehensive understanding of how ergonomic factors influence AL performance. It offers a foundation for future research to incorporate diverse ergonomic models and fuzzy rule thresholds, allowing for further customization and refinement of risk evaluations. The Ergo4All-Pro™ model enhances this approach by applying it to virtual environments, making it a valuable tool for DHM systems.
- Human-Centric Design in Industry 5.0: This thesis advances the conceptualization of human-centric design in the context of Industry 5.0. By integrating ergonomics into AL design and optimization processes, the research demonstrates how human well-being can be prioritized alongside operational efficiency. The fuzzy expert system and ergonomic assessment methods introduced in this work lay the groundwork for further studies on HRC in manufacturing, providing a scalable framework for future investigations into human-centered and ergonomic-aligned manufacturing systems. Future studies with some real case studies can better analyze the direct contribution of the proposed fuzzy expert systems and ergonomic assessments to improving worker well-being and job satisfaction.
- Fuzzy Inference Systems for Fatigue and Recovery Assessment: The research contributes to academic discussions on workplace fatigue management by developing a FIS to evaluate worker fatigue levels. It is important to acknowledge that deterministic methods still dominate certain areas of fatigue management, especially where standardized tasks and fixed conditions are present. The research presented here expands on this by showing that fuzzy systems offer a more adaptable and human-centric solution, particularly in environments where variability is the norm. However, this innovation provides new directions for fatigue and recovery analysis, particularly in AL settings that involve high task repetition. Future research could explore other fuzzified fatigue models and integrate them with AL optimization problems, such as ALWABPs or disassembly cells, offering valuable comparative data across different ergonomic contexts.

8.1.2 Practical Contributions

The findings of this thesis hold significant industrial implications for industries seeking to improve worker safety, enhance operational efficiency, and integrate human-centric considerations into their manufacturing processes. The developed frameworks demonstrate practical solutions that can be customized for different industrial environments, aligning with the broader goals of Industry 4.0 and Industry 5.0.

- Ergonomic Optimization in Assembly Lines: The proposed fuzzy expert system framework provides an adaptable solution for assessing and mitigating ergonomic risks in ALs. By implementing ergonomic assessments at the task, worker, and AL levels, industries can ensure that worker safety is considered from the outset of the design process. This customizable ergonomic evaluation framework allows for adjustments based on industry-specific requirements, such as integrating fatigue models and alternative ergonomic metrics (e.g., recovery needs, worker satisfaction, or overall operational performance). For instance, the practical implementation of the ergonomic optimization framework might face challenges related to real-time data collection and the adaptability of the system to dynamic changes in the AL. The Ergo4All-Pro™ model demonstrates how this approach can be applied in virtual environments, allowing for proactive design interventions that prioritize long-term worker well-being. Future research may develop and test real-time ergonomic monitoring and adaptive optimization systems that can respond to dynamic changes in worker conditions and task demands.
- Human-Robot Collaboration for Enhanced Productivity and Safety: The research highlights the growing importance of HRC in modern manufacturing environments. By integrating supportive robots and collaborative robots (cobots) into ALs, industries can improve both productivity and worker safety. The fuzzy fatigue evaluation and task optimization framework introduced in this thesis demonstrates how adaptive workload management can reduce ergonomic risks and worker fatigue, particularly in automated and human-interactive ALs. This makes the framework especially relevant for industries adopting Industry 4.0 and transitioning to Industry 5.0, where balancing human and robotic capabilities is key to sustainable operations. Future research can investigate the psychological and social factors influencing HRC to develop guidelines for effective

collaboration and communication between humans and robots in manufacturing environments.

- Cost Efficiency and Adaptability in Manufacturing Systems: The proposed solutions offer significant cost-saving potential for industries by reducing recovery time and minimizing additional capacity requirements. The fuzzy expert systems can be adapted to assess ergonomic risks and optimize task assignment, resulting in up to 47% reduction in system costs, as seen in the fatigue management scenarios. The research demonstrates that customizable fuzzy rules and ergonomic scoring systems can be tailored to assess alternative concepts such as recovery requirements and worker satisfaction, enabling industries to design ALs that are both cost-efficient and human-centric.
- Virtual Ergonomic Risk Assessments in Industry 5.0: The Ergo4All-Pro™ model represents a significant advancement in virtual ergonomic risk assessment by enabling industries to assess cumulative risks across various body parts in virtual environments. This approach allows for more precise ergonomic interventions in DHM systems, providing a proactive solution for optimizing workplaces during the design phase. By incorporating worker-specific characteristics (e.g., different percentiles for male and female workers), the model can be customized to enhance workplace safety and productivity for diverse worker groups. This ability to personalize ergonomic assessments paves the way for industries to develop safer and more efficient assembly and disassembly lines, ensuring long-term sustainability.

8.2 Limitations and Future Research

This thesis has advanced the integration of fuzzy expert systems and ergonomic assessments in the design of ALs. However, several limitations across the studies may affect the generalizability and robustness of the findings. These limitations point to promising avenues for future research.

- Data Quality and Quantity: Across all three studies, the quality and quantity of synthesized data or developed scenarios used in validating the proposed models pose potential limitations to the generalizability of the findings. Despite efforts to generate comprehensive datasets and define appropriate ergonomic parameters, the reliance on benchmark datasets may not fully capture the complexity of real-world industrial environments.

Future Directions: Future studies should focus on collecting and utilizing real-world datasets to validate the proposed frameworks. By incorporating diverse ergonomic data from actual industrial settings, researchers can improve the robustness and applicability of fuzzy expert systems in ALBP and risk assessments.

- Evaluator Expertise and Subjectivity: A recurring limitation across the studies is the potential subjectivity introduced by the varying levels of expertise among evaluators. While standardized assessment tools were employed to mitigate this, differences in expertise could have influenced the consistency and reliability of ergonomic evaluations.

  Future Directions: Developing objective ergonomic assessment frameworks that minimize human bias is a key area for future research. Integrating AI-based assessment tools or automating parts of the evaluation process could provide more consistent and reliable results, reducing the impact of evaluator variability.

- Solution Framework Scalability: The complexity and size of the optimization problems, particularly in ALWABPs and RALDPs, challenge the scalability of the proposed solution frameworks. In large-scale instances, the frameworks may not guarantee optimal or Pareto-optimal solutions.

  Future Directions: To enhance the scalability and efficiency of the models, future research could explore the integration of metaheuristic techniques such as GA, SA, or PSO. These approaches may offer better solutions for large-scale problems, improving both solution quality and computational efficiency.

- Limitations of Ergonomic Risk Assessments: While the proposed ergonomic evaluation frameworks provide a valuable foundation for assessing fatigue and repetitive motion risks, they do not encompass all critical ergonomic factors, such as posture, load, vibration, and environmental conditions. Furthermore, the ergonomic models primarily focus on repetitive tasks and fatigue, potentially limiting the comprehensiveness of risk assessments in diverse industrial contexts.

  Future Directions: Future studies should aim to develop more holistic ergonomic assessment frameworks that incorporate additional factors such as posture, environmental stressors, and physical load. These comprehensive assessments could provide deeper insights into workplace ergonomics, leading to more effective interventions.

- Optimization Model Constraints: The optimization models presented in this thesis focus primarily on minimizing ergonomic risk factors, fatigue levels, and overall system costs. However, other objective functions—such as minimizing cumulative ergonomic risk across body parts or balancing the deviation of fatigue levels among workers—could be explored to address additional aspects of AL optimization.

  Future Directions: Expanding the objective functions to address multi-objective optimization problems could provide more nuanced solutions that consider both operational efficiency and worker well-being. Future studies could also explore new constraints related to cycle time, worker assignment, or throughput, leading to the development of more flexible and adaptable optimization models for ALs.

- Ergonomic Risk Assessments in Virtual Environments: The Ergo4All-Pro™ model offers a pioneering framework for conducting ergonomic risk assessments in virtual environments using DHM systems. However, the inclusion of only three ergonomic assessment tools (OCRA, RULA, and REBA) limits the comprehensiveness of the model, potentially overlooking certain ergonomic risk factors.

  Future Directions: To improve the accuracy and applicability of virtual ergonomic risk assessments, future studies should integrate additional EATs and test the model in real-world case studies. This would provide a more thorough understanding of the strengths and weaknesses of virtual ergonomic methodologies and offer more robust solutions for industrial applications.

- Ethical Implications of Automation & AI in Manufacturing: The increasing adoption of automation and AI-driven decision-making tools, such as fuzzy expert systems, raises ethical concerns, particularly regarding the impact on employment and the potential displacement of workers in manual or repetitive roles. While automation enhances productivity, it may reduce the demand for human labor, highlighting the need for retraining and upskilling initiatives to help workers adapt. Additionally, the responsible use of AI in decision-making is critical to avoid bias and ensure transparent, human-centered outcomes.

Ensuring that AI systems prioritize worker safety and are subject to human oversight is essential for maintaining ethical standards in industrial environments.

Future Directions: Future research should not only focus on improving the technical aspects of AI and fuzzy systems in assembly line optimization but also investigate how these innovations can be implemented in an ethically responsible manner. This includes evaluating the societal impact of automation, developing frameworks for responsible AI governance, and ensuring that human well-being remains at the center of AI-driven systems.

8.3 Ethical Considerations

This research focused on developing a decision-support framework and models for the design of human-centric ALs. The primary aim was to integrate ergonomic considerations and address uncertainties in the design phase using fuzzy logic and expert systems. The research utilized numerical examples and simulations to demonstrate the operationalization of the proposed approach.

It is important to clarify that this research did not involve the collection or use of human subject data. The models and framework were developed and validated using synthesized datasets and scenarios. As such, the research did not require direct interaction with human participants, and therefore, an application for ethical certification was not deemed necessary.

However, it is imperative to acknowledge that the application of this research in real-world industrial settings necessitates full adherence to all ethical considerations and regulations. Future research endeavors and practical implementations of the proposed framework must prioritize the safety, privacy, and well-being of workers. This includes obtaining necessary ethical approvals, ensuring informed consent, and strictly complying with Polytechnique Montréal’s guidelines and procedures for research involving human participants, as well as all relevant regional and national ethical standards.

Specifically, when implementing the proposed systems in real-world scenarios, researchers and practitioners should consider the following ethical principles:

- Respect for Persons: Ensuring voluntary participation, informed consent, and the right to withdraw from any study or intervention.

- Beneficence: Maximizing potential benefits to workers and minimizing any potential risks or harm.
- Justice: Ensuring fair and equitable selection of workers, and fair distribution of benefits and risks.

Furthermore, any research involving the use of DHM and EATs should be conducted with careful consideration of the data's accuracy and the potential impact of the simulations on real-world applications.

In conclusion, while this thesis did not require ethical certification due to the nature of the data used, future research and practical applications must rigorously adhere to ethical principles and regulations to protect the rights and well-being of workers in assembly line environments.

CHAPTER 9 CONCLUSION

This thesis has successfully demonstrated the power of integrating fuzzy expert systems and ergonomic principles to revolutionize assembly line optimization, toward a more human-centric and sustainable manufacturing future. Through the development of innovative frameworks for ergonomic risk assessment and assembly line optimization, this research has bridged critical gaps in the literature while offering practical solutions for real-world industrial applications.

1. Integration of Fuzzy Logic in Assembly Line Optimization:

The first major contribution of this thesis is the development of a fuzzy expert system for the Ergo-ALWABP. The proposed model addresses the uncertainties in task execution times and ergonomic risk levels by leveraging fuzzy set logic to represent imprecise task times caused by workforce heterogeneity. This approach enabled the effective evaluation of cumulative ergonomic risks at multiple levels (task, worker, and AL), providing a robust framework for enhancing both worker safety and operational efficiency.

The research demonstrated that the proposed fuzzy expert system could be integrated into existing manufacturing systems, with extensive customization options for various industrial contexts. This adaptability ensures that the framework can address the unique challenges faced by different industries, contributing to safer and more efficient AL designs. Moving forward, further research should focus on improving the quality of data used in these systems, incorporating additional fuzzy number types to better capture the diversity of workers and task variability.

2. Human-Centric Robotic Assembly Line Design:

The second key contribution lies in the FIS approach to optimizing RALDPs, which emphasizes the integration of human-robot collaboration and fatigue management. This research offers a novel solution for minimizing operator fatigue while simultaneously optimizing system costs, demonstrating the potential of robotic support systems to enhance both worker well-being and operational performance.

The incorporation of fuzzy fatigue evaluation into the decision-making process represents a significant advancement in ergonomic assessments, especially within automated and semi-automated ALs. The results of the numerical experiments validated the effectiveness of this approach, showing that it could significantly reduce operator fatigue and system costs across a variety of scenarios. These findings align with the principles of Industry 4.0 while anticipating the human-centric focus of Industry 5.0, where worker well-being is prioritized alongside technological advancements.

Future research should explore additional optimization objectives, such as multi-objective optimization models that balance ergonomic risks, system costs, and productivity. Incorporating more real-world case studies and refining the solution framework to address evolving challenges in collaborative robotic environments will be essential for advancing this field.

3. Ergo4All-Pro: A Comprehensive Virtual Ergonomic Assessment Model

The third contribution is the development of Ergo4All-Pro™, a comprehensive and innovative ergonomic risk assessment model designed for use in DHM systems. This model integrates insights from established ergonomic tools such as OCRA, RULA, and REBA, providing a more refined and holistic approach to assessing cumulative risks across various body parts, particularly within virtual environments.

The model's validation through both real-world and synthesized scenarios highlights its potential for precise and adaptable ergonomic evaluations, making it a valuable tool for industries transitioning to Industry 5.0. By incorporating fuzzy rules based on expert ergonomic knowledge, Ergo4All-Pro™ addresses the limitations of traditional ergonomic assessment tools and offers a flexible framework that can be customized to meet the needs of different worker groups.

Despite its strengths, this study acknowledges the need for further validation through additional case studies and the inclusion of other EATs. Future research should focus on expanding the model's scope, incorporating more factors through exploring other initial ergonomic evaluation approach in task level to provide a more comprehensive understanding of workplace ergonomics, particularly in virtual environments.

In conclusion, this thesis has demonstrated the potential of fuzzy expert systems to address the complex interplay between ergonomics, human-robot collaboration, and AL optimization. The findings highlight the importance of prioritizing worker safety, satisfaction, and operational performance in the context of Industry 5.0, where human-centric values and technological advancements converge. By integrating these methodologies, companies can expect to see tangible improvements in worker well-being through more accurate fatigue management, reduced physical strain, and a safer working environment.

The adoption of these methods in real-world industrial settings can also lead to substantial improvements in productivity and efficiency. With reduced operator fatigue and more intelligent task allocation, industries will benefit from a more resilient and capable workforce. In turn, this contributes to the sustainability of manufacturing systems by minimizing downtime, reducing worker turnover, and optimizing resource utilization, which aligns with both economic and environmental sustainability goals.

Moreover, the human-centric design principles embedded in these frameworks can significantly enhance worker engagement and satisfaction, fostering a more adaptable and productive workforce. As industries move towards adopting these methods, they will be better equipped to meet the demands of Industry 5.0, where collaboration between humans and robots plays a critical role in achieving sustainable, efficient, and ethical production systems.

The contributions of this research offer a strong foundation for future studies and practical implementations, as Figure 9.1 shows. By integrating ergonomic considerations into both physical and virtual environments, the proposed frameworks pave the way for safer, more efficient, and sustainable manufacturing systems. As industries continue to evolve, the insights from this thesis will support the ongoing transition towards human-centric design, fostering innovation in both academic and industrial settings. Based on this research, there is a considerable potential for future research to involve interdisciplinary collaboration between engineers, ergonomists, computer scientists, and psychologists to develop more comprehensive and human-centered solutions for Industry 5.0.

Moving forward, continued research should focus on refining these models by incorporating real-world data, exploring multi-objective optimization approaches, and expanding the scope of ergonomic assessments to encompass a wider range of factors. This will ensure that ALs remain adaptable to the diverse needs of workers and the ever-changing demands of modern manufacturing systems, contributing to a more sustainable, productive, and human-centric manufacturing landscape.

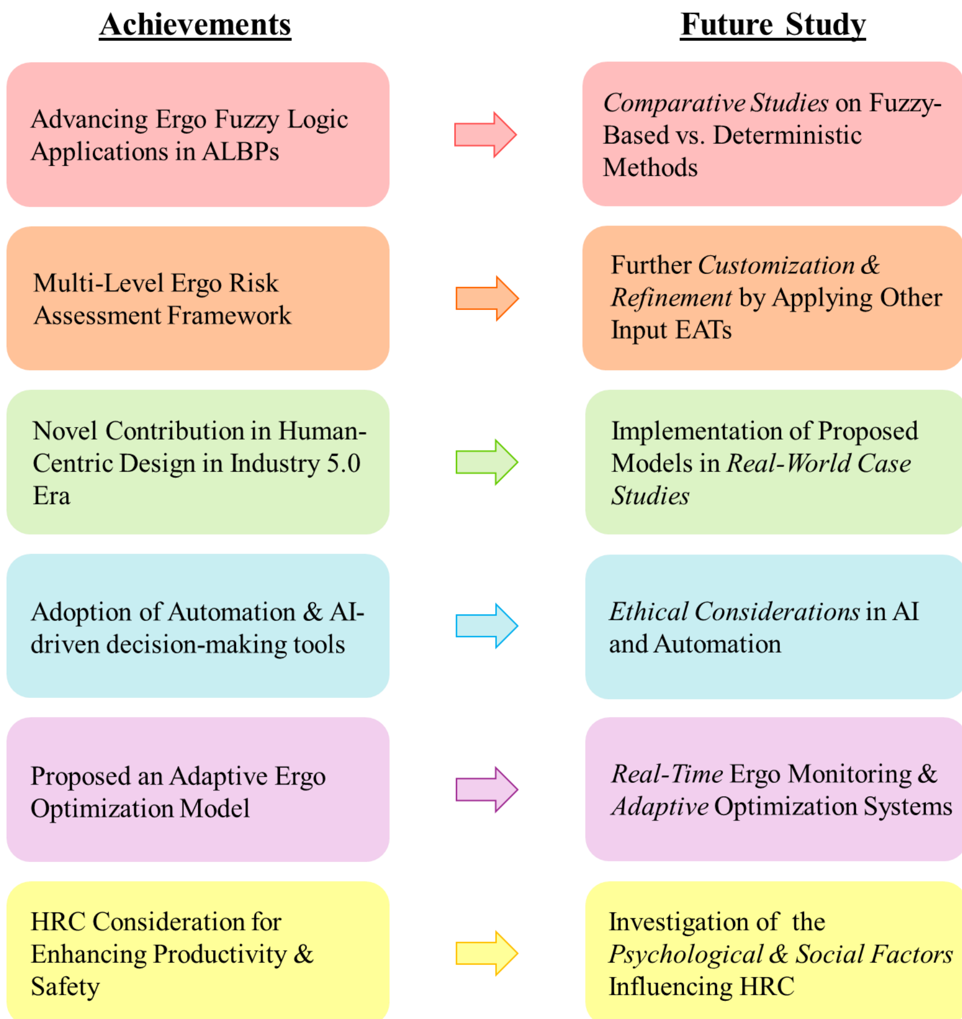


Figure 9.1 The main contributions and future research directions of the current thesis

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APPENDIX A CONFERENCE PAPER 1

Optimization Framework for Assembly Line Design Problem with Ergonomics Consideration in Fuzzy Environment

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Abstract

This paper presents a framework for solving assembly line design problems by considering ergonomics aspects. Although ergonomics factors have been ignored in conventional optimization problems in this area, in the long term, ergonomics risks and work-related injuries can impose considerable expenses on production systems. Moreover, in the design stage, different types of uncertainty in operational and ergonomics aspects can affect the optimization model. Therefore, the optimization framework in this study includes the results of ergonomics assessment tools and employs fuzzy logic to tackle imprecise factors. In the context of our problem, the sources of imprecision are twofold: environmental uncertainty and system uncertainty. Environmental uncertainty is related to demand uncertainty derived from market variations and customers' behavior. System uncertainty includes the uncertainties within the production process that partially relate to human aspects, such as uncertainty in task execution time and the physical capacity of the operators.

Keywords: Assembly Line Balancing Problem; Ergonomics; Fuzzy Set Theory

A.1 Introduction

The main goal of planning ALs is to increase productivity and efficiency. This is achieved through optimization problems called ALBP (Hazır et al., 2015). However, market fluctuations and changing customer needs introduce uncertainty and require flexible production systems. Manual tasks in ALs contribute to system flexibility but also pose risks to operators' ergonomics and line efficiency. Therefore, Ergo-ALBP considers both operational and ergonomics factors in optimizing the AL system. Manual tasks also introduce variability due to workers' physical characteristics, gender, age, experience, and skills, impacting the optimization model (Baykasoglu et al., 2017; Ozdemir et al., 2021; Vig, 2020).

There are two critical research gaps in Ergo-ALBP literature. Firstly, traditional optimization models have overlooked HF/E in favor of operational factors like cost and time. Additionally, most studies have considered ergonomics aspects in existing ALs rather than in the design stage. However, considering ergonomics parameters in the design stage (Ergo-ALDP) is strategic planning that can prevent future costs for redesigning and taking corrective actions to solve ergonomics problems (Falck & Rosenqvist, 2014). Secondly, vague and imprecise factors, such as market uncertainty and varying worker characteristics, need to be included in the optimization problem. This includes accounting for variable takt time, inconsistent ergonomics risk levels, and task times that depend on individual workers. Notably, no previous Ergo-ALBP studies have addressed both uncertain conditions and HF/E aspects during the design phase of ALs.

This study contributes by proposing a framework to optimize Ergo-ALDPs in un-certain conditions. Fuzzy logic is used to handle imprecise parameters and variables. The framework is applicable to any type of AL in the design step and beneficial for engineers and ergonomics practitioners in production systems.

This manuscript is organized as follows: In Section A.2, a brief introduction to Ergo-ALBP is provided. Section A.3 and Section A.4 present the optimization model and solution approach, respectively. In Section A.5, the practical perspective of the pro-posed framework is discussed. Finally, Section A.6 presents the concluding remarks.

A.2 Background

In the early 1900s, Ford's car manufacturing plants were a good example of assembly lines used in the context of mass production. Since then, this crucial element of mass and lean production systems has significantly evolved and transformed into a more agile system. ALs are the final stage of most production systems and are the closest part to customers. Thus, optimizing them involves balancing them and eliminating any issues that prevent them from working smoothly. In the following subsections, the main aspects of these optimization problems are explained.

A.2.1 Assembly Line Balancing Problem (ALBP)

Optimization models ALs aim to eliminate unbalanced points, such as bottlenecks, that decrease efficiency and worsen KPIs. Balancing ALs involves optimizing them with respect to productivity and efficiency goals (Hazır et al., 2015). The formulation of ALBPs as LP models dates back to 1955 (Salveson, 1955). While a solution approach was introduced in 1961 (Halgeson & Birnie, 1961), trial-and-error techniques have been the primary solving method for several decades. ALBPs are NP-hard COPs that require finding an optimal solution from a finite set of feasible solutions (FSs). ALBPs are categorized into simple (SALBP) and general (GALBP) problems (Baybars, 1986). SALBPs consider one-sided straight ALs with deterministic operation times, optimizing one or two objectives. They are classified into four types: Type 1 minimizes the number of workstations based on a given cycle time, Type 2 minimizes the cycle time based on a fixed number of workstations, Type F checks the feasibility of the problem with a fixed number of workstations and cycle time, and Type E minimizes both the cycle time and the number of workstations. GALBPs encompass more complex conditions, such as multiple product types, multiple sides, or non-straight assembly lines.

While SALBPs have been extensively studied, there is a need for more research on GALBPs to tackle sophisticated real-world problems (Becker & Scholl, 2006). The past decade has seen a positive trend towards considering these general problems to address complexity.

A.2.2 Assembly Line Balancing Problem with Ergonomics Aspect (Ergo-ALBP)

Assembly tasks pose ergonomics risks and WMSDs due to their repetitive and prolonged nature. Considering ergonomics and operational factors together is crucial for preventing injuries, and Gunther et al. were the first to consider ergonomics risks in the ALBPs in 1983 (Gunther et al., 1983). Since then, there have been few contributions in this domain until 2011 when Otto and Scholl included an ergonomics objective in the optimization model (Otto & Scholl, 2011). Their study motivated other scholars to focus on Ergo-ALBPs.

Although many research studies have examined the balancing of different types of ALs, limited research has been conducted in Ergo-ALBPs. It is proved that neglecting ergonomics factors in the design stage can lead to health-related issues for workers in the long run, which may require corrective measures that cost 9.2 times more than preventive actions taken during the design phase (Falck & Rosenqvist, 2014). However, in the case of Ergo-ALBPs, few studies have focused on design problems (Ergo-ALDPs). Baykasoglu et al. (2017) addressed a SALBP in the design phase and developed a heuristic solution to solve it. Finco et al. (2019) modeled an optimization problem for designing a semi-automatic AL. They attempted to minimize the design cost and ergo-nomics risks by analyzing the vibration of automatic hand-held tools. In recent years, CALBPs or RALBPs that integrate ergonomics aspects with assigning exoskeletons and robots have become more common. For instance, Abdous et al. (2020) examined a CALDP and developed an optimization model to reduce the overall equipment cost (design cost of AL) and minimize the ergonomics risk level.

Based on the definition by the IEA, HF/E is a scientific discipline that examines interactions between humans and system components, aiming to enhance operator safety and system performance. Numerous EATs, such as OCRA, REBA, RULA, OWAS, and NIOSH's RNLE, have been developed to evaluate ergonomics risk factors in workspaces. Some of these methods serve as foundations for national and international ergonomic standards, including EN1005-2, EN1005-5, ISO11228-1, and ISO11228-3. While no method is universally superior (Takala et al., 2010), EATs categorize ergonomics risk levels into ranges from low to high (Vig, 2020).

A.2.3 Uncertainties

Limited research has incorporated ergonomics aspects into optimization models for ALBPs, particularly in the design stage (Ergo-ALDP). Most studies have focused on deterministic problems, overlooking the impact of uncertainty. However, in the design phase, uncertainty affects the assembly design in some way. In general, there are two types of uncertainty: environmental and system uncertainty (Ho, 1989). In the context of the problem under study, environmental uncertainty includes uncertainties in demand variations resulting from market fluctuations.

Moreover, system uncertainty is related to any imprecision in the manufacturing process. It partially consists of human aspects, such as uncertainty in system reliability, task time, and the physical capacity of the workers. In addition, Golabchi et al. (2016) found that the inputs of EATs are often imprecise, which could significantly impact the results. To model these uncertainties, researchers employ stochastic programming models when historical data is available to identify the probability distribution of imprecise factors. Otherwise, fuzzy programming is helpful.

To the best of the authors' knowledge, only Tiacci and Mimmi (2018) have included uncertainty in their Ergo-ALBP model. They incorporated stochastic task times and introduced penalties for cases where ergonomics constraints and/or predicted cycle times were not addressed. To evaluate ergonomics parameters, they utilized OCRA, and for cost minimization, they employed a GA.

A.2.4 Fuzzy Approaches in Balancing Problems

Ergonomics aspects and operational parameters in optimization problems of ALs represent conflicting objectives. To overcome the vagueness in multi-objective models with ergonomics and operational functions, some articles such as Rajabalipour Cheshmehgaz et al. (2012) and Ozdemir et al. (2021) employed fuzzy goal programming. Although considerable research studies in ALBPs have employed FST to address uncertain and imprecise conditions in ALs, only Mutlu and Özgörmüş (2012) considered ergonomics risks as fuzzy numbers among Ergo-ALBPs literature. They applied Bellman and Zadeh (1970)’s approach to minimize the number of workstations and perceived workload.

A.3 Problem Context

As mentioned in previous sections, in the design stage of Ergo-ALBP, two types of uncertainty must be addressed in the optimization model. Since takt time, derived from the demand rate, is not deterministic in the design phase, cycle time is imprecise. Task execution times also vary based on the worker’s skill and experience level. Furthermore, ergonomics risk factors are vague because, in the planning step, the works situations are not precisely determined nor who will perform the task in each workstation. Various characteristics of workstations (e.g., the force required to use tools or lift parts to be assembled, types of tools used, physical dimensions of work-station components, repetition and frequency of sub-tasks, thermal environment) and of operators (e.g., gender, age, skill level, experience, and physical and work capacity, prior training), can impact the ergonomics risk level of each task. Therefore, this section defines the optimization problem by taking some steps and developing the model from an initial mathematical problem, SALBP-Type1, to the final state by identifying fuzzy time and ergonomics parameters.

A.3.1 Initial Model

In the design stage, the optimum number of workstations should be identified, thus the mathematical problem is the same as SALBP-Type1. The notations of the initial optimization model are as follows:

Sets & Indexes:

N Set of tasks (i,j = Indices for tasks: i,j ∈ {1, …, n}

S Set of workstations (s = Index for workstations: s ∈ {1, …, m_{max}}

P_i Set of immediate predecessors of task i

Parameters:

n = number of tasks m = number of workstations

t_i = execution time of task CT = cycle time

Decision variables:

x_{si} = Binary variable, if task i is assigned to station s, it will be equal to 1 otherwise 0

y_s = Binary variable, if at least one task is assigned to station s, it will be equal to 1 otherwise 0

Then the initial mathematical model for the proposed ALDP is the same as SALBP-Type1:

$$\text{Min} \sum_{s=1}^{m_{max}} y_s \tag{A.1}$$

$$\text{Subject to: } \sum_{s\in S} x_{si} = 1 \ , \forall i \in N \tag{A.2}$$

$$\sum_{s\in S} s.x_{si} \leq \sum_{s\in S} s.x_{sj} \ , \forall\, i,j \in N | i \in P_j \tag{A.3}$$

$$\sum_{i\in N} x_{si}.t_i \leq CT \ , \forall\, s \in S \tag{A.4}$$

$$\sum_{i\in N} x_{si} \leq M.y_s \ , \forall\, s \in S \ \sum_{i\in N} t_i < M \tag{A.5}$$

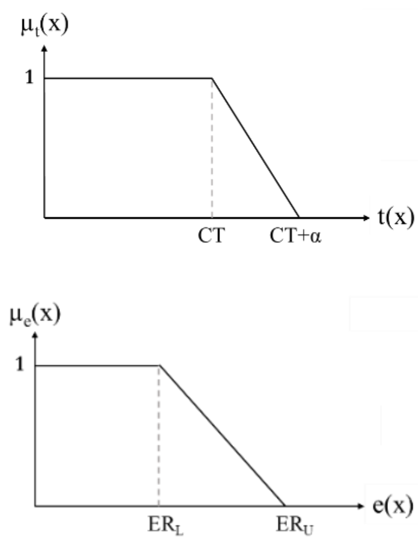
$$x_{si}, y_s \in \{0,1\}, \forall\, s \in S;\ \forall\, i \in N \qquad (A.6)$$

In equation (A.1), the objective function minimizes the number of workstations. The constraint in equation (A.2) guarantees that every task i is assigned to a single workstation. Equation (A.3) checks that the assigned stations satisfy precedence relations between tasks i and j. Equation (A.4) ensures that the total stations' time cannot exceed the cycle time. Equation (A.5) guarantees the utilization of a workstation when any task is assigned to it. The last equation indicates that decision variables x_{si} and y_s are binary variables.

A.3.2 Fuzzy Ergo-ALDP

As mentioned before, in the design step, time-related parameters are imprecise. Cycle time depends on takt time (available time divided by demand) and the execution time of tasks. Thus, according to inconstant demand and variable task times, cycle time is imprecise and varies to some extent (α). As a result, fuzzy logic can help us to define this parameter's variability. Figure A.1(a) illustrates the membership function of CT by considering α as an acceptable increase in CT which imposes some overtime in the production system, and it should be minimized.

Based on the output of most EATs and considering the imprecise input of these tools which brings uncertainty to our model, fuzzy sets can define the results in the best way. Figure A.1(b) depicts the membership function for a typical EAT. In this function, if the result of EAT is between ERL and ERU, it is interpreted as a moderate risk. While the results lower than ERL show a low-risk level, the outputs upper than ERU entail a high ergonomics risk. Taking advantage of the research done by Rajabalipour Cheshmehgaz et al. (2012), ergonomics risks can be evaluated as accumulated factors. As a result, various EATs can be applied to assess desired ergonomics parameters in the final optimization model. Some studies employed fuzzy set theory in literature to tackle the uncertainty in assessing ergonomics parameters. For instance, Ghasemi and Mahdavi (2020) developed a new REBA scoring system based on fuzzy sets and several fuzzy membership sets. Furthermore, Wang et al. (2021) integrated a 3D automated posture-based ergonomics risk assessment with a specialized rule-based fuzzy inference algorithm to solve the issue derived from the imprecise nature of inputs.



(*a*)

$$\mu_t(x) = \begin{cases} 1 & \text{if } \sum t_i x_{ij} < CT \\ 1 - \dfrac{\sum t_i x_{ij} - CT}{\alpha} & \text{if } CT \le \sum t_i x_{ij} \le CT+\alpha \\ 0 & \text{if } \sum t_i x_{ij} > CT+\alpha \end{cases}$$

(*b*)

$$\mu_e(x) = \begin{cases} 1 & \text{if } \sum e_i x_{ij} < ER_L \\ 1 - \dfrac{\sum e_i x_{ij} - ER_L}{ER_U - ERL} & \text{if } ER_L \le \sum e_i x_{ij} \le ER_U \\ 0 & \text{if } \sum e_i x_{ij} > ER_U \end{cases}$$

Figure A.1 The membership functions: (a) For cycle time (b) For ergonomics risk factor

A.4 Proposed Optimization Framework

In Ergo-ALBP literature, Mutlu and Özgörmüş (2012) were the only ones to consider fuzzy ergonomics risks in their research and solve their model using the Bellman-Zadeh method. However, in their approach (Bellman & Zadeh, 1970), the constraints and objectives are treated together, even though they convey different meanings. Therefore, the proposed solution procedure in this paper employs a bipolar view (Dubey & Mehra, 2012). In this perspective, negative preferences play the role of constraints and restrict the number of FSs. In contrast, positive preferences act as the objective function(s) and evaluate FSs to find the best one. Figure A.2 shows the procedure of the proposed heuristic method for solving the fuzzy Ergo-ALDP. This heuristic approach combines the COMSOAL (Computer Method of Sequencing Operations for Assembly Lines), Fuzzy goal programming, and a fuzzy inference system.

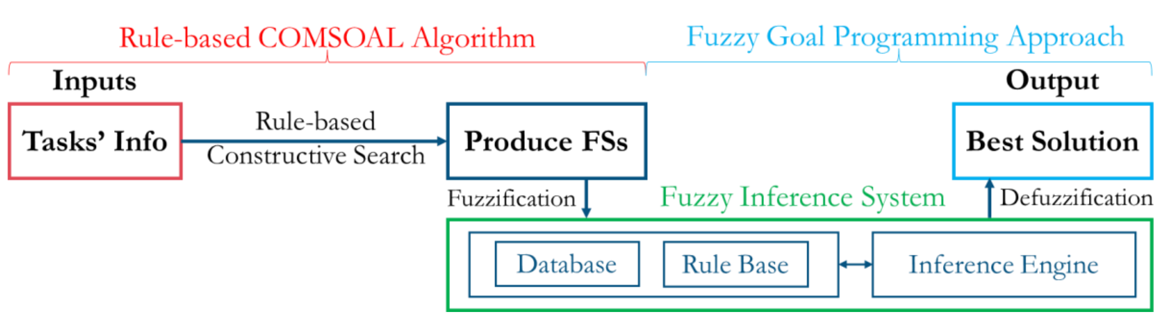


Figure A.2 Schematic of the proposed heuristic solution approach

The first step involves identifying FSs based on time and precedence constraints, using the mathematical model developed in the previous section. The task assignment rules for this step are consistent with those proposed by Baykasoglu et al. (2017), and the pseudo-code for the first part is presented in Figure A.3. It is worth noting that FSs can be generated using different CTs by varying the value of α. Moreover, tasks' execution times vary in a range of $[t_i, t'_i]$, t_i is the average time of executing the task and t'_i is the maximum duration for doing it by the lowest skill operator.

```
Input: The set of tasks and their information
Output: Feasible solutions
BEGIN
Create a set of assignable task(s)
WHILE set of assignable task(s) ≠ Ø
    Consider a workstation for allocation,
    FOR each assignable task
        Calculate the probability according to task selection rules,
    END FOR
    Select a task by applying the Roulette Wheel Selection method,
    Assign the selected task to the current workstation,
    IF the total execution time of assigned tasks for the current workstation ≥ CT
        Assign the selected task to a new workstation,
    ELSE
        Assign to the current workstation,
    Update the opened workstation(s) and assignable task(s) sets,
END WHILE
```

Figure A.3 Pseudo code of the rule-based COMSOAL approach

The solution method's second part involves applying a fuzzy inference system, as illustrated in Figure A.2. In this stage, ergonomics considerations are expressed as rules, and FSs are evaluated based on these rules, including the membership function defined in Section A.3.2.

A.5 Application Perspective

The fuzzy optimization framework is advantageous for real-world scenarios due to its ability to handle complex and uncertain information that is challenging to quantify precisely. It is particularly useful in ergonomics risk prediction during the design phase, where data may be incomplete or uncertain. The proposed framework can incorporate multiple objectives and constraints, enabling a more balanced approach to decision-making and comprehensive analysis of the optimized system. This framework is suitable for various industries, including the automotive sector, which is prominent in Ergo-ALBP literature. Incorporating realistic uncertain conditions in planning and designing production systems is a challenge. Thus, addressing uncertainty in optimization problems is expected to become more prevalent in the future to identify robust solutions.

As mentioned before, the proposed optimization approach consists of two steps. In the first step, FSs are identified based on technical parameters and constraints, making it useful for different configurations of assembly lines (e.g., 2-sided, U-shape lines). The second step involves considering ergonomics aspects by developing fuzzy rules to evaluate FSs and determine the best among them. Various ergonomics fuzzy rules can be applied, such as the assessment methodology developed by (Ghasemi & Mahdavi, 2020), which uses fuzzy sets and REBA, or the fuzzy REBA and RULA risk rating proposed by (Wang et al., 2021).

A numerical example is provided to exhibit the relevance of the suggested mathematical model and the efficiency of the proposed solution approach. The example is generated randomly and consists of 10 tasks with the precedence diagram that is shown in Figure A.4.

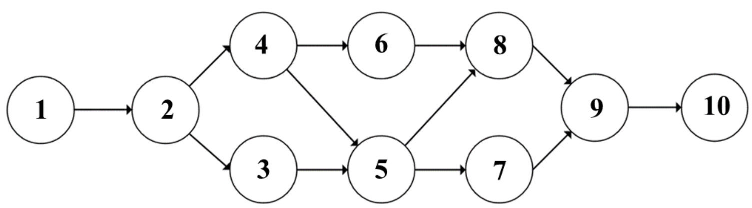


Figure A.4 Precedence diagram of the example

By applying the proposed heuristic algorithm, four FSs are found with the minimum number of workstations which is four stations. For each workstation, ergonomics risk factors are assessed by the model developed in the Gallagher and Heberger (2012) study. They evaluated MSD risk factors by examining the interaction of force and repetition of tasks. Table A.1 indicates the results of their model in the form of fuzzy rules. By applying four fuzzy rules, the ergonomics risk level of each workstation is calculated as shown in Figure A.5. In the next step, the FSs should be evaluated to find the best solution. For this final step, we can consider the following three approaches to detect the optimum solution:

- Highly Conservative Approach: No red area task assignment is permitted.
- Conservative Approach: Limiting the number of moderate-risk task assignments (minimize orange area).

- Less Conservative Approach: Limiting the number of minor-risk task assignments (minimize yellow area).

Table A.1 Ergonomics assessment fuzzy rules derived from (Gallagher & Heberger, 2012)

Rule No.	Rule Statement
1	**IF** Repetition AND Force are low, **THEN** the Risk Level is Acceptable
2	**IF** Repetition is high AND Force is low, **THEN** the Risk Level is minor
3	**IF** Repetition is low AND Force is high, **THEN** the Risk Level is moderate
4	**IF** Repetition AND Force are high, **THEN** the Risk Level is high

Based on the first approach, the first FS is eliminated in finding the optimum solution. The second approach removes the third FS. Finally, the optimum solution, in this case, will be the fourth FS which does not have any high-risk level and the number of its moderate-risk and minor-risk workstations is minimum in comparison with other FSs.

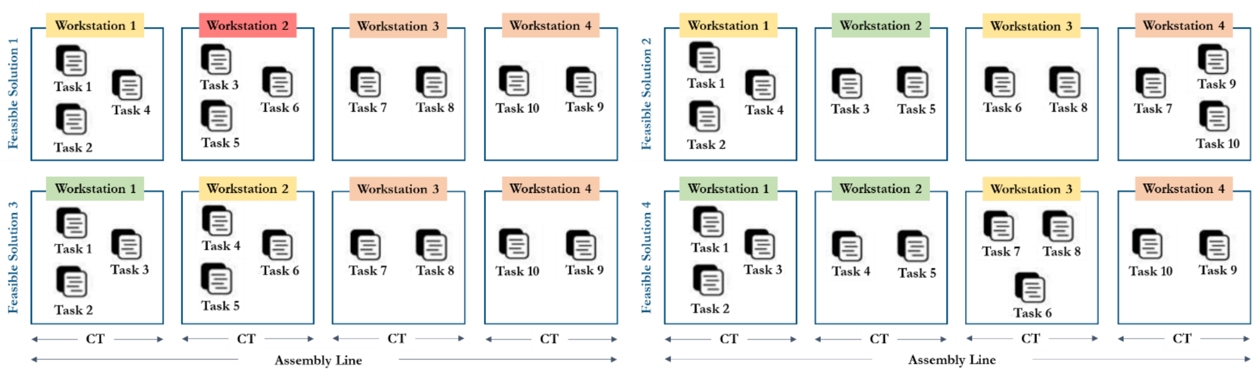


Figure A.5 Ergonomics assessment of workstations in each FS

This numerical example was developed just for explanation of our proposed optimization framework. However, it is expected that implementation of this algorithm on real case studies with proper fuzzy ergonomics rules and optimum detection approaches can find an effective solution in Ergo-ALDPs. The developed optimization framework is a versatile tool that can be customized to solve a wide range of problems under uncertain conditions, making it applicable to various domains.

A.6 Conclusions

Due to the importance of considering HF/E in the design of manual assembly processes, as well as the vital role of ALs in manufacturing systems, this paper presents a practical procedure for optimizing the Ergo-ALDP. This study proposes a framework that integrates ergonomics factors with operational parameters to optimize the ALDP in uncertain conditions. The objective is to determine the optimal task assignments for a minimum number of workstations while adhering to time restrictions and minimizing the ergonomics risk level. To achieve this objective, the study adopts a bipolar view, where operational aspects are considered negative preferences for producing FSs, while ergonomics aspects are positive preferences for evaluating FSs and identifying the best one. The fuzzy set theory is employed through several membership functions and a fuzzy inference system that conveys various rules based on different EATs.

Based on the importance of considering inconsistent conditions in the design phase of ALs, future study directions can include stochastic optimization models for general industries with typical tasks and historical data. Furthermore, more sophisticated ALs can be considered, and more complicated optimization models can be developed to probe more realistic problems. This proposed fuzzy framework could be applied to some case studies to be verified and validated.

APPENDIX B CONFERENCE PAPER 2

Fuzzy Ergonomic Expert System for Assembly Line Design Problem

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Abstract

In the era of Industry 5.0, prioritizing ergonomics in manufacturing systems is crucial. ALBPs are integral to efficient manufacturing, optimizing lines to eliminate bottlenecks and enhance productivity. Recent developments emphasize Ergo-ALBPs and the integration of HF/E to address ergonomic risks. A research gap exists in applying ergonomic considerations in the design phase known as Ergo-ALDPs as corrective ergonomic interventions cost significantly more than preventive measures taken during the design phase. This study presents a novel approach, the fuzzy Ergo-ALDP, which extends the Ergo-ALBP to handle imprecise task times and ergonomic risks in the design phase.

It introduces a fuzzy ergonomic expert system, utilizing fuzzy logic and DHM to simulate worker interactions in assembly line optimization. The proposed fuzzy Ergo-ALDP addresses this gap with a constructive heuristic integrated with fuzzy logic, emphasizing feasibility. Our research introduces a unique fuzzy ergonomic assessment method to evaluate task, workstation, and assembly line ergonomics using an expert system. We validate this approach using one synthesized numerical instance. This research contributes to assembly line optimization, aligning with Industry 5.0's human-centric vision. The comprehensive fuzzy ergonomic assessment model bridges gaps and optimizes ALDPs under uncertainty, promising improvements in productivity, worker satisfaction, and operational efficiency. By addressing the intersection of ergonomics, uncertainty, and assembly line optimization, this paper significantly contributes to advancing the field and promoting a safer and more efficient manufacturing environment.

Keywords: Ergonomic Assembly Line Balancing Problem; Assembly Line Design; Fuzzy Ergonomic Expert System; Fuzzy Ergonomic Assessment

B.1 Introduction

ALs play a crucial role in manufacturing, ensuring efficient production in response to market demands. ALBPs optimize these lines, aiming to eliminate bottlenecks and enhance productivity. The historical evolution of optimization problems, initially formulated as LP models by (Salveson, 1955), witnessed the introduction of solution approaches in (Halgeson & Birnie, 1961). After that for decades, historical developments primarily revolved around LP models and trial-and-error techniques. In recent times, the emergence of Ergo-ALBPs has emphasized the necessity to address ergonomic risks in assembly tasks, expanding the scope beyond traditional optimization approaches.

While traditional ALBPs concentrate on operational efficiency, the repetitive nature of tasks introduces ergonomic risks, leading to increased MSDs, errors, and absenteeism, ultimately affecting productivity. The integration of HF/E becomes essential to prevent injuries, resulting in the inception of Ergo-ALBPs. Gunther et al. (1983) pioneered the consideration of ergonomics risks in ALBPs, and subsequent efforts by Otto and Scholl (2011) have motivated further exploration of Ergo-ALBPs.

Existing EATs, including OCRA, REBA, and RULA, have contributed significantly to ergonomic standards. However, these tools face limitations in evaluating cumulative risk at each workstation and the entire assembly line. Despite the growing importance of considering ergonomic aspects during assembly line planning, a critical research gap exists in applying these considerations to ALDPs (Ergo-ALDPs). Neglecting ergonomic aspects in the design phase can lead to health-related issues, necessitating corrective actions that can cost significantly more than preventive measures taken during the design phase (Falck & Rosenqvist, 2014). However, the incorporation of ergonomic aspects in ALDP is not a straightforward process, and uncertainties must be addressed during the design phase. Such uncertainties arise from both environmental factors, such as market demand, and system factors, including task time variability and operator capacity. Furthermore, imprecision in EAT outputs results from subjective evaluations prone to errors due to practitioners' personal views and workers' characteristics (Ghorbani et al., 2024e). Limited research has explored Ergo-ALDPs, leaving a gap in addressing uncertainties arising from environmental and system factors (Ghorbani et al., 2023).

To fill these gaps, this research introduces a fuzzy ergonomic expert system to assess vague ergonomic aspects during the design phase. The proposed system utilizes fuzzy logic to evaluate imprecise ergonomic factors, providing a balanced and ergonomically friendly work environment. Additionally, DHM is integrated to simulate worker interactions within assembly lines, offering a comprehensive analysis and predictive capabilities to identify ergonomic issues early in the design process.

The DHM plays a crucial role in ergonomic assessment by providing a unique possibility to evaluate risks for a worker before an assembly line is built. It allows for the determination of risk and acceptability of design very early in the product development cycle. DHM software offers a significant number of biomechanical and anthropometrical data, enabling the comparison of different scenarios in a measurable way (Bourret et al., 2021). While DHM has significantly improved human factor engineering and ergonomic risk assessment, most studies focus on DHM for workplace and tool designs, with limited exploration of their application in ALBPs (Bortolini et al., 2017). Popular DHM software like Dassault Delmia, Siemens, and Jack exist but have limitations, highlighting a research gap in integrating DHM and ergonomic simulation into assembly line optimization (Ozdemir et al., 2021). The proposed fuzzy Ergo-ALDP addresses this gap with a two-phase framework, combining a constructive heuristic approach and a fuzzy ergonomic expert system. The framework assesses ergonomic risks at various levels, categorizing them into three levels (task level, workstation level, and assembly line level) and integrating them into the optimization model.

Validation using a numerical example confirms the proposed method's capability to identify high-quality solutions, showcasing its potential to enhance productivity, worker satisfaction, and operational efficiency. This study contributes to assembly line optimization by incorporating ergonomic considerations and managing uncertainty through fuzzy logic, aligning with the human-centric vision of Industry 5.0. The comprehensive fuzzy ergonomic assessment model aims to bridge existing research gaps and optimize ALDPs under uncertain conditions.

In the following section of this manuscript, the optimization model is presented. Then, the solution approach is proposed in the next one. After providing a numerical example and explaining the practical perspective of this study, in the final section the concluding remarks are discussed.

B.2 Problem Context

In the Ergo-ALDP, the optimization model must account for two types of uncertainty, as discussed earlier. During the design phase, the nature of CT is not deterministic, given the imprecision in takt time derived from a variable demand rate. Furthermore, task execution times exhibit variability influenced by the worker's skill and experience level. Additionally, ergonomic risk factors remain ambiguous due to the lack of precise determination of work situations and task performers during the planning step. Workstation characteristics (e.g., force required for tool usage, lifting parts, types of tools, physical dimensions, task repetition, and frequency) and operator attributes (e.g., age, gender, experience, skill, physical capacity, and training) contribute to the varying ergonomics risk levels for each task. This section outlines the optimization problem that incorporates fuzzy ergonomics parameters to address Ergo-ALDP.

The initial mathematical problem is Simple ALBP (SALBP) that focuses on one-sided straight assembly line that mass-produces a single-type product with a deterministic CT to optimize the desired objective while considering precedence and time constraints. The optimization problem in this study aims to find the minimum ergonomic risk level across all workstations. Furthermore, this problem is a sort of Type F, meaning to find FSs based on defined CT and the number of workstations. Table B.1 presents the notations of this optimization model.

Table B.1 Notations of mathematical model of Ergo-ALDP

Sets	**Indexes**
Set of tasks: I	Indices for tasks: i, i’ ∈ {1, …, n}
Set of stations: W	Indices for workstations: j, j’, j” ∈ {1, …, m}
Set of predecessors of task i: P_i	
Parameters	
Fuzzy execution time of task i: $\tilde{\boldsymbol{t}}_{\boldsymbol{i}}$	
Fuzzy risk of task i based on the DHM output: $\tilde{\boldsymbol{r}}_{\boldsymbol{i}}$	
Fuzzy CT: $\widetilde{\boldsymbol{CT}}$	
Decision Variable	
$x_{ij} = \begin{cases} 1, & \text{if task i is assigned to the station j} \\ 0, & \text{otherwise} \end{cases}$	
$y_j = \begin{cases} 1, & \text{if workstation j is opend} \\ 0, & \text{otherwise} \end{cases}$	
$z_{jj'} = \begin{cases} 1, & \text{if workstation j must precede station j}' \\ 0, & \text{otherwise} \end{cases}$	

The constraints of the proposed optimization problem can be defined as follow:

$$\sum_{j \in W} x_{ij} = 1 \qquad \forall i \in I \tag{B.1}$$

$$\sum_{j \in W} y_j = m \tag{B.2}$$

$$z_{jj'} \geq x_{i'j} + x_{ij'} - 1 \qquad \forall\, i' \in P_i | j, j' \in W \tag{B.3}$$

$$z_{jj"} \geq z_{jj'} + z_{j'j"} - 1 \qquad \forall\, j, j', j" \in W, |\{j, j', j"\}| = 3 \tag{B.4}$$

$$z_{jj'} + z_{j'j} \leq 1 \qquad \forall\, j \in W, j' \in W \backslash \{j\} \tag{B.5}$$

$$\sum_{i \in I} x_{ij}.\tilde{t}_i \leq \widetilde{CT} \qquad \forall\, j \in W \tag{B.6}$$

$$x_{ij}, y_j,\ z_{jj'} \,\&\, c_j \in \{0,1\} \quad \forall i \in I\ \ j \in W, j' \in W \backslash \tag{B.7}$$

Equation B.1 ensures that each task i is assigned to only one workstation. In Equation B.2, the fixed number of available workstations is checked. Constraint B.3 defines the sequence of workstations based on the precedence relations between tasks. Constraints B.4 and B.5 ensure that the location of workstations adheres to the principles of transitivity and anti-symmetry, resulting in workstations being in a linear order. Constraint B.6 verifies that the total operation time does not exceed the CT. Finally, the last equation indicates that decision variables x_{ij}, y_j, and $z_{jj'}$ are binary variables.

As Equation B.6 illustrates, in this problem, the execution time of tasks and CT are considered as fuzzy numbers to show the uncertainty of time prediction in the design stage. To develop fuzzy numbers that present the imprecision of task times, we assume three skill levels for future operators (e.g., high, average, and low skilled). Then the execution time for the tasks can be defined as TFNs and shown as a triplet: $\widetilde{t_i} =$ (t_{i_min}, t_{i_avg}, t_{i_max}). Equation B.8 and Figure B.1 present the membership function of task time.

.

$$\widetilde{t_i} = \begin{cases} \dfrac{t_i - t_{i\_min}}{t_{i\_avg} - t_{i\_min}} & if\ t_{i\_min} < t_i \leq t_{i\_avg} \\ \dfrac{t_{i\_max} - t_i}{t_{i\_max} - t_{i\_avg}} & if\ t_{i\_avg} < t_i \leq t_{i\_max} \\ 0 & if\ t_i < t_{i\_min}\ or\ t_{i\_max} < t_i \end{cases} \tag{B.8}$$

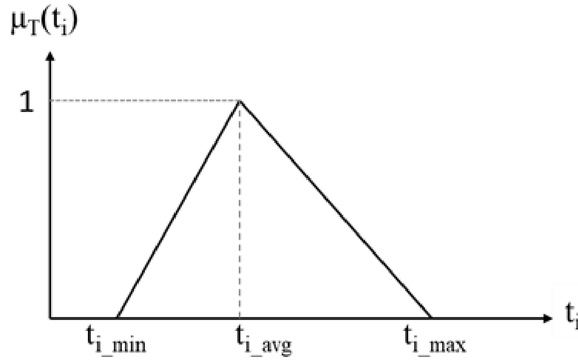

Figure B.1 The membership function of each task execution time

After finding FSs based on all mentioned constraints, we try to find the optimum solution that minimizes the ergonomic risks across all workstations. Therefore, at first, the ergonomic risk level of each workstation should be assessed, and then the ergonomic score of the whole line can be calculated to help us compare the FSs and select the optimum one.

In this study, it is assumed that the ergonomic risk level of tasks is evaluated by DHM, and the output is reported in three levels: low risk (green), medium risk (yellow), and high risk (red). However, to evaluate and compare FSs, cumulative risks are needed to assess the final ergonomic risk of each workstation. By calculating this cumulative ergonomic risk, we will have the proper input to assess the desirability of FSs and find the best one with the minimum ergonomic risk.

In the next section, the solution approach is explained in detail to show how the fuzzy logic approach and expert system based on the knowledge of ergonomic experts can help us find the optimum ergonomic design for the assembly line.

B.3 Proposed Optimization Framework

To solve the optimization problem presented in the previous section, a constructive randomized search algorithm is developed. This heuristic approach, in the first step finds FSs and then evaluates the ergonomic aspects of each solution through the proposed fuzzy expert system.

In the proposed fuzzy ergonomic expert system, ergonomic evaluation is conducted at three levels:

- Task level: In this stage, tasks are assessed by DHM. The assumed that the EAT categorizes the output into three risk levels, akin to a traffic light system. Low risk is denoted by green, medium risk by yellow, and high risk by red.
- Workstation level: In the next step, the cumulative risk of assigned tasks to each worker is assessed. To address the uncertainty stemming from task time variability, four risk levels: low, minor, medium, and high; are proposed. These ergonomic risk levels are established based on the required interventions to reduce the risk of MSDs. Assignments with higher risk levels need more significant investments of time and resources for the implementation of effective ergonomic interventions, such as preventive measures or redesign, compared to tasks with medium-risk levels, which require more investment than those with minor-risk levels for the implementation of suitable ergonomic interventions.
- Assembly line level: In the concluding section of addressing ergonomics within our optimization model, the objective is to assess and prioritize different operationally feasible assignments. The goal is to identify the combination of assignments that minimizes ergonomic risks, thereby necessitating the fewest ergonomic interventions. For this purpose, ergonomic Risk Score (RS) is evaluated based on the risk levels of workstations in each FS.

To determine the risk level at each workstation, an expert system is employed to generate fuzzy rules, using ergonomic experts' knowledge, to assess cumulative ergonomic risks for individual workers. Fuzzy rules, structured as "If…, Then…" statements, utilize fuzzy logic to evaluate conditions and draw conclusions. The analysis focuses on the interplay between task risk levels and DC. For each task i, DC is defined as its execution time (t_i) divided by CT, representing the proportion of time allocated to tasks within a CT. For the sake of simplicity, the centroid method (Equation B.9) is employed to defuzzify the task time and final CT of each solution.

$$C(\tilde{t}_i) = \frac{t_{i\_min} + t_{i\_avg} + t_{i\_max}}{3} \tag{B.9}$$

$$DC_i = \frac{C(\tilde{t}_i)}{C(\widetilde{CT})} \tag{B.10}$$

This approach is particularly relevant for interpreting risks in assembly tasks involving repetitive and prolonged activities. Recognizing variations in task durations among different workers (referred to as fuzzy task times), the methodology is developed to evaluate risk based on the tasks assigned to each worker. Fatigue in the form of ergonomic risk levels is estimated through fuzzy logic for each task set, leading to the creation of fuzzy rules to compare tasks within each CT. The methodology emphasizes limiting the time allocated to high-risk tasks in each cycle to prevent excessive fatigue, while low-risk tasks could help mitigate cumulative risk levels.

To operationalize this logic, five time-based fuzzy rules are established, drawing upon the expertise of ergonomic professionals. These rules comprehensively interpret and assess cumulative ergonomic risks at the workstation level. The fuzzy expert system relies on primary thresholds, identified with the input of ergonomist experts, forming the basis for fuzzy rule formulation. The two crucial thresholds are defined as follows:

- L= Minimum percentage of operation time allocated to low-risk tasks to mitigate the risk.
- U = Maximum acceptable percentage of a CT devoted to executing high-risk tasks.

Table B.2 Set of fuzzy rules for interpreting cumulative ergonomic risk in workstation level

No	Condition (IF)	Risk Level (THEN)
R1	No high-risk tasks are assigned, and the cumulative DC of medium-risk tasks exceeds L%,	Medium (orange)
R2	No high-risk tasks are assigned, and the cumulative DC of low-risk tasks exceeds L%,	Low (green)
R3	Cumulative DC of high-risk tasks surpasses U%,	High (red)
R4	Cumulative DC of high-risk tasks is lower than U%, and the cumulative DC of low-risk tasks exceeds L%,	Minor (yellow)
R5	Cumulative DC of high-risk tasks is lower than U%, and the cumulative DC of low-risk tasks is lower than L%,	Medium (orange)

Based on the stated assumptions, five fuzzy rules, as presented in Table B.2, are employed to assess each worker's potential ergonomic risk level. After evaluating the risk level of each workstation, the risk level of each FS can be calculated by defining a fuzzy RS that shows the cost of ergonomic interventions that must be applied to mitigate the potential risks of MSDs. Therefore, in the final ergonomic assessment of the assembly line, assignments categorized as low risk at the workstation level are considered with no risk and take RS equal to 0, while those exposing workers to high risk are deemed most risky ones with RS equal to 1. Likewise, assignments with minor and medium risks can receive RS of MI and ME, respectively, representing partial ergonomic risk. Equation B.11 is utilized to compute the overall ergonomic RS for each FS.

$$RS = \frac{(\#low \times 0) + (\#minor \times MI) + (\#medium \times ME) + (\#high \times 1)}{\#workstation} \tag{B.11}$$

B.4 Application Perspective

The incorporation of the suggested fuzzy ergonomic model into the optimization framework of ALDP presents significant advantages in practical situations. This model excels in handling uncertain information during the design phase, enabling decision makers to navigate imprecise data challenges. Its value lies in predicting cumulative ergonomic risks during design, particularly when data is incomplete or vague due to environmental and system uncertainties. The framework accommodates multiple objectives and constraints, promoting a balanced decision-making approach applicable across various industries. The adaptable nature of this framework assists in predicting ergonomic risk levels and adjusting the design before establishing assembly lines.

The optimization process follows a two-step approach. Feasible solutions based on operational parameters are identified in the initial step, making the model suitable for various assembly line configurations. In the second step, ergonomic risks are evaluated in a fuzzy environment, allowing for the comparison of different scenarios ergonomically.

To illustrate the solution's effectiveness, a numerical example is presented in Figure B.2, involving 15 tasks with fuzzy triangular execution times and corresponding precedence relationships. It is assumed that tasks were assessed through DHM, and any EAT, and their output reported as low, medium, or high-risk level that is shown in green, yellow, and red, respectively. This example considers five workstations, and the desired fuzzy CT is equal to (44, 60, 76). As explained before, defuzzified task times are calculated based on Equation B.9 and written in red on top of each task’s fuzzy time. Defuzzified CT with the same equation is equal to 60 seconds.

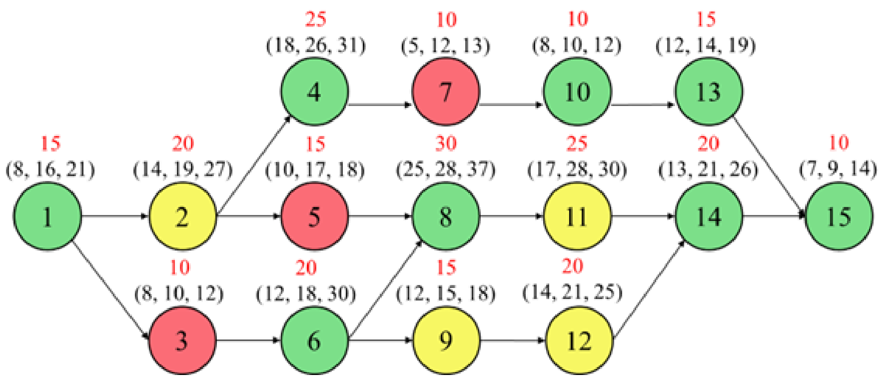

Figure B.2 Precedence network of a sample assembly line

Based on previous discussions, insights from research studies, and contributions of ergonomist experts, specific thresholds and parameters have been assumed for the solution algorithm when applied to this numerical example. The assigned values are L=50%, U=20%, MI=0.3, and ME=0.6. Three feasible solutions are identified, and their ergonomic risk scores, assessed using the proposed fuzzy expert model, determine a better solution with a lower RS. As Table B.3 presents the first solution is better since its fuzzy ergonomic risk is lower than the second FS.

Table B.3 Comparison of two FSs based on fuzzy assessment approach

WS No.	**FS1**		**FS2**	
	Tasks	**Risk Level**	**Tasks**	**Risk Level**
1	1, 3, 6	R4	1, 2, 5	R3
2	2, 9, 12	R1	3, 4, 6	R4
3	4, 5, 7, 10	R3	8, 11	R2
4	8, 11	R2	9, 12, 14	R1
5	13, 14, 15	R2	7, 10, 13, 15	R4
	RS = 0.38		RS = 0.44	

While this example is crafted for explanatory purposes, the algorithm's application to real case studies holds potential for effective and robust solutions in Ergo-ALDPs.

B.5 Conclusion

In conclusion, this paper introduces a novel approach to tackle the challenges posed by Ergo-ALBPs. While the historical evolution of assembly line optimization, rooted in LP models, has witnessed significant advancements, the emergence of Ergo-ALDPs has added complexity to the optimization landscape.

Traditional approaches, emphasizing operational efficiency, often overlook the ergonomic risks associated with repetitive tasks, potentially resulting in health-related issues and diminished productivity. The proposed fuzzy ergonomic expert system, integrated into the optimization framework, provides a comprehensive solution to navigate uncertainties during the design phase. By utilizing fuzzy logic and DHM, the framework assesses and categorizes ergonomic risks at various levels—task, workstation, and assembly line. This holistic approach ensures a balanced consideration of both operational efficiency and ergonomic factors, aligning with the principles of Industry 5.0 and human-centric design.

The application perspective demonstrates the practical advantages of the proposed model. The two-step optimization process identifies feasible solutions based on operational parameters, followed by a fuzzy evaluation of ergonomic risks. A numerical example showcases the model's effectiveness in predicting and comparing different scenarios, considering fuzzy task times, precedence relationships, and ergonomic risk levels.

Moreover, the incorporation of an expert system with fuzzy rules, drawing on the knowledge of ergonomic professionals, adds sophistication to the assessment of cumulative ergonomic risks. The proposed fuzzy RS offers a quantifiable measure to compare and prioritize different assembly line configurations, considering the cost of ergonomic interventions required to mitigate potential risks of MSDs.

In practical applications, this approach equips decision-makers with a valuable tool to handle imprecise data challenges during the design phase. The framework's adaptability makes it suitable for various assembly line configurations across different industries. By predicting ergonomic risk levels and allowing for adjustments in the design before implementation, the proposed model contributes to the creation of safer, more efficient assembly lines.

However, it is crucial to acknowledge certain limitations and areas for future study. The model assumes tasks compatibility without explicit consideration of potential conflicts or dependencies between different tasks. Future research could explore more sophisticated task compatibility assessments to enhance the accuracy of assembly line design. Additionally, the variability of human operators, encompassing skills, characteristics, and learning curve effects, is a critical aspect that requires further investigation. Integrating more dynamic models that account for individual differences and adapt to changing operator conditions could enhance the model's predictive capabilities.

Furthermore, considering layout and equipment effects is another avenue for future research. The current model focuses on ergonomic risks at the task, workstation, and assembly line levels, but the physical layout and equipment configurations may introduce additional variables that impact overall ergonomics. While DHM has been integral to ergonomic risk assessment, it is essential to recognize its limitations. Future studies could delve into refining and expanding the capabilities of DHM, addressing challenges such as more accurate representation of worker movements and interactions with the environment.

In summary, while the integration of fuzzy logic, DHM, and an expert system in the proposed optimization framework stands as a promising advancement in Ergo-ALDPs, acknowledging these limitations and charting paths for future study is crucial. Addressing these aspects will contribute to the ongoing evolution of Ergo-ALDP optimization, ensuring a more comprehensive and adaptable framework that aligns with the evolving needs of manufacturing industries. This research not only contributes to the existing body of knowledge in assembly line optimization but also provides a robust solution for industries seeking to align with human-centric design principles and tackle uncertainties inherent in ergonomic considerations during the design phase. The proposed model stands as a promising advancement in the realm of assembly line design, emphasizing the importance of both operational efficiency and worker well-being.

APPENDIX C CONFERENCE PAPER 3

Fuzzy Fatigue Model for Ergonomic Design of Assembly Lines under Uncertainty

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Abstract

In the context of Industry 5.0, the significance of prioritizing ergonomics within manufacturing systems cannot be overstated. This paper introduces an innovative methodology, the Fuzzy Ergo-ALDP-F, which extends the traditional Ergo-ALBP) into the design stage to address imprecise task durations and ergonomic risks effectively. This approach encompasses a two-phase framework, integrating a constructive heuristic with fuzzy logic. The first phase focuses on ensuring feasibility, while the second phase is dedicated to finding the ergonomically optimum solution among all feasible options. Our research enriches the existing knowledge by incorporating a fuzzy extension of Potvin's fatigue model. It is worth noting that integrating fuzziness in fatigue evaluation across tasks, workers, and assembly lines is a novel and pivotal aspect of our work. This study is rooted in the fundamental recognition that, in the long term, work-related injuries and ergonomics-related issues can impose substantial costs on production systems. Moreover, in the design phase, various types of uncertainty relating to operational aspects and ergonomics can significantly impact the optimization model. Consequently, this paper makes substantial progress in the research landscape by synergistically addressing the critical intersection of ergonomics, uncertainty, and assembly line optimization, significantly contributing to the ongoing pursuit of a safer and more efficient manufacturing environment and underlining its broader implications within the field.

Keywords: Ergonomic Assembly Line Design; Knowledge-based Expert System; Fuzzy Logic

C.1 Introduction

The primary objective of planning assembly lines is to enhance productivity and efficiency, which is achieved through optimization problems known as ALBPs. However, market fluctuations and evolving customer demands introduce uncertainty, necessitating flexible production systems (Ghorbani et al., 2024e). Manual tasks within assembly lines contribute to this flexibility but simultaneously introduce risks to ergonomics and productivity. Consequently, Ergo-ALBP strives to harmonize operational and ergonomics parameters in the optimization of assembly processes. Moreover, manual tasks introduce variability to the process stemming from factors such as workers' physical attributes, age, gender, skills, and experience, impacting the optimization model (Ghorbani et al., 2024e).

Evidence from literature uncovered some notable research gaps as follows:

- Optimization models of assembly lines have traditionally prioritized operational factors like cost and time while largely overlooking HF/E. Within a limited number of studies that considered ergonomic aspects of assembly lines in their models, more than half of them applied semi-quantitative EATs to evaluate posture risk factors. Furthermore, 78% of the rest of the studies that considered fatigue risks employed quantitative approaches like evaluating energy expenditure rates to assess the generalized fatigue (Ghorbani et al., 2023). Therefore, integrating other fatigue models into optimization models of ALBPs remains a research gap that can be addressed in this study.
- Most studies have concentrated on ergonomics considerations within existing assembly lines, rather than addressing them during the design phase. However, incorporating ergonomics parameters at the design stage (Ergo-ALDP) represents strategic planning that can prevent future costs associated with redesigning and implementing corrective measures to resolve ergonomics issues (Falck & Rosenqvist, 2014).
- The optimization problem must encompass vague and imprecise aspects, such as market fluctuations and diverse worker characteristics. Thus, the design optimization model should address variable takt times, fluctuating ergonomics risk levels, and task durations related to individual workers (Ghorbani et al., 2023). In our previous research (Ghorbani et al., 2024e), we attempted to simultaneously address uncertain conditions and HF/E aspects during the design phase of assembly lines. Since this research gap requires further

exploration, the current study aims to consider uncertainty in fatigue models to minimize the required recovery time within the assembly line.

This study makes a significant contribution by introducing a novel fuzzy fatigue model to optimize ALDPs under uncertain conditions. Fuzzy logic is applied to manage imprecise parameters and variables. A novel fuzzy risk assessment method is developed for ergonomic evaluation, analyzing by employing experiments and the knowledge of ergonomic experts. For this purpose, a customized fuzzy fatigue model is developed based on Potvin's equation (Potvin, 2011). This fuzzy fatigue assessment method is integrated into the assembly line optimization model for the first time to evaluate the cumulative fatigue level of each workstation and the whole assembly line.

Therefore, this paper represents significant progress in the ongoing endeavor to harmonize ergonomics, uncertainty, and assembly line optimization. In doing so, it makes a substantial contribution to the goal of developing a manufacturing environment that is not only safer but also more efficient. This multifaceted approach to the ALDP holds broad and profound implications for the field. This framework is also applicable to diverse types of assembly lines during the design phase, proving advantageous for both engineers and ergonomics practitioners in production systems.

This study contributes to the literature in the field of Ergo-ALBPs in several aspects to address the abovementioned research gaps. Our research adopts an optimization framework that considers ergonomics aspects, addressing the long-term implications of ergonomics-related challenges on production systems. This framework incorporates the results of a fatigue assessment tool and applies fuzzy logic to address imprecise factors. In this context, imprecision arises from two primary sources: environmental uncertainty and system uncertainty. Environmental uncertainty is linked to demand variations stemming from market fluctuations and customer behavior. In contrast, system uncertainty encompasses uncertainties within the production process, some of which pertain to human factors, such as uncertain task execution times and operator physical capacities.

The structure of this manuscript is as follows: Section C.2 offers a brief introduction to ALBP, ergonomics aspects, and uncertainty in the design phase of assembly lines. Section C.3 and Section C.4 delineate the optimization model and the approach for finding solutions, respectively. In Section C.5, the practical implications of the proposed framework are discussed. Finally, Section C.6 presents concluding remarks.

C.2 Literature Review

This study concentrates on the overlap of three necessary fields: the design type of assembly line optimization problems, ergonomics aspects of these problems, fatigue models, and the uncertainty considerations in these models. The following subsections present a brief review of these three areas.

C.2.1 Assembly Line Design Problem (ALDP)

Optimization models of assembly lines are designed to address imbalances, such as bottlenecks, which can diminish efficiency and adversely affect KPIs. The core objective in balancing assembly lines revolves around optimizing their performance concerning productivity and efficiency objectives (Ghorbani et al., 2024e). The history of formulating ALBPs can be traced back to 1955 (Salveson, 1955). Although a solution approach was introduced in 1961 (Halgeson & Birnie, 1961), trial-and-error approaches remained the predominant method for solving these problems for several decades. ALBPs fall within the category of NP-hard COPs, implying the search for the best solution within a finite set of feasible solutions (FSs). ALBPs are typically classified into two main categories: simple (SALBP) and general (GALBP) problems. SALBPs refer to one-sided linear assembly lines with deterministic operation times and aim to optimize one or two objectives. These can be further divided into four classes: Type 1, which minimizes the number of workstations given a specified cycle time; Type 2, which minimizes the cycle time while having a fixed number of workstations; Type F, which assesses the problem's feasibility under fixed workstation numbers and cycle time; and Type E, which strives to minimize both the cycle time and the number of workstations. In contrast, GALBPs encompass more complex scenarios, which may involve multiple product types, multiple sides, or non-linear assembly lines (Ghorbani et al., 2023).

While significant research has been dedicated to optimizing existing assembly lines, there is an obvious need for further investigation into ALDP to address the complexities posed by real-world scenarios in the design phase. Over the past decade, there has been a growing trend towards addressing these problems to meet the demands of increasingly complex manufacturing environments (Ghorbani et al., 2023).

C.2.2 Ergonomics Considerations in Assembly Line

Assembly tasks inherently carry ergonomic risks and the potential for WMSDs because they are primarily repetitive and prolonged activities. For optimizing an assembly line, it is vital to consider ergonomics factors in addition to operational parameters to prevent injuries. Gunther et al. was a pioneer in the integration of ergonomics risks into ALBPs as early as 1983 (Gunther et al., 1983). However, progress in this area was limited until 2011, when Otto and Scholl introduced an ergonomics objective into their optimization model (Otto & Scholl, 2011), subsequently inspiring other scholars to delve into Ergo-ALBPs.

While there has been substantial research into the balancing of various types of assembly lines, limited attention has been devoted to Ergo-ALBPs (Ghorbani et al., 2023). Neglecting ergonomics factors during the design stage has led to long-term health issues for workers, necessitating corrective actions that can cost up to 9.2 times more than preventive measures taken during the design phase (Potvin, 2011). However, in Ergo-ALBPs, most of the studies have been directed towards existing assembly lines, and limited research has focused on design problems, known as Ergo-ALDPs. Baykasoglu et al. (2017) considered a simple problem within the design phase and devised a heuristic solution for its resolution. Meanwhile, Finco et al. (2019) considered the design optimization of a semi-automatic assembly line, seeking to minimize both design costs and ergonomics risks by examining the vibration associated with automatic hand-held tools. More recently, CALBPs or RALBPs, which include ergonomics factors simultaneously with robots and exoskeletons assignments, have become more prominent (Ghorbani et al., 2023). For example, Abdous et al. (2020) examined a CALDP and developed an optimization model to reduce the overall equipment cost (design cost of the assembly line) while minimizing ergonomics risk levels.

Diverse EATs, including OCRA, REBA, and RULA, have been devised to assess ergonomic risk factors within workspaces. While there is no universally superior method (Takala et al., 2010), EATs generally categorize ergonomics risk levels into a spectrum ranging from low to high (Ghorbani et al., 2023).

C.2.3 Fatigue Models in Optimization Models

In manufacturing systems, ergonomic risks include various aspects, such as physical, cognitive, and psychosocial elements. Physical work involves activities that engage muscles through dynamic or static efforts. These activities may lead to excessive fatigue, pain, and, if not adequately addressed, can result in MSDs. Ergonomics practitioners and engineers focus on identifying risk factors and devising strategies to mitigate them within the work environment. For instance, continuous or prolonged static muscle exertion can contribute to WMSD. To alleviate these conditions, a practical approach involves incorporating scheduled recovery to reduce fatigue in the relevant muscle groups (Ghorbani et al., 2023).

It's worth highlighting that fatigue can exist in two forms: localized muscle fatigue, which affects specific muscle groups, and generalized fatigue, which impacts the entire body. To quantify generalized fatigue, energy expenditure or metabolic rate is typically assessed, especially when the activity engages approximately 70% or more of the body's muscular mass, such as upper-body activities that don't involve walking and carrying objects. Conversely, localized fatigue in specific muscle groups like the shoulder, arm, or back is evaluated using models based on EMG measurements, blood lactate levels, or rated perceived exertion using the Borg scales, each customized to different body parts.

Based on Ghorbani et al.’s review paper (Ghorbani et al., 2023), 35% of all studies in Ergo-ALBPs have considered fatigue aspects in their optimization models. Approximately 66% of these fatigue-focused articles employed the “energy expenditure” parameter to estimate generalized fatigue, while the remainder utilized either the Borg scales (Katiraee et al., 2023; Katiraee et al., 2021; Keshvarparast et al., 2022) or Ma et al. (2009) model (Abdous et al., 2020; Abdous et al., 2018b; Abdous, Delorme, Battini, Sgarbossa, et al., 2023). A significant research gap in these limited studies is the lack of consideration for the muscular fatigue model during the design phase and under uncertain conditions. During the design phase, workstations do not yet exist, and consequently, no worker is available to rate exertion or fatigue using the Borg scales. Therefore, the primary contribution of this paper is to apply a fuzzy knowledge-based fatigue model in the ALDP to address the vague and imprecise potential fatigue in our optimization model.

The integration of a knowledge-based expert system provides several advantages in solving the ergonomic design problem of assembly lines under uncertainty. Firstly, it allows for the utilization of domain-specific knowledge acquired from experts in the field of ergonomics, thus enabling the system to make informed decisions in complex and uncertain environments. Secondly, by employing fuzzy logic, the expert system can handle imprecise and uncertain inputs inherent in ergonomic assessments, providing a more robust and flexible approach to modeling fatigue. Additionally, the expert system can facilitate real-time decision-making during the design phase, enabling designers to quickly evaluate and iterate upon different assembly line configurations to optimize ergonomics and productivity.

C.2.4 Uncertainty in Assembly Line Optimization Problems

Compared to abundant studies in the ALBP domain, limited research has integrated ergonomic considerations into ALBPs, particularly during the design phase, known as Ergo-ALDP. Many previous studies have primarily focused on deterministic scenarios, disregarding the influence of uncertainty, despite its significance during the design phase (Ghorbani et al., 2024e). Generally, two main categories of uncertainty can be identified: environmental and system uncertainty (Ho, 1989). In the current problem, environmental uncertainty encompasses variations in demand based on market fluctuations, while system uncertainty depends on imprecisions in the production process. This system vagueness includes human-related aspects, such as uncertainties in system reliability, task durations, and the physical capabilities of the workforce (Ghorbani et al., 2023). Furthermore, the imprecise nature of inputs in EATs can profoundly impact the outcomes of such studies (Golabchi et al., 2016). To address these uncertainties, researchers typically turn to stochastic programming models when historical data is accessible to determine the probability distribution of these imprecise factors. When such data is lacking, fuzzy programming emerges as a valuable alternative (Ghorbani et al., 2023).

To the best of our knowledge, Tiacci and Mimmi (2018) are the sole researchers who have integrated uncertainty into their problem. Their approach involved incorporating stochastic task durations and introducing penalties for instances where ergonomics constraints and predicted cycle times were not met. They employed the OCRA method to assess the ergonomics factors and applied a GA to minimize the cost.

Ergonomics considerations and operational aspects within optimization problems for assembly lines often represent conflicting objectives. Some studies applied fuzzy goal programming to address the inherent vagueness in multi-objective models that include ergonomics and operational functions (Ozdemir et al., 2021; Rajabalipour Cheshmehgaz et al., 2012). Although many studies related to ALBPs have applied fuzzy set theory (FST) to handle uncertain and imprecise conditions, only Mutlu and Özgörmüş (2012) have considered ergonomics risks in the form of fuzzy numbers within the Ergo-ALBPs literature. They employed Bellman and Zadeh (1970) methodology to minimize workstation numbers as well as perceived workload.

C.3 Problem Context

As mentioned in previous sections, during the design phase of an assembly line, we should confront two types of uncertainty in our optimization model. First, based on the non-deterministic nature of takt time, which is influenced by the demand rate, the desired cycle time becomes imprecise. Additionally, the execution times of tasks exhibit variations regarding the skill and experience level of the worker assigned to them. Second, the vagueness of ergonomics risk factors stems from the fact that during the design, precise information about the work situations or the specific individuals who will perform tasks at each workstation are not available. A multitude of factors related to workstations (e.g., the force required for tool usage or part lifting, types of tools employed, physical dimensions of workstation components, the repetition and frequency of sub-tasks, thermal conditions) and the attributes of operators (e.g., gender, age, skill proficiency, experience, physical and work capabilities, prior training) can significantly influence the fatigue level (ergonomics risk level) associated with each task. Consequently, in this section, we try to define the optimization problem of designing an assembly line that includes uncertain factors through fuzzy set logic.

C.3.1 Optimization Model

The optimization problem in this study aims to find the minimum fatigue level across all workstations by considering different scenarios, in each of them there are specific fuzzy CT and a fixed number of workstations. Thus, the mathematical model of our problem is the same as SALBP-Type F. Table C.1 presents the notations of this optimization model (Liu et al., 2022).

Table C.1 Sets, indexes, parameters, and decision variables for Ergo-SALDP

Sets	
I	Set of assembly tasks
W	Set of workstations
P_i	Set of immediate predecessors of task i
Indexes	
i	Index for assembly tasks
j	Index for workstations
Parameters	
n	Number of tasks
m	Number of workstations
$\tilde{t}_i$	Fuzzy execution time of task i
$\tilde{r}_i$	Fuzzy risk of task i based on the Potvin model
$\widetilde{CT}$	Fuzzy cycle time
Decision Variables	
$x_{ij} = \begin{cases} 1, & \text{if task i is assigned to station j} \\ 0, & \text{otherwise} \end{cases}$	
$y_{jj'} = \begin{cases} 1, & \text{if workstation j must precede station j'} \\ 0, & \text{otherwise} \end{cases}$	
$z_j = \begin{cases} 1, & \text{if workstation j is opened to be allocated to one or more tasks} \\ 0, & \text{otherwise} \end{cases}$	

Then the mathematical model for the proposed fuzzy Ergo-ALDP is as follows:

$$Min \sum_{j \in W} \sum_{i \in I} x_{ij} \,.\, \tilde{r}_i \tag{C.1}$$

Subject to:

$$\sum_{j \in W} x_{ij} = 1 \qquad \forall i \in I \tag{C.2}$$

$$\sum_{j \in W} z_j = m \tag{C.3}$$

$$y_{jj'} \geq x_{i'j} + x_{ij'} - 1 \qquad \forall\, i' \in P_i | j, j' \in W \tag{C.4}$$

$$y_{jj''} \geq y_{jj'} + y_{j'j''} - 1 \qquad \forall\, j, j', j'' \in W, |\{j, j', j''\}| = 3 \tag{C.5}$$

$$y_{jj'} + y_{j'j} \leq 1 \qquad \forall\, j \in W, j' \in W \backslash \{j\} \tag{C.6}$$

$$\sum_{i \in I} x_{ij}.\tilde{t}_i \leq \widetilde{CT} \qquad \forall\, j \in W \tag{C.7}$$

$$x_{ij}, y_{jj'}, \qquad z_j \in \{0,1\} \quad \forall i \in I \;\; j \in W, j' \in W \backslash \{j\} \tag{C.8}$$

In Equation (C.1), the objective is to minimize the cumulative ergonomic risks experienced by all operators in the assembly line. In our model, this ergonomic risk is the fuzzy fatigue level evaluated by the customized Potvin model. Constraint (C.2) guarantees that each task is exclusively assigned to a single workstation. The limited number of workstations is checked by constraint (C.3). Equation (C.4) defines workstation dependencies, which are determined by the precedence relationships among tasks. Constraints (C.5) and (C.6) enforce the principles of transitivity and anti-symmetry on station dependencies, resulting in a linear order of workstation allocation in all feasible solutions. Equation (C.7) verifies that the aggregated fuzzy operational time of all tasks in each workstation does not exceed the fuzzy cycle time. Equations (C.8) clearly specify that the decision variables, denoted as "x_{ij}", "$y_{jj'}$", and "z_j" are binary in nature, representing assignment, dependency relationships, and workstations existence, respectively.

C.3.2 Fuzzy Parameters Definition

As previously mentioned, in the design optimization model of this study, time and ergonomic risk parameters exhibit imprecision, as Equations C.1 and C.6 show. The following two subsections explain the details of employing fuzzy set logic to address the uncertainty in related parameters.

Fuzzy Task and Cycle Time. CT is the total time it takes to complete one cycle of the assembly process for a product. It depends on two parameters: takt time and tasks execution time. Takt time is a customer-driven concept representing the maximum allowable time for producing one product to meet customer demand. Thus, fluctuations in customer demand can affect takt time and consequently impact the desired CT. Additionally, the duration of task execution may vary based on factors such as operator skills, fatigue, and task complexity.

Given the variability inherent in both task execution times and customer demand, the precise determination of CT becomes challenging. Fuzzy logic offers a robust methodology for modeling and managing this variability effectively. In this study, we adopt a TFN to represent the task execution time. Equation C.9 and Figure C.1 represent the membership function of the execution time for each task, depicted as a triplet: (t_l, t_0, t_u). The TFN captures the uncertainty in task execution times by defining three breaking points. Here, t_l refers to the lower bound of execution time, t_0 indicates the average and most possible task time, and t_u shows the upper bound of task execution time. By employing the TFN approach, we can effectively model the variability and uncertainty associated with task execution times, thereby enhancing the robustness of our optimization model in the face of fluctuating demand and variable task durations.

$$\tilde{t} = \begin{cases} \dfrac{t - t_l}{t_0 - t_l} & if\ t_l < t \leq t_0 \\ \dfrac{t_u - t}{t_u - t_0} & if\ t_0 < t \leq t_u \\ 0 & if\ t < t_l\ or\ t_u < t \end{cases} \tag{C.9}$$

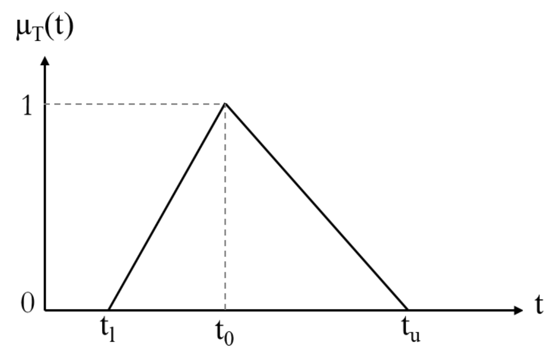

Figure C.1 Membership function of the operation time

Fuzzy Ergonomic Factors. In the ergonomic part of our optimization model, we aim to minimize the fatigue level by considering the uncertain nature of the load and, consequently, the required recovery for each workstation. The load parameter is imprecise, partially due to the variable capacity between workers. The imprecision on load means that fatigue level and recovery time calculated for that load with any model, will be imprecise. Therefore, using fuzzy set logic on the fatigue/recovery calculation is a research gap we aim to cover in the current study. In this study, Potvin's proposed equation (Potvin, 2011), for localized fatigue in the upper limbs, as shown in Equation C.10 and Figure C.2, is applied to calculate fatigue level or recovery time.

$$MAE = 1 - [DC - \frac{1}{28800}]^{0.24} \quad (C.10)$$

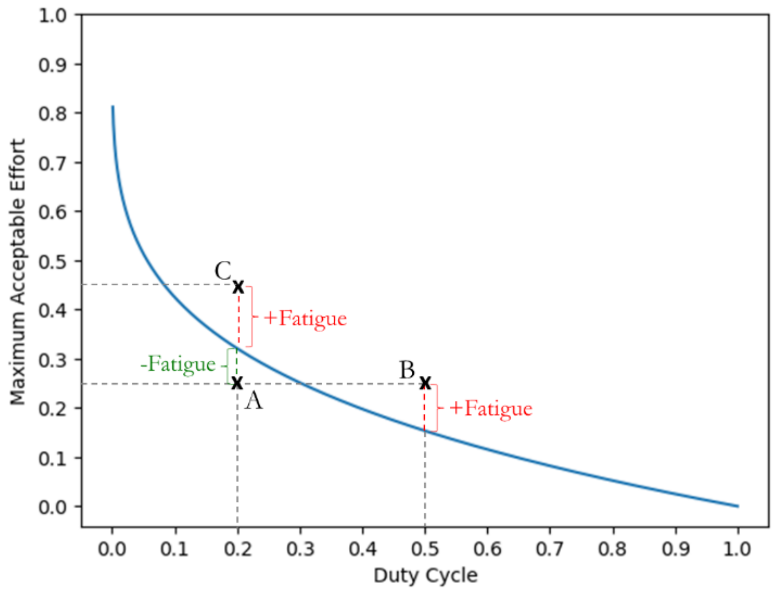

Figure C.2 The curve from the Potvin's proposed equation

Potvin's equation aims to establish the relationship between the MAE and the DC, which represents the percentage of effort duration in each CT. This provides valuable insights for interpreting assembly tasks that involve repetitive and prolonged activities, focusing specifically on ergonomic risks to the upper limbs. Based on this equation, tasks can be categorized as risky (above the curve, positive fatigue, or insufficient recovery time within the cycle) or not risky (under the curve, negative fatigue, or ample recovery time within the cycle). Figure C.2 illustrates the predominantly inverse relationship between MAE and DC. The fatigue level depends on task duration time compared to CT and the task load level based on MAE. For example, consider tasks A and B with the same load level (both have a load equal to 25% of MAE). Task A, with a DC equal to 20%, remains under the curve and causes no fatigue. It means that with a negative fatigue level, task A has ample recovery time to not cause residual fatigue at the end of the cycle. However, task B with a DC equal to 50% causes positive fatigue for the worker. On the other hand, tasks A and C have the same DC (equal to 20%), however, unlike task A, task C has a positive fatigue because its load level is around 45% of MAE. For task C, the acceptable DC that causes no fatigue is lower than 10%.

For the cumulative concept at the worker level, Potvin’s equation helps estimate the total recovery time needed within the cycle to avoid residual fatigue that would accumulate over repeated cycles. However, in uncertain conditions, we have neither the exact task load level nor their exact duration in each cycle. As a result, under uncertainty, fatigue levels can be estimated through possibility sets and employing fuzzy set logic can help us to interpret the ergonomic risk levels under uncertainty in the design stage.

For this purpose, a fuzzy expert system was utilized that comprises three main components: a knowledge base, an inference engine, and fuzzification-defuzzification modules. The knowledge base contains the expertise of ergonomic specialists, incorporating fuzzy rules to interpret potential ergonomic risks associated with localized fatigue in the upper limbs. The inference engine employs these rules to make reasoned judgments about ergonomic risks based on input data. fuzzification and defuzzification processes facilitate the conversion of crisp input data into fuzzy sets and subsequent defuzzification of fuzzy output into actionable insights. These components collectively enable the system to interpret ergonomic risks efficiently and accurately, integrating Potvin's proposed equation to further refine its assessments.

The root mean square (RMS) error of Potvin’s model was indicated to be equal to 7.2% MAE (Potvin, 2011). This error estimation was derived based on the analysis conducted by Potvin and provides a measure of the accuracy of the model in predicting MAEs. To be more precise, we consider 3 × 5% MAE distances from the initial curve from both sides to divide the whole possible area into eight fuzzy fatigue categories, as shown in Figure C.3.

As Figure C.3 illustrates, for measuring the fatigue possibility in the generated fuzzy model, a fuzzy risk score in the range of [0, +1] is allocated to risky zones, and a fuzzy risk score in the range of [-1, 0] is assigned to the zones under the initial curve. The score of each zone is defined by considering the distance from the initial curve. It means that the zone nearer to the initial curve has a score near zero (negative and positive 0.25), which increases as the zones get far from the base curve.

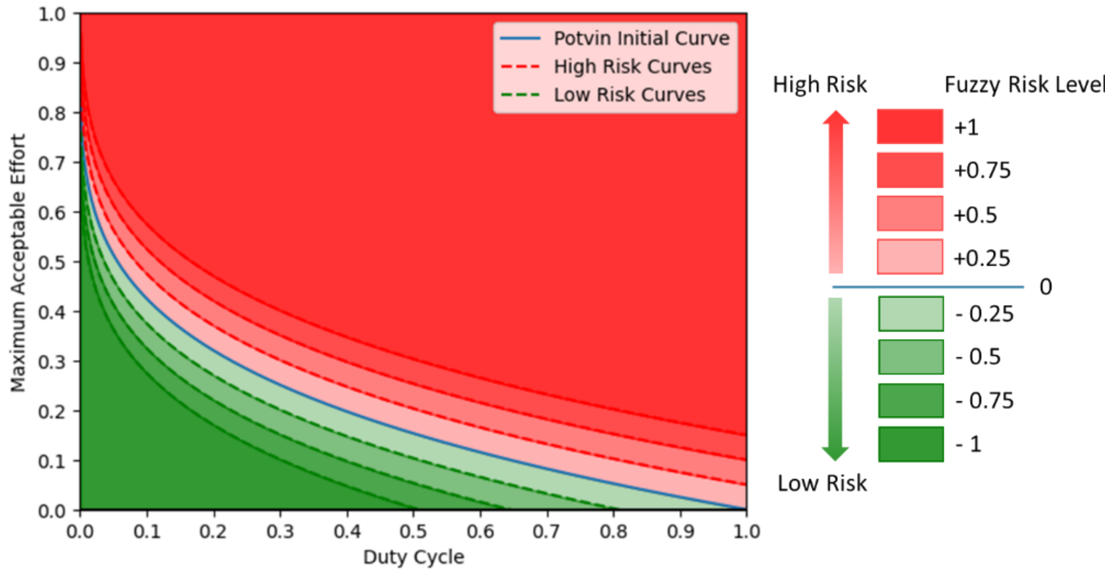

Figure C.3 Proposed fuzzy fatigue model based on Potvin's equation

C.4 Proposed Solution Method

To solve the optimization problem presented in this paper, the heuristic approach proposed by Ghorbani et al. (2024e) is customized with a novel fuzzy fatigue model. This developed heuristic algorithm combines COMSOAL (Computer Method of Sequencing Operations for Assembly Lines), fuzzy goal programming, and a fuzzy knowledge-based system, see Figure C.4.

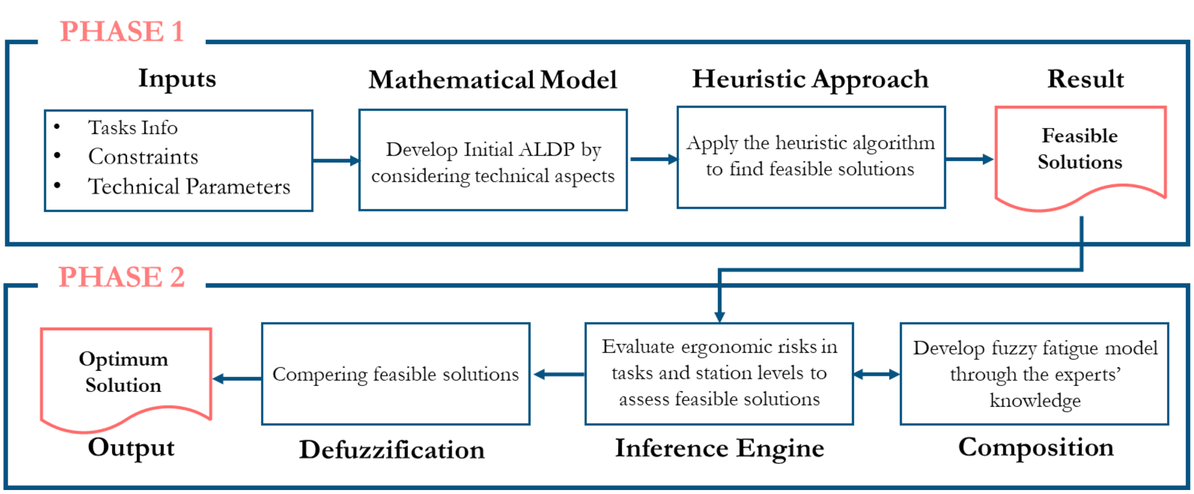

Figure C.4 Flowchart of the proposed solution for fuzzy Ergo-ALDP

This solution approach contains two main steps. The first step is consistent with the approach developed in (Ghorbani et al., 2024e), and the only difference is that feasible solutions are found based on desired scenarios (defined fuzzy CT and the number of workstations). The pseudo code of the first phase of our solution algorithm is presented in Figure C.5.

In the second step of this solution algorithm, feasible solutions are investigated and compared through a fuzzy fatigue approach. Firstly, the fuzzy fatigue score of each task in any feasible solution is calculated. Each task has an estimated load in the form of percentage of MAE. Then, the fuzzy task time is compared to the fuzzy CT to find the DC for each task. It is assumed that the calculated DC for all three parts of the triplet will conclude the same fatigue zone; otherwise, the centroid defuzzification method (Equation C.11) can be applied, as it is the most applicable approach in the literature (MathWorks, 2023).

$$C(\tilde{t}) = \frac{1}{3}(t_l + t_0 + t_u) \tag{C.11}$$

After finding the fatigue score of each task through the model illustrated in Figure C.3, the fatigue risk level for each workstation will be the cumulative fatigue score of all assigned tasks to that workstation. Then, for each feasible solution, the total risk score is equal to the summation of risk scores of all workstations. The optimum solution will be the one with the least risk score.

C.5 Application Perspective

Utilizing the proposed fuzzy fatigue model in the optimization framework of ALDP offers notable advantages in real-world scenarios due to its capacity to manage uncertain information in the design stage and help decision makers deal with challenging imprecise data. It is particularly valuable in predicting ergonomics risks during the design phase, where data may be incomplete or vague due to uncertainties in the environment and system. The proposed framework can include multiple objectives and constraints, thereby facilitating a more balanced decision-making approach. This adaptable proposed framework can be applicable across diverse industries and assists them in predicting fatigue levels and adjusting the recovery time before establishing the assembly line. Integrating realistic uncertain conditions into the planning and design of assembly lines presents a significant challenge. Therefore, to identify robust solutions, the resolution of uncertainty within optimization problems is anticipated to become more widespread in the future.

```
Procedure: Rule-based task assignment method
Input: The set of tasks, their information, and the scenario information
Output: Pool of feasible solutions
BEGIN
Create an empty set as a pool of feasible solutions
FOR x times iterations:
    Create a set of assignable task(s)
    WHILE set of assignable task(s) ≠ Ø
        Consider a workstation for allocation,
        FOR each assignable task
            Calculate the score according to task selection rules,
        END FOR
        Select a task by applying the Roulette Wheel Selection method,
        Assign the selected task to the current workstation,
        IF the total execution time of assigned tasks for the current workstation ≥ C̃T
            Assign the selected task to a new workstation,
        ELSE
            Assign to the current workstation,
        Update the opened workstation(s) and assignable task(s) sets,
    END WHILE
    Check the new feasible solution with the other solutions in the pool
        IF new feasible solution is equal to one of the solutions in the pool
            Ignore this feasible solution,
        ELSE
            Add it to the pool of feasible solutions
END FOR
```

Figure C.5 Pseudo code of the first step of the solution method for finding feasible solutions

As previously explained, the proposed optimization method follows a two-step process. Feasible solutions are found based on operational parameters and constraints in the initial step; thus, this model can be suitable for various assembly line configurations (e.g., U-shaped, or 2-sided lines). As fatigue levels are evaluated in the second step, recovery time can be calculated in the fuzzy environment, and based on various scenarios, job rotation or rest allowance can be defined in optimum situations.

To explain the effectiveness of the solution approach, a numerical example is presented. This example is generated randomly and encompasses ten tasks with the corresponding precedence relationship displayed in Figure C.6.

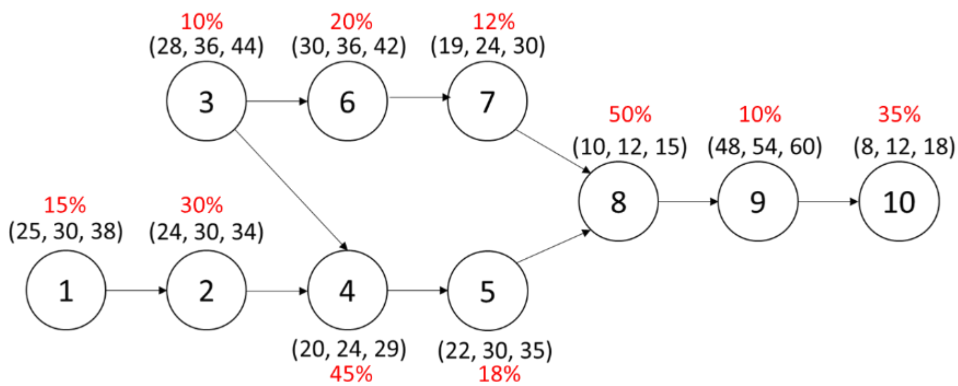

Figure C.6 Precedence diagram of the example

As Figure C.6 shows, each task has a fuzzy triangular execution time that has been indicated on top or below of the circles that represent the tasks. Furthermore, red numbers show each task's load based on the MAE percentage. This numerical example considers four workstations with desired fuzzy CT equal to (50, 90, 107).

Consider two feasible solutions identified by employing the proposed heuristic algorithm, as shown in Table C.2. The ergonomic risk score for each workstation is assessed using the fuzzy fatigue model proposed in section 4, which evaluates fuzzy risks based on the fuzzified Potvin model in Figure C.3. Table C.2 presents the results for two feasible solutions. In this case, solution 2 with a lower risk score is chosen as the better solution in this problem.

Table C.2 Comparison of two FSs based on proposed model

Workstations	**Solution 1**	**Risk Score**	**Solution 2**	**Risk Score**
1	3, 6	-0.5 + 0.25 = -0.25	1, 3	-0.5 – 0.5 = -1
2	1, 2, 4	-0.5 + 0.5 + 1 = +1	2, 6	0.5 + 0.25 = 0.75
3	5, 7	-0.25 – 0.75 = -1	4, 5, 7	1 – 0.25 – 0.75 = 0
4	8, 9, 10	0.75 + 0.25 – 0.25 = 0.75	8, 9, 10	0.75 + 0.25 – 0.5 = 0.5
Solution Risk Score		0.5	0.25	

This numerical example is solely crafted for explanatory purposes to illustrate our proposed optimization framework. However, the application of this algorithm to real case studies has the potential to yield more effective and robust solutions in Ergo-ALDPs.

C.6 Conclusions

The optimization of assembly lines is paramount to enhancing productivity and efficiency, yet the presence of uncertainties poses challenges, especially regarding ergonomics. This paper has introduced an innovative approach, the Fuzzy Ergo-ALDP-F, which extends the traditional Ergo-ALBP into the design stage in the fuzzy environment. The objective is to address imprecise task durations and ergonomic risks related to localized fatigue, recognizing that the design phase is critical for preventing future costs associated with redesigning and resolving ergonomics issues.

The research enriches existing knowledge by incorporating a fuzzy extension of Potvin's fatigue model, marking a novel and pivotal aspect of the work. This study strategically addresses the intersection of ergonomics, uncertainty, and assembly line optimization, making substantial progress toward a safer and more efficient manufacturing environment. The practical implications of this framework extend to various industries, offering a tool to predict fatigue levels and adjust recovery times proactively.

Preliminary results from applying the Fuzzy Ergo-ALDP-F approach show promise in reducing ergonomic risks during the assembly line design phase. By incorporating a fuzzy extension of Potvin's fatigue model, we have achieved a more comprehensive understanding of how uncertainties impact the ergonomics of assembly line operations. This early evidence suggests that the approach can effectively predict and mitigate fatigue levels, ultimately leading to safer and more efficient manufacturing processes.

However, it is important to acknowledge the limitations of this research. Firstly, the real-world applicability and effectiveness of our approach need further validation through case studies and comprehensive data-driven analyses. Given that ours is the pioneering fuzzy fatigue model in this field, direct comparison with existing approaches from literature is not feasible. This represents a limitation as well as an opportunity for future research to build upon our findings and explore the efficacy of alternative methodologies. Moreover, the success of our approach may depend on the specific industry contexts, assembly line configurations, and the availability of relevant data. Additionally, the fuzzy logic used in the approach may introduce complexities in implementation and require specialized expertise. By highlighting these limitations, we aim to underscore the need for continued research efforts to refine and augment our approach, ultimately advancing our understanding of ergonomic risk management in industrial settings.

In the future, the resolution of uncertainty within optimization problems is expected to become more widespread as industries seek robust solutions to improve manufacturing processes. The framework presented in this paper not only contributes to addressing current research gaps in Ergo-ALDP but also offers a versatile approach with broader applications across diverse industries.

In summary, this paper underscores the significance of integrating ergonomics and uncertainty management into assembly line design, offering an innovative solution that can lead to safer and more efficient manufacturing processes. As the manufacturing landscape continues to evolve, this research provides a timely and valuable contribution to the ongoing pursuit of a safer and more efficient manufacturing environment.

APPENDIX D PYTHON CODE FOR CHAPTER 5

Ergonomic Assembly Line Worker Assignment & Balancing Problem Codes

```
import numpy as np
import pandas as pd
from math import *
import matplotlib.pyplot as plt
from scipy.stats import norm
import statistics
import time
#insert .csv file
D = pd.read_csv('FileName.csv')
D = D.set_index('Task')
#create a DataFrame to put the results of FSs:
df4 = pd.DataFrame(columns=['FS','CTmin', 'CTavg', 'CTmax', 'CT_Centroid','CT_Distance','W1_Risk'
                  ,'W2_Risk','W3_Risk','W4_Risk', 'ErgoScore'])
#cosider cintroid defuzzification method for tasks execution time:
CT = 290
#create lists for workers and tasks
FS_Pool4 = []
# Start measuring CPU time
start_time = time.process_time()
# Create a list to store all the different FS outputs
for _ in range(1000):
    Assigned_Tasks=[]
    Assigned_Workers = []
    worker1 = []
    worker2 = []
    worker3 = []
    worker4 =[]
    worker5 =[]
    worker6 =[]
    worker7 =[]
    while len(Assigned_Tasks) < D.shape[0]:
        Assignable_Tasks = []
        for i in np.arange(0,D.shape[0]-1):
            if (int(i)+1) in Assigned_Tasks:
```

```
        continue
    else:
        if int(D.iloc[i,0])==0 or (int(D.iloc[i,0]) in Assigned_Tasks):
            Assignable_Tasks=Assignable_Tasks+[int(i)+1]
if all(element in Assigned_Tasks for element in PCS_28):
    Assignable_Tasks=Assignable_Tasks+[28]
select_task = int(np.random.choice(Assignable_Tasks, size=1))
#we should assign the selected task to a worker:
if 'worker1' not in Assigned_Workers:
    if (D.loc[worker1, 'Ct'].sum()+D.loc[select_task, 'Ct']) <= CT:
        #update all related lists by adding or eliminating selected task:
        worker1 = worker1 + [select_task]
        Assigned_Tasks = Assigned_Tasks + [select_task]
        D.loc[select_task,'W1']=1
    else:
        Assigned_Workers = Assigned_Workers + ['worker1']
else:
    if 'worker2' not in Assigned_Workers:
        if (D.loc[worker2, 'Ct'].sum()+D.loc[select_task, 'Ct']) <= CT:
            worker2 = worker2 + [select_task]
            Assigned_Tasks = Assigned_Tasks + [select_task]
            D.loc[select_task,'W2'] =1
        else:
            Assigned_Workers = Assigned_Workers + ['worker2']
    else:
        if 'worker3' not in Assigned_Workers:
            if (D.loc[worker3, 'Ct'].sum()+D.loc[select_task, 'Ct']) <= CT:
                worker3 = worker3 + [select_task]
                Assigned_Tasks = Assigned_Tasks + [select_task]
                D.loc[select_task,'W3'] =1
            else:
                Assigned_Workers = Assigned_Workers + ['worker3']
        else:
            if 'worker4' not in Assigned_Workers:
                if (D.loc[worker4, 'Ct'].sum()+D.loc[select_task, 'Ct']) <= CT:
                    worker4 = worker4 + [select_task]
                    Assigned_Tasks = Assigned_Tasks + [select_task]
```

```
                D.loc[select_task,'W4'] =1
            else:
                Assigned_Workers = Assigned_Workers + ['worker4']
        else:
            break
FS = list(map(sorted,[worker1, worker2, worker3, worker4]))
if FS not in FS_Pool4:
    FS_Pool4.append(FS)
    #Calculate CT for this FS:
    #calculate TFN for each worker:
    w1a = D.loc[worker1, 'Min'].sum()
    w1b = D.loc[worker1, 'Mean'].sum()
    w1c = D.loc[worker1, 'Max'].sum()
    w2a = D.loc[worker2, 'Min'].sum()
    w2b = D.loc[worker2, 'Mean'].sum()
    w2c = D.loc[worker2, 'Max'].sum()
    w3a = D.loc[worker3, 'Min'].sum()
    w3b = D.loc[worker3, 'Mean'].sum()
    w3c = D.loc[worker3, 'Max'].sum()
    w4a = D.loc[worker4, 'Min'].sum()
    w4b = D.loc[worker4, 'Mean'].sum()
    w4c = D.loc[worker4, 'Max'].sum()
    #define the fuzzy triangular membership function:
    def fuzzy_triangular(x, a, b, c):
        if x <= a:
            return 0
        elif x > a and x <= b:
            return (x - a) / (b - a)
        elif x > b and x <= c:
            return (c - x) / (c - b)
        else:
            return 0
    #by considering the desired CT=(a,b,c) we should calculate the possibility of
    #each number by membership function
    a=12
    b=290
    c=572
```

```
ww1a = fuzzy_triangular(w1a, a, b, c)
ww1b = fuzzy_triangular(w1b, a, b, c)
ww1c = fuzzy_triangular(w1c, a, b, c)
ww2a = fuzzy_triangular(w2a, a, b, c)
ww2b = fuzzy_triangular(w2b, a, b, c)
ww2c = fuzzy_triangular(w2c, a, b, c)
ww3a = fuzzy_triangular(w3a, a, b, c)
ww3b = fuzzy_triangular(w3b, a, b, c)
ww3c = fuzzy_triangular(w3c, a, b, c)
ww4a = fuzzy_triangular(w4a, a, b, c)
ww4b = fuzzy_triangular(w4b, a, b, c)
ww4c = fuzzy_triangular(w4c, a, b, c)
#Calculate the summation of triple points of final CT:
a= (ww1a*w1a) + (ww2a*w2a) + (ww3a*w3a) + (ww4a*w4a)
b= (ww1b*w1b) + (ww2b*w2b) + (ww3b*w3b) + (ww4b*w4b)
c= (ww1c*w1c) + (ww2c*w2c) + (ww3c*w3c) + (ww4c*w4c)
#Calculate the cumulative weight for each point:
wa = ww1a + ww2a + ww3a + ww4a
wb = ww1b + ww2b + ww3b + ww4b
wc = ww1c + ww2c + ww3c + ww4c
#Calculate the final fuzzy CT:
if wa == 0:
    CTa = a/(wa+1)
else:
    CTa = a/wa
CTb = b/wb
CTc = c/wc
CT_Centroid = (CTa + CTb + CTc)/3
CT_Distance = (CTa + 2*CTb + CTc)/4
#Calculate Ergo Score for this FS:
#calculate the cumulative execution times of Low, Medium and High risk tasks for each worker:
W1_L = 0
W1_M = 0
W1_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'W1'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'L':
        W1_L = W1_L + D.loc[int(i)+1, 'Ct']
```

```
    else:
        if D.loc[int(i)+1, 'W1'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'M':
            W1_M = W1_M + D.loc[int(i)+1, 'Ct']
        else:
            if D.loc[int(i)+1, 'W1'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'H':
                W1_H = W1_H + D.loc[int(i)+1, 'Ct']
W2_L = 0
W2_M = 0
W2_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'W2'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'L':
        W2_L = W2_L + D.loc[int(i)+1, 'Ct']
    else:
        if D.loc[int(i)+1, 'W2'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'M':
            W2_M = W2_M + D.loc[int(i)+1, 'Ct']
        else:
            if D.loc[int(i)+1, 'W2'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'H':
                W2_H = W2_H + D.loc[int(i)+1, 'Ct']
W3_L = 0
W3_M = 0
W3_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'W3'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'L':
        W3_L = W3_L + D.loc[int(i)+1, 'Ct']
    else:
        if D.loc[int(i)+1, 'W3'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'M':
            W3_M = W3_M + D.loc[int(i)+1, 'Ct']
        else:
            if D.loc[int(i)+1, 'W3'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'H':
                W3_H = W3_H + D.loc[int(i)+1, 'Ct']
W4_L = 0
W4_M = 0
W4_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'W4'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'L':
        W4_L = W4_L + D.loc[int(i)+1, 'Ct']
    else:
```

```
        if D.loc[int(i)+1, 'W4'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'M':
          W4_M = W4_M + D.loc[int(i)+1, 'Ct']
        else:
          if D.loc[int(i)+1, 'W4'] == 1 and D.loc[int(i)+1, 'Ergo Risk'] == 'H':
            W4_H = W4_H + D.loc[int(i)+1, 'Ct']
    #apply fuzzy rules to evaluate final ergo risk for each worker:
    #WORKER1
    if W1_H/(D.loc[worker1, 'Ct'].sum()) == 0 and W1_M/CT > 0.5:
      W1_Risk = 'Medium'
    else:
      if W1_H/(D.loc[worker1, 'Ct'].sum()) == 0 and W1_M/CT <= 0.5 and W1_L/(D.loc[worker1, 'Ct'].sum())>=
0.5:
        W1_Risk = 'Low'
      else:
        if W1_H/(D.loc[worker1, 'Ct'].sum()) == 0 and W1_M/CT <= 0.5 and W1_L/(D.loc[worker1, 'Ct'].sum())<
0.5:
          W1_Risk = 'Minor'
        else:
          if 0 < W1_H/CT <= 0.15 and W1_L/(D.loc[worker1, 'Ct'].sum())>= 0.5:
            W1_Risk = 'Minor'
          else:
            if 0 < W1_H/CT <= 0.15 and W1_L/(D.loc[worker1, 'Ct'].sum())< 0.5:
              W1_Risk = 'Medium'
            else:
              if W1_H/CT > 0.15:
                W1_Risk = 'High'
    #WORKER2
    if W2_H/(D.loc[worker2, 'Ct'].sum()) == 0 and W2_M/CT > 0.5:
      W2_Risk = 'Medium'
    else:
      if W2_H/(D.loc[worker2, 'Ct'].sum()) == 0 and W2_M/CT <= 0.5 and W2_L/(D.loc[worker2, 'Ct'].sum())>=
0.5:
        W2_Risk = 'Low'
      else:
        if W2_H/(D.loc[worker2, 'Ct'].sum()) == 0 and W2_M/CT <= 0.5 and W2_L/(D.loc[worker2, 'Ct'].sum())<
0.5:
          W2_Risk = 'Minor'
        else:
```

```
            if 0 < W2_H/CT <= 0.15 and W2_L/(D.loc[worker2, 'Ct'].sum())>= 0.5:
                W2_Risk = 'Minor'
            else:
                if 0 < W2_H/CT <= 0.15 and W2_L/(D.loc[worker2, 'Ct'].sum())< 0.5:
                    W2_Risk = 'Medium'
                else:
                    if W2_H/CT > 0.15:
                        W2_Risk = 'High'
    #WORKER3
    if W3_H/(D.loc[worker3, 'Ct'].sum()) == 0 and W3_M/CT > 0.5:
        W3_Risk = 'Medium'
    else:
        if W3_H/(D.loc[worker3, 'Ct'].sum()) == 0 and W3_M/CT <= 0.5 and W3_L/(D.loc[worker3, 'Ct'].sum())>=
0.5:
            W3_Risk = 'Low'
        else:
            if W3_H/(D.loc[worker3, 'Ct'].sum()) == 0 and W3_M/CT <= 0.5 and W3_L/(D.loc[worker3, 'Ct'].sum())<
0.5:
                W3_Risk = 'Minor'
            else:
                if 0 < W3_H/CT <= 0.15 and W3_L/(D.loc[worker3, 'Ct'].sum())>= 0.5:
                    W3_Risk = 'Minor'
                else:
                    if 0 < W3_H/CT <= 0.15 and W3_L/(D.loc[worker3, 'Ct'].sum())< 0.5:
                        W3_Risk = 'Medium'
                    else:
                        if W3_H/CT > 0.15:
                            W3_Risk = 'High'
    #WORKER4
    if W4_H/(D.loc[worker4, 'Ct'].sum()) == 0 and W4_M/CT > 0.5:
        W4_Risk = 'Medium'
    else:
        if W4_H/(D.loc[worker4, 'Ct'].sum()) == 0 and W4_M/CT <= 0.5 and W4_L/(D.loc[worker4, 'Ct'].sum())>=
0.5:
            W4_Risk = 'Low'
        else:
            if W4_H/(D.loc[worker4, 'Ct'].sum()) == 0 and W4_M/CT <= 0.5 and W4_L/(D.loc[worker4, 'Ct'].sum())<
0.5:
```

```
                    W4_Risk = 'Minor'
                else:
                    if 0 < W4_H/CT <= 0.15 and W4_L/(D.loc[worker4, 'Ct'].sum())>= 0.5:
                        W4_Risk = 'Minor'
                    else:
                        if 0 < W4_H/CT <= 0.15 and W4_L/(D.loc[worker4, 'Ct'].sum())< 0.5:
                            W4_Risk = 'Medium'
                        else:
                            if W4_H/CT > 0.15:
                                W4_Risk = 'High'
    FS_Risk = [W1_Risk, W2_Risk, W3_Risk, W4_Risk]
    ErgoScore = (FS_Risk.count('Low') + (FS_Risk.count('Minor')*0.6) + (FS_Risk.count('Medium')*0.3))
/len(FS_Risk)
    df4 = df4.append({'FS': FS, 'CTmin': CTa, 'CTavg': CTb, 'CTmax': CTc, 'CT_Centroid': CT_Centroid,
            'CT_Distance': CT_Distance,'W1_Risk': W1_Risk, 'W2_Risk': W2_Risk, 'W3_Risk':
            W3_Risk,'W4_Risk': W4_Risk,'ErgoScore': ErgoScore}, ignore_index=True)

# Stop measuring CPU time
end_time = time.process_time()
# Calculate the total CPU time
cpu_time = end_time - start_time
# Print the CPU time
print("Total CPU time:", cpu_time, "seconds")
#Optimum solution
opt_index = df4['ErgoScore'].idxmax()
opt_value = df4.loc[opt_index, 'ErgoScore']
print("Optimum Ergo Score is:", opt_value)
print("Optimum solution is:", FS_Pool4[opt_index])
CT_Centroid = df4.loc[opt_index, 'CT_Centroid']
CT_Distance = df4.loc[opt_index, 'CT_Distance']
RISKofW1 = df4.loc[opt_index, 'W1_Risk']
RISKofW2 = df4.loc[opt_index, 'W2_Risk']
RISKofW3 = df4.loc[opt_index, 'W3_Risk']
RISKofW4 = df4.loc[opt_index, 'W4_Risk']
print(CT_Centroid)
print(CT_Distance)
print("Risk of 1st worker is:", RISKofW1)
```

```
print("Risk of 2nd worker is:", RISKofW2)
print("Risk of 3rd worker is:", RISKofW3)
print("Risk of 4th worker is:", RISKofW4)
```

APPENDIX E PYTHON CODE FOR CHAPTER 6

Fatigue-Aware Robotic Assembly Line Design Problem

```
import numpy as np
import pandas as pd
from math import *
import matplotlib.pyplot as plt
from scipy.stats import norm
import statistics
import time
#insert .csv file
D = pd.read_csv('FileName.csv')
D = D.set_index('Task')
#create a DataFrame to put the results of FSs:
df = pd.DataFrame(columns=['FS','Fatigue1', 'Fatigue2', 'Fatigue3', 'Fatigue4','Fatigue5','Fatigue_M',
                    'Fatigue_S1', 'Fatigue_S2','Fatigue_S3','SRL1', 'SRL2', 'SRL3','Cost_M',
                    'Cost1','Cost2','Cost3','Save1','Save2','Save3'])
#cosider centroid defuzzification method for tasks execution time:
CT = 60
D['DC'] = D['Time']/CT
D['MAE'] = 1 - (D['DC'] - (1/28880))**0.24
D['Distance'] = D['Load'] - D['MAE']
# Define Fuzzy Fatigue
# Define a function that returns the value based on the condition
def check_fatigue(x):
    if 0.144 <= x:
        return 1
    elif 0.072 <= x < 0.144:
        return 0.75
    elif 0 <= x < 0.072:
        return 0.6
    elif -0.072 <= x < 0:
        return 0.4
    elif -0.144 <= x < -0.072:
        return 0.25
    else:
        return 0
```

```
# Apply the function to the 'Fatigue' column to create a new column
D['Fatigue'] = D['Distance'].apply(check_fatigue)
#create lists for workers and tasks
FS_Pool = []
# Start measuring CPU time
start_time = time.process_time()
# Create a list to store all the different FS outputs
for _ in range(1000):
    Assigned_Tasks=[]
    Assigned_Stations = []
    Station1 = []
    Station2 = []
    Station3 = []
    Station4 = []
    Station5 = []
    Station6 =[]
    Station7 =[]
    Station8 =[]
    Station9 =[]
    Station10 =[]
    Station11 =[]
    Station12 =[]
    while len(Assigned_Tasks) < D.shape[0]:
        Assignable_Tasks = []
        for i in np.arange(0,D.shape[0]):
            if (int(i)+1) in Assigned_Tasks:
                continue
            else:
                if int(D.iloc[i,0])==0 or (int(D.iloc[i,0]) in Assigned_Tasks):
                    if int(D.iloc[i,1])==0 or (int(D.iloc[i,1]) in Assigned_Tasks):
                        Assignable_Tasks=Assignable_Tasks+[int(i)+1]
        select_task = int(np.random.choice(Assignable_Tasks, size=1))
        #we should assign the selected task to a worker:
        if 'Station1' not in Assigned_Stations:
            if (D.loc[Station1, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
                #update all related lists by adding or eliminating selected task:
                Station1 = Station1 + [select_task]
```

```
        Assigned_Tasks = Assigned_Tasks + [select_task]
        D.loc[select_task,'W1']=1
    else:
        Assigned_Stations = Assigned_Stations + ['Station1']
else:
    if 'Station2' not in Assigned_Stations:
        if (D.loc[Station2, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
            Station2 = Station2 + [select_task]
            Assigned_Tasks = Assigned_Tasks + [select_task]
            D.loc[select_task,'W2'] =1
        else:
            Assigned_Stations = Assigned_Stations + ['Station2']
    else:
        if 'Station3' not in Assigned_Stations:
            if (D.loc[Station3, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
                Station3 = Station3 + [select_task]
                Assigned_Tasks = Assigned_Tasks + [select_task]
                D.loc[select_task,'W3'] =1
            else:
                Assigned_Stations = Assigned_Stations + ['Station3']
        else:
            if 'Station4' not in Assigned_Stations:
                if (D.loc[Station4, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
                    Station4 = Station4 + [select_task]
                    Assigned_Tasks = Assigned_Tasks + [select_task]
                    D.loc[select_task,'W4'] =1
                else:
                    Assigned_Stations = Assigned_Stations + ['Station4']
            else:
                if 'Station5' not in Assigned_Stations:
                    if (D.loc[Station5, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
                        Station5 = Station5 + [select_task]
                        Assigned_Tasks = Assigned_Tasks + [select_task]
                        D.loc[select_task,'W5'] =1
                    else:
                        Assigned_Stations = Assigned_Stations + ['Station5']
                else:
```

```
if 'Station6' not in Assigned_Stations:
    if (D.loc[Station6, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
        Station6 = Station6 + [select_task]
        Assigned_Tasks = Assigned_Tasks + [select_task]
        D.loc[select_task,'W6'] =1
    else:
        Assigned_Stations = Assigned_Stations + ['Station6']
else:
    if 'Station7' not in Assigned_Stations:
        if (D.loc[Station7, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
            Station7 = Station7 + [select_task]
            Assigned_Tasks = Assigned_Tasks + [select_task]
            D.loc[select_task,'W7'] =1
        else:
            Assigned_Stations = Assigned_Stations + ['Station7']
    else:
        if 'Station8' not in Assigned_Stations:
            if (D.loc[Station8, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
                Station8 = Station8 + [select_task]
                Assigned_Tasks = Assigned_Tasks + [select_task]
                D.loc[select_task,'W8'] =1
            else:
                Assigned_Stations = Assigned_Stations + ['Station8']
        else:
            if 'Station9' not in Assigned_Stations:
                if (D.loc[Station9, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
                    Station9 = Station9 + [select_task]
                    Assigned_Tasks = Assigned_Tasks + [select_task]
                    D.loc[select_task,'W9'] =1
                else:
                    Assigned_Stations = Assigned_Stations + ['Station9']
            else:
                if 'Station10' not in Assigned_Stations:
                    if (D.loc[Station10, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
                        Station10 = Station10 + [select_task]
                        Assigned_Tasks = Assigned_Tasks + [select_task]
                        D.loc[select_task,'W10'] =1
```

```
            else:
                Assigned_Stations = Assigned_Stations + ['Station10']
        else:
            if 'Station11' not in Assigned_Stations:
                if (D.loc[Station11, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
                    Station11 = Station11 + [select_task]
                    Assigned_Tasks = Assigned_Tasks + [select_task]
                    D.loc[select_task,'W11'] =1
                else:
                    Assigned_Stations = Assigned_Stations + ['Station11']
            else:
                if 'Station12' not in Assigned_Stations:
                    if (D.loc[Station12, 'Time'].sum()+D.loc[select_task, 'Time']) <= CT:
                        Station12 = Station12 + [select_task]
                        Assigned_Tasks = Assigned_Tasks + [select_task]
                        D.loc[select_task,'W12'] =1
                    else:
                        Assigned_Stations = Assigned_Stations + ['Station12']
                else:
                    Assigned_Tasks=[]
                    Assigned_Stations = []
                    Station1 = []
                    Station2 = []
                    Station3 = []
                    Station4 = []
                    Station5 = []
                    Station6 = []
                    Station7 = []
                    Station8 = []
                    Station9 = []
                    Station10 = []
                    Station11 = []
                    Station12 = []
                    break
 FS = list(map(sorted,[Station1, Station2, Station3, Station4, Station5, Station6, Station7, Station8, Station9, Station10, Station11, Station12]))
 if FS in FS_Pool or FS == [[],[],[],[],[],[],[],[],[],[],[],[]]:
```

```
        continue
    else:
        FS_Pool.append(FS)
        #Calculate Ergo Risk for this FS:
        #calculate Fatigue for each workestation:
        Fatigue1 = D.loc[Station1, 'Fatigue'].sum()
        Fatigue2 = D.loc[Station2, 'Fatigue'].sum()
        Fatigue3 = D.loc[Station3, 'Fatigue'].sum()
        Fatigue4 = D.loc[Station4, 'Fatigue'].sum()
        Fatigue5 = D.loc[Station5, 'Fatigue'].sum()
        Fatigue6 = D.loc[Station6, 'Fatigue'].sum()
        Fatigue7 = D.loc[Station7, 'Fatigue'].sum()
        Fatigue8 = D.loc[Station8, 'Fatigue'].sum()
        Fatigue9 = D.loc[Station9, 'Fatigue'].sum()
        Fatigue10 = D.loc[Station10, 'Fatigue'].sum()
        Fatigue11 = D.loc[Station11, 'Fatigue'].sum()
        Fatigue12 = D.loc[Station12, 'Fatigue'].sum()
        #for i in np.arange(0,D.shape[0]):
        #OBJ1: min Fatigue
        #Calculate the number of Cobot(s) and recovery change based on various scenarios:
        FatigueAL_M = [Fatigue1, Fatigue2, Fatigue3, Fatigue4, Fatigue5, Fatigue6, Fatigue7, Fatigue8, Fatigue9, Fatigue10, Fatigue11, Fatigue12]
        Fatigue_M = max(FatigueAL_M)
        CostFatigue_M = sum(FatigueAL_M)
        Cost_M = CostFatigue_M

        #Scenario1
        FatigueAL_S1 = [0 if f > 1 else f for f in FatigueAL_M]
        Fatigue_S1 = max(FatigueAL_S1)
        CostFatigue_S1 = sum(FatigueAL_S1)
        SRL1 = sum(1 for f in FatigueAL_M if f > 1)
        Cost_S1 = CostFatigue_S1 + (0.5 * SRL1)
        Save_S1 = Cost_M  - Cost_S1

        #Scenario2
        FatigueAL_S2 = [0 if f > 0.75 else f for f in FatigueAL_M]
        Fatigue_S2 = max(FatigueAL_S2)
```

```
    CostFatigue_S2 = sum(FatigueAL_S2)
    SRL2 = sum(1 for f in FatigueAL_M if f > 0.75)
    Cost_S2 = CostFatigue_S2 + (0.5 * SRL2)
    Save_S2 = Cost_M  - Cost_S2

    #Scenario3
    FatigueAL_S3 = [0 if f > 0.5 else f for f in FatigueAL_M]
    Fatigue_S3 = max(FatigueAL_S3)
    CostFatigue_S3 = sum(FatigueAL_S3)
    SRL3 = sum(1 for f in FatigueAL_M if f > 0.5)
    Cost_S3 = CostFatigue_S3 + (0.5 * SRL3)
    Save_S3 = Cost_M  - Cost_S3
    df = df.append({'FS': FS,'Fatigue1': Fatigue1, 'Fatigue2': Fatigue2, 'Fatigue3': Fatigue3, 'Fatigue4': Fatigue4,
            'Fatigue5': Fatigue5,'Fatigue_M': Fatigue_M, 'Fatigue_S1': Fatigue_S1,'Fatigue_S2':Fatigue_S2,'Fatigue_S3':Fatigue_S3,
            'SRL1': SRL1, 'SRL2': SRL2,'SRL3': SRL3, 'Cost_M': Cost_M,'Cost1': Cost_S1,'Cost2': Cost_S2,
            'Cost3': Cost_S3,'Save1': Save_S1,'Save2': Save_S2,'Save3': Save_S3},ignore_index=True)
#Stop measuring CPU time
end_time = time.process_time()
# Calculate the total CPU time
cpu_time = end_time - start_time
# Print the CPU time
print("Total CPU time:", cpu_time, "seconds")
#Lexicographical Method
sorted_df = df.sort_values(by='Fatigue_M', ascending=True)
Best_FSs = sorted_df.head(20)
opt_index = Best_FSs['Cost_M'].idxmin()
opt_FS = Best_FSs.loc[opt_index, 'FS']
print("Optimum Solution with Minimum Required Recovery is:", opt_FS)

#Manual AL:
opt_Fatigue = Best_FSs.loc[opt_index, 'Fatigue_M']
print("\nOptimum Fatigue Level is:", opt_Fatigue)
opt_Cost = Best_FSs.loc[opt_index, 'Cost_M']
print("Initial Cost is:", opt_Cost)
#Lexicographical Method for Scenario1:
sorted_df1 = df.sort_values(by='Fatigue_S1', ascending=True)
```

```
Best_FSs_1 = sorted_df1.head(20)
opt_index1 = Best_FSs_1['Cost1'].idxmin()
opt_FS_1 = Best_FSs_1.loc[opt_index1, 'FS']
print("Optimum Solution with Minimum Cost in Scenario1 is:", opt_FS_1)

opt_SRL1 = Best_FSs_1.loc[opt_index1, 'SRL1']
print("\nNumber of SRLs needed in scenario 1 is:", opt_SRL1)
opt_S1_Fatigue = Best_FSs_1.loc[opt_index1, 'Fatigue_S1']
print("Fatigue Level in scenario 1 is:", opt_S1_Fatigue)
S1_Cost = Best_FSs_1.loc[opt_index1, 'Cost1']
print("The cost of scenario 1 is equal to", S1_Cost)
S1_Save = Best_FSs_1.loc[opt_index1, 'Save1']
print("The saving of scenario 1 is equal to ", S1_Save)
#Lexicographical Method for Scenario2:
sorted_df2 = df.sort_values(by='Fatigue_S2', ascending=True)
Best_FSs_2 = sorted_df2.head(20)
opt_index2 = Best_FSs_2['Cost2'].idxmin()
opt_FS_2 = Best_FSs_2.loc[opt_index2, 'FS']
print("Optimum Solution with Minimum Cost in Scenario2 is:", opt_FS_2)

opt_SRL2 = Best_FSs_2.loc[opt_index2, 'SRL2']
print("\nNumber of SRLs needed in scenario 2 is:", opt_SRL2)
opt_S2_Fatigue = Best_FSs_2.loc[opt_index2, 'Fatigue_S2']
print("Fatigue Level in scenario 2 is:", opt_S2_Fatigue)
S2_Cost = Best_FSs_2.loc[opt_index2, 'Cost2']
print("The cost of scenario 2 is equal to", S2_Cost)
S2_Save = Best_FSs_2.loc[opt_index2, 'Save2']
print("The saving of scenario 2 is equal to ", S2_Save)
#Lexicographical Method for Scenario3:
sorted_df3 = df.sort_values(by='Fatigue_S3', ascending=True)
Best_FSs_3 = sorted_df3.head(20)
opt_index3 = Best_FSs_3['Cost3'].idxmin()
opt_FS_3 = Best_FSs_3.loc[opt_index3, 'FS']
print("Optimum Solution with Minimum Cost in Scenario3 is:", opt_FS_3)

opt_SRL3 = Best_FSs_3.loc[opt_index3, 'SRL3']
print("\nNumber of SRLs needed in scenario 3 is:", opt_SRL3)
```

```
opt_S3_Fatigue = Best_FSs_3.loc[opt_index3, 'Fatigue_S3']
print("Fatigue Level in scenario 3 is:", opt_S3_Fatigue)
S3_Cost = Best_FSs_3.loc[opt_index3, 'Cost3']
print("The cost of scenario 3 is equal to", S3_Cost)
S3_Save = Best_FSs_3.loc[opt_index3, 'Save3']
print("The saving of scenario 3 is equal to ", S3_Save)
```

APPENDIX F PYTHON CODE FOR CHAPTER 7

Ergo4All-Pro Risk Assessment Model

```
import numpy as np
import pandas as pd
from math import *
import matplotlib.pyplot as plt
from scipy.stats import norm
import statistics
import time
#insert .csv file
D = pd.read_csv('Sample.csv')
D = D.set_index('Task')
#create a DataFrame to put the results:
df = pd.DataFrame(columns=['RBack','RNeck', 'RRShoulder', 'RLShoulder', 'RRwrist','RLwrist'])
#time calculations:
#Back:
TB_M = 0
TB_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'Back'] == 'M':
        TB_M = TB_M + D.loc[int(i)+1, 'DC']
    else:
        if D.loc[int(i)+1, 'Back'] == 'H':
            TB_H = TB_H + D.loc[int(i)+1, 'DC']
#apply fuzzy rules to evaluate final ergo risk for Back:
if TB_H <= 10 and TB_M <= 25:
    RBack = 'Acceptable'
else:
    if TB_H <= 10 and 25 < TB_M <= 50:
        RBack = 'Very Low'
    else:
        if TB_H <= 10 and 50 < TB_M <= 80:
            RBack = 'Medium Low'
        else:
            if TB_H <= 10 and 80 < TB_M:
                RBack = 'High'
```

```
if 10 < TB_H <= 25 and TB_M <= 25:
    RBack = 'Very Low'
else:
    if 10 < TB_H <= 25 and 25 < TB_M <= 50:
        RBack = 'Medium Low'
    else:
        if 10 < TB_H <= 25 and 50 < TB_M <= 80:
            RBack = 'Medium'
        else:
            if 10 < TB_H <= 25  and 80 < TB_M:
                RBack = 'High'
if 25 < TB_H <= 50 and TB_M <= 25:
    RBack = 'Medium Low'
else:
    if 25 < TB_H <= 50 and 25 < TB_M <= 50:
        RBack = 'Medium'
    else:
        if 25 < TB_H <= 50 and 50 < TB_M:
            RBack = 'High'
if 50 < TB_H <= 80 and TB_M <= 25:
    RBack = 'Medium'
else:
    if 50 < TB_H <= 80 and 25 < TB_M:
        RBack = 'High'
    else:
        if 80 < TB_H:
            RBack = 'High'
print("Risk of Back is:", RBack)
#Right Shoulder:
TRSh_M = 0
TRSh_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'RShoulder'] == 'M':
        TRSh_M  = TRSh_M  + D.loc[int(i)+1, 'DC']
    else:
        if D.loc[int(i)+1, 'RShoulder'] == 'H':
            TRSh_H = TRSh_H + D.loc[int(i)+1, 'DC']
```

```
#apply fuzzy rules to evaluate final ergo risk for Right Shoulder:
if TRSh_H <= 10 and TRSh_M <= 25:
    RRShoulder = 'Acceptable'
else:
    if TRSh_H <= 10 and 25 < TRSh_M <= 50:
        RRShoulder = 'Very Low'
    else:
        if TRSh_H <= 10 and 50 < TRSh_M <= 80:
            RRShoulder = 'Medium Low'
        else:
            if TRSh_H <= 10 and 80 < TRSh_M:
                RRShoulder = 'High'
if 10 < TRSh_H <= 25 and TRSh_M <= 25:
    RRShoulder = 'Very Low'
else:
    if 10 < TRSh_H <= 25 and 25 < TRSh_M <= 50:
        RRShoulder = 'Medium Low'
    else:
        if 10 < TRSh_H <= 25 and 50 < TRSh_M <= 80:
            RRShoulder = 'Medium'
        else:
            if 10 < TRSh_H <= 25  and 80 < TRSh_M:
                RRShoulder = 'High'
if 25 < TRSh_H<= 50 and TRSh_M <= 25:
    RRShoulder = 'Medium Low'
else:
    if 25 < TRSh_H <= 50 and 25 < TRSh_M <= 50:
        RRShoulder = 'Medium'
    else:
        if 25 < TRSh_H <= 50 and 50 < TRSh_M:
            RRShoulder = 'High'
if 50 < TRSh_H <= 80 and TRSh_M <= 25:
    RRShoulder = 'Medium'
else:
    if 50 < TRSh_H <= 80 and 25 < TRSh_M:
        RRShoulder = 'High'
    else:
```

```
        if 80 < TRSh_H:
            RRShoulder = 'High'
print("Risk of Right Shoulder is:", RRShoulder)
#Left Shoulder:
TLSh_M = 0
TLSh_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'LShoulder'] == 'M':
        TLSh_M  = TLSh_M  + D.loc[int(i)+1, 'DC']
    else:
        if D.loc[int(i)+1, 'LShoulder'] == 'H':
            TLSh_H = TLSh_H + D.loc[int(i)+1, 'DC']
#apply fuzzy rules to evaluate final ergo risk for Left Shoulder:
if TLSh_H <= 10 and TLSh_M <= 25:
    RLShoulder = 'Acceptable'
else:
    if TLSh_H <= 10 and 25 < TLSh_M <= 50:
        RLShoulder = 'Very Low'
    else:
        if TLSh_H <= 10 and 50 < TLSh_M <= 80:
            RLShoulder = 'Medium Low'
        else:
            if TLSh_H <= 10 and 80 < TLSh_M:
                RLShoulder = 'High'
if 10 < TLSh_H <= 25 and TLSh_M <= 25:
    RLShoulder = 'Very Low'
else:
    if 10 < TLSh_H <= 25 and 25 < TLSh_M <= 50:
        RLShoulder = 'Medium Low'
    else:
        if 10 < TLSh_H <= 25 and 50 < TLSh_M <= 80:
            RLShoulder = 'Medium'
        else:
            if 10 < TLSh_H <= 25  and 80 < TLSh_M:
                RLShoulder = 'High'
if 25 < TLSh_H <= 50 and TLSh_M <= 25:
    RLShoulder = 'Medium Low'
```

```
else:
    if 25 < TLSh_H <= 50 and 25 < TLSh_M <= 50:
        RLShoulder = 'Medium'
    else:
        if 25 < TLSh_H <= 50 and 50 < TLSh_M:
            RLShoulder = 'High'
if 50 < TLSh_H <= 80 and TLSh_M <= 25:
    RLShoulder = 'Medium'
else:
    if 50 < TLSh_H <= 80 and 25 < TLSh_M:
        RLShoulder = 'High'
    else:
        if 80 < TLSh_H:
            RLShoulder = 'High'
print("Risk of Left Shoulder is:", RLShoulder)
#Neck:
TN_M = 0
TN_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'Neck'] == 'M':
        TN_M = TN_M + D.loc[int(i)+1, 'DC']
    else:
        if D.loc[int(i)+1, 'Neck'] == 'H':
            TN_H = TN_H + D.loc[int(i)+1, 'DC']
#apply fuzzy rules to evaluate final ergo risk for Neck:
if TN_H <= 25 and TN_M <= 50:
    RNeck = 'Acceptable'
else:
    if TN_H <= 25 and 50 < TN_M <= 80:
        RNeck = 'Medium Low'
    else:
        if TN_H <= 25 and 80 < TN_M:
            RNeck = 'High'
if 25 < TN_H  <= 50 and TN_M <= 50:
    RNeck = 'Medium Low'
else:
    if 25 < TN_H  <= 50 and 50 < TN_M:
```

```
        RNeck = 'High'
if 50 < TN_H <= 80:
    RNeck = 'Medium'
else:
    if 80 < TN_H:
        RNeck = 'High'
print("Risk of Neck is:", RNeck)

#Right Wrist:
TRw_M = 0
TRw_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'Rwrist'] == 'M':
        TRw_M = TRw_M + D.loc[int(i)+1, 'DC']
    else:
        if D.loc[int(i)+1, 'Rwrist'] == 'H':
            TRw_H = TRw_H + D.loc[int(i)+1, 'DC']
#apply fuzzy rules to evaluate final ergo risk for Right Wrist:
if TRw_H <= 25 and TRw_M <= 50:
    RRwrist = 'Acceptable'
else:
    if TRw_H <= 25 and 50 < TRw_M <= 80:
        RRwrist = 'Medium Low'
    else:
        if TRw_H <= 25 and 80 < TRw_M:
            RRwrist = 'High'
if 25 < TRw_H  <= 50 and TRw_M <= 50:
    RRwrist = 'Medium Low'
else:
    if 25 < TRw_H  <= 50 and 50 < TRw_M:
        RRwrist = 'High'
if 50 < TRw_H <= 80:
    RRwrist = 'Medium'
else:
    if 80 < TRw_H:
        RRwrist = 'High'
print("Risk of Rigt Wrist is:", RRwrist)
```

```
#Left Wrist:
TLw_M = 0
TLw_H = 0
for i in np.arange(0,D.shape[0]):
    if D.loc[int(i)+1, 'Lwrist'] == 'M':
        TLw_M = TLw_M + D.loc[int(i)+1, 'DC']
    else:
        if D.loc[int(i)+1, 'Lwrist'] == 'H':
            TLw_H = TLw_H + D.loc[int(i)+1, 'DC']

#apply fuzzy rules to evaluate final ergo risk for Left Wrist:
if TLw_H <= 25 and TLw_M <= 50:
    RLwrist = 'Acceptable'
else:
    if TLw_H <= 25 and 50 < TLw_M <= 80:
        RLwrist = 'Medium Low'
    else:
        if TLw_H <= 25 and 80 < TLw_M:
            RLwrist = 'High'
if 25 < TLw_H  <= 50 and TLw_M <= 50:
    RLwrist = 'Medium Low'
else:
    if 25 < TLw_H  <= 50 and 50 < TLw_M:
        RLwrist = 'High'
if 50 < TLw_H <= 80:
    RLwrist = 'Medium'
else:
    if 80 < TLw_H:
        RLwrist = 'High'
print("Risk of Left Wrist is:", RLwrist)
```