University of Aveiro
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AFETAÇÃO E ESCALONAMENTO DE TAREFAS EM ROBÓTICA COLABORATIVA

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Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Engenharia e Gestão Industrial, realizada sob a orientação científica da Doutora Carina Maria Oliveira Pimentel, Professora Auxiliar do Departamento de Economia, Gestão, Engenharia Gestão Industrial e Turismo da Universidade de Aveiro e do Doutor Vítor Santos do Departamento de Engenharia Mecânica da Universidade de Aveiro.

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Dedico a minha dissertação aos meus pais e aos meus avós. Aos meus pais por serem os meus protetores na Terra e aos meus avós por serem os meus anjos da guarda no Céu.

o júri

presidente	Prof.º Doutor Carlos Manuel dos Santos Ferreira Professor Associado C/ Agregação do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro
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keywords

Task Scheduling, Task Allocation, Collaborative Robotics, Cobot, Systematic Literature Review, Taxonomy, Task Assignment and Scheduling Algorithm, GRASP, Greedy Randomized Adaptive Search Procedure

abstract

The current technological challenges that industries face, are characteristic of the Fourth Industrial Revolution or, also called, Industry 4.0 (I4.0) and to overcome them, industries must have flexibility and a greater focus on the human being in their processes. One of the brand-new technologies that I4.0 brings are the collaborative robots. Therefore, in order to face the challenge of increasing productivity together with increasing flexibility, collaborative robots or cobots can represent a greater help for production systems to overcome these challenges. In fact, when compared to traditional industrial robots, cobots are lighter, occupy less shop-floor space, can interact with the human worker and are easier to change their location, bringing versatility and adaptability that allows companies to adapt their processes more easily to the unstable demand patterns. As a result of the implementation of collaborative robotics on the factory floor, cobots will share the workspace and tasks with human workers and, thus, it is essential to assign and schedule tasks between humans and robots for an efficient and effective collaboration, considering the strengths and limitations of each agent.

It is in this context that the present dissertation is inserted, having as main objective the exhaustive study of the allocation and scheduling of tasks in collaborative robotics. Therefore, a systematic review of the literature is presented, respective quantitative and qualitative analyses, a taxonomy is elaborated, processes of three industries are mapped in BPMN 2.0. Finally, the development of an algorithm to solve the problem of allocation and scheduling tasks between a robot and a human through tan algorithm inspired in the GRASP (Greedy Randomized Adaptive Search Procedure) metaheuristic, minimizing the total time and the ergonomic risk for workers.

palavras-chave

Escalonamento de Tarefas, Afetação de Tarefas, Robótica Colaborativa, Cobot, Revisão Sistemática de Literatura, Taxonomia, Metaheurística, GRASP, Greedy Randomized Adaptive Search Procedure

resumo

Os atuais desafios tecnológicos que as indústrias enfrentam, são característicos da Quarta Revolução Industrial ou, também chamada, Indústria 4.0 (I4.0) e para os superar, as organizações têm de ter flexibilidade e um maior foco no ser humano e nos seus processos. Uma das tecnologias características da I4.0 são os robots colaborativos. Então, de forma a enfrentar o desafio de aumentar a produtividade conjuntamente com o aumento da flexibilidade, os robots colaborativos ou cobots podem representar uma grande ajuda para os sistemas produtivos superarem estes desafios. De facto, quando comparados com os robots industriais tradicionais, os cobots são mais leves, ocupam menos espaço fabril, podem interagir com o ser humano e são mais fáceis de alterar a sua disposição, trazendo uma versatilidade e adaptabilidade que permite às empresas adaptar mais facilmente os seus processos aos instáveis padrões de procura. Com a implementação da robótica colaborativa no chão de fábrica, os cobots irão partilhar o espaço de trabalho e tarefas com os trabalhadores humanos e, por isso, é essencial atribuir e escalonar tarefas entre humanos e robots para que haja uma colaboração eficiente e eficaz, considerando as potencialidades e limitações de cada um dos diferentes agentes.

É neste contexto que a presente dissertação se insere, tendo como principal objetivo o estudo exaustivo da alocação e escalonamento de tarefas na robótica colaborativa. Para isso, é apresentada uma revisão sistemática de literatura sobre a alocação e escalonamento de tarefas na robótica colaborativa, bem como as respetivas análises quantitativa e qualitativa. É também proposta uma taxonomia para o problema em estudo, bem como se apresenta o mapeamento de três processos industriais em BPMN 2.0, que auxiliaram na identificação do problema a estudar. Por fim, apresenta-se o desenvolvimento de um algoritmo para solucionar o problema da alocação e escalonamento de tarefas entre um robot e um humano num posto de trabalho, através de um algoritmo inspirado na metaheurística GRASP (*Greedy Randomized Adaptive Search Procedure*), com o objetivo de minimizar o makespan, tendo em consideração o risco ergonómico para os trabalhadores.

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List of Abbreviations

ACGHI TLV	American Conference of Governmental Industrial Hygienists Threshold Limit Value
ALBP	Assembly Line Balancing Problem
ANP	Analytic Network Process
Augmanity	Augmented Humanity
BOF	Board On Frame
BPMN	Business Process Model and Notation
BPM	Business Process Management
BPMo	Business Process Modelling
Cobot	Collaborative Robot
Cobotics	Collaborative Robotics
CR	Collaborative Robotics
DD	Duration per Day
DE	Duration of Exertion
EM	Efforts per Minute
ER	Ergonomic Risk
FCFS	First-Come-First-Serve
FEDER	European Fund of Regional Development
FMEA	Failure Mode and Effect Analysis
FSSP	Flow Shop Scheduling Problem
GA	Genetic Algorithm
GRASP	Greedy Randomized Adaptive Search Procedure
HWP	Hand/Wrist Posture
HRC	Human-Robot Collaboration
HRI	Human-Robot Interaction
HRT	Human-Robot Team
HTA	Hierarchical Task Analysis
HUMANT	Humanoid Ant
I4.0	Industry 4.0
IE	Intensity of Exertion
ILP	Integer Linear Programming
ILS	Iterated Local Search
JSSP	Job Shop Scheduling Problem
MILP	Mixed Integer Linear Programming
LPT	Longest-Processing-Time
MCPTSC	Multiagent Coordination Problem with Temporal and Spatial Constraints
MMTSP	Multimode Multiprocessor Task Scheduling Problem

MSD	Musculoskeletal Disorder
MSP	Multiagent Scheduling Problem
MTSP	Multiprocessor Task Scheduling Problem
MTM	Methods-Time Measurement
NOK	Not OK
OCRA	Occupational Repetitive Actions
OWAS	Ovako Working Posture Assessment System
PATH	Posture, Activity, Tools and Handling
PCB	Printed Circuit Boards
PFF	Pigment Furniture Factory
POCI	Operational Program Competitivity and Internationalization
PRISMA	Preferred Reporting Items for Systematic Reviews
PSOP	Planning and Scheduling Optimization Problem
QEC	Quick Exposure Check
REBA	Rapid Entire Body Assessment
ROSA	Recursive Optimization-Simulation Approach
RSI	Revised Strain Index
RULA	Rapid Upper Limb Assessment
SA	Simulated Annealing
SBP	Single Board Problem
SeBP	Sequence of Boards Problem
SI	Strain Index
SLR	Systematic Literature Review
SPT	Shortest-Processing-Time
STPP	Simple Temporal Problem with Preferences
SW	Speed of Work
TAP	Task Allocation/Assignment Problem
TASP	Task Allocation/Assignment and Scheduling Problem
TASSP	Task Allocation, Sequencing and Scheduling Problem
TPN	Timed Petri Nets
TPS	Task Planning and Sequencing
USA	United States of America
VNS	Variable Neighborhood Search
WEEE	Waste Electric and Electronic Equipment
WMSDs	Work-related Musculoskeletal Disorders
WoS	Web of Science

Chapter I - General Introduction

I.1. Introduction

Nowadays, the changing production and demand patterns, customization, along with the increasing attention to the worker's conditions, boost the transition towards more human-care solutions built upon synergies between robots and humans (Ronzoni et al., 2021). However, nowadays, the fittest and feasible solution does not rely on fully automated systems because it discourages flexibility and adaptability of systems, which are needed to keep up with the constant changes on customers' orders. In addition, maintaining competitiveness against the background of globalized markets is also an ongoing challenge. Therefore, high-quality requirements, the capability to respond quickly to market challenges, and the control and reduction of production costs are important known strategies for organizations to survive (Müller et al., 2016).

Nevertheless, to face the challenge of increasing productivity while having flexibility, collaborative robots (cobots) represent a clear added value as they promise to increase production rates when compared to manual operations and provide flexibility to industrial environments (Ronzoni et al., 2021; Sherwani et al., 2020). Interestingly, assembly systems have a high proportion of manual work which bring drawbacks such as low productivity. Whereas, through the ability of robots to work in collaboration with humans, new applications in automation have appeared over the last years (Müller et al., 2016).

The main purpose of these technologies is not to replace human's job. Conversely, human workers will find support from these innovative robots for improving the efficiency of processes (Ronzoni et al., 2021). Therefore, Human-Robot Collaboration (HRC) enables the combination of the strength and accuracy of a robot with the intelligence, adaptability, and dexterity of a human worker (Smith et al., 2020; Wang et al., 2020).

Hashemi-Petroodi et al., (2020) stated that the relevance of collaboration between humans and automated systems is rising productivity and flexibility and in terms of ergonomics, safety and reconfigurability of production systems, which is setting up new challenges to industries.

Therefore, to provide effective HRC, one important factor is the correct assignment and scheduling of tasks. Thus, decisions must be made regarding which tasks should be allocated and scheduled to the cobot and which tasks should be left to the human workers while respecting change-over times, temporal and spatial safety distances, and precedencies (Bogner et al., 2018). Thus, one intelligent approach, for instance, is a skills-oriented task allocation (Müller et al., 2016).

Concerning the objectives of this dissertation, a Systematic Literature Review (SLR) and taxonomy regarding the assignment and scheduling of tasks in Collaborative Robotics (CR) are presented. Then, based on the research results, a quantitative and qualitative analysis and a taxonomy are presented. Secondly, the presentation and mapping of three industrial use cases is focused. Finally, an algorithm is developed to the problem of assigning and scheduling tasks between a human worker and a cobot.

I.2. Motivation

This dissertation is integrated in an investigation scholarship in the Activity 3 of Operational Planning of the Augmented Humanity (Augmanity) Project with the funding of the European Fund of Regional Development (FEDER) with the Operational Program Competitivity and Internationalization (POCI). Therefore, the initial source of motivation for the development of this dissertation comes from this project.

In addition, despite the relevance of the topic, the literature has highlighted the lack of scientific work capable of adequately identify and organize the research already done regarding the assignment and scheduling or sequencing of tasks in collaborative robotics, especially in industrial environments. It is precisely this gap that is at the root of the motivation, leading to the development of this research project. Thus, it has the purpose of identifying, analyzing and, consequently design a taxonomy which groups the problems and methods that have been studied in the field of interest and its characteristics. Then, based on the research results, an overview of the collaborative tasks and types of collaboration is presented as well as other important features. Afterwards, three case studies that are being adapted to collaborative robotics are presented along with the mapping of relevant process in BPMN 2.0. Finally, an algorithm was developed which enables the assignment and scheduling of tasks between a robot and a human sharing a workstation and considering the minimization of time and the ergonomic risk.

I.2.1. Augmanity Project: a brief presentation

In Portugal, like in other countries, we are facing challenges such as products customization, which is the opposite of mass automated production, work intensive industries, especially in low-cost countries such as Portugal, where it is difficult to keep low investments for improving processes and still ensure competitiveness. In addition, developed countries are facing the problem of aging population, which will make it harder to hire young people. Thus, industries will have to assure that older workers adapt to the work and are able to deal with new technologies. The main goal of Augmanity is to reinforce research, technological development, and innovation. Therefore, the Augmanity Project which logo is presented in Figure **1**, aims to respond to these social challenges by developing technologies that make the labor in industry more appealing; optimize the definition of tasks to minimize or eliminate health problems and improve ergonomics; develop technologies to the new paradigm of digitalization; use smart technologies to measure and promote the performance, motivation and valorization of co-workers and use the integration of cyber-physics systems and ultra-connectivity in the value chain (Critical Manufacturing, 2022).

Figure **1** - Logo of the Augmanity Project

I.3. Objectives and Methodology

Regarding the overall objectives of the present dissertation, the main goal is to study how to assign and schedule tasks in collaborative robotics. In fact, having both human workers and robots working together it is essential to guarantee human safety and adopt the processes so that the HRC can be effective and efficient.

In this dissertation, with the exception of the introductory chapter, (Chapter **I**) each chapter has an specific methodology. Firstlty, Chapter **II** focuses on developing a theoretical background for the following chapters in order to expand the knowledge and comprehension of the the content of each chapter. Secondly, in Chapter **III** a Systematic Literature Review is presented, therefore, the methodology of this section focuses on the Preferred Reporting Items for Systematic reviews and Meta-Analyses methodology (PRISMA). PRISMA methodology was first published in 2009 and it was the methodology chosen because its goal is to help systematic literature reviewers to transparently report (Page et al., 2021), and it has an extremely useful checklist which is a very helpful tool in every step of the process. In Chapter **IV** because it focuses on the mapping of processes and tasks in order to find the best workstation to implement a collaborative robot and which tasks are best to assign to the human or to the robot, a Business Process Management (BPM) methodology was followed. The BPM methodology followed was the BPM lifecycle proposed by Dumas et al. (2018). Finally, in Chapter **V**, an algorithm for the assignment and scheduling of tasks aiming to minimize makespan considering ergonomics is developed. For this chapter, an adapted Agile Software Development Cycle was adopted. This was the method adopted because it is characterized by the existence of feedback, which was essential to the development of the code in order to make sure that the algorithm had the same characteristics of the problem studied. Figure **2** represents a scheme of the methodologies that were adopted along the different chapters.

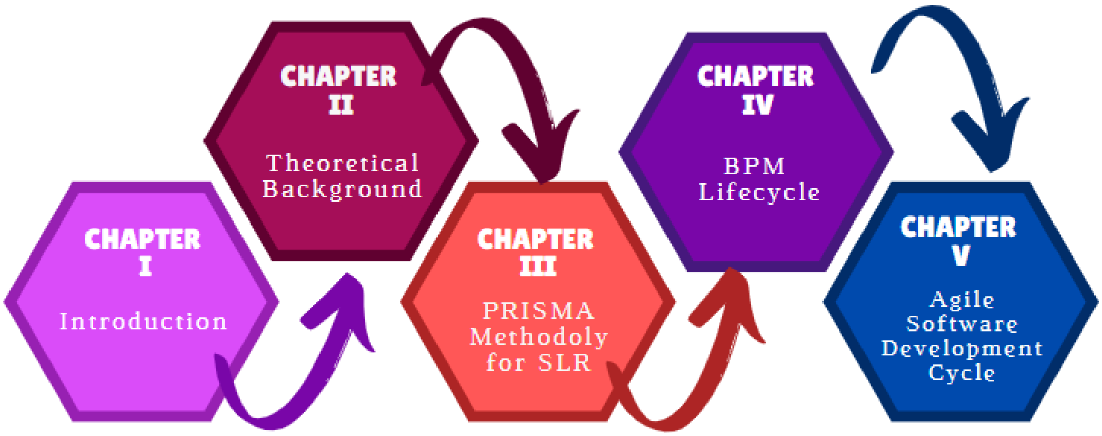


Figure **2** - Overall Dissertation Methodology

I.4. Dissertation Structure

The present dissertation is structured into five parts, each part represented by a chapter. More details about each part will be described below and in Figure **3** a scheme of the dissertation structure is presented.

Chapter I includes the general introduction, the motivation for the research, and the overall objectives and methodology carried out, concluding with the presentation of the dissertation structure.

Chapter II consists of a theoretical background for all the following chapter and begins with a brief introduction and methodology, then the relevant topics are studied: Industry 4.0, Collaborative Robotics, Ergonomic Assessment Tools, Task Allocation and Scheduling in Human-Robot Teams and Business Process Management.

Chapter III presents a systematic literature review and taxonomy about task assignment and scheduling in collaborative robotics. The SLR includes a quantitative and a qualitative analysis. Moreover, it is important to state that this chapter is an adaptation of a submitted article to a scientific journal.

Chapter VI focuses on the mapping of processes of the industrial partners that belong to the Augmanity Project. The primer driver of this chapter was to gain knowledge about industry processes with the potential to be adapted to collaborative robotics. Firstly, the companies and corresponding use cases are described and then the mapping in BPMN 2.0 as-is and to-be of the processes are presented.

Chapter V focuses on the development of an algorithm for the problem of assignment and scheduling tasks in collaborative robotics. To solve the problem an algorithm inspired in the metaheuristic Greedy Randomized Adaptative Search Procedure (GRASP) was developed.

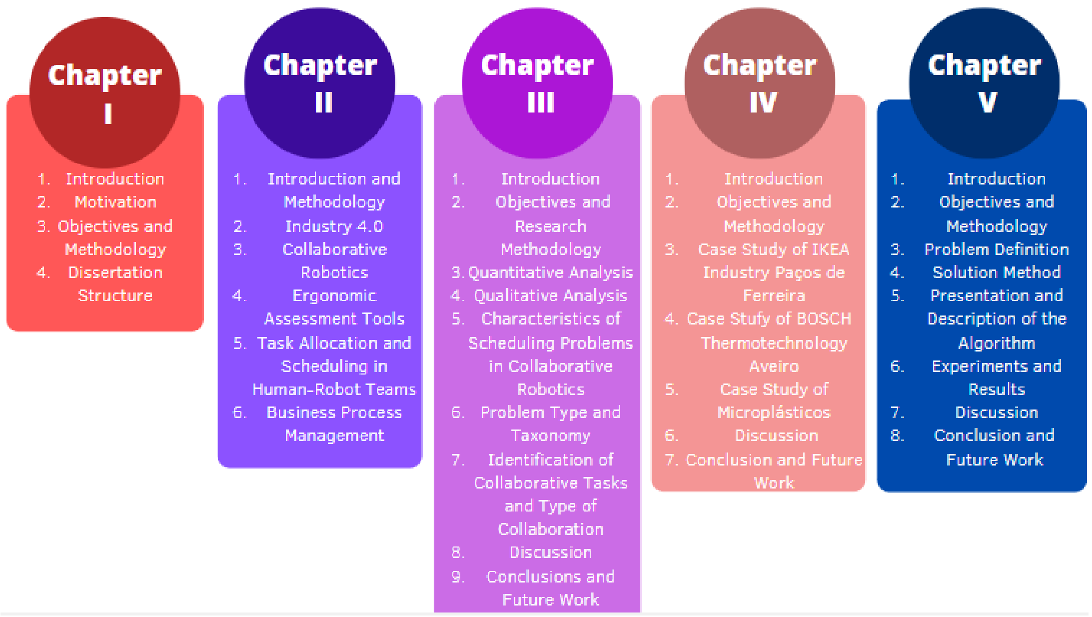


Figure **3** - Dissertation Structure

Chapter II – Theoretical Background

II.1. Introduction and Methodology

II.2. Industry 4.0

II.3. Collaborative Robotics

II.4. Ergonomic Assessment Tools

II.5. Task Allocation and Scheduling In Human-Robot Teams

II.6. Business Process Management

II.1. Introduction and Methodology

This chapter was developed in order to expand the theoretical background about the content discussed in the next chapters. For **Chapter III** the topics of Industry 4.0, Collaborative Robotics, Ergonomic Assessment Tools, Task Allocation and Scheduling in Human Robot Team were studied in order to provide a broader vision and knowledge before the elaboration of the systematic literature review. Concerning **Chapter IV**, the topic of Business Process Management and other that are relative to them were discussed.

This chapter aims to develop a relevant theoretical background that could help fully understand the content of the following chapters and to provide some interesting background knowledge for those topics. In Figure **4** the methodology for the development of the content is presented. Firstly, it was necessary to identify key concepts for each chapter. Then, the identified topics were studied and described. Thirdly, with the learning process and getting to know better the topic it is normal to found other relevant topics that must also be described. Finally, a review step tries to verify any improvements that can be implemented, and the cycle can be started again.

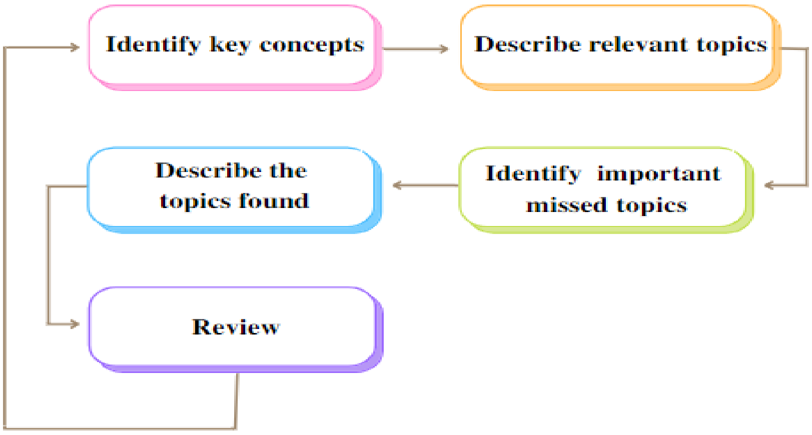


Figure **4** - Method for the development of the theoretical background

II.2. Industry 4.0

Following the motivation of having a broader vision besides the content of the 58 articles included in the sample for analysis of the SLR, a brief theoretical background, regarding important concepts is presented. The main topics of this dissertation are collaborative robotics and task assignment and scheduling. Thus, it is important to understand where these paradigms come from and what other aspects are important to discuss around them. Therefore, a scheme in Figure **5** was created so that, the relations between CR and Task allocation and Scheduling and the other discussed concepts can be understood better.

In a nutshell, collaborative robotics or cobotics is a technology that emerged with Industry 4.0 (I4.0) in which the human workers' role has been changing and will tend to continue changing as robots take over tasks in industries. As robots and humans start to interact on the shopfloor, the concept of Human Robot Interaction (HRI) it is also important to explore in order to understand the best way of assigning and scheduling tasks in a Human-Robot Team (HRT) and to assure human safety. In fact, cobotics can be used to support the job of humans in I4.0 as they can take over dull, dangerous or heavy tasks. In addition, as the workforce turns into a mix of cobots and humans, ergonomics can be assessed in order to analyze if the adoption of robots can improve the ergonomic situation of jobs. Finally, a set of ergonomic assessment tools are described.

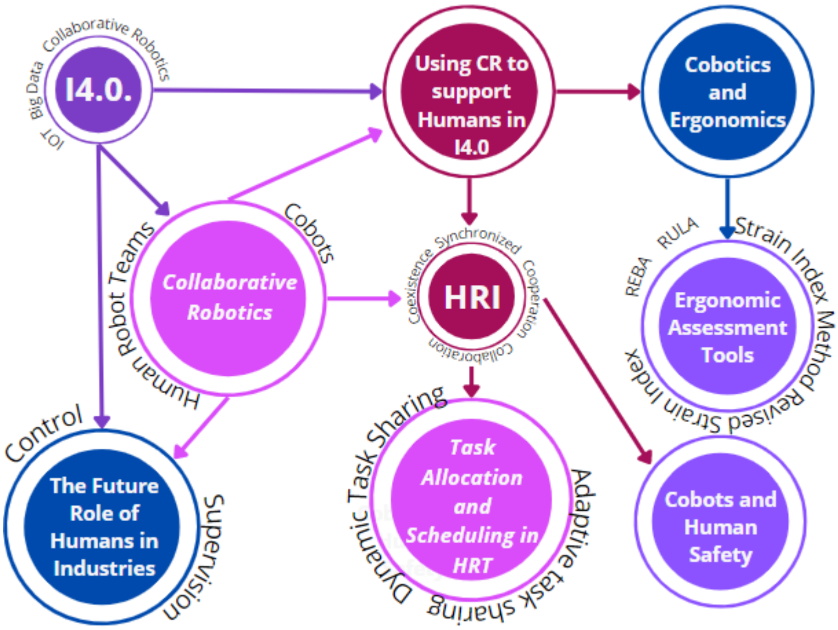


Figure **5** - Relations between the topics discussed

Since the beginning of industrialization, technological leaps have led to paradigm shifts which today are the previous industrial revolutions. The first one was in the field of mechanization. The second one, was characterized by the intensive use of electrical energy and the third industrial revolution, began with the widespread digitalization (Lasi et al., 2014; M. Xu et al., 2018). Later, the combination of the internet and future-oriented technologies resulted in a new industrial paradigm shift. Consequently, the term Industry 4.0 was established to name the fourth industrial revolution (Lasi et al., 2014; M. Xu et al., 2018). This fourth industrial revolution is enabling the progression of embedded systems to cyber-physical systems, which, know how to bring together both virtual and physical spaces. Therefore, the focus of I4.0 is the integration of digital industrial ecosystems, providing end-to-end digitization (L. da Xu et al., 2018).

The term Industry 4.0 had its origin in 2011 and it came from a German government project in which it was promoted a strategy for the digital transformation of the manufacturing industry (Martinez, 2019; Rojko, 2017). The goal behind the concept was the creation of intelligent factories (Ré & Teixeira, 2018). The principles of I4.0 include the interconnection of tools, workers, machines, processes and even systems, which enable organizations to create value which results in a faster response of the industrial processes to the changes that may occur (Ré & Teixeira, 2018). To achieve this, there are many technologies that need to be set in place as the internet of things (IoT), big data, cloud computing, augmented reality, robotics, collaborative robots, additive manufacturing, digital twins, etc. (Bragança et al., 2019; Pires et al., 2019). I4.0 technologies can be able of boosting the accomplishment of high-performance levels however, they require structural adjustments in the modus operandi of organizations which is quite be quite challenging (Rossini et al., 2019).

I4.0 has become a phenomenon since the presence of reputable databases with the emergence of new information and communication technologies (Nasution, 2020). Nowadays, the biggest challenge that companies face is to incorporate I4.0 into their systems because, for example, process automation may imply high implementation costs and results do not appear right away (Agostinho & Baldo, 2020)

According to Lasi et al. (2014) I4.0 includes a wide range of concepts such as smart factories equipped with sensors, actors, and autonomous systems; cyber-physical systems where the physical and the digital level merge and self-organization so that manufacturing systems become decentralized. In addition, I4.0 allows new systems in distribution, procurement and in the development of products and services. However, the adaptation to human needs in manufacturing systems is a critical aspect. Nevertheless, corporate social responsibility must also be the focus so that sustainability and resource-efficiency are increasingly in the focus of the design of processes.

I4.0 when well implemented and incorporated, it enables the reduction of complexity of the production environment (Mohamed, 2018) and the increase of transparency through the digital involvement of each element involved in production (Bragança et al., 2019). However, most of the conducted studies in the field of I4.0 relate to the use and implementation of new technologies in industries. Despite considering humans as an important part of the system, few studies consider human factors and ergonomics (Bragança et al., 2019; Neumann et al., 2021). Consequently, this flaw might result in unsuccessful implementations of this new paradigm. In addition, workers will tend to feel frustrated, neglected and overpowered by robots. In an environment filled with intelligent machines where the human plays an important role, it is important to have a greater understanding of how they can interact. These complex human–robot systems need incorporate human factors and ergonomics to maintain the safety of human workers (Bragança et al., 2019).

II.3. Collaborative Robotics

Industrial systems have been facing an unprecedented emergence of disruptive technologies, especially since the beginning of I4.0 (Kumar et al., 2020; Simões et al., 2019). In addition, industries deal with competitive pressures coming from changes such as the shorter product life cycles, product complexity, customized orders, and international competition. To face these challenges successfully, organizations must seek for the flexibility and adaptability of their processes. In order to achieve it, it is necessary a close cooperation between workers and automated systems (Simões et al., 2019).

As the industrial paradigm shifts to I4.0, new areas of robotics applications emerge. One of those applications are collaborative robots or cobots (Bragança et al., 2019). Cobots are an advanced manufacturing technology characterized by the fact that the robot and the human share a common workspace, without safety barriers which cooperate with humans in a hybrid human-robot team (Simões et al., 2019). Collaborative robots have been advancing in the last decades and have been extremely relevant to the domain of the manufacturing industry after the arrival of I4.0 and have evolved as one of the key drivers. Contrary to traditional industrial robots, cobots besides productivity, can also offer flexibility and safety because they are designed to execute tasks alongside humans. In addition, they allow physical interaction with humans in a shared workspace and are designed to be reprogrammed easily (Sherwani et al., 2020).

Cobotics is a concept formed by the two terms collaborative and robotics and it was first used to conceptualize the direct interaction between a robot and a human (Hentout et al., 2019). According to Hentout el al. (2019, p. 767) cobotics can be defined as "*the science and techniques of design, construction, study and evaluation of a (...) workstation comprising a robot and a collaborating human*". First industrial applications of HRC that are already implemented, are the example Volkswagen in Wolfsburg (Bänziger et al., 2018). In fact, cobots can be extremely useful, in assembly tasks, especially in small batch size products with high variability because the robot can improve quality by reducing the human errors (Makrini et al., 2019). In addition, cobots can improve as well, the working conditions of humans by decreasing their workload and the risks of injuries like musculoskeletal disorders which are the major cause of absenteeism and productivity loss in industry (Makrini et al., 2019). Therefore, HRC brings new opportunities to the assignment of tasks providing the allocation depending on capabilities, execution time, performance, etc. (Makrini et al., 2019).

One important aspect to have in consideration, especially for industrial companies, is the cost of changing from traditional robotics to collaborative robots. In fact, the investment needed for changing the productive system can be a deterrent. However, organizations do not need to completely modify the shopfloor. Most industrial robots don't have safety functions which are required for HRC, whereas such controllers are available. Some safety features can be added to industrial robots, which enable the control of the robot movements (Dianatfar et al., 2019). In a nutshell, an industrial cobot is designed for direct actuation with human co-workers to provide flexibility and to assist them during tasks by reducing the physical effort and/or the cognitive overload. This type of systems has been adopted in several industries such as the automotive industry, the food-processing industry, aerospace exploration, health industry, construction industry and assembly (Hentout et al., 2019).

Along with the growing implementation of cobots in the manufacturing systems, and the integration of humans and technology, the alignment between the automation decisions and the company' strategic goals are critical for the company overall success (Simões et al., 2019).

II.3.1. Using Collaborative Robots to Support Humans in I4.0

Cobots represent one of the major advantages of implementing I4.0. In fact, cobots can be used in manufacturing to support human workers with tasks in two different areas: the support of physical work and the support of cognitive work (Bragança et al., 2019). Relatively, to the physical work, collaborative robots can be use, for instance to automate monotonous tasks or even replace humans when they need to rest. The paradigm of I4.0 implies that industrial work becomes more knowledge-intensive which, by consequence makes the support for cognitive work extremely relevant. Apart from help in heavy and dangerous jobs, there are several tasks that robots can do better and faster than humans at a cognitive level (e.g., looking for a pre-defined pattern in a large database). Moreover, collaborative robots can help reduce biases in decision-making from humans, store large amounts of information thus reducing the need for short-term memory effort, can substitute the worker while on a break, which can improve performance and concentration (Bragança et al., 2019).

However, it is important that the organization makes sure that the introduction of cobots in the shopfloor is seen as a tool to support humans rather than a machine that will steal the human job. Therefore, it is advisable to perform workshops focusing on this matter in order to maintain motivation levels high in the human workforce.

II.3.2. The Future Role of Human Workers in industries

Globalization, mass customization and servitization push industrial systems to shift the organizational strategy in the direction of customer-oriented and personalized production. However, industries try at the same time to maintain the advantages of mass production systems in terms of productivity and costs (Pellegrinelli et al., 2017). In addition, taking into consideration the characteristics of I4.0. the presence of human workers in flexible and reconfigurable environments like collaborative systems is essential, especially for the accomplishment of operations that require excessive investments to be automatized and for dexterity that is still needed in operations that cannot be achieved with robots (Pellegrinelli et al., 2017). However, the potential of HRC can only be fully exploited if humans accept the system. In fact, although we envision a more automated shop floor, with less humans, they will have a greater importance in future industries as they assume roles with more responsibility. Therefore, allocating and scheduling tasks to an operator in HRC systems is challenging and vital (Malvankar-Mehta & Mehta, 2015).

On the other hand, the future self-learning and self-decision-making manufacturing systems might also limit the future industrial roles for humans. But it does not mean that they will be completely replaced by robots whereas, humans will work alongside robots in a collaborative manner. In fact, instead of a competition, the integration of cobots in the industrial environment should be seen as a profitable partnership as I4.0 workers will spend their time collaborating with robots in complex tasks. In addition, with cobots taking over dull tasks, humans can focus on lighter, better and more interesting tasks. Nevertheless, human creativity and adaptably skills should not be replaced by robots. By contrast, humans will assume more leadership and supervisory type of roles on the shop floor, as they still have a greater ability of reasoning and making decisions (Bragança et al., 2019).

Humans and robots will each take on the tasks for which they are best-suited, with interaction and shared procedures or resources. However, it is fundamental to ensure that the human is kept in the center of the decision process for highly flexible assembly. Effectively, it becomes clearer and clearer that the past and actual roles of humans in manufacturing environments is rapidly changing. Consequently, human workers will have to adapt to the new systems by acquiring and improving a set of skills that might have been neglected until the present date by organizations (Bragança et al., 2019).

II.3.3. Cobots and Human Safety

Cobots allow the reduction of ergonomics concerns while improving safety, quality, productivity, and flexibility (Simões et al., 2019). Therefore, combining robots with humans allows achieving the best of both worlds: robots can perform heavy, repetitive, and dangerous tasks and, meanwhile, humans can assist, supervise, and take over tasks that require dexterity, flexibility or that are too challenging for robots. This new role which leans more towards the supervisory for human workers has the potential to shift human conditions of labor (Chatzikonstantinou et al., 2020).

Despite seeing all type of robots take over industries, human workers are still present. Therefore, it is mandatory to guarantee the safety of human beings. Collaborative robots are quite different from traditional robots: they are smaller, lighter and do not need to be encaged, as they are embedded with sensors that provide the maintenance of safety for humans. Cobots are designed to interact closely with humans so, as a consequence, they must adhere to strict safety requirements (Liu et al., 2022). Embedded safety features in cobots include detection of collisions, power and speed limiting, safe axis ranges, and position and orientation supervision. However, there is no absolutely safe robot. Hence, a wide range of studies have focused on the safety matter (Liu et al., 2022). For instance, (Amin et al., 2020) studied the safety of cobots by designing a monitoring system and it is important to keep on study safety issues in collaborative robotics. In addition, organizations that opt to implement cobots must always keep safety a priority.

II.3.4. Human-Robot Interaction

HRI is a relatively recent term which started to emerge in the mid-1990s and early 2000 and has been gaining the attention of academic over the past recent years due to the growth of human’s exposure to robots. The HRI field includes many challenges but has the potential to generate solutions with positive social impact. In fact, the HRI paradigm is dedicated to evaluating, designing, and understanding robotic systems in order to provide a safe environment for the human workers. Interaction between humans and robots require communication which may take different forms that are influenced by the level of proximity and interaction. Therefore, communication and interaction can be separated into remote or proximate (Goodrich & Schultz, 2007).

Concerning HRI levels, considering the way the human and the robot interact, different levels of HRI can be identified. According to Matheson et al. (2019) four levels of HRI can be depicted: Coexistence, Synchronized, Cooperation and Collaboration.

- Firstly, the simpler one is designated by Coexistence and represents a situation where the operator and the cobot are in the same environment but do not interact with each other (Matheson et al., 2019). **Coexistence**, also called coaction, is defined as the capability of sharing the dynamic workspace between different agents without a common task or, without requiring mutual contact or coordination and the agent’s intentions may have different aims and commonly is limited to collisions avoidance (Hentout et al., 2019).

- Secondly, the next level is **Synchronized** where the operator and the cobot work in the same workspace, but at different times (Matheson et al., 2019). Synchronized acts on a higher level because, humans and robots have the same purpose and fulfill the requirements of time and space, simultaneously. Moreover, it may also require more advanced technologies such as force-feedback sensing or advanced machine vision (Hentout et al., 2019).
- Thirdly, **Cooperation** is when the human operator and cobot work in the same workspace at the same time, though each focuses on separate tasks.
- Finally, the level with a higher HRI is **Collaboration** and translates a situation where the operator and the cobot execute a task together. The action of one has immediate consequences on the other, thanks to special sensors and vision systems (Hentout et al., 2019).

HRC there is direct human interaction which can be divided in two forms: Physical Collaboration and Contactless Collaboration. In Physical Collaboration there is intentional contact between human and robot. In Contactless Collaboration there is no physical interaction so, the actions are coordinated from information exchange (via direct communication - speech, gestures, etc., or indirect communication - intentions recognition, eye gaze direction, facial expressions, etc. (Hentout et al., 2019).

To sum-up, HRI provides promising methods to achieve strategic goals of organizations such as increased productivity and reduction of costs by combining the decision-making ability of humans with the strength of robots (Sherwani et al., 2020).

II.3.5. Cobotics and Ergonomics

Ergonomics was first proposed as a scientific discipline with a broad scope and a wide range of interests and applications, encompassing all aspects of human activity (labor, entertainment, reasoning, etc.) (Karwowski et al., 2006). The term ergonomics is also generally used synonymously with human factors, and focuses on the nature of human interactions, viewed from the unified perspective of the science, engineering, design, technology, and management of human-compatible systems. Moreover, ergonomists contribute to the design and evaluation of jobs, tasks, products, environments, and systems to make them compatible with humans, especially, their needs, abilities, and limitation (Karwowski et al., 2006). In addition, ergonomics promotes a human-centered approach to design systems considering cognitive. physical, organizational, social, environmental, and other fundamental factors (Karwowski et al., 2006).

Regarding cobotics, in a system composed by humans and robots, one important component to measure is undoubtedly, ergonomics, in order to make sure that the workstation, production line, or even the whole system is adapted to humans. Collaborative robots by enabling the parallelization of tasks and taking over jobs with a higher strain index can undoubtedly enhance productivity and ergonomics. However, with the increasingly coexistence of cobots and humans in factories, balancing productivity and ergonomics has become a new challenge in HRI. A lot of studies analyze the performance of the system having makespan as criteria, whereas ergonomics must also be considered (Liu et al., 2022). For example, (Pearce et al., 2018) proposed a framework that generated task assignments and schedules for a team of a robot and a human, using the strain index method to quantify human physical stress. Therefore, a couple of ergonomic assessment tools that can be used by organizations to evaluate ergonomic conditions will be identified and described in the following subsections.

II.4. Ergonomic Assessment Tools

Ergonomic assessment can be an activity enrolled in every type of organization. In fact, poor body posture or forceful working can lead to permanent damage in humans. Therefore, it is important to assess body postures and force and then, improve the design of the job and workplace. In fact, people do not assume poor posture deliberately, instead, they are forced to do so because of the characteristics of the task or because of poor ergonomics in the design of the job or workplace. In addition, one thing that organizations are starting to understand is that Work-Related Musculoskeletal Disorders (WMSDs) do not only prejudice workers but also the organization. Musculoskeletal disorders are among the most widely spread occupational problems, in industries and services, with increasing expenses of salary compensation and health costs, declining productivity and lower quality of life (al Madani & Dababneh, 2016). According to Eurostat, nearly 40% of the occupational diseases in the European Union are related to MSDs. In addition, they are the leading cause of time off work and permanent incapacity for work (European Trade Union Institute, n.d.). Moreover, almost 50% of those who do not go back to work after six months will never do so. However, there are no exact value of the cost of MSDs to European business and society, but some it is estimated to be between 0.5 and 2% of the gross domestic product (European Trade Union Institute, n.d.).

Ergonomic assessment of WMSDs involves the evaluation of risk of developing a range of disorders to muscles, nerves and joints (al Madani & Dababneh, 2016). Relatively of how to measure ergonomics there are two methods: subjective and objective methods. Subjective methods include for example the use of questionnaires, whereas objective observational techniques include for instance, Ovako Working Posture Assessment System (OWAS), Posture, Activity, Tools and Handling (PATH), Quick Exposure Check (QEC), Rapid Upper Limb Assessment (RULA), American Conference of Governmental Industrial Hygienists Threshold Limit Value (ACGHI TLV), Strain Index (SI), Occupational Repetitive Actions (OCRA), NIOSH Lifting Equation, Rapid Entire Body Assessment (REBA), Strain Index Method, etc. (al Madani & Dababneh, 2016).

II.4.1. Strain Index Method

To quantify ergonomics, a widely job analysis method called Strain Index (SI) can be used. The SI is a tool that can be used to quantify the risk of development of a musculoskeletal disorder (MSD). In fact, repeated tasks can lead to discomfort in the hands, wrists, and elbows. The SI was first proposed by Moore and Garg (1995) as a mean to assess the risk of work-related musculoskeletal disorders (WMSDs), especially in distal upper extremities (hand, wrist, elbow). The calculation of the index is based on the following 6 task variables: intensity of exertion; duration of exertion; efforts per minute; hand/wrist posture; speed of work and duration of task per day. To each variable a rate is assigned and then a corresponding multiplier. Finally, to each task a value is attributed which corresponds the following categories:

- $SI \leq 3$ Job is probably safe
- $SI > 3$ and ≤ 7 Job may place individual at increased risk WMSDs
- $SI > 7$ Job is probably hazardous

Although the SI variables are rated subjectively, it has been demonstrated the attribution of values amongst interrater are similar and repeatable (Pearce et al., 2018). Regarding the Strain Index calculation, as previously mentioned, SI is measured by rating six parameters on a scale of 1–5: intensity of exertion (IE), duration of exertion (DE), efforts per minute (EM), hand/wrist posture (HWP), speed of work (SW), and duration per day (DD). Then, each rating is matched to a multiplier value. Details for determining each parameter rating are as follows.

Intensity of Exertion: All work elements are ranked subjectively by their perceived IE using a scale. The IE value for the entire task is the maximum value amongst the work-elements assigned to the human worker (Pearce et al., 2018). In

1) Figure **6** it is presented the section from the SI worksheet where the IE evaluation occurs.

Risk Factor	Rating Criterion	Observation	Multiplier	Left	Right
Intensity of Exertion (Borg Scale - BS)	Light	Barely noticeable or relaxed effort (BS: 0-2)	1		
	Somewhat Hard	Noticeable or definite effort (BS: 3)	3		
	Hard	Obvious effort; Unchanged facial expression (BS: 4-5)	6		
	Very Hard	Substantial effort; Changes expression (BS: 6-7)	9		
	Near Maximal	Uses shoulder or trunk for force (BS: 8-10)	13		

Figure **6** - Intensity of Exertion Evaluation Section

2) **Duration of Exertion:** DE is the percentage of time in a cycle when exertion occurs. The duration for each work element assigned to the human worker that consists of an exertion, is summed, and then divided by the cycle time. Then, the result is matched to a multiplier. Figure **7** presents the section dedicated to the DE evaluation.

Duration of Exertion (% of Cycle)	< 10%	**Calculated Duration of Exertion** (from inputs below)			0.5		
	10-29%	**User Inputs**	**Left**	**Right**	1.0		
	30-49%	Total observation time (sec.)			1.5		
	50-79%	Single exertion time (sec.)			2.0		
	≥ 80%	Number of exertions during observation time			3.0		
	Calculated Duration of Exertion (%)						

Figure **7** - Duration of Exertion Evaluation Section

3) **Efforts Per Minute**: Similarly, to *DE*, the sum of efforts for all work elements assigned to the human worker is done and then, the result is divided by the cycle time in minutes, and then select the corresponding rating. Figure **8** presents the section for assessing EF.

Efforts Per Minute	< 4	**Calculated Efforts Per Minute** (from inputs above)			0.5		
	4 - 8		**Left**	**Right**	1.0		
	9 - 14				1.5		
	15 - 19				2.0		
	≥ 20				3.0		

Figure **8** - Efforts per Minute Evaluation Section

4) **Hand/Wrist Posture:** This rating uses the same approach as *IE*: rank all work elements and then select the maximum value amongst work elements assigned to the human. Figure **9** represents the section for analyzing HWP.

Hand/Wrist Posture	Very Good	Perfectly Neutral	1.0		
	Good	Near Neutral	1.0		
	Fair	Non-Neutral	1.5		
	Bad	Marked Deviation	2.0		
	Very Bad	Near Extreme	3.0		

Figure **9** - Section for evaluating HWP

5) **Speed of Work:** The interrater selects a category between (very slow, slow, fair, fast and very fast) and then the corresponding multiplier. Figure **10** presents the section for evaluating SW.

Speed of Work	Very Slow	Extremely relaxed pace	1.0		
	Slow	Taking one's own time	1.0		
	Fair	Normal speed of motion	1.0		
	Fast	Rushed, but able to keep up	1.5		
	Very Fast	Rushed and barely/unable to keep up	2.0		

Figure **10** - Section for evaluating SW

6) **Duration Per Day:** DD is assessed at the task level. Figure **11** presents the section for evaluating DD. Finally, the total SI is determined by taking the product of the multipliers for each parameter. The method for calculating the final value for SI is presented in Figure **12**.

Duration of Task Per Day (hours)	<1		0.25		
	1 < 2		0.50		
	2 < 4		0.75		
	4 ≤ 8		1.00		
	> 8		1.50		

Intensity of Exertion	×	Duration of Exertion	×	Efforts per Minute	×	Hand/Wrist Posture	×	Speed of Work	×	Duration of Task	=	SI Score

Figure **12** - Method for calculating final SI score (Moore & Garg, 1995)

II.4.2. Revised Strain Index

Despite the 1995 SI has served well to the determination of the risk of getting MSDs, it has some limitations such as: the use of fixed variables and corresponding multipliers which leads to very different SI scores with a one unit change in IE, number of exertions or duty cycle; lack of differentiation power between extremely low and up to moderate intensity of force; tasks with >20 efforts per minute may not be appropriately penalized; use of duty cycle – which may be misunderstood with efforts per minute. To address these limitations, Garg et al. (2017) propose the Revised Strain Index (RSI) method. Comparing the RSI to the 1995 SI there are three main differences: the RSI omits speed of work, relies on duration per exertion instead of duty cycle and uses continuous variables and multipliers rather than fixed values (Garg et al., 2017). Thus, the RSI is a five variable model while the 1995 SI is a six-variable model.

II.4.3. Rapid Upper Limb Assessment

Rapid Upper-Limb Assessment (RULA) is an ergonomic assessment tool that provides an easy way of analyzing the risk that human workers have of developing neck and upper-limb musculoskeletal disorders. The tool rates posture, force, and movement endorsed while performing tasks especially associated with sedentary tasks. Such as screen-based or computer tasks, manufacturing, or retail tasks where the worker is seated or standing without moving about. Then, the risk is calculated into a score of 1 to 7 which are corresponding to four action levels (Colim et al., 2020).

Like the Strain Index Method, the RULA method focuses only on upper parts of the human body (shoulders, neck, trunk, arm, forearm, and wrist) taking also in consideration frequency and load. However, RULA was not designed to provide a detailed postural information, such as the finger position (Colim et al., 2020). Figure **13** presents the RULA worksheet.

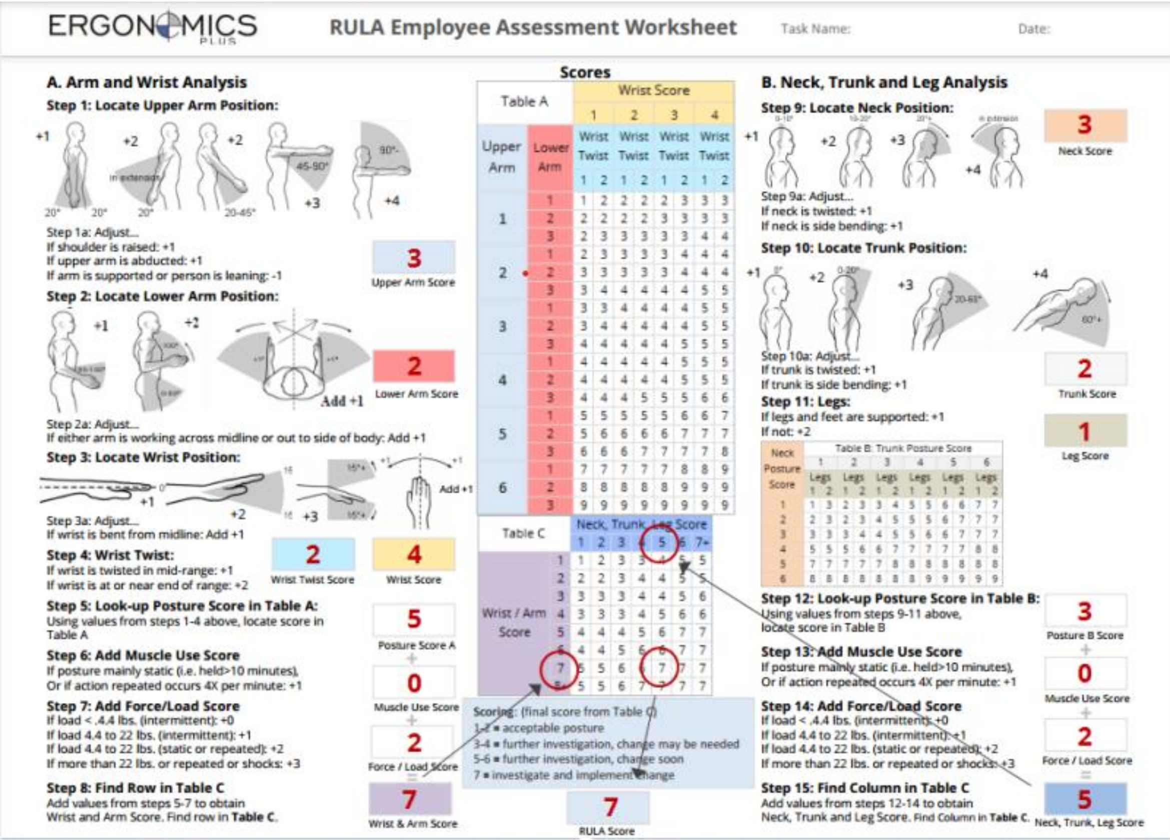


Figure **13** - RULA Employee Assessment Worksheet (Middlesworth, n.d.)

II.4.4. Rapid Entire Body Assessment

Rapid Entire Body Assessment or REBA is one of the most widely used observational ergonomic assessment tool and it was first proposed in the United Kingdom as a requirement for postural analysis (al Madani & Dababneh, 2016). REBA provides a fast and easy way to assess a variety of working postures for risk of WMSDs (al Madani & Dababneh, 2016). One of its advantages when compared do other methos, such as RULA and the Strain Index Method, is that it does not only, take into consideration the upper part of the body, but the entire body. Regarding the description of the scoring method, it divides the human body into sections to be scored independently (al Madani & Dababneh, 2016). The REBA assessment worksheet can be seen in Figure **14.**

The body posture is analyzed by articular angles measurement, observing the force load, the repetition of movements and postural changes. Therefore, REBA can be used by any organization when it is important to assess the entire body posture (dynamic or static) of the human worker and it also considers loads when handled. The REBA score for a task can be 1, 2-3, 4-7, 8-10 or 11-15, and each score has a corresponding risk level and the urgency of action (al Madani & Dababneh, 2016) as it can be seen in Table **1**. The final score translates the risk level of getting musculoskeletal disorder.

The neck, trunk, upper and lower arms, legs and wrists' postures are divided into different scores. Firstly, score A represents the sum of the scores for the neck, trunk and legs plus the load score. Secondly, score B is the sum of the scores for the upper and lower arms and wrists plus the coupling score. Then, scores

A and B are combined in Table C and finally an activity score (which describes any posture held for more than 1 minute and a repetition more than 4 times per minute or rapid change in postures, or an unstable base) is added to give the final REBA score (al Madani & Dababneh, 2016).

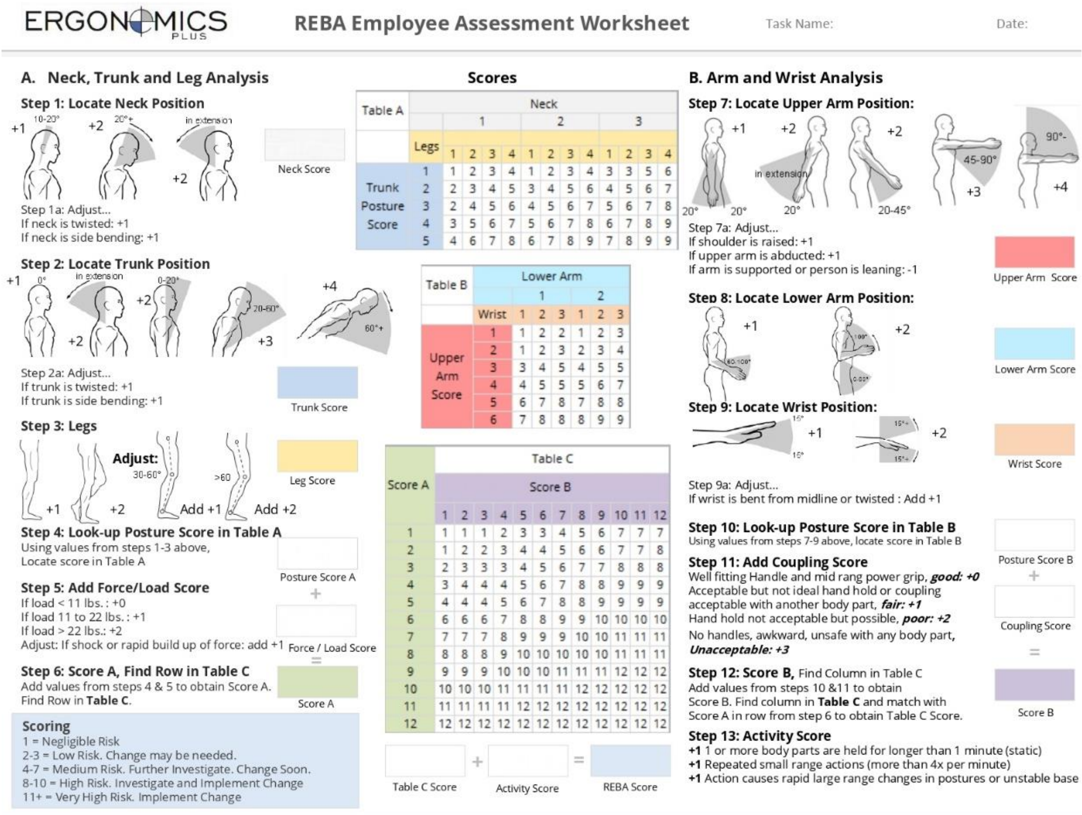


Figure **14** - REBA Assessment Worksheet

Table **1** - REBA Scores and corresponding Action levels (al Madani & Dababneh, 2016)

Action level	REBA score	Risk level	Action (including further assessment)
0	1	Negligible	None necessary
1	2-3	Low	May be necessary
2	4-7	Medium	Necessary
3	8-10	High	Necessary soon
4	11-15	Very high	Necessary NOW

II.5. Task Allocation and Scheduling in Human-Robot Teams

In HRI, a major challenge is to determine the optimal assignment and scheduling of tasks between cobots and humans. To achieve this, along with the enhancement of the overall production the task allocation between humans and cobots is extremely important. In fact, while humans are better at performing adaptive and extremely flexible work and responding to the unexpected, robots should be assigned to tasks involving awkward postures, repetition, sustained forces for long periods of time and that have a higher risk of developing musculoskeletal injuries (Pearce et al., 2018).

Task assignment and scheduling in collaborative robotics has been gaining the attention of researchers, which recognizes the importance of studying the field. Dalle Mura and Dini (2019) and Maderna et al. (2020) try to improve the efficiency while solving the task assignment problem, (Kinast et al., 2021) studies a job shop scheduling problem and proposes a genetic algorithm with a biased random-key encoding, aiming to find a solution to the assignment of cobots to workstations, the assignment of tasks to workstations, and the priority of tasks (Liu et al., 2022). To the best of the author's knowledge, most publications in collaborative robotics focuses on human-robot interaction interface technologies (Li et al., 2019). However, the scheduling of tasks between the human and the robot is also an important aspect of collaborative systems that need to be studied. Regarding the scheduling of tasks in collaborative robotics, different authors have been using different designations such as tasks allocation, tasks assignment, tasks scheduling and rarely tasks sequencing.

Effectively, task allocation is one of the most important steps in the implementation of HRC. In fact, an efficient task allocation process ensures the safety of the human and the performance of the team during the collaborative task (Liau & Ryu, 2020). In addition, the scheduling literature has modelled this problem, in different ways. Ferreira et al. (2021) studied this problem as a Multimode Multiprocessor Task Scheduling Problem (MMTSP) where multiprocessor tasks represent collaborative tasks. Moreover, jobs can also be executed in alternative modes – the human operator or the robot. The MMTSP, therefore, consists of assigning modes to jobs, in addition to their scheduling, being a generalization of the Parallel Machine Scheduling problem (Ferreira et al., 2021). Some other studies deal with this problem simply as a sequencing problem instead of a scheduling problem.

Other studies report dynamic scheduling problems, such as Johannsmeier and Haddadin (2017) where "dynamic scheduling defines the strategy of how to generate the original baseline and the strategy of how to respond to real-time events" (Fahmy et al., 2014). Cyclic scheduling with HRTs is also the focus of some works, such as, Bogner et al. (2018). For non-cyclic scheduling problems, a set of operations is given, each of which must be processed exactly once. On the other hand, in cyclic scheduling problems a set of operations is given, each of which must be processed infinitely often. The goal is to find a periodic schedule which minimizes a given objective function (Kampmeyer, 2006). The Flow shop scheduling problem has also been addressed for HRC in industrial scenarios. This type of problem "is a production problem where a set of *n* jobs have to be processed with identical flow patterns on m machines" (Kumar & Jadon, 2014). In order to organize, resume, understand and extend the content of this brief topic about the field of cobotics and task assignment and scheduling, a systematic literature review will be presented then.

II.5.1. Adaptive Task Sharing

In order to try to increase productivity and flexibility, Schmidbauer et al. (2020) propose adaptive human-cobot task sharing. This approach focuses on establishing a set of tasks that may be assigned to the human worker or to the cobot, instead of defining a priori which task is carried out by each agent. However, in most assembly systems, there are still some tasks that can only be done by robots or by humans alone, therefore in these cases, these tasks cannot be implemented as shareables tasks.

In this approach, the workers have a range of variants in the assignment of tasks and the distribution of tasks can be changed depending on defined criteria. Thus, the task sharing approach offers greater flexibility and productivity. Furthermore, it provides additional learning opportunities for workers, especially in contrast to the static task allocation approach (Schmidbauer et al., 2020) as it can be seen in Figure **15**.

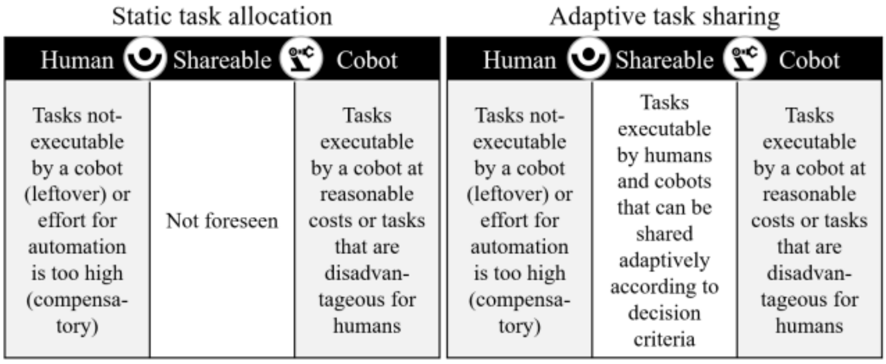


Figure **15** - Static task allocation approach versus adaptive task sharing approach (Schmidbauer et al., 2020)

II.5.2. Dynamic Task Sharing

The dynamic task sharing approach, considers that there are tasks that could be performed more proficiently by humans or robots alone, and others collaboratively. The dynamic approach proposed by Antonelli et al. (2017) consists in firstly, create a set of indicators to describe the features of the task (weight of assembled part, displacement, accuracy requirements and dexterity requirements) that which will be used as a decision factor in the selection of the type of collaboration. Then, based on the indicators, a classifier assigns tasks to the following categories: executable only by a robot, executable only by a human, indifferently by human or robot, executable by both human and robot collaboratively. Finally, the assignment procedure uses the task duration and the task precedencies to create the schedule of the job, and then applies the following logic: assign to the human the task classified as H, assign to the robot the tasks classified as R, assign to both workers the tasks classified as H+R and tasks classified with H/R, tries to assign to the robot (Antonelli & Bruno, 2017). A summary of the dynamic approach can be seen in Figure **16**.

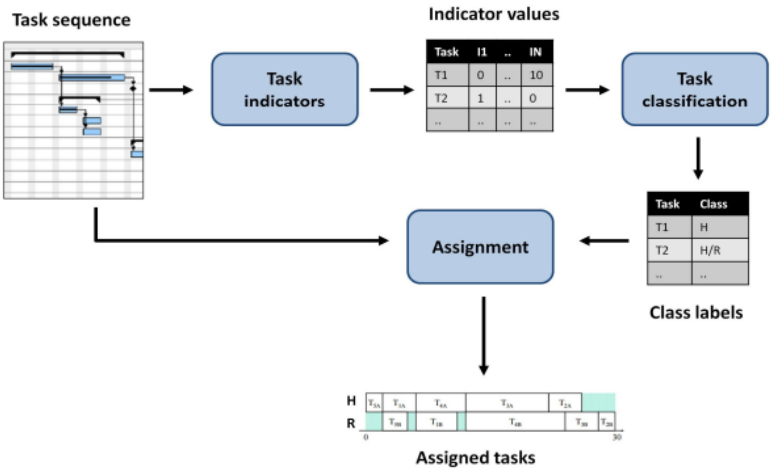


Figure **16** - Dynamic Task Allocation Approach proposed by Antonelli et al. (2017)

II.6. Business Process Management

Globalization, innovation, integration, standardization, agility, and operational efficiency along with the opportunities raised by digital technologies, have finally increased the motivation for reflecting on and improving existing as well as designing new business processes (Dumas et al., 2018). Consequently, tools, techniques and methods to support all stages of the business process lifecycle have emerged over the past two decades. It is called Business Process Management (BPM), and it consolidates a plethora of approaches coming from diverse disciplines such as Industrial Engineering, Operations Management, Quality Management, Human Capital Management, Corporate Governance, Computer Science, and Information and Systems Engineering (Dumas et al., 2018).

Business Process Management aims to improve efficiency of a business through the process management. The processes must deliver value to the customer, and in order to improve them, they must be modeled, automated, integrated and continuously optimized. Business Process Management provides companies with tools that facilitate, simplify, and unify the decision-making management operation (Leh Qine, 2021). Business Process Management brings together several tools and techniques that combine information technologies, management, and even engineering to improve business processes. Therefore, BPM can be extremely relevant to evaluate processes from a strategic level, increasing the company's productivity and competitiveness (Fernandes et al., 2021).

Furthermore, sharing business processes between companies has become a difficult task due to the lack of a single unified language and standards for executing business processes. To solve this problem, BPMN emerged, which is a standard language that can graphically represents processes. In addition, in some industries such as the automotive industry, processes are often complex and difficult to describe, which is why they are more susceptible to errors. Thus, BPMN can help overcome these challenges (Fernandes et al., 2021)

II.6.1. Business Process Model and Notation

Business Process Modeling (BPMo) according to Závadský & Závadská (2014) as cited by Castro e Teixeira (2020), is “an orientation by processes, of a management system, which can be achieved through the application of a process approach”, which involves the process of understanding how, who and when the activities/tasks are developed. This approach involves the mapping of processes using a universal language: BPMN (Castro & Teixeira, 2020). The majority of process modeling languages take a transformational approach (input–process–output), in other words, processes are divided into activities, which can also be divided further into sub-activities. Then, each activity takes inputs, that are then transformed to outputs. It is the relations between inputs and outputs that define the sequence of work in a process (Aagesen & Krogstie, 2015).

The Business Process Modeling Notation (BPMN) was presented in 2004 as a standard business process modeling language and its development is considered to have a huge impact in the reduction of fragmentation in existing process modeling tools and notations (Aagesen & Krogstie, 2015). BPMN 2.0 which is the latest version of BPMN (Aagesen & Krogstie, 2015) is a graphical notation used for modeling or even designing processes which enables the description of dependencies between subprocesses and tasks. This notation has a wide variety of applications so, many companies use it as their standard modeling technique. The process steps are represented expressing the control logic, such as sequences, choices, parallel tasks, and iterations. BPMN models consist of sets of nodes connected through sequence flows or other types of flows (Raedts et al., 2007).

The strategy of modelling processes provides a visual and general idea of processes which stimulates the truth understanding of processes by everyone. In fact, BPM offers the necessary knowledge for the organizations to map, analyze and manage the processes efficiently (Castro & Teixeira, 2020). In addition, knowledge permits the development of an organization. However, sometimes this advantageous tool is not documented, which can make the organization to lose it. (Kalpic & Bernus, 2002, as cited in Salvadorinho & Teixeira, 2020). Therefore, modelling provided capture of the knowledge and easy access for the process state, integration with people, information systems and resources (Salvadorinho & Teixeira, 2020).

Furthermore, BPMN 2.0 enables the establishment of the connection between processes and systems and is a useful tool to help understanding where a process can be automated. BPM and BPMN have been gaining an increasing importance, because they promote better communication and transparency in the decision-making process (Fernandes et al., 2021a). Through BPMN, it is possible to represent a process, and guarantee its consistency, when compared to the documented version. As a result, BPMN can be an interesting application so that all those involved in the process understand it clearly. In addition, well-defined processes eliminate redundant activities, improving the efficiency of processes (Fernandes et al., 2021a).

For all the previous reasons identified, BPMN will be used in Chapter **IV**, in the three case studies presented, as a tool that will provide the documentation of the As-Is process, which did not exist, help identify the workstations where it can be added automation (with the implementation of the cobot), as well as mapping the to-be process and help the future work, defining the assignment and scheduling problem to consider for the development of an algorithm, since BPMN clearly identifies the tasks of each agent.

Chapter III – Systematic Literature Review and Taxonomy

III.1. Introduction

III.2. Objectives and Research Methodology

III.3. Quantitative Analysis

III.4. Qualitative Analysis

III.5. Characteristics of Scheduling Problems in Collaborative Robotics

III.6. Problem Type and Taxonomy

III.7. Identification of Collaborative Tasks and Type of Collaboration

III.8. Discussion

III.9 Conclusions and Future Work

III.1. Introduction

The importance and value of a literature review reminds in its explicit, systematic, and reproducible design which enables the identification, evaluation, and interpretation of the existing literature (Seuring & Müller, 2008).

As a matter of fact, literature reviews are an essential feature of academic research. However, in the planning field, it can be noticed a lack of rigorous systematic reviews (Xiao & Watson, 2019). Knowledge advancement must be built on prior existing work and reviewing relevant literature provides the understanding of the depth of the existing work and the identification of the gaps (Paré et al. 2015 as cited in Xiao & Watson, 2019). By summarizing, analyzing, and synthesizing a group of related literature, it is possible to test a specific hypothesis, develop new theories, evaluate the validity and quality of existing work against a criterion to reveal weaknesses, inconsistencies, and contradictions (Paré et al. 2015 as cited in Xiao & Watson, 2019).

In fact, there are already some relevant systematic literature reviews in collaborative robotics such as Costa et al., (2022), Hopko et al., (2022), Simões et al., (2022) Pinheiro et al., (2021) and Gualtieri et al (2021). These SLR discuss topics such as augmented reality, human factors, ergonomics, safety and the design of workplaces. However, regarding the author's knowledge, until the actual date there is no systematic literature review in collaborative robotics that focuses only on the matter of assigning and scheduling tasks between robots and humans. Therefore, the motivation for the elaboration of a SLR in the mentioned field, which is presented hereafter, comes from this gap in the literature.

III.2. Objectives and Research Methodology

Literature reviews usually have two objectives: they summarize existing research by identifying patterns, themes and issues and help to identify the conceptual content of the field and can contribute to theory development. Though, it is unfeasible to read everything. It might only be possible to provide complete reviews for emerging fields or narrowly defined issues (Seuring & Müller, 2008). For these reasons, a SLR is presented to identify, and interpret all available research relevant to the phenomenon of interest. The approaches proposed by Seuring & Müller (2008) and Thomé et al. (2016) are followed, and The Preferred Reporting Items for Systematic Reviews (PRISMA) statement was used as a formal systematic review guideline. A summary of the methodology adopted is shown in Figure **17**.

Systematic reviews often present a lack of awareness of shared guidelines which enable replicability. Thus, PRISMA provides a standard peer accepted methodology guideline checklist, which was followed to contribute to the quality assurance of the literature revision process and to its replicability (Abelha et al., 2020).

III.2.1. Data Sources and Search Strategies

The SLR began with a reading of frequently cited articles on the topic under study which allowed to establish the most relevant keywords but, on the other hand, specific enough to bring only the studies related to the topic, as suggested by Thomé et al. (2016). Then, aiming at collecting the most relevant papers to this research, the search process was conducted on two electronic databases: Scopus and Web of Science (WoS). These databases were the ones used because they are the two most highly valued databases for the Portuguese scientific system for and funding and evaluation (Abelha et al., 2020). In this analysis there was no time restriction and it aimed only at papers written in English. Moreover, there was no exclusion regarding the document type. The search was under the fields "title, abstract, keywords", with a final string built in three levels.

Table **2** shows the assembly structure where level one defines the search context (Collaborative Robotics), level 2 outlines scheduling problems related keywords, and level 3 concentrates research on Operations. The asterisk "*" was used at the end of the search keyword to broaden the range of results and identify as many eligible studies as possible. This resulted in a total of 247 papers in Scopus and 182 in WoS. After the exclusion of duplicates, it resulted in a total of 278 publications. It was intended to convey an international dimension to the analysis, whereas the search was limited to two databases acknowledged by their quality and contribution to science to guarantee rigor and quality of studies included. In this way, quality was prioritized over the breadth of the analysis (Abelha et al., 2020).

Table **2** - Keywords used in the literature search

Level 1: CR keywords	**Level 2: Scheduling Problems keywords**	**Level 3: Operations keywords**
"Collaborative robot"* OR *"cobot*"* OR *"Human-robot* collaboration"* OR *"Collaborative task*"* OR *"Human-robot team*"* OR *"Human-cobot* team"*	*"scheduling"* OR *"sequencing"* OR *"assignment*" OR* *"allocation"* OR "Task programming" OR "operations programming"	*"task*" OR* "operation*" OR "job*" OR "process*"

III.2.2. *Selection of Studies*

Following the process illustrated in Figure **18**, the papers were screened in a two-step process. The first reading of the papers (step 1) was restricted to the title and abstract with the objective of selecting articles that could answer the research questions under study (Thomé et al., 2016) and that would meet the eligibility criteria abovementioned. After the first step, 80 articles were selected for full-text review (step 2). Consequently, through a second reading, a full-text analysis was performed to select which articles would be included in the study sample, thus excluding the papers without adherence to the present investigation. It is important to note that, in some cases, the abstract did not clarify if the paper fulfilled the inclusion criteria, and those papers were kept for step 2. Moreover, regarding the data extraction process and quality assessment, the important characteristics of each paper were recorded in a spreadsheet.

III.2.3. *Eligibility Criteria and Constitution of the Sample for Analysis*

According to Seuring & Müller (2008), for a literature review it is particularly important to define clear boundaries to delimitate the research. Thus, subject to the scope of the study, only studies that clearly discuss scheduling problems in collaborative robotics, or related terms, and that clearly discuss human-robot collaboration were selected. Moreover, publications that only referred to this matter in the future or that focused on the programming instead of the scheduling were also excluded. Furthermore, paid publications or that were unavailable were also excluded. In this context, two prone exclusion criteria were applied to the selection of LR (i) publications where the concept was merely mentioned in future research were not considered; (ii) publications that despite talking about collaboration, do not develop human-robot collaboration but human-human or robot-robot collaboration. The publications that only refer lightly to the concept of task scheduling or focus more on the programming of the robot, in control systems or task planning were excluded. In addition, publications with common authors and identical investigations were also excluded. A summary of the search process can be found in Figure **17**.

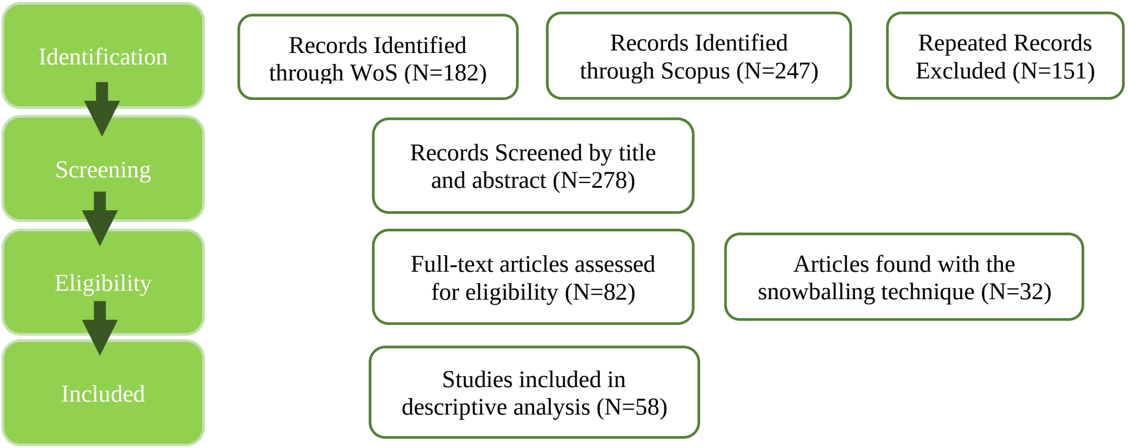


Figure **17** - Summary of the process for the composition of the sample

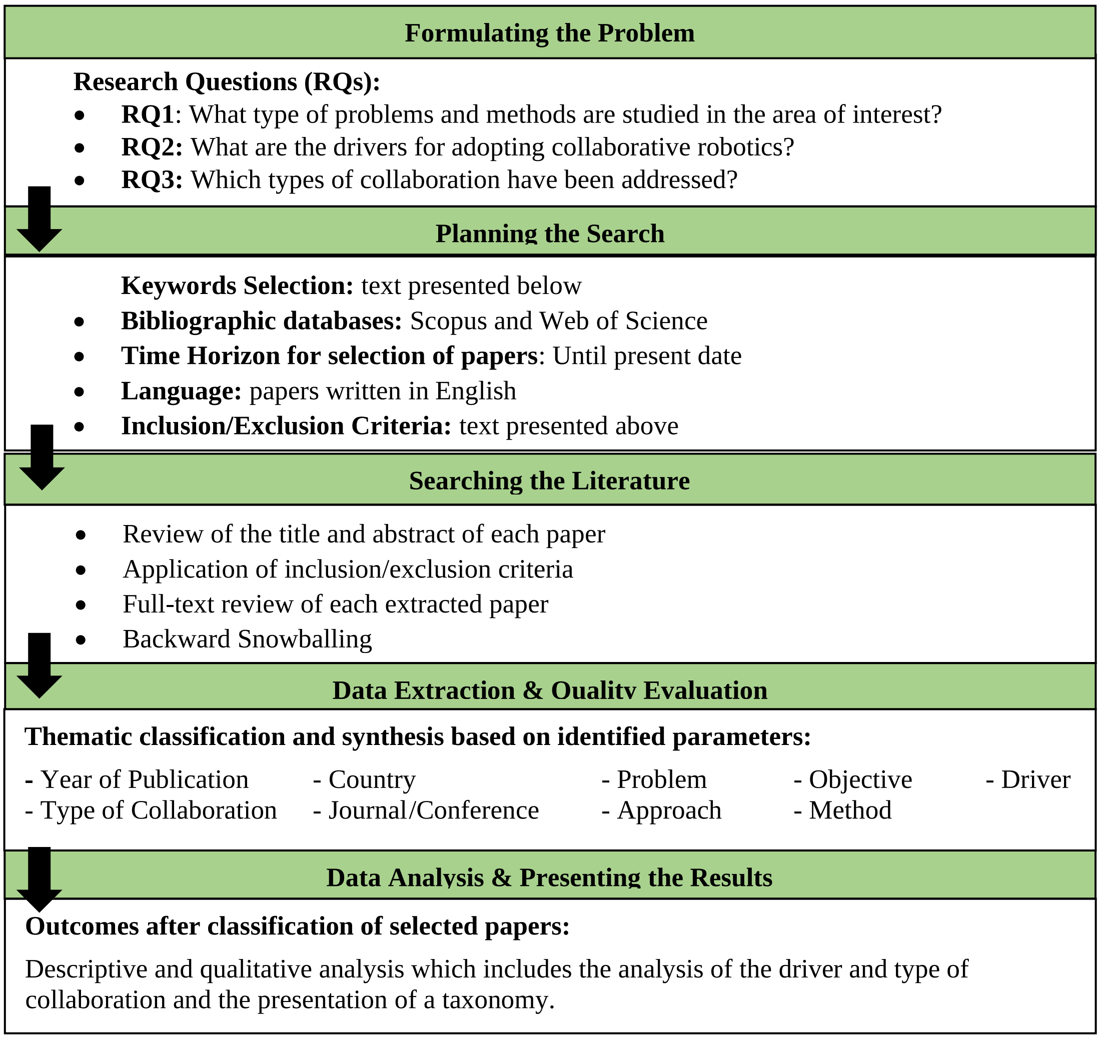


Figure **18** - Systematic Literature Review Methodology

III.3. Quantitative Analysis

This section is dedicated to the description of the knowledge obtained in the paper's sample, bringing an initial overview of the literature analyzed. The content of the papers was further assessed by means of a descriptive analysis aimed to answer the following questions: How is the distribution of publications across time? In which journals or conferences were the articles published? Where are the authors from? Which approaches were presented? What type of problems were studied? What methods were used to study the problems? What were the objectives defined? What were the drivers for adopting CR? What types of HRC are presented?

III.3.1. Time distribution of publications

Concerning the evolution of the number of published articles, Figure **19** shows the growing interest of researchers in the field and its potential for further growth and research. As it can be seen, there was a slow growth until 2016 and since then, the number of published articles in the field has been increasing.

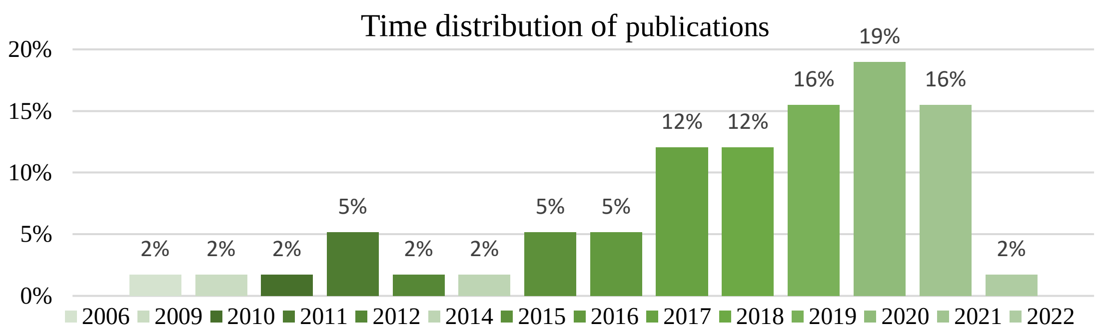


Figure **19** - Time distribution of publications

III.3.2. Journal and Conference Distribution

Although the time distribution analysis demonstrates that the field is relatively new, this analysis showed that the problem of allocating or scheduling tasks in CR is of interest to researchers from diverse areas. A total of 34 journals and 24 conferences covering different areas were found and are shown in Table **3**.

Furthermore, the journal with more published articles regarding the field of interest is the International Journal of Computer Integrated Manufacturing with 5 published papers, followed by Robotics and Automation Letters, the International Journal of Production Research and CIRP Annals - Manufacturing Technology with 4 publications and then by Transactions on Automation Science and Engineering with 3 published papers. In addition, it can be seen by analyzing the pie chart in Figure **20** that most papers found are published in academic journals. Papers presented in workshops or symposiums were integrated in the conference type category.

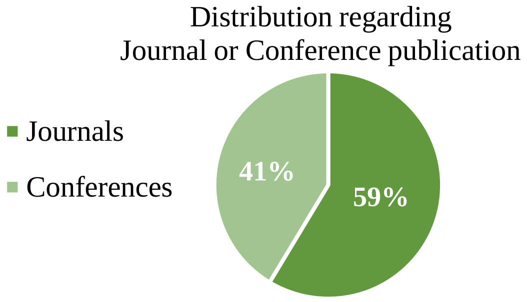


Figure **20** - Distribution of papers regarding type of publication

Table **3** - List of Conferences and Journals

	Name of the Journal or Conference	#
Conference	International Conference on Industry 4.0 and Smart Manufacturing	1
	International Conference on Robotics and Automation	2
	Human-Friendly Robotics 2020	1
	SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI	1
	International Conference on Computer Supported Cooperative Work in Design	1
	American Control Conference	2
	AAAI Fall Symposium Series on AI-HRI	1
	CIRP Global Web Conference	1
	International Conference on Flexible Automation and Intelligent Manufacturing	1
	Automated Action Planning for Autonomous Mobile Robots	1
	Robotics: Science and Systems	1
	International Conference on Control, Mechatronics and Automation	1
	Conference on Systems, Process and Control	1
	Conference on Industrial Product-Service Systems	1
	Conference on Learning Factories	1
	Conference on Manufacturing Systems	2
	International Conference on Intelligent Human Systems Integration	1
	CIRP Conference on Assembly Technologies and Systems	1
	International Conference on Biomimetic and Biohybrid Systems	1
	International Conference on Robotics and Biomimetics	1
	Dynamic Systems and Control Conference	1
Journal	International Journal of Production Economics	2
	Robotics and Automation Letters	4
	International Journal of Production Research	4
	Journal of Mechanical Engineering Science	1
	Journal of Business Research	1
	Computers and Electronics in Agriculture 172	1
	International Journal of Computer Integrated Manufacturing	5
	Robotics and Computer–Integrated Manufacturing	1
	Future Internet	1
	International Journal of Advanced Manufacturing Technology	1
	CIRP Annals - Manufacturing Technology	4
	Transactions on Automation Science and Engineering	3
	Journal of Intelligent Manufacturing	1
	Interaction Studies	1
	Journal of Manufacturing Science and Technology	1
	Acta Astronautica	1
	International Journal of Intelligent Computing and Cybernetics	1
	Mechatronics	1

III.3.3. Country Distribution

The distribution of articles concerning countries is shown in Figure **21**. In total, 17 countries around the globe were found suggesting widespread interest on the field. Undoubtedly, the largest number of contributions on this subject come from the United States of America (USA) with 14 publications and from

Italy with 10 publications. This analysis highlights that scheduling and allocating tasks in HRC is starting to receive much attention from academics all over the world.

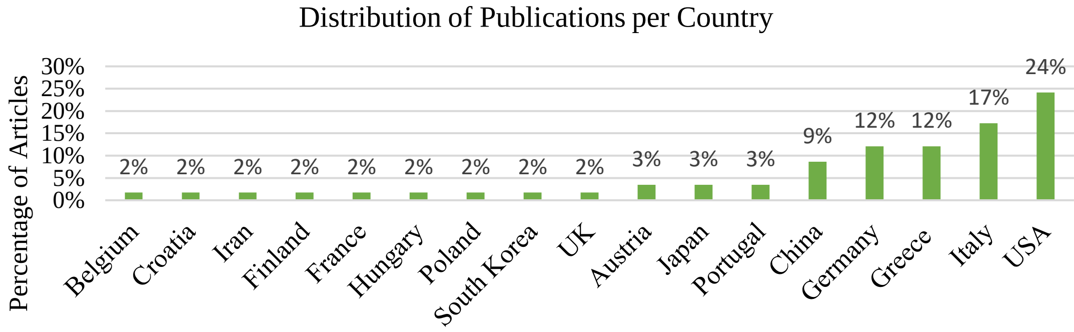


Figure **21** - Distribution of Publications per Country

III.3.4. Approaches applied

Three types of approaches were differentiated: case study (48%), experimental setup (32%) and theoretical problem (20%). The Theoretical Problem category includes examples that had no inspiration at all on real problems. The Experimental Set Up category includes studies where the system or cell analyzed was created, however, the authors could still have been inspired by some real use case. Finally, the Case Study category includes use cases that had inspiration by real industrial applications or benchmarked problems. It is also important to state that the total is 60 instead of 58 inputs because there are papers that present case studies and experimental set ups or that study more than one case study, for instance. Figure **22** shows the assignments of the papers to the respective methodologies.

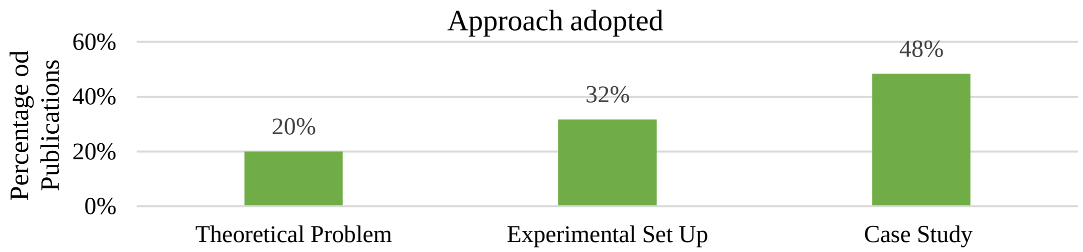


Figure **22** - Approaches adopted by researchers

III.3.5. Type of Problems discussed

As a matter of fact, there is a wide range of problems that are being studied while tackling scheduling tasks in collaborative robotics. Whereas, as it can be seen in Figure **23**, the majority of publications are related to Scheduling problems or variants, as the ones discriminated in Figure **24**.

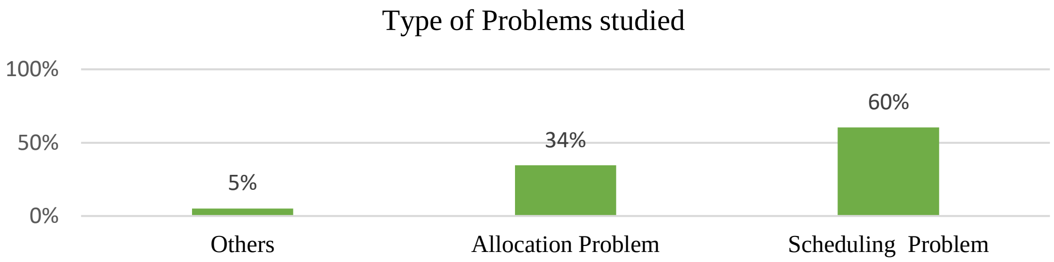
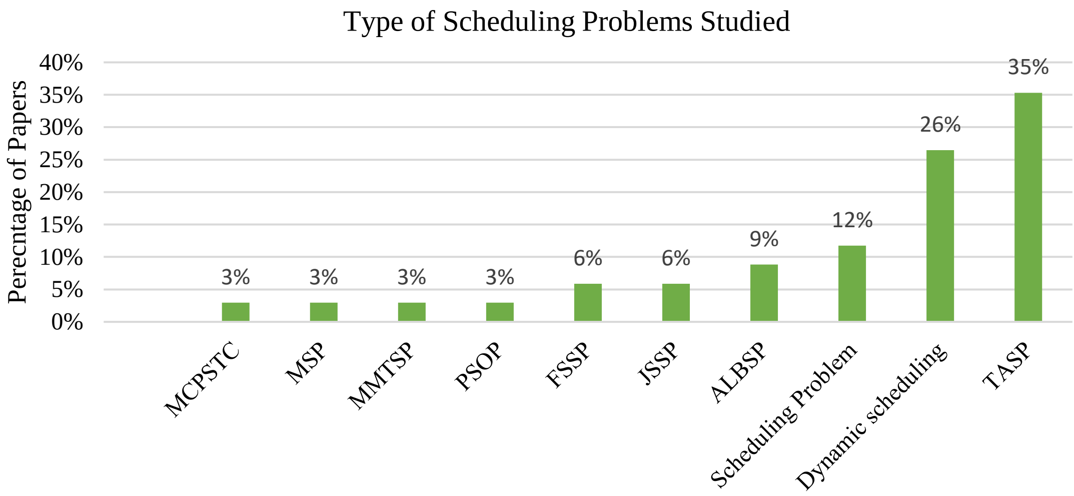


Figure **23** - Type of Problems studied



Legend:
MCPTSC - Multiagent Coordination Problem with Temporal and Spatial Constraints
MSP - Multiagent Scheduling Problem
MMTSP - Multimode Multiprocessor Task Scheduling Problem
PSOP - Planning and Scheduling Optimization Problem
FSSP - Flow Shop Scheduling Problem
JSSP - Job Shop Scheduling Problem
ALBP - Assembly Line Balancing and Scheduling Problem
TASP - Task Allocation/Assignment and Scheduling Problem

Figure **24** - Scheduling Problems and Variants studied

III.3.6. Solution Methods

The methods used to study or solve the problems of allocating and/or scheduling tasks were also assessed. As can be seen in Figure **25** the method with a higher percentage is Metaheuristics (22%) followed by Simulation with 21%. Then, with 19% appear other methods that include for instance Hierarchical Task Analysis and Dynamic Cost Functions.

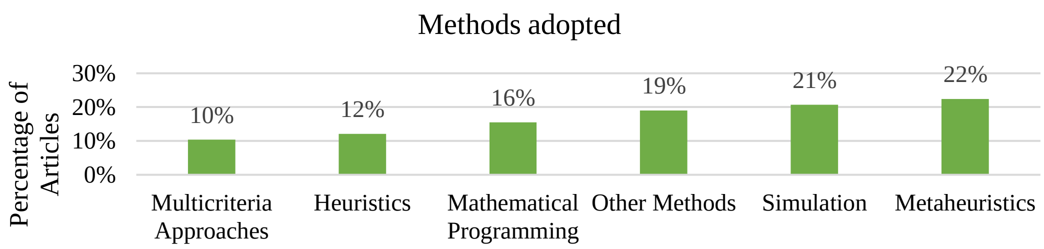


Figure **25** - Different Methods Used

After this analysis, it was important to understand if the strategies adopted were optimal or not optimal, in other words, exact or non-exact. This resulted in 62% of publications that adopted non-exact methods and 38% that studied exact methods, as it can be seen in Figure **26**.

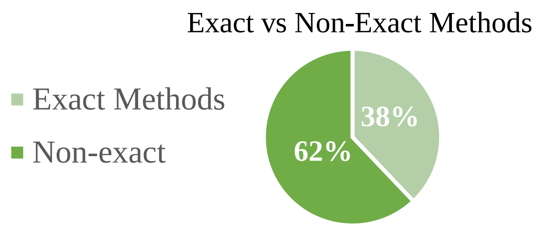


Figure **26** - Exact Methods and Non-Exact Methods

III.3.7. Objectives

It is also important to understand and analyze which objectives were chosen by researchers when it comes to the definition and formulation of the problem. As can be seen in Figure **27**, a wide number of authors (39%) chose to minimize time, such as makespan, cycle time, waiting time, etc. In addition, other papers (19%) consider the minimization of costs, such as investment cost, labor cost or overall cost. In the "Others" category there is a wide variety of different objectives, reason why they were all grouped in the same category, like for instance: travelled distance, maximization of parallelism, maximize trust, etc. Each of these objectives included in "Others" category was only referred once, so they were grouped. It is also important to highlight that "Ergonomics" represent 12% of the objectives including factors such as, e.g., the worker's effort.

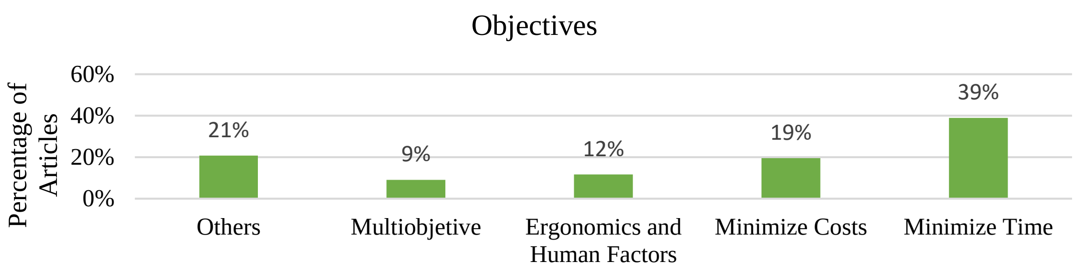


Figure **27** - Objectives used in the problems studied

III.3.8. Drivers

This section and the next, in the authors' opinion represent a greater contribution to the literature because of their distinguished academic interest and novelty. Nowadays, industrial systems are increasingly pressured to become more flexible, and that can be achieved with HRC (Simões et al., 2019). However, to make full use of CR, it is necessary to understand the drivers for their adoption. In fact, understanding these drivers can help motivating industrial organizations companies to adopt cobots, facilitate their adoption, and see the benefits of the technology implementation (Simões et al., 2019). Therefore, following Simões et al. (2019) qualitative study, an overview of the sub drivers and drivers is presented in Figure **28** and Figure **29** respectively.

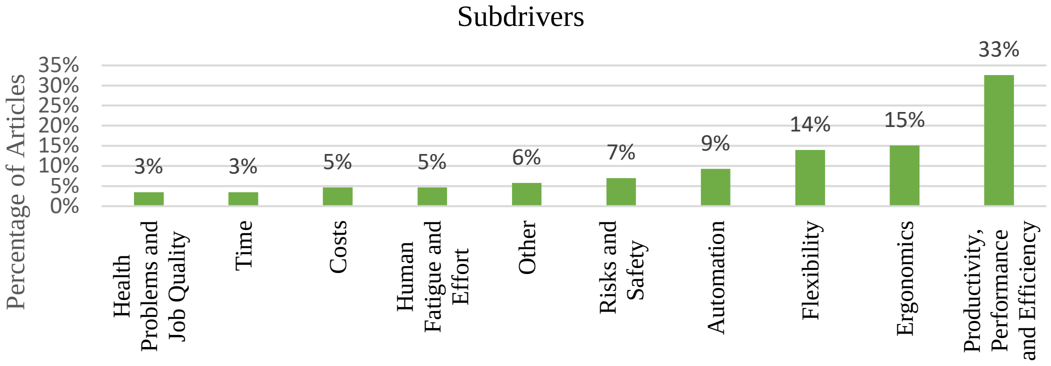


Figure **28** - Sub drivers for adopting Collaborative Robots

By interpreting Figure **29**, it can be seen that "Operational Efficiency" is the driver that is mentioned more often by researchers, representing 64% of publications. Then, appears "Ergonomics and Human Factors" with 30%. Finally, 6% represent other drivers

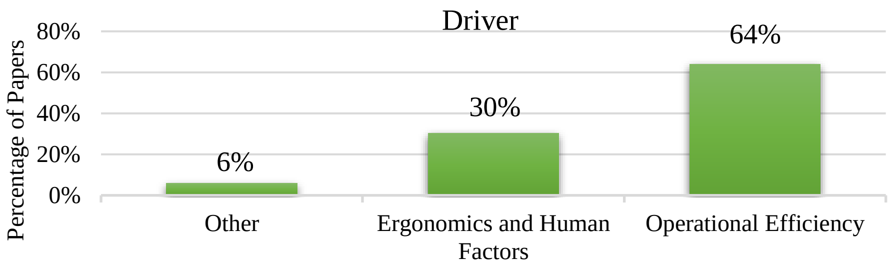


Figure **29** - Drivers for adopting Collaborative Robots

III.3.9. Type of Collaboration

The publications in the sample were then assessed considering the tasks studied under the HRC paradigm, the operations performed by the human versus the ones undertaken by the robot, and the type of collaboration presented. In addition, as there are different types of human-robot interaction, the type of collaboration is identified. The different types of collaboration were classified according to Matheson (2019) who divides human-robot interaction in the categories presented in Table **4** and in Figure **30**.

Table **4** - Types of HRC (Matheson et al., 2019)

Coexistence	Synchronized	Cooperation	Collaboration
When the operator and the cobot are in the same environment but do not interact with each other	When the operator and the cobot work in the same workspace, but at different times	When the human operator and cobot work in the same workspace at the same time, though each focuses on separate tasks	When the operator and the cobot execute a task together. The action of one has immediate consequences on the other, thanks to special sensors and vision systems

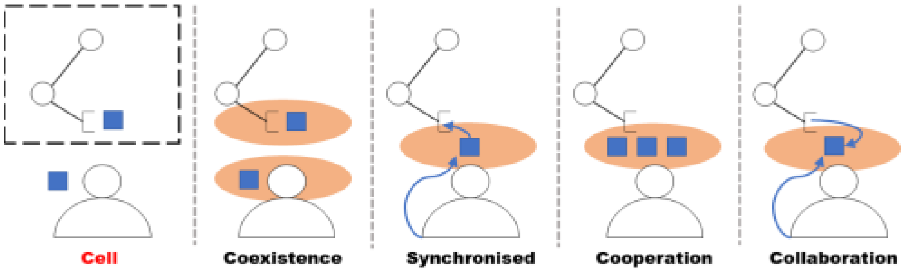


Figure **30** - Types of Collaboration Studied (Matheson et al., 2019)

Concerning the process of identification of the type of collaboration usually, the type of collaboration is not clearly specified in the publication. However, after the interpretation and analysis it is possible to understand the type of collaboration studied. The results of the identification of types of collaboration are presented in Figure **31**. As it can be seen in Figure **31**, 31% of papers study the Cooperation level followed by 26% that study the Collaboration paradigm which is understandable since higher levels of HRI are more challenging and interesting for the academic world.

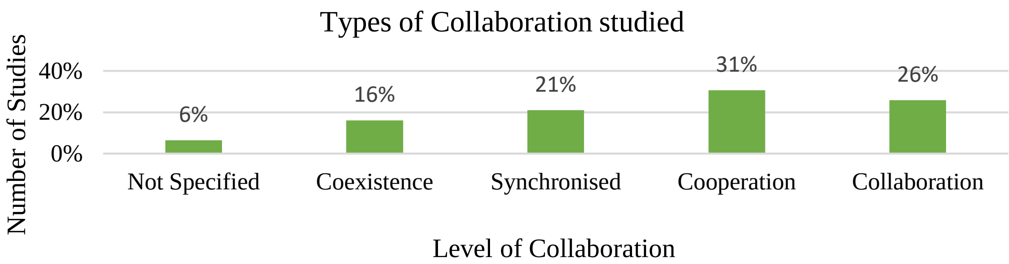


Figure **31** - Types of Collaboration Studied

III.4. Qualitative Analysis

In this section a qualitative analysis will be presented regarding the different methods used to solve scheduling or simply allocation problems that have been studied in the literature. As a matter of fact, this analysis will be helpful for the next task of developing algorithms for scheduling tasks in HRC as it will help to primarily organize the different methods that can be used to solve these kinds of problems. It is important to state that some studies do use more than one method, thus, the corresponding paper was included and described in the method that the authors gave more focus. In fact, among the diversity of solution approaches that can be used, from mathematical programming to metaheuristics, the hybrid combination of different methods has been gathering significant relevance in the reduction of the solution search space towards near-optimal tactical and operational decisions (Vieira et al., 2021).

III.4.1. Heuristics

While task allocation is a general problem and has been discussed intensively, less effort has been devoted to the factors that should be considered in allocating tasks among a heterogeneous team. For this reason, Lamon et al. (2019) investigate the agent characteristics that should be considered in the task allocation problem of fast-reconfigurable systems in industrial assembly processes. The proposed framework presented a modular capability aware solution to the task allocation problem.

Exact methods, heuristic or metaheuristics are commonly used to solve task scheduling problems. However, there are other methods that can be found in the literature. As an example, Hari et al. (2020) presents an approximation algorithm with a greedy heuristic for Task Allocation, Sequencing and Scheduling Problem (TASSP) involving a team with humans and robots (unmanned vehicles). The problem is a generalization of the single Traveling Salesman Problem and aims to find a schedule of tasks for each robot while minimizing the maximum mission time. In this way, the authors presented an innovative method for solving this type of problems as currently, there is no approximation algorithm in the literature available for solving TASSP.

The problem of schedule cooperative tasks in real time among workers and cobots can be reduced to a special case of the flow-shop scheduling problem. Sadik et al. (2017) found a method for planning the interaction between agents and scheduling jobs amongst them. For this, the task under consideration was divided into two steps - the distribution of work between the production stages and the distribution of work within the production stage. For the first case, Johnson's Algorithm was used. Whereas the distribution of work among workers was based on a more complex pattern of predictions using worker average time. The solution was implemented based on multi-agent Holonic Control Architecture.

Undoubtedly, one common studied theme is the allocation of tasks Ranz et al., (2017) proposes an approach based on a heuristic procedure to determine task allocation by considering the actual capabilities of humans and robots in order to improve work quality. The first step includes the breakdown of process sequence. Then the process attributes are matched with capabilities followed by invariable task allocation, where it might be tasks that are uniquely suitable for humans and vice-versa. The next step is variable task allocation considering capabilities indicators. Finally, the allocation task decision can be made.

Takata and Hirano (2011) propose a method for planning human and robot allocation in hybrid assembly systems. The method enables the selection of a selection of an initial allocation, that minimizes the production cost which includes robot investment and labor cost and takes into consideration of future changes in products and production volumes. The authors consider the synchronized type of collaboration and assume that the number of modules of the product is kept constant. However, the results shows that the hybrid system is ineffective when the module changes take place among processes.

Normally, it is common to attribute to the cobot, tasks such as pick and place and assign other more complex tasks to the human. This is done because the worker can easily adapt his performance to assemble a new customized product, yet the cobot can easily adapt to operations based on previously programmed positions. In other words, it is much easier for the worker to adapt to manufacturing operations which require human experience such as assembly. And it is more efficient for a cobot to adapt to simpler operations (Sadik & Urban, 2017). An exact example of these collaborative tasks is presented by Sadik and Urban (2017). This research combines the flow shop scheduling problem with CR. Flow shop scheduling tries to find the solution to optimize the sequence order of jobs and obtain the continuity of the flow of the jobs over the machines which can be obtained by minimizing the delays between two consequent jobs, therefore the overall makespan can be minimized. The case study involves one cobot in cooperation with one worker. Therefore, the first two jobs were scheduled as First-Come-First-Served, then the solution started to schedule based on Johnson's algorithm. Afterwards, it implemented an intelligent control solution which can optimize the flow shop scheduling problem. The case-study implementation optimized two kinds of delay: the first delay is a result of worker starvation and the second was the buffer delay. To minimize this delay, the shortest jobs of the worker were held to the end of the scheduling.

Pellegrinelli et al. (2017) presents an integrated motion planning and scheduling methodology that minimizes cycle time through trajectory selection, task sequence and task allocation. The approach represents a novelty since a task planner and scheduler can manage human unpredictably and robot temporal uncertainty. The proposed methodology is composed by three modules: a Motion Planner, a Flexible temporal Task Planner, and a Plan Executive. As results, the authors state that is useless to pre-allocate a high number of tasks since the initial reduction of the total execution becomes, in the end very small. Moreover, the presented framework is able to reduce the payback time of a robot.

III.4.2. Metaheuristics

Bogner et al. (2018) describe an integer linear programming model which optimally coordinates the distribution of tasks between humans and robots in a realistic production process of printed circuit boards, where the objective is the minimization of the completion time. After the integer linear programming (ILP) formulation, two approaches for the computationally solving are proposed: an order-based heuristic approach and a matheuristic applying a truncated variant of the ILP model. The computational evaluation is based on a real-world use case from the PCB industry

The involvement of repetitive motion with force and heavy component handling during the manual mold assembly causes problems of ergonomics which can be eliminated using a robot. For coping with this issue, Liau and Ryu (2020) propose a task allocation model for the HRC that consists of three agents (one human and two robots. First, assembly operation is decomposed into functional actions. Second, the action assignment is evaluated using the Analytic Network Process (ANP) based on the characteristics and capabilities of each agent. Third, the tasks are allocated to the using the Genetic Algorithm (GA) to minimize the operation cycle time and maximize the agent capability.

According to Calis and Bulkan (2013) as cited in Kinast et al. (2021), in job shop scheduling problems, most of the papers focus on method development and only 8% address real world industrial applications. In addition to this, a lot of research focuses on problems in assembly as industrial environment whereas, Kinast et al. (2021) use a real-world data set and proposes a genetic algorithm with a biased random-key encoding to a collaborative assignment combined with the job shop scheduling problem to the disassembly of electric vehicle batteries. To be recycled, the batteries must be disassembled, which involves dealing with hazardous substances for humans. In fact, it is difficult to program traditional industrial robots for these tasks since there is a huge variance in the batteries. Cobots, by contrast, can be assigned to many tasks of disassembly and by working closely together with a human, they provide the reduction of costs and risks. The objective function is a weighted function between production cost and makespan that must be minimized.

However, characteristic differences between human and robot bring challenges to collaboration task scheduling. Therefore, M. Zhang et al., (2021) studied the task scheduling of a HRC assembly cell to achieve a trade-off between job cycle and human fatigue by integrating microbreaks inside job cycles. To achieve this, a genetic algorithm was developed aiming to minimize the job cycle while having human fatigue as a constraint.

Indeed, scheduling problems are very much explored in assembly scenarios. A much less explored application in the field of HRC concerns the disassembly of electric and electronic devices, which is highly relevant to Waste Electric and Electronic Equipment (WEEE) recycling. Despite the increasing importance of WEEE recycling, much of the disassembly is still performed by human workers. Hence, Chatzikonstantinou et al. (2019) present a hybrid approach between a global search metaheuristic and an adaptive greedy operation assignment and scheduling algorithm to tackle the problem of task assignment and scheduling in human-robot teams that undertake collaborative disassembly tasks.

Balancing assembly line problems are also important to study in collaborative robotics. For that reason, Weckenborg et al. (2020) developed a novel approach for the human-robot collaborative assembly line and scheduling problem which is characterized by the possibility of humans and robots simultaneously executing tasks either in parallel or in collaboration. In fact, since robots are additional resources, they need to be allocated. Consequently, it is interesting to enrich the Assembly Line Balancing Problem (ALBP) with scheduling problems. For this reason, a MIP model, and a metaheuristic, a hybrid genetic algorithm, was developed. Furthermore, Weckenborg et al. (2020) refer those common approaches do not consider the optional collaboration of multiple resources on one task, instead each task is assigned to only one resource. In fact, most research only considers assigning a task to the human or to the robot. However, the option of assigning the robot and the human to the same task has a major importance for scheduling tasks with collaborative robots. Moreover, the results indicate that substantial productivity gains can be achieved by deploying cobots in manual assembly lines.

Dalle Mura and Dini (2019) propose a genetic algorithm to approach the ALBP to establish a proper task assignment combining robot productivity and human flexibility. The case study explores an assembly line of scooters' chassis which is characterized by repetitive handling operations and quite heavy components. The results demonstrate a reduction of the cost of the line and of the energy load variance among workers, optimizing the allocation of collaborative robots, equipment and achieving a proper assignment of humans, according to their skills.

Raatz et al. (2020) propose a user-friendly approach to find an eligible division of tasks that renounces expert knowledge and simulations. The approach includes task scheduling, hardware selection and layout. However, the focus of this paper lies on the task scheduling part, which is based on the Methods-Time Measurement (MTM) and uses a Genetic Algorithm (GA) for task scheduling. The user does not require expert knowledge but rather a good understanding of the characteristics of the production process. Therefore, process planners, who had little experience with HRC so far, can plan workplaces and gain additional skills. Expert evaluation and real implementation in an industrial use case prove the effectiveness of the proposed approach.

Ferreira et al. (2021) study the performance of a human-robot team by solving the scheduling problem under different production settings. Thus, the problem is formulated as a Multimode Multiprocessor Task Scheduling Problem, where tasks may be allocated by two different types of resources (humans and robots), or by both simultaneously. A Constraint Programming model and a Genetic Algorithm are proposed. Then, computational experiments are conducted on a large set of instances generated. The experiments suggest that collaborative tasks reduce total work time, especially in settings with numerous precedence constraints and low robot eligibility. The results indicate that collaborative work can shorten cycle time, which may motivate investment in this technology.

When it comes to task sequencing in human-robot collaboration it is clear that most publications focus on an assembly system. However, Li et al. (2019) studies disassembly which plays an essential role in remanufacturing and is starting to gain importance because of sustainability reasons. The authors integrate human fatigue into the sequencing of tasks. The proposed method includes the modeling of product constraint and human fatigue, then the task allocation method considering the weight, quality and difficulty of parts, and the characteristics of humans and robots and finally a discrete Bee's algorithm. During the performance analysis it was clear that the Bee Algorithm outperforms other metaheuristics. One important comment to state is that most studies study sequencing planning on a single product, but in this paper the disassembly sequence planning is based on batch products.

Howard (2006) focus on maximizing system performance for future space exploration missions involving a team composed by humans and robots. Therefore, the author proposes a methodology for task allocation where tasks are allocated to the human or to the robot, taking into consideration the system's performance. This methodology based on genetic algorithms includes the concept of task switching and considers the capabilities of each agent and the effect of repetitive workload or stress on the human. Despite the interesting work in a brand-new topic for the time, the paper only focuses on the simplest level of collaboration which can be interpreted as coexistence leaving the collaboration for future work.

Chen et al. (2014) develop a genetic based revolutionary algorithm for offline or online task scheduling and reliable subtask allocation. This task allocation strategy is built for a human who collaborates with various robots. The performance of the proposed algorithm is experimentally studied on an electronic assembly case. The scheduling problem is modeled as Resource Constraint Project Scheduling Problem (RCPSP) and two scenarios are studied: sequential and parallel task scheduling between the human and several robots, while minimizing the assembly time and the payment cost. The algorithm proved to be fast in reaching a semi-optimal solution, therefore it can be used for offline or online scheduling.

Chatzikonstantinou et al., (2020) present a new approach to topological and temporal orchestration of HRC, considering the capabilities of each type of agent. They propose a two-stage approach to orchestrating large HRC teams. Firstly, a topological and task assignment problem is solved, however it does not take into consideration the sequence of tasks. Secondly, the result of the previous step is used to initialize a constrained search: Variable Neighborhood Search, for an efficient schedule. The human-robot collaboration is performed in two ways. On the one hand, at the workstation, the humans can cooperate with a fixed robotic manipulator arm, which undertakes disassembly steps. On the other hand, in terms of device transport, Autonomous Ground Vehicles (AGVs) are used to pick components from the respectively workstations. The scheduling problem is formulated as a Mixed-Integer Linear Problem (MILP) and then solved using computation.

III.4.3. Mathematical Programming Approaches

III.4.3.1. Linear Programming Approaches

Adding robots to workstations to assist human workers provide many advantages. Koltai et al. (2021) analyze this matter by developing and comparing mathematical programming models for the following three cases: only workers are assigned to workstations; either a worker or a robot is assigned to a workstation and a robot, and a worker are assigned to workstations. The results showed that the use of robots may decrease cycle time but does not reduce the number of stations, however other considerations must be considered like for example, adding robots to workstations may reduce the exposure of workers to hazards.

Collaborative robots can also bring value not just for industrial scenarios but also for office environments. Coltin et al. (2011) deploy a mobile robot at an office environment, focusing on the challenge of planning a schedule for a robot to accomplish user-requested actions. The cobot executes navigational based tasks requested by users, such as telepresence or picking up and delivering messages or objects at different locations. The scheduling problem is converted to a mixed integer programming problem.

Aiming at increasing productivity and ergonomics, Maderna et al. (2020) introduces an online scheduling algorithm to guide the picking operations of the human and the robot. Kitting is the process of grouping separate items together to be supplied as one unit to the assembly line. Overall, the proposed online scheduling algorithm enables effective HRC with good performance if compared to both the traditional human kitting process and an offline scheduler.

In collaborative robotic systems, a human operator and a robot share the workspace to execute a common job which has a set of tasks. Therefore, a proper allocation of the tasks is crucial for achieving an efficient HRC (Pupa, Landi, et al., 2021). To deal with the unpredictability of humans and allowing the communication between the human and the robot, Pupa, Landi, et al. (2021) proposes a two layers architecture for solving the task allocation and scheduling problem. The first layer solves the task allocation problem considering nominal execution times. The second layer adapts online the sequence of tasks considering deviations and the requests from the human or from the robot. One particular and important feature of this article is the integration of the communication between the different agents, which most of the research does not take into consideration.

Regarding HRC, one important factor that must be considered is job quality. In fact, cobots can take over dangerous tasks. To ensure that the distribution of tasks is favorable to the human, job quality must be considered when scheduling tasks between a human and a robot. Pupa, van Dijk, et al. (2021) proposes a two-layered architecture for task allocation and scheduling in a collaborative cell where job quality is explicitly considered. In addition, the tasks are dynamically scheduled based on the real time monitoring of the human's activities.

Pearce et al. (2018) propose an optimization framework that generates task assignments and schedules for a human–robot team aiming at improving time and ergonomics. Six real-world manufacturing processes that are currently performed manually are studied. A set of solutions is created with assigned priorities on each goal using the strain index method to quantify human physical stress. The resulting schedules provide engineers with insight into selecting the appropriate level of integration for the robot in the way that best fits the needs of a process.

III.4.3.2. Constraint Programming Approaches

HRC can increase productivity and reduce ergonomic risk but the numbers and types of robots and stations in which robots are allocated need to be determined. Stecke and Mokhtarzadeh (2021) study a collaborative human-robot assembly line problem integrated with an ALBP with operation assignment and scheduling problems. Mixed Integer Linear Programming (MILP) and Constraint Programming (CP) models were developed, and Bender's decomposition algorithm was used to analyze advantages of cobots in assembly lines. In addition, in this work it is given a huge importance to ergonomic risk and an energy expenditure method was used to evaluate it. Operational advantages and scheduling constraints from HRC were studied when immobile and mobile robots were used, and regression lines were developed which help managers determine how many and what types of robots are best for a line. The best configuration found was when (number of robots)/ (number of stations) is near 0.7 (Stecke & Mokhtarzadeh, 2021).

A sector that specifically utilizes human-robot collaboration is the printed circuit boards industry. Therefore, proper allocation of tasks to humans and robots is crucial in this industry. Mokhtarzadeh et al. (2020) investigates this type of allocation to minimize makespan. A Constraint Programming approach is developed to solve the problem. A single board problem is also developed. Then, experimental instances are generated and solved to analyze the performance and the sensitivity of idle time and makespan to key parameters of the problem. The superiority of the computational results of constraint programming over mathematical programming is evident.

Human-robot collaboration presents an opportunity to improve efficiency of manufacturing and assembly processes, particularly for aerospace manufacturing. Wilcox et al. (2012) developed a robotic scheduling and control capability that adapts to the changing preferences of a human while providing guarantees for synchronization and timing. The Adaptive Preferences Algorithm is developed which computes the flexible scheduling policy and show empirically that its execution is fast and adaptable to the changing preferences.

III.4.4. Multicriteria Approaches

Dianatfar et al (2019) had the goal to demonstrate that human-robot collaboration could have the capability to increase productivity compared to manual workstations, however, according to conducted time work study the productivity did not increase. Whereas it can be concluded that the workload for the operator decreased significantly. The method for tasks allocation focuses on factors such as: task complexity, ergonomics, payload and repeatability. One important comment to state is that the method provided the allocation of both human and robot to the same tasks which few publications. In the case study, three levels of interaction were studied where the higher level included a shared task with physical interaction: “handing-over”.

The traditional task assignment methods in the intuitionistic fuzzy environment only consider two options, the task is executed by humans or robots. However, some tasks may need to be completed by humans and robots. Therefore, it is important to consider the three possibilities. (L. Zhang et al., 2021) propose a human robot task assignment method using TOPSIS.

Michalos et al. (2018) propose a multicriteria method along with a search algorithm to the generation of possible assignments while considering the spatial layout of the assembly workplace. The paper focuses on two different problems: layout planning and task assignment based on the agent characteristics. The criteria that can be used include: the robot reach, strength, robot payload, ergonomics, cost, investment, floor space, time saturation, fatigue, and handling time. The developed tool has been tested on a case study in automotive assembly of a vehicle’s rear axle. However, the authors state that some assumptions were made such as: the scope of the process planning is limited to a single workstation and the exact motion plans of the robots or the actions to be performed by the humans are not addressed.

Nikolakis et al. (2018) also developed a method for scheduling shared HR tasks supporting on-line rescheduling considering the suitability of resources. For a given task, there may be one or more suitable resources (human, robot, human and robot, or human and human). The suitability is decided upon the skills and availability of resources. The decision-making framework involves multiple criteria: total weight, total duration of human tasks execution per cycle, production rate and operating cost. The result of criteria evaluation multiplied with the selected weights is named “utility”. The results of the automotive industry case study showed that the highest achieved utility was when the human was less involved in tasks requiring heavy lifting which minimized the operating costs.

Tsarouchi et al. (2016) propose a method for task planning and sequencing based on a multicriteria decision-making that could include criteria such as: average resource utilization, mean flowtime, ergonomics, etc. In this paper, only the first and the second previously criteria are studied. The method is implemented into a graphical software tool and applied to the automotive industry in the assembly of a dashboard. The tasks can be performed by a single arm robot, by a dual-arm robot or by the human. The best alternative scenario demonstrated that the involvement of the human can be significantly reduced, enabling him/her to have a more supervisor job. However, ergonomics is not addressed in this paper, but the method can be replicated by others who can choose ergonomics as an additional criterion.

Clearly, HRC, as a part of Industry 4.0 strategy, requires a completely new type of robots able to co-work with humans. This kind of collaboration is especially needed in assembly systems, which are known for having a low level of automation. However, some assembly tasks are still irreplaceable. On the other hand, others might be assigned to cobots. Therefore, Gjeldum et al. (2021) propose a different approach to properly allocate tasks between humans and cobots. In fact, a task allocation procedure is presented for identification of different improvement options that utilize cobots into the assembly line. The decision support system is based on the HUMANT (humanoid ant) algorithm, and a multi-criteria approach is used with the following criteria: reduction of the cycle time, total investment cost, increase of workspace layout and worker effort reduction. The procedure is experimentally tested on an assembly line with car gearboxes. More importantly, although most case studies deal with simpler types of HRC as coexistence or cooperation, this case study approaches the highest level of HRI: collaboration.

III.4.5. Simulation

Another field that can be found regarding scheduling problems is unmanned vehicles. Shannon et al. (2016) developed algorithms that integrate humans into the planning problem to produce allocations for human-robot teams, in this case, unmanned aerial vehicles. In fact, other approaches to multi-agent task allocation and scheduling do not extend well to missions in which humans coordinate closely with robotic teammates due to the dynamic and stochastic nature of human performance which Shannon et al. (2016) tried to fix.

Hu and Chen (2017) studies an optimal task allocation problem for human-machine collaboration which is extremely challenging because of the stochastic nature of manufacturing processes as well as the human fatigue. The problem of interest is how to allocate tasks between humans and machines so that human and process performance can be optimized while considering human constraints. First, the authors model human fatigue as a continuous-time Markov decision process. Secondly, a controlled stochastic petri net to model the process is presented. Thirdly, the problem is solved by linear programming. Finally, the findings were simulated.

Vieira et al. (2021) explores a planning and scheduling optimization problem of a multistage assembly line, where tasks can be collaboratively performed by human operators and mobile robots shared among workstations using Recursive Optimization-Simulation Approach (ROSA) methodology which involves simulation. The proposed methodology is studied in an industrial case study of an integrated production planning and scheduling solution with the corresponding collaborative human–robot allocation, while minimizing operational costs and production makespan.

Bänziger et al. (2020) introduces a simulation tool based on standardized work descriptions. The tool is capable of calculating different objective parameters such as production time or ergonomics as a function of task allocation for the human-robot team- The simulation is validated with a real case study in a Volkswagen automotive assembly line. In addition, a method for the task allocation using the simulation as a fitness function in a genetic algorithm. The tool provides the simulation of different tasks allocations of the worker and the robot aiming to reduce the waiting time and the walking distance.

Casalino, Zanchettin, et al. (2019) propose a scheduling algorithm for collaborative tasks that allows to optimally plan assembly activities based on the collected data from the manufacturing process during runtime and so adapts to variations along the life cycle of a process. The goal is to reduce idle time and the scheduler is based on time Petri nets and solved with Monte Carlo Simulation. The method is demonstrated on a realistic case study, where two robots and a human cooperate to assemble a USB/microSD adapter.

Chen et al., (2011) propose a model to the human and robot coordinated cell assembly within the high-mix low-volume environment. A dual Generalized Stochastic Petri Net (GSPT) model is theoretically studied. Then, the task is decomposed into subtask in order to be allocated to the human or to the robot. Secondly, dual GSPN is generated for each allocation. Thirdly, a Monte Carlo Simulation is performed. Fourthly, the allocation is optimized using Multiple Objective Optimization. Finally, Semi-Optimal Allocations are generated and experimented.

Mutual trust is a key factor in human-human collaboration. Inspired by Wang et al. (2015) analyze human-agent mutual trust in the collaboration of human and (semi)autonomous multi-agent systems. The authors propose time-series human agent mutual trust models. To avoid both over-trust and under-trust, dynamic timing models for the multiagent scheduling problem are set up. The effectiveness of the proposed Model Predictive Control (MPC) scheduling algorithm is tested using Matlab simulations which showed that the proposed algorithm guarantees the effective real-time scheduling of the human multi-agent collaboration system while ensuring a proper level of mutual trust.

Pini et al. (2020) suggest a design method to identify the best scheduling for human-robot collaboration considering the balance between safety constraints and production goals. In addition, the authors stress the usage of virtual simulation to replicate the actions of humans and robots and propose a safety index formulation. The method studied, firstly, focuses on product analysis. Secondly, process analysis and resources definition are focused. Thirdly, a virtual simulation is conducted. Finally, a scheduling algorithm is developed for the task scheduling.

Collaborative Robotics can be used in very diverse environments such as assembly, disassembly, manufacturing and even in agriculture! Seyyedhasani et al. (2020) analyze scheduling strategies for harvest-aid robots that transport trays during manual harvesting which can increase harvest efficiency, by reducing pickers' non-productive walking times. As a matter of fact, in addition to labor cost, increasing farm labor shortages are driving the harvest automation, however, fully automatic harvesters have not successfully replaced yet the dexterity and speed of humans. As an alternative, teams of small transport robots have been proposed. Seyyedhasani et al. (2020) modeled and simulated the collaboration of humans and robots. Moreover, the described case study, aimed to predict the waiting times and harvest efficiencies of a crew of strawberry pickers when transport robot teams of increasing sizes were deployed, and three different priority-based reactive scheduling strategies were used to schedule robots: First-Come-First-Serve (FCFS), Shortest-Processing-Time (SPT) and Longest- Processing-Time (LPT). Overall, LPT had the worst performance. Deploying five robots enhanced the harvest efficiency up to 92% and 86.5% for morning and afternoon harvesting respectively, which was 81.8% for morning and 78.2% for afternoon manual harvesting. However, despite being such an interesting case of human-robot collaboration, the scheduling policies only refer to the robots, which means that humans are not incorporated in the scheduling methods.

Tsarouchi, Michalos, et al. (2017) studied workplace design and task allocation for a human-robot team. The proposed method includes a multicriteria decision-making framework and simulation to the estimation of the criteria values which provides the analysis of different alternatives. The user can decide the criteria most adequate for the analyzed systems such as payload, reachability, capability, number of resources, shop floor utilization, total completion time, investment cost and human ergonomics. Two case studies are addressed one from the white goods industry and the other one from the automotive industry. The tasks under analysis are discriminated and the proposed schedules are presented. Some tasks are performed parallelly and in one of the use cases the human even guides the movement of the robot which is an example of pure collaboration. Whereas, this work does not focus on a real-time planning method, but instead an offline approach.

Tsarouchi, Matthaiakis, et al., (2017) propose an intelligent decision-making algorithm for tasks allocation, through the evaluation of multiple criteria. The analysis about the decision steps in task allocation includes the resources suitability, availability, and processing time. This method allows human-robot task allocation and is then integrated within a Robot Operating System framework. The proposed approach enables the allocation of sequential tasks assigned to a robot and a human in separate workspaces, so the focus is given to the human–robot coexistence for the execution of sequential tasks, to increase the level of automation. The proposed framework is then implemented on a manual assembly line of an automotive industry.

Typical applications of collaborative assemblies, require humans and robots to share a common space to accomplish common tasks which imposes to predict human's actions and control the robot for safety reasons. Moreover, the uncontrollable nature and variability of the human introduce other sources of uncertainty. Therefore, Casalino, Mazzocca, et al. (2019) propose a fuzzy scheduling approach for managing in an optimal way the uncertainties arising. A scheduling algorithm is proposed which makes use of predictions about the human future behavior to produce an optimal plan for robotic actions, minimizing the waiting time. The fuzzy theory is adopted for computing the reachability trees of fuzzy timed Petri Nets. Then, realistic experiments, involving the assembly of two products, are performed using a dual arm robot.

III.4.6. Other Methods

Bruno and Antonelli (2018) address the task assignment problem by proposing an interesting task assignment procedure. This strategy consists of 3 activities. First, a set of indicators is associated with each task to describe the features of the task. Secondly, based on the indicator values, a classifier assigns tasks to the following classes: executable by a human, executable by a robot, executable by human or robot, executable by a human and a robot. Thirdly, the final assignment is provided by considering task length and precedence constraints. One interesting aspect of the method is that it considers the characteristics of the job and the different skills of humans and robots. The proposed method was tested on a proof-of-concept scenario and in an actual industrial process. Another important comment to make is that, differently from classical workload balancing problems, Bruno & Antonelli (2018) were not interested in balancing the work between a human and a robot, since it is better to assign to the robot the heaviest workload. In addition, there was no interest in solving an optimization problem, since the times for executing tasks can be variable, so they can be reassigned dynamically during the process.

HRC is expected to add flexibility to production lines (Maderna et al., 2022). In this context, versatile scheduling algorithms are needed to exploit the gained flexibility. As a matter of fact, offline scheduling is commonly used for sequencing tasks. However, increasingly there is more research in online scheduling. Static schedulers are commonly used because of their simplicity. However, when a high degree of flexibility is required, static schedulers are not robust to the uncertainties. In these cases, the use of dynamic schedulers is preferable. For these reasons, Maderna et al. (2022) presents a dynamic scheduler that adapts to the system variability. The scheduling algorithm was based on Timed Petri Nets (TPN) to predict the future evolution of the system and determine the optimal control action. The proposed strategy accounts for the variability in the duration of human tasks and the occurrence of robot faults, allows the concurrent assembly of multiple products and solves on-line task allocation and sequencing. The advantages of the dynamic scheduling over the static one was clear: the use of a dynamic scheduler attains better performance, and the average cycle time decreases by 15.6%. Another interesting aspect is that the concept of HRC proposed, goes beyond the pure human–robot coexistence.

Scheduling human-robot teams is a challenging problem which must consider several variables. Gombolay et al. (2015) developed a scheduling algorithm that integrates the preferences of the humans - Tercio Algorithm. In addition, this article also analyses how decision-making authority over scheduling decisions should be shared between team members and how these preferences should be included. The case study created is the assembly of Lego and while the human can fetch and build, the robot can only fetch. The results showed, for instance, that humans would rather work with a robot that considers teammate preferences as opposed to a robot that is unaware. However, it was also found that a robot prioritizing the preferences of human workers may decrease team efficiency.

The implementation of collaborative robots should be supported through procedures and guidelines. Stadnicka and Antonelli (2019) approach the problem of collaborative cell design with lean thinking. The authors propose a procedure of seven steps which can be useful to implement HRC: step 1 - Identification of the work elements; step 2 - measurement of the duration of a work element; step 3 - work analysis; step 4 -t ask assignment where the tasks should be assigned to robots and humans, taking into account the nature of the tasks, safety and weight of parts; step 5- experiments; step 6 - comparison of the cycle time and the takt time and step 7 - FMEA. For the task assignment step, it is recommended the use of Hierarchical Task Analysis, Unified Modelling Language Activity Diagram, and a Gant chart to present the sequence of the activities together with their durations.

Makrini et al., (2019) propose a novel framework for task allocation of human-robot assembly tasks of a gearbox considering their capabilities and ergonomics aspects. The method is composed of 4 modules: the task decomposer, the capability evaluator, the ergonomics evaluator, and the task allocation module. The ergonomics is determinate by evaluating the posture of the human using the Rapid Entire Body Assessment. The paper presents the description of the tasks, its sequence and valuates the approach in an experimental setup where the robot truly collaborates with the human using cameras and a button which is used for the human-robot interaction. The experiments are tested for 2 values of workload: 0.75 and 1.5.

One different but interesting field that could be found in the process of the SLR was Space Missions. Singer and Akin (2010) extend the task allocation and scheduling methodology from(Singer & Akin, 2008) to assess the impact of the robot in the overall team performance. The methodology considers real world and precedence constraints to produce schedules. In addition, the method includes the strengths and limitations of each type of agent and is capable of minimizing the involvement of the astronaut as well as his/her workload. The first step of the methodology is the task decomposition where each task is decomposed into subtasks which are further decomposed into activities. One of the conclusions of the author was that if a cooperative robot were implemented in the mission studied in the case study, twice the volume of tasks could have been accomplished. However, having tasks performed by a human-robot team introduces interferences issues that were not addressed in the paper.

Müller et al., (2016) present an approach to process-dependent task assignment of humans and robots which is based on the analysis skills of humans and robots, in order to balance the product and process characteristics. Two scenarios are studied are studied: coexistence and synchronized considering the assembly of an airplane fuselages. The analysis of skills is an appropriate basis for an initial task assignment; however, it must be integrated into an overall assessment, taking into account layout, ergonomics, acceptability, and cost. The results described do not include ergonomic analysis or detailed profitability calculation.

Tan et al. (2009) aim to model the collaboration between human and robots in a cell production system by task. Therefore, the processes are modeled into Hierarchical Task Analysis (HTA) with the extension of collaboration modeling to enable further investigation on the collaboration between human and robot. The model is then validated in an experimental setup inspired by an actual assembly operation of the cable harness assembly. The first step is to identify possible collaboration tasks in the entire operation, which were found independent coexistence) and assisted (collaboration) operations. Then, once the collaboration tasks are identified, collaboration roles: ‘Human-Robot’, ‘Human’ or ‘Robot’ are assigned to lower hierarchical task components.

According to Smith et al. (2020) the core limitation of current research into HR collaborative task planning, is that human abilities are assumed offline which limits the abilities of task planners to adapt to unpredictable changes. However, Smith et al. (2020) proposed to instead infer the current state of human and robot abilities by monitoring them to make task allocations based on current worker capabilities in a semi-online manner. To achieve this, dynamic cost functions that quantify capabilities and performance of the human and the robot were developed. Two cost functions are presented, one regarding completion time and other regarding fatigue. Fatigue was chosen as it can affect human performance. As expected in the bolt tightening task, the robot had a larger cost than the human worker regardless of the level of fatigue experienced. In the pick & place task, the robot had a lower cost than the human. However, it was possible to identify some limitations. In fact, the human and the robot are modeled separately in the two tasks and only the performance-based cost functions were tested, and the quality of task execution is assumed to be sufficient.

Rahman and Wang (2018) and Rahman et al. (2015) study an interesting aspect of the collaboration between the robot and the human: mutual trust. The authors state that in order to have efficient human robot collaboration, the agents must trust each other, in other words, the human should trust the robot, but the robot should also trust in the human. A two-level feedforward optimization strategy is developed and tested in an experimental set up where a human and a robot assemble LEGOs together. However, fatigue and ergonomics of humans is not the focus of this paper.

In Figure **32** it can be seen an overview of the methods identified. In Table **14**, all the papers included in the sample are specified, along with the environment, type of problem, main characteristics, objective, method, and the driver for adopting collaborative robotics.

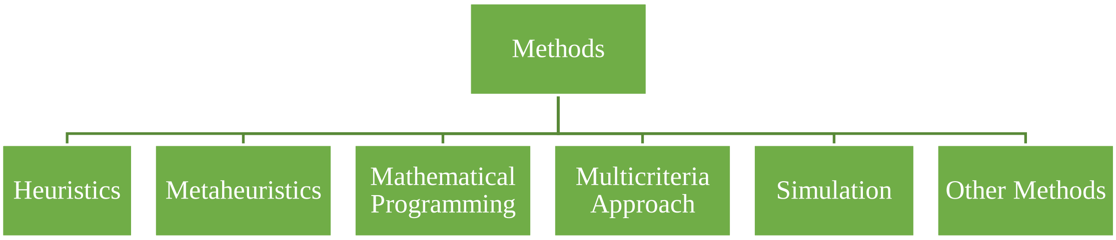


Figure **32** - An overview of the methods identified

III.5. Characteristics of Scheduling Problems in Collaborative Robotics

Grounded on our sample analysis, since Table **5** to Table **9** it is presented a characterization of scheduling problems in collaborative robotics. The main objective of this category is to clearly identify the main characteristics used in the literature for studying scheduling problems in collaborative robotics which can help researcher in the phase of the problem formulation. Moreover, it is important to state that for this analysis only 26 papers were included because they tackled a scheduling problem and presented a formal formulation of the problem. In order to make sure that all the important characteristics were included, Graham's Notation for scheduling was taken into consideration.

In Table **5**, the Task group comprehends an operation that cannot be subdivided. In fact, in the literature, besides the latter concept of "task", it is also referred, subtask, work-element, or operation. We considered that a Job is concept which is composed by a group of tasks (non-divided elements). This statement is important to make because of the diversity of vocabulary found. No-overlap of tasks or jobs means that an agent (robot or human) can only perform one task at a time, which mean that only one task at a time will be assigned to the agent. Preemption means that a task or job can be interrupted before its end. The section of capability indicators means that a robot has tasks which is more capable of doing or, in other words, are more indicated to the robot than the human or vice-versa. In Table **6**, passive resources represent machines, tools, etc. In Table **7**, unrelated machines represent machines when the processing time depends on job/task and machine, on the other hand, parallel machines represent identical machines.

Table **5** – Job and Task characteristics of Scheduling Problems in Collaborative Robotics

Characteristics	Papers
Jobs	(Sadik & Urban, 2017) (Chatzikonstantinou et al., 2019) (Chatzikonstantinou et al., 2020) (Chen et al., 2014) (Kinast et al., 2021) (M. Zhang et al., 2021) (Ferreira et al., 2021) (Pearce et al., 2018) (Pupa, Landi, et al., 2021) (Pupa, van Dijk, et al., 2021) (Maderna et al., 2022)
Throughput rate per job	(Chatzikonstantinou et al., 2020)
Job Quality	(Pupa, van Dijk, et al., 2021)
Tasks	(Bogner et al., 2018) (Hari et al., 2020) (Chatzikonstantinou et al., 2019) (Chatzikonstantinou et al., 2019) (Chen et al., 2014) (Kinast et al., 2021) (M. Zhang et al., 2021) (Weckenborg et al., 2020) (Coltin et al., 2011) (Koltai et al., 2021) (Maderna et al., 2020) (Pearce et al., 2018) (Pupa, Landi, et al., 2021) (Pupa, van Dijk, et al., 2021) (Mokhtarzadeh et al., 2020) (Stecke & Mokhtarzadeh, 2021) (Wilcox et al., 2012) (L. Zhang et al., 2021) (Chen et al., 2011) (Shannon et al., 2016) (X. Wang et al., 2015) (Gombolay et al., 2015) (Maderna et al., 2022)
Task execution time	(Hari et al., 2020) (Weckenborg et al., 2020) (Coltin et al., 2011) (Koltai et al., 2021) (Maderna et al., 2020) (Pearce et al., 2018) (Pupa, Landi, et al., 2021) (Pupa, van Dijk, et al., 2021) (Mokhtarzadeh et al., 2020) (Shannon et al., 2016) (Stecke & Mokhtarzadeh, 2021) (Wilcox et al., 2012) (Maderna et al., 2022)
Task Precedence	(Vieira et al., 2021) (Bogner et al., 2018) (Chatzikonstantinou et al., 2019) (Chen et al., 2014) (Kinast et al., 2021) (M. Zhang et al., 2021) (Ferreira et al., 2021) (Weckenborg et al., 2020) (Coltin et al., 2011) (Koltai et al., 2021) (Pearce et al., 2018) (Pupa, van Dijk, et al., 2021) (Mokhtarzadeh et al., 2020) (Stecke & Mokhtarzadeh, 2021) (Gombolay et al., 2015)
No Task Precedence	(Hari et al., 2020) (Sadik & Urban, 2017) (Chatzikonstantinou et al., 2020) (Maderna et al., 2020) (Pupa, Landi, et al., 2021) (L. Zhang et al., 2021) (Shannon et al., 2016) (X. Wang et al., 2015) (Maderna et al., 2022)
No Preemption	(Bogner et al., 2018) (Hari et al., 2020) (Kinast et al., 2021) (Ferreira et al., 2021) (Pearce et al., 2018) (Mokhtarzadeh et al., 2020)
No overlap	(Bogner et al., 2018) (Chatzikonstantinou et al., 2019) (Ferreira et al., 2021) (Coltin et al., 2011) (Pearce et al., 2018) (Mokhtarzadeh et al., 2020) (Gombolay et al., 2015)
Overlap	(Maderna et al., 2020) (Maderna et al., 2022)
Sequence dependent set up times	(Vieira et al., 2021) (Bogner et al., 2018) (Kinast et al., 2021) (Maderna et al., 2020) (Mokhtarzadeh et al., 2020)
Time windows	(Coltin et al., 2011) (Shannon et al., 2016)
Fatigue/ Strain/ Ergonomic Risk of the task	(Chen et al., 2014) (M. Zhang et al., 2021) (Maderna et al., 2020) (Pearce et al., 2018) (Stecke & Mokhtarzadeh, 2021)
Waiting time	(Bogner et al., 2018) (Chen et al., 2014) (Casalino, Zanchettin, et al., 2019) (Hari et al., 2020) (Mokhtarzadeh et al., 2020) (Stecke & Mokhtarzadeh, 2021)
Rest Breaks	(M. Zhang et al., 2021)
Task assigned to the robot or to the human	(Vieira et al., 2021) (Bogner et al., 2018) (Chatzikonstantinou et al., 2019) (Chatzikonstantinou et al., 2020) (Maderna et al., 2020) (Pearce et al., 2018) (Pupa, Landi, et al., 2021) (Pupa, van Dijk, et al., 2021) (Casalino, Zanchettin, et al., 2019) (Gombolay et al., 2015)
Task assigned to the human and to the robot	(Hari et al., 2020) (Chen et al., 2014) (M. Zhang et al., 2021) (Ferreira et al., 2021) (Weckenborg et al., 2020) (Mokhtarzadeh et al., 2020) (Stecke & Mokhtarzadeh, 2021) (L. Zhang et al., 2021) (Shannon et al., 2016) (X. Wang et al., 2015)
Capability Indicators	(Chatzikonstantinou et al., 2019) (M. Zhang et al., 2021) (Weckenborg et al., 2020) (Koltai et al., 2021) (Maderna et al., 2020) (Pearce et al., 2018) (Pupa, van Dijk, et al., 2021) (Mokhtarzadeh et al., 2020) (Stecke & Mokhtarzadeh, 2021) (Shannon et al., 2016) (X. Wang et al., 2015)

Table **6** - Resources Characteristics in Scheduling Problems in Collaborative Robotics

Characteristics	**Papers**
Single-Human and Single Robot	(Sadik & Urban, 2017) (Chatzikonstantinou et al., 2019; Koltai et al., 2021; Maderna et al., 2020; Pearce et al., 2018; Pupa, Landi, et al., 2021; Pupa, van Dijk, et al., 2021; Weckenborg et al., 2020) (Koltai et al., 2021) (Maderna et al., 2020) (Pearce et al., 2018) (Pupa, Landi, et al., 2021) (Pupa, van Dijk, et al., 2021)
Multi-Human and Multi-Robot	(Vieira et al., 2021) (Bogner et al., 2018) (Hari et al., 2020) (Chatzikonstantinou et al., 2019) (M. Zhang et al., 2021) (Mokhtarzadeh et al., 2020) (Chen et al., 2011) (Shannon et al., 2016) (Stecke & Mokhtarzadeh, 2021)
Single-Human and Multi-Robot	(Chen et al., 2014) (X. Wang et al., 2015)
Skills of the agents	(Chatzikonstantinou et al., 2019) (Chatzikonstantinou et al., 2020) (Pupa, Landi, et al., 2021) (L. Zhang et al., 2021)
Cost of the agent	(Vieira et al., 2021) (Hari et al., 2020) (Chatzikonstantinou et al., 2019) (Pupa, van Dijk, et al., 2021) (Chen et al., 2011) (Shannon et al., 2016)
Speed of the Agent	(Chatzikonstantinou et al., 2019)
Availability of the agent	(Vieira et al., 2021) (Bogner et al., 2018) (Hari et al., 2020) (Koltai et al., 2021) (Maderna et al., 2020) (Pearce et al., 2018) (Pupa, Landi, et al., 2021) (Pupa, van Dijk, et al., 2021) (Casalino, Zanchettin, et al., 2019)
Downtime of the robots	(Vieira et al., 2021)
Preferences	(Wilcox et al., 2012) (Gombolay et al., 2015)
Passive Resources	(Stecke & Mokhtarzadeh, 2021) (Maderna et al., 2022)

Table **7** - Shop Environment characteristics in Scheduling in CR

Characteristics	**Papers**
Multi-Station	(Vieira et al., 2021) (Bogner et al., 2018) (Chatzikonstantinou et al., 2019) (Chatzikonstantinou et al., 2020) (Kinast et al., 2021) (Ferreira et al., 2021) (Weckenborg et al., 2020) (Koltai et al., 2021) (Stecke & Mokhtarzadeh, 2021)
Identical Parallel Machines	(Ferreira et al., 2021)
Unrelated Machines	(Stecke & Mokhtarzadeh, 2021)
Job Shop	(Kinast et al., 2021) (Raatz et al., 2020)
Flow Shop	(Sadik et al., 2017) (Sadik & Urban, 2017)

Table **8** - Other Characteristics of Scheduling Problems in CR

Characteristics	**Papers**
Multi Order	(Vieira et al., 2021) (Kinast et al., 2021)
Multi-Product	(Vieira et al., 2021) (Stecke & Mokhtarzadeh, 2021) [59]
Spatial Constraints	(Chatzikonstantinou et al., 2020) (Koltai et al., 2021) (Maderna et al., 2020) (Pearce et al., 2018) (Stecke & Mokhtarzadeh, 2021)
Inter-workstation travel distances	(Chatzikonstantinou et al., 2019)
Limited Buffer Size	(Bogner et al., 2018) (Maderna et al., 2022)

Table **9** - Objective Characteristics in Scheduling Problems in Collaborative Robotics

Characteristics	**Papers**
Minimize ergonomic risk	(Stecke & Mokhtarzadeh, 2021)
Minimize time (makespan, cycle time, waiting time, etc.)	(Vieira et al., 2021) (Bogner et al., 2018) (Hari et al., 2020) (Sadik & Urban, 2017) (Chatzikonstantinou et al., 2019) (Chen et al., 2014) (Kinast et al., 2021) (M. Zhang et al., 2021) (Ferreira et al., 2021) (Coltin et al., 2011) (Koltai et al., 2021) (Pupa, Landi, et al., 2021) (Pupa, van Dijk, et al., 2021) (Mokhtarzadeh et al., 2020) (Stecke & Mokhtarzadeh, 2021)
Minimize costs	(Chatzikonstantinou et al., 2019) (Chen et al., 2014) (Kinast et al., 2021) (Maderna et al., 2020) (Maderna et al., 2022; Stecke & Mokhtarzadeh, 2021; Vieira et al., 2021)
Min Weighted sum	(Chatzikonstantinou et al., 2019) (Kinast et al., 2021) (Pupa, Landi, et al., 2021) (Pupa, van Dijk, et al., 2021) (Stecke & Mokhtarzadeh, 2021)

III.6. Problem Type and Taxonomy

A taxonomy is a scientific classification which enables the study of general principles of a specific matter (*Merriam-Webster Dictionary*, 2022). The purpose of the taxonomy presented in this paper is twofold: categorize existing solution procedures to the task assignment and scheduling problem, which enable and facilitate their comprehension and present a framework for future research. The taxonomy may also provide awareness about specific areas that have not yet been considered (Quadt & Kuhn, 2007). Inspired by Lopes et al. (Lopes et al., 2013) three different two-level classifications are presented, despite tackling a different type of problem, from the one \considered by the authors of (Lopes et al., 2013). The taxonomy groups the solution procedures according to their approach. Firstly, papers are divided in two classes depending on the type of approach adopted: exact or non-exact. Afterwards, in Figure **34**, we primarily classify the papers considering the method applied (exact or non-exact) and then if the system was defined as deterministic or stochastic. Then, at level two, in Figure **33**, articles are categorized taking into consideration if the problem is defined as a single or multi objective. Regarding the latter categorization, it is important to state that some of the articles, despite not presenting the problem formulation, the refer their objectives, so they were not excluded from the schematization. Finally, in Figure **35** the taxonomy divides the sample firstly regarding if the method used was exact or not, and secondly, concerning the type of scheduling, which was divided in online and offline scheduling.

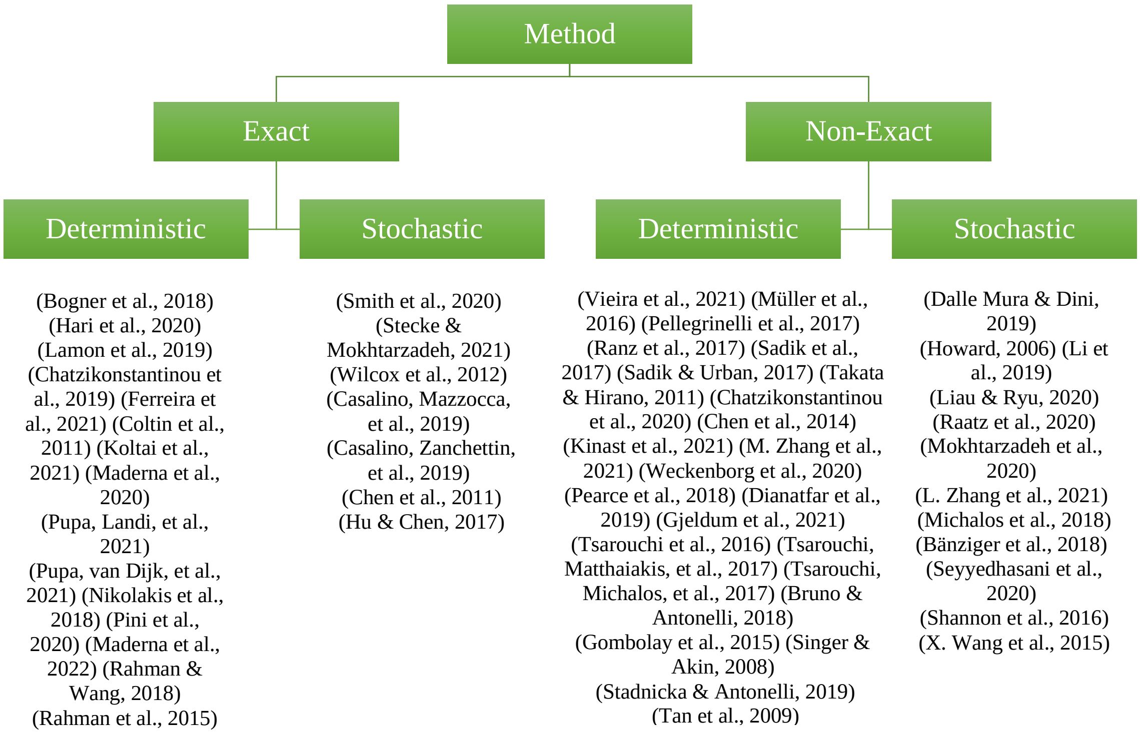


Figure **34** - Branch of the Taxonomy that divides papers by the type of method and type of system formulation

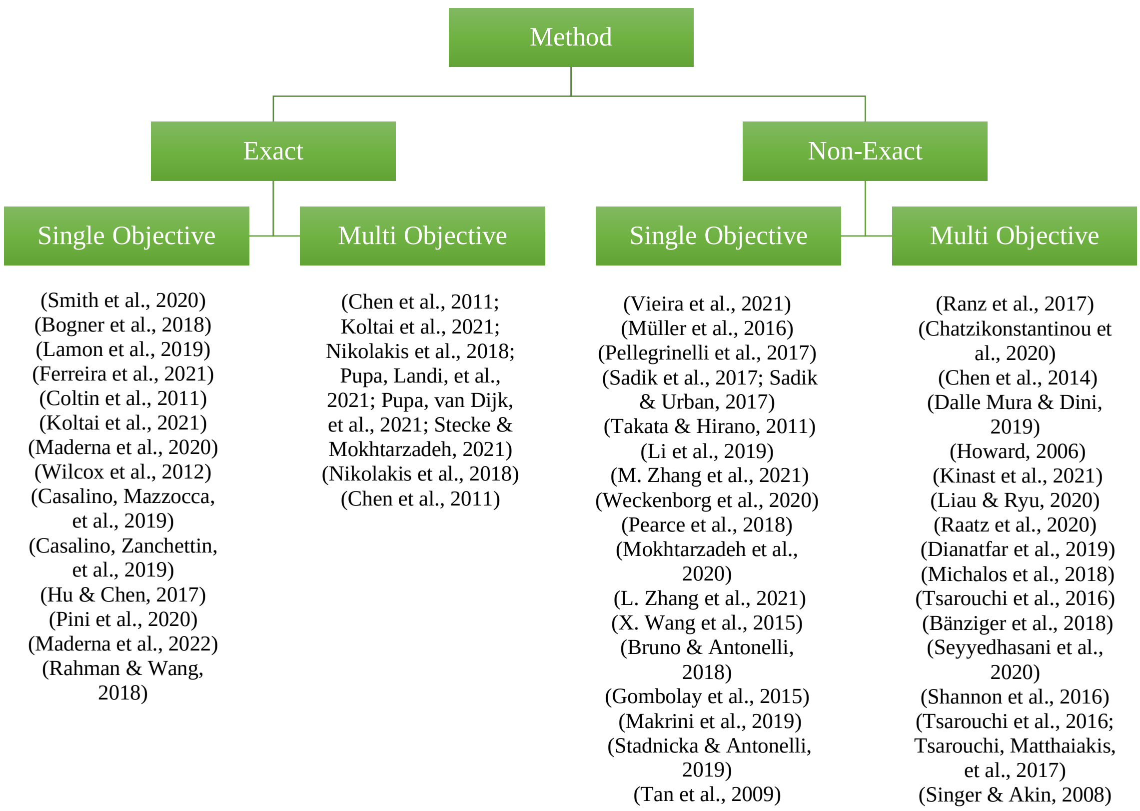


Figure **33** - Branch of the Taxonomy that divides papers by the type of method and type objective

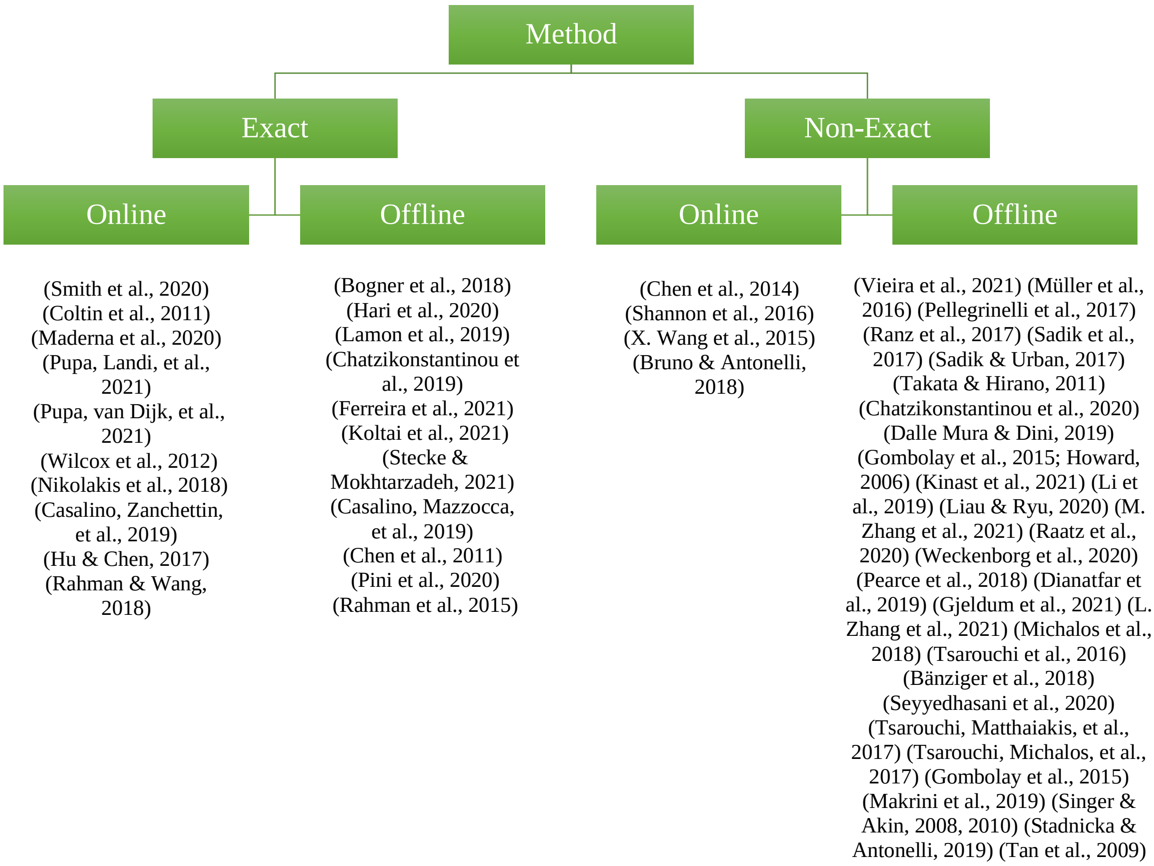


Figure **35** - Branch of the Taxonomy that divides papers by type of method and type of scheduling

Regarding Figure **34**, the category that includes the least number of papers is the one that represents publications with exact methods and stochastic settings with only 12% of the publications. On the other hand, the group with the highest percentage is non-exact methods with deterministic systems representing 50% of the papers. In addition, it can be concluded that 65% of the papers define deterministic setting while only 35% define stochastic systems.

Analyzing Figure **33**, regarding the papers included in the analysis, it can be seen that the category with the least number of articles is exact methods with multi-objective problems with just 7% of the papers. In contrast, the most adopted approach is the non-exact methods with single-objective problems. Moreover, single objective problems represent 57% of the papers while multi-objective represent 43% of the published articles. In Figure **35** it can be seen that non-exact methods with offline scheduling ais, undoubtedly, the most adopted approach with 57% of the articles of the sample. In contrast, non-exact methods with online scheduling is the least adopted approach with only 7% of the papers. In addition, online scheduling is studied by 24% of the papers, whereas offline scheduling is adopted by 76% of papers.

III.7. Identification of Collaborative Tasks and Type of Collaboration

The publications in the sample were assessed considering the task studied under the HRC paradigm, the operations performed by the human and the ones undertaken by the robot, and the type of collaboration presented. There is already some research done by El Zaatari et al. (2019) where collaborative tasks were identified given the literature example as it can be seen in Figure **36**.

Scenario	E.g.	Human Task	Cobot Task
Co-manipulation	[25]	The human and the cobot both hold and move an object. The human guides the object's path.	The cobot handles the object's weight.
Fixture	[26]	The human polishes the held box.	The cobot hold the box in a position according to learnt human preference.
Handover	[27]	The human takes objects from the cobot and places them aside.	The cobot hands objects to the human. Handover pace changes according to the human's readiness to take an object.
Assembly	[28]	Assembly actions are distributed between the human and the cobot according to expected workload and energy consumed.	
Pick-and-place	[29]	The human chooses objects randomly to pick and place.	The cobot chooses objects to pick and place while accounting for distance, reachability and the human's predicted motion plans.
Fetch	[30]	The human takes the table part from the cobot and performs assembly actions.	The cobot fetches table part according to the human's progress in the assembly task.
Soldering	[31]	The human adjusts the pose at which the cobot is holding the solder wire, and then he performs soldering.	The cobot holds the soldering wire at the tip of soldering point, in human-controlled orientation and position.
Illumination	[32]	The human operates on parts on a table.	The cobot, with a light source mounted as a tool, provides direct illumination on the human's work space while avoiding collision.
Inspection	[33]	The human screws bolts in holes.	The cobot inspects if all holes are screwed and issues a warning in case of missing bolt.
Drilling	[34]	The human specifies the drill location, during run-time.	The cobot drills a hole in specified location while having motion automatically constrained to drill bit's axis.
Surface Finish	[34]	The human specified surface to sand.	The cobot sands the surface, while having motion automatically constrained parallel to the surface.
Screwing	[35]	The human inserts bolts in holes on one side of a plate.	The cobot tightens the bolts from the other side of the plate.

Figure **36** - HRC scenarios from research presented by (el Zaatari et al., 2019)

However, the work presented in this deliverable takes into account the collaborative tasks presented in scheduling in HRC. In addition, as there are different types of human-robot interaction, the type of collaboration is also identified. The different types of collaboration were classified according to Matheson et al. (2019) who divides human-robot interaction. It is important to refer that for the identification of the type of collaboration, when the authors refer that the HRC was the type of cooperation, for instance, and do not give further details to justify the level given, the word of the authors was trusted and so that was the level of collaboration considered.

If a human worker and a robot work in the same workstation, at the same time but locally separated it is an example of coexistence between humans and robots, for example, when they work on different sides of a vehicle like shown by Müller et al. (2014) (as cited in Bänziger et al., 2020). This situation represents the simplest level of collaboration and Human-Robot Interaction (HRI). Thus, a safety stop strategy is sufficient for this workspace, as the agents work do not overlap at any time (Bänziger et al., 2018). Synchronized is the level of HRC, where a human and a robot, despite sharing the workspace, have sequential tasks. Cooperation is the next level of HRC, where the level of interaction is more complex and defined as performing different tasks to achieve a common goal, like for instance the transport and handling of a part by a robot and the following assembly by the worker. In this paradigm, human and robot share the workspace, but not at the same time which allows the implementation of speed and distance surveillance safety strategies. An example for this scenario is shown by Morioka and Sakakibara (2010) (as cited in Bänziger et al., 2020). Finally, the highest degree of interaction is the collaboration, defined as the work on a common task to achieve a common goal where humans and robots share the workspace at the same time and physical interaction exists. Hand guiding or force and power limiting safety strategies must be implemented in order to achieve an efficient collaboration like presented by Michalos et al. (2014) or Cherubini et al. (2016) (as cited in Bänziger et al., 2020).

However, the majority of HRC scenarios portrayed in the research regarding task assignment, do not focus on the highest level of HRI: collaboration. Instead, most publications study cases where the human and the robot only coexist or have synchronized collaboration. This is due to technological challenges present in the highest levels of HRI.

Concerning the process of identification of the type of collaboration usually, the type of collaboration is not clearly specified in the publication. However, after the interpretation and analysis it is possible to understand the type of collaboration studied. The results of the identification of collaborative tasks and types of collaboration are presented in Table **15** in the Appendix.

III.8. Discussion

This section aims to explore the significance of the results of this research. The present article had the major purpose of looking for foundations that help answer the following RQs: **RQ1**: What type of problems and methods are studied in the area of interest? **RQ2:** What are the drivers for adopting CR? **RQ3:** Which types of collaboration have been addressed? The research methodology started with the SLR which enabled the creation of a theoretical basis to understand the problem domain. Moreover, besides the specific research questions, other general research questions were created based on knowledge of the literature review.

The main goal of this section is to explore the significance of the main results of the work, which are summarized in the following list:

- Regarding the temporal evolution, 44 of the 58 papers included in the sample, in other words, 76% of the articles, are from 2017 until present date which reinforces the exponential growth in the research of assignment and scheduling tasks in CR.
- In fact, the field studied has gained interest in a wide variety of areas since the sample is composed by papers published in a wide variety of conferences and journals.
- Concerning geographical distribution, USA, Italy, Greece, Germany, and China, make up 43 of the 58 papers, representing 74% of the sample. Moreover, it is undoubtedly that the field has gained interest all over the world, specifically in the continents of Europe, Asia, and America.
- In regard of the approach chosen, it is important to highlight the great number of case studies, which represents an increasing need and concern of researchers to include real data such that the findings can be closer to the reality.
- Taking into consideration **RQ1**, scheduling problems and task allocation problems represent 44 of the total number of paper (76%), which highlights the pertinence of the selected studies of the sample towards the work paradigm which is assignment and scheduling of tasks. It is also important to state that taking a closer look inside the scheduling problems we find a great interest of allocating tasks before the scheduling in order to guaranty a higher success rate and efficiency of the adoption of CR. In concern of the opted methods, metaheuristics drive the front which is understandable since they grant near-optimal solutions in a short time, issue of major importance for manufacturing systems when time is money.

- Continuing the flow of thinking, regarding the objectives chosen, it makes all the sense that the most chosen objective is about the minimization of time. In addition, i tis interesting to stress that the minimization of time and costs represent 57% of the total number.
- Still in the same line of thinking, but in regard of **RQ2**, it is comprehensible that the most mentioned driver for the adoption of CR is Operational Efficiency. However, with the increasing concerns for the human and human-centered systems, i tis expected that Ergonomics and Human Factors will rise.
- Last but not least, concerning **RQ3**, the research behind the topic type of collaboration studied, might be the most interesting and valuable finding of this article since a paradigm Shift has occurred since, researchers have been given a great focus to higher levels of HRI. In fact, Cooperation and Collaboration levels make up 35 of the 58 articles, in other words 60% of results. To sum up, higher levels of collaboration have been studied especially in recent years which represents an evolution, since a great number of authors refer that only the simplest levels of collaboration are studied. Whereas this do not mean that pure collaboration has been fully implemented in real industries which is normal due to technological challenges present in the highest levels of HRI. In fact, clear evidence that the academic scenarios do not mirror the majority of industries was presented in a study carried out in German companies as cited in Simões et al., (2019). This study found that humans and robots work alongside each other in a form of coexistence, in other words, both agents may have tasks at the same time in a shared workspace, but they do not work simultaneously on the same product. In addition, pure collaborative systems are virtually non-existent in present industries (Simões et al., 2019).

Regarding the Taxonomy presented, some main conclusions can be identified: non-exact methods with single-objective problems, non-exact methods with deterministic systems and non-exact methods with offline scheduling are the most adopted approaches that can be identified. In fact, non-exact methods can retrieve a possible solution in a shorter period of time when compared to exact methods. In addition, single objective is more adopted than multi-objective problems, deterministic systems are also preferable than stochastic ones and offline is more adopted than online scheduling. This can be explained by an increase of complexity of studying multiple objectives, stochasticity and real time scheduling.

III.9. Conclusions and Future Work

This study lies in the research field of allocating and scheduling of tasks under a context of collaborative robotics and is aimed to provide an overview of the scientific contributions to the area. So, a Systematic Literature Review was carried out, which represents a clear contribution for the field as, until the present date, in the best knowledge of the authors none other work of this kind is available in the literature. In addition, quantitative and qualitative analysis were performed, which provided awareness and acknowledgement of the field of assignment and scheduling in collaborative robotics. Then, a classification of the problems found in the field, regarding their features and solutions approaches were presented, summarizing, and grouping the papers included in the sample, providing an overview of the methods, objectives, type of studied system, and type of scheduling studied. The taxonomy categorizes the procedures along their general solution approach, which may help to understand existing procedures and guide future research. In fact, scheduling tasks in HRC is a recent topic which has been gaining the attention of researchers. Afterwards, the main characteristics of scheduling problems were are depicted which can help future research as it functions as a repository of possible characteristic that can be included when formulating a scheduling problem. Despite high levels of collaboration have been identified in the studies, this does not mean that CR has been fully implemented in real industrial systems, which is plausible because of the technological challenges sub intended. A lot of research must be done in order to understand in fullness the problem of scheduling in collaborative robotics.

To conclude, it is important to highlight some limitations of the study. In fact, regarding the SLR methodology, only two databases were used; even if they are representative of the majority of the research worldwide, it is not certain that all publications were detected in the queries; Nonetheless, the application of the backward snowballing technique aimed to look for articles that could have missed the first steps, and that may have reduced the risk ok missing relevant publications. In addition, despite the fact that the English language is considered the universal language in the academic world, the linguistic matter could have also excluded important articles, mainly in oriental languages that have their own domains of publication. In addition, concerning the categorization made, some articles adopt more than one method, for example a metaheuristic and then simulation; however, the work could only be included in just one of the methods, but in those cases, a more detailed overview was given when summarizing the paper.

Regarding future work, a lot of research can still be done concerning scheduling problems in CR, especially in exact methods with stochastic system's formulations. Moreover, there is clearly, fewer studies that adopt an overlapping situation of tasks. Non-exact with online scheduling is also an approach where there are few studies. Regarding shop environments, parallel machines also show the need for future research. In addition, it is clear the lack of objectives related to ergonomics. Finally, future research should also focus on single-Human and multi-Robot systems, integrating the speed of the agents, and the downtime of the robots.

The developed work will certainly help the future research in this field because it provided awareness about the problems studied and the methods that have been used to develop such algorithms, as well as the main drivers to consider.

Chapter IV - Mapping of Processes in BPMN 2.0

IV.1. Introduction

IV.2. Methodology

IV.3. Case Study of an Industry in Paços de Ferreira

IV.4. Case Study of BOSCH Aveiro Thermotechnology

IV.5. Case Study of Microplásticos

IV.6. Discussion

IV.7. Conclusions and Future Work

IV.1. Introduction

To face the challenge of increasing productivity while having flexibility, collaborative robots represent a clear added value to manufacturing or assembly systems. Consequently, it is essential to schedule tasks between humans and robots to provide an effective and efficient human-robot collaboration while considering the agent's potentials and limitations. Thus, the main goals of this chapter are threefold: present three industrial use cases where a collaborative robot will be implemented; mapping selected processes (as it is and future version) in BPMN 2.0. in order to help the decision of where to implement a cobot; and present the match of the collaborative tasks with the literature. To provide an effective scheduling of tasks between the robot and the human, BPMN 2.0. was used to map the production process to clearly identify the tasks that are going to be allocated to the agents. As a result, the to-be process was modeled which helped the clear identification of tasks that should be attributed to be cobot and to the human. and demonstrated that humans will have ergonomic benefits since the cobot will perform repetitive tasks.

In fact, concerning the author's knowledge, in the present day, there is only one published article that addresses jointly collaborative robotics in an industrial use case and BPMN which is Schmidbauer et al. (2021). For this reason, it is clear that modelling collaborative robotic processes is an innovative field which should encourage researchers to publish regarding this matter. As a matter of fact, collaborative robotics is a growing technology and BPMN has been demonstrating to be a very powerful and useful tool. Nevertheless, other authors have used BPMN in industry environments. One benefit of the utilization of collaborative robots is the possibility of cobots cooperate and support humans' activities. Schmidbauer et al., (2021) reviewed the state of the art regarding human-cobot interaction (HRI) in manufacturing environments and present a digital worker assistance system, based on BPMN, which enables adaptive task sharing processes between humans and robots.

Knoch Sönke and Herbig (2019) suggest technologies to automatically detect material picking and placing in assembly to gather data about human behavior. Moreover, the detected worker activities are then correlated to a BPMN model of the assembly, which enables the measurement of production time and quality. Laswad et al. (2016) analyzes requirements for cloud manufacturing and proposes a new architecture that includes a business process modeling layer to fulfill this gap. Therefore, BPMN was used to model, and virtualize process steps. The use case studied belongs to the automotive industry where BPMN helped investigate expected manufacturing issues.

Dong and Vogel-Heuser (2021) reports an industrial use case at an electronics manufacturer during its plant relocations where BPMN was used to visualize the use case. In fact, relocating manufacturing systems is increasing because of the changes in consumers' needs, but also in materials, and labor cost. For these reasons, while transferring the manufacturing systems, some technical compromises might be taken to start the production as soon as possible. A technical shortcut can provide a short-term benefit but may introduce a long-term negative impact. So, BPMN can be a useful and tool regarding important decisions such as relocating industrial plants. El-Sharef et al. (2016) examines the suitability of BPMN to model a semiconductor manufacturing system. The model was built to represent some challenges present in manufacturing systems but not normally seen in business operations. This allows the evaluation of the capacity of BPMN representation to deal with complex processes. Parameters such as breakdowns, changeover times and shift schedules, were evaluated using BPMN to address the issues of a particular manufacturing system.

Polderdijk et al. (2018) introduces an extension that visualizes human physical risks (such as heavy lifting or repetitive work) to support the analysis of human factors in manufacturing processes. Thus, an existing human risk analysis method is integrated with BPMN which facilitates process' wide analysis. Based on BPMN and its graphical representation, it can be seen where in the process workers may encounter physical risks that should be mitigated. Jasiulewicz-Kaczmarek et al., (2018) presents modeling tools and process management within BPM practices in the maintenance processes in a medical devices manufacturing company. In fact, the quality of processes is more and more dependent on the maintenance process. Therefore, it must be carefully designed so the use of BPMN is an approach that can be applied for efficient and effective maintenance management.

Furthermore, with the continuous development of I4.0 and its applications, business models have been adapted to accompany the incorporation of new technologies. In addition, as industrial companies increasingly operate in competitive environments, with very short technological innovation cycles, it is necessary and fundamental that exists optimization and automation of processes so that the survival of the company is not compromised.

IV.2. Objectives and Methodology

The objective that motivated this chapter was the implementation of a collaborative robot in three industrial organizations: an Industry in Paços de Ferreira, BOSCH Thermotechnology and Microplásticos, in order to improve processes. In fact, the implementation of a cobot in the shopfloor can have a great impact on the processes such that: they can optimize the total makespan, reduce the ergonomic risk for human workers, provide flexibility to the shopfloor, etc. The methodology followed was the BPM lifecycle which can be seen in Figure **37**. The BPM lifecycle can help to understand the role of technology in BPM (Dumas et al., 2018).

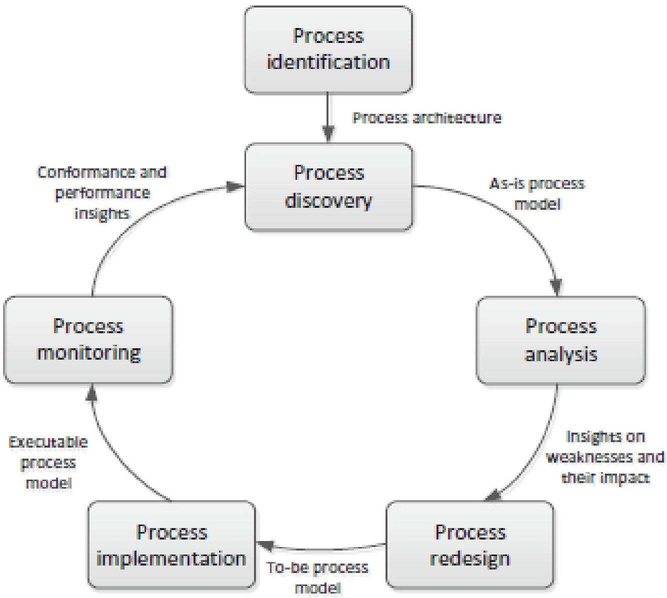


Figure **37** – BPM Lifecycle (Dumas et al., 2018)

- ❖ Firstly, in **Process Identification**, the processes relevant to the problem being addressed are identified and delimited. The result of this phase is an updated overall picture of the processes in an organization and their relationships. Then, the outcome is used to select which processes or to manage through the remaining phases of the lifecycle (Dumas et al., 2018).

- ❖ Secondly, in **Process Discovery**, the current state of the relevant processes is documented. This model is typically called the as-is model (Dumas et al., 2018).

- ❖ Thirdly, in **Process Analysis**, the issues associated with the as-is process are identified, documented, and quantified using performance measures (KPIs), when possible. The outcome of this phase is a structured collection of issues which are then prioritized (Dumas et al., 2018).

- ❖ Fourthly, in **Process Redesign**, the aim is to identify changes that could be implemented in processes in order to help solve the problems previously identified. The output of this phase is typically the modelling of the to-be process (Dumas et al., 2018).

- ❖ Then, in **Process Implementation**, the changes required to move from the as-is process to the to-be process are adopted. Process implementation includes two aspects: organizational change management and automation. Organizational change management consists in the required activities to change the way of working of all participants of the process. Automation refers to the development and deployment of IT systems that support the to-be process (Dumas et al., 2018).

- ❖ Finally, in **Process Monitoring**, relevant data is collected and analyzed to determine how well the process is performing. Moreover, new issues may then arise, which requires the BPM cycle to be repeated on a continuous basis (Dumas et al., 2018). In this dissertation, the stages of Process Implementation and Process Monitoring will not be discussed, because until they were not enrolled in time of the end of this project.

IV.3. Case Study of an Industry in Paços de Ferreira

IV.3.1. Presentation of the organization

Because of confidentiality reasons, the name of the company will not be identified and only a brief presentation will be presented. The company was not always the large organization it is known today. The business grew and the organization became a well-known furniture brand. The group focuses on creating products with excellent design, optimal function and with a sustainable approach guaranteeing maximum quality at a low cost.

IV.3.2. Process Identification

Following the BPM Lifecycle as a methodology, and regarding process identification, this use case is integrated in the packing area of the industry. The packing process is the last step in the production process of all final products from previous production areas. After the previous step, the palletized parts go to an intermediate warehouse. Then, one of the 3 following paths is followed: the parts go from the warehouse to a buffer and then to the packing line; or the parts go from the warehouse to a stock point and then to the line; or the parts go from the warehouse to the buffer then to a stock point and afterwards to the line. The path taken depends on decisions concerning the production planning department. This area consists of 6 lines, which basically consist of a conveyor belt through which a cardboard box is transported, and along it, several employees, alongside or individually, introduce the various elements necessary for a given reference. In this area, there is a warehouse responsible for supplying the material needed for packing, such as cardboard, boxes, screws, etc.

However, the line does not always keep the same configuration. In fact, depending on the reference, the line may be longer, that is, with a greater number of jobs, therefore more people are needed, which happens when there is a need to introduce more elements. In addition, for heavier or larger pieces, two employees are used, one on each side, to move them to the line. An employee may introduce more than one element into the box, as accessories are also packed that help the customer to assemble the furniture, such as assembly instructions, table legs, etc. In addition, fillings – cardboard fillings to fill the unoccupied space, and fittings – screws, keys, and other tools may also be needed. In this way, each component is placed in the package according to predefined instructions. The most important aspect to consider is the order in which the components are packed and the correct identification (Vaz, 2015).

IV.3.3. Process Discovery

In this phase, the current state of the relevant processes is documented. Firstly, the Industry was visited in order to get to know the process which is essential. At the organization, visual observation was performed along with writing of important aspects. In addition, some useful documents were also provided such as layout schemes, process flowcharts, and operations standardization sheets which were analyzed. Moreover, it was essential to communicate with the operators as these are the people that know the process best. Secondly, the actual process was mapped in BPMN 2.0. as there was no mapping of the process so it was an important task to perform to have a clear and visual image of the process and make sure that the process was well comprehended. The as-is model can be seen in Figure **38** and Figure **39**.

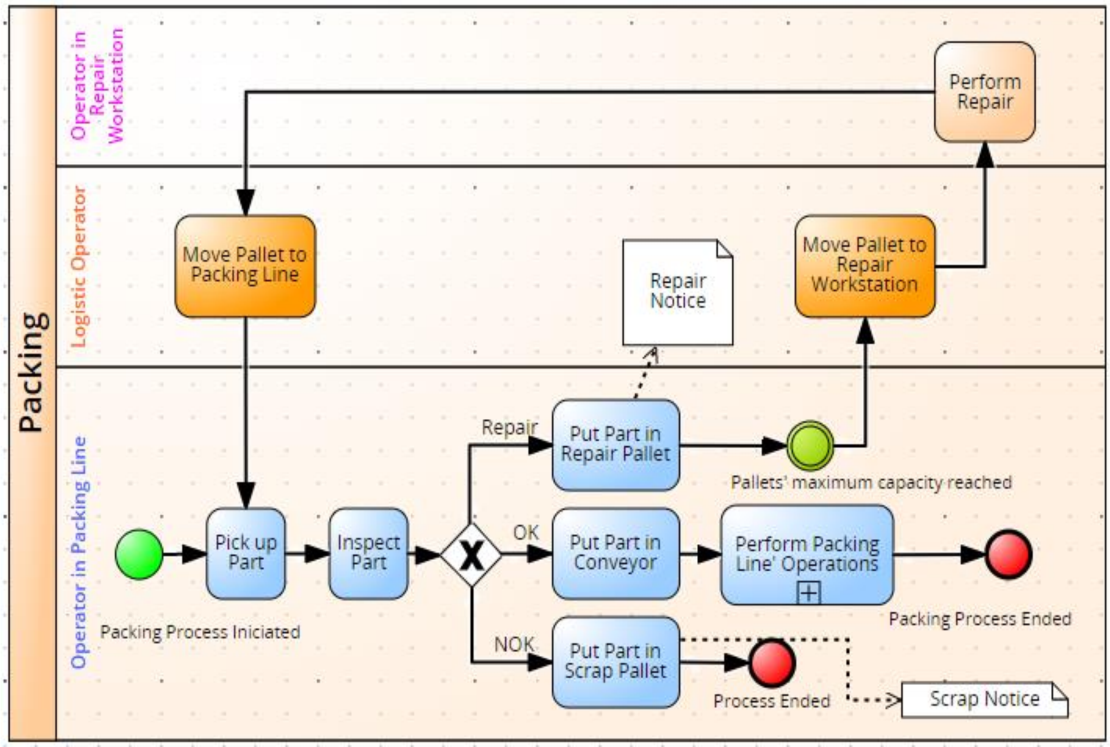


Figure **38** - As-is model of a packaging workstation

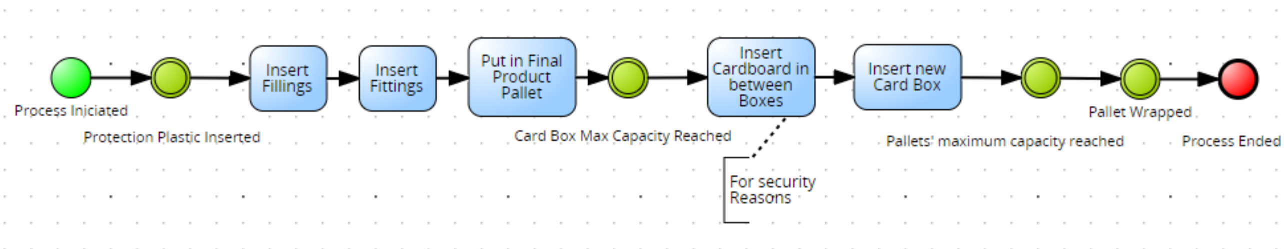


Figure **39** - Packing line additional operations

IV.3.4. Process Analysis and Redesign

In this phase the issues associated with the as-is process are identified as well as the changes that could be implemented in processes in order to help solve the problems identified. The company demonstrates an enormous concern for the health of employees. In fact, in the processes modeled, it could be identified, that the workers would have to do repetitive movements of picking and placing, increasing the risk of getting work related musculoskeletal disorders. In addition, sometimes, in order to accomplish productivity goals, another worker would be needed. So, two necessary changes were needed: diminish the ergonomic risk that the human worker was subjected to and diminish the overall makespan. Therefore, this packing workstation would be the best to implement a collaborative robot because it could help the human worker, performing the more heavy and repetitive tasks and improving makespan because with the parallelization of tasks, there could be gains in time.

The use case is in the beginning of a line and a simple sketch of the design with the introduction of the cobot is presented in Figure **40**. The use case consists of a worker and a cobot which are separated by a conveyor with 1.2m wide. The additional main elements of the use case consist of two pallets with components to process (Pallet1 and Pallet2), one pallet with “Not Ok” products which will be rejected and placed by the cobot (NOK), pallet with products to repair near the operator (Repair) and one pallet with rejected products by the operator (NOK op).

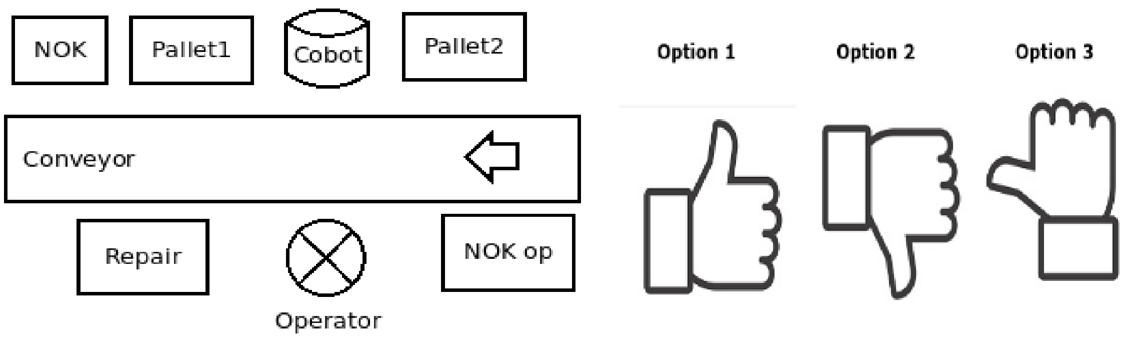


Figure **40** - Possible layout the use case and possible gesture communication

The operation starts with the cobot picking one or more parts from Pallet1 or Pallet2 (or both). Secondly, the cobot presents the opposite side to the operator, in a frontal position, on the conveyor. Thirdly, the worker inspects visually the product and will decide one of the following options:

- The product is OK, so the worker tells the cobot that and the cobot puts the product on the conveyor.
- The product is not Ok so the worker rejects the product and tells that to the cobot that will immediately put the product in the pallet NOK.
- The worker is not sure about the condition of the product and so he tells the cobot to give him the product to be inspected closer. In fact, the cobot will release the product when it feels the force action of the worker. After the manual inspection, the worker will decide about the product’s destination which can be repaired or rejected or accepted and put it at the respective place.

Furthermore, it is important to state that this communication between the cobot and the worker is expected to be done by gestures. Therefore, possible gesture communication is presented in Figure **40**. It is important to state that it is only symbolic representations. The actual communication may be different and based on other channels or interfaces.

However, there are some conditioning factors that may pose some challenges to the implementation of the cobot in the described workplace. Firstly, the collocation of the parts is made directly to the conveyor.

Secondly, the organization of pallets in fixed places. Thirdly, the dimension of the parts must be adequate to the limits of manipulation between worker and cobot. Fourthly, there is uncertainty if the worker can inspect the upside of the parts considering the distance between the products and the operator. Given this, the to be model can be seen in Figure **41**. The subtasks of additional packing line operations are common to the ones of the as-is model presented in Figure **39**.

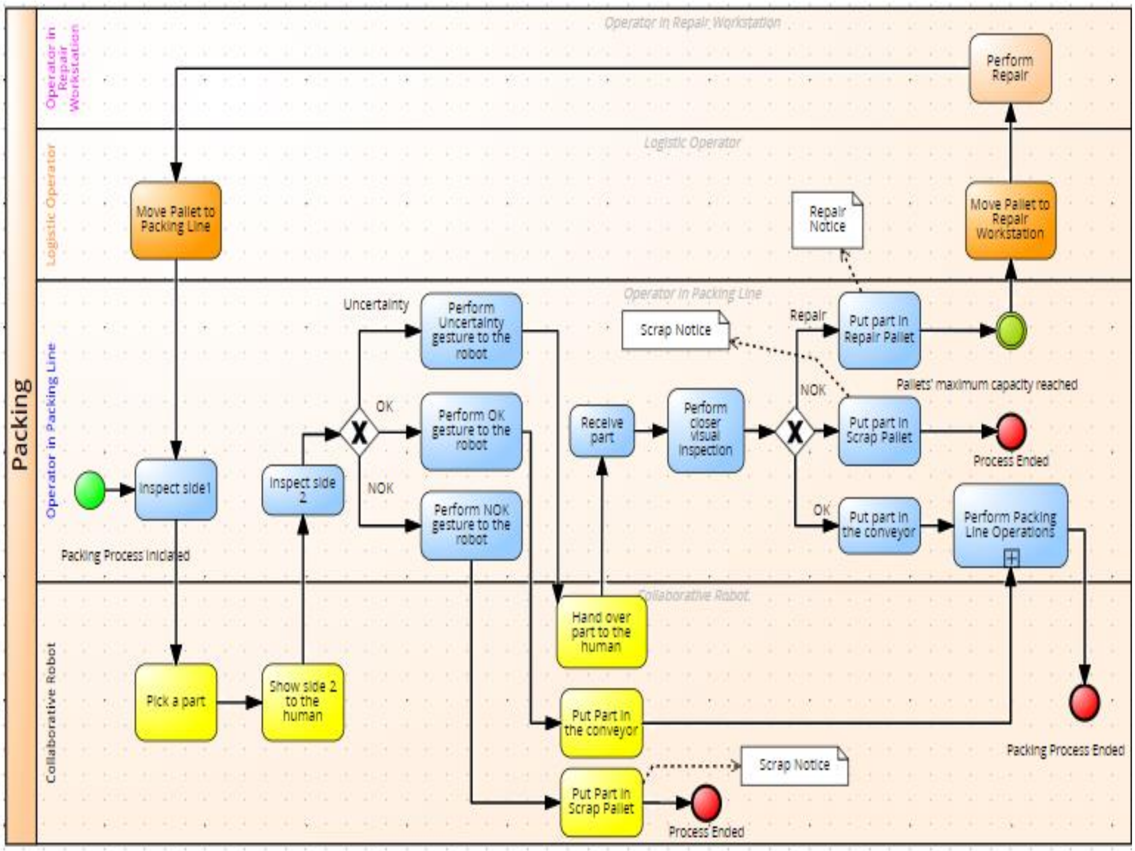


Figure **41** - Mapping of the Packing Process with the cobot's implementation

IV.3.5. Use Case Analysis and match with the literature

The presented use case refers to the highest HRI which following Matheson et al. (2019) is an example of pure collaboration the human operator and the cobot share the workspace and components and the cobot is able to react in real-time to the communication gestures of the human worker. Two main collaborative tasks can be identified:

- **Visual inspection:** While the cobot holds the part, the human worker performs visual inspection and communicates with the cobot.
- **Handover:** In case the human worker is not sure if the part is OK or NOK, the cobot will hand over the part to the human so he/she can have a closer look at the part.

IV.4. Case Study of Bosch Thermotechnology Aveiro

IV.4.1. Presentation of the organization

Bosch Thermotechnology Aveiro as presented in Figure **42**, is a world leader in the market for heating systems in buildings and is the only company in the Thermotechnology division of the Group that produces products for 3 different product groups (Gas and Electrical Water Heaters, Gas Boilers and Electrical Heat Pumps). It began its activity in 1977, in Aveiro, under the name Vulcano Termodomésticos, SA. The company with national capital grew, betting on the sales strategy and after-sales services, as well as the quality of its products. In 1983, it managed to launch its own Vulcano brand, shortly after achieving leadership in the national water heater market (Freire, 2017). It was in 2008 that it assumed the name of Bosch Thermotechnology, becoming the center of competence to produce water heaters, being responsible for the design, development, production, and marketing of new products (Freire, 2017).

Figure **42** - BOSCH Termotechnology in Aveiro

IV.4.2. Process Identification

Following the BPM Lifecycle as a methodology, and regarding process identification, the use case of BOSCH refers to the Riveting L7 workstation presented in Figure **43**. In fact, after visiting BOSCH Thermotechnology Aveiro the organization presented the use case which has more interested to be studied. This process, presented as a riveting challenge, involves other tasks, in particular placing parts in a workspace that the operator must handle, place, and often rivet. At least 7 pieces have been identified that are freely placed (with no fixed location) in the area where the operator will work to place at no specific location and then he/she will rivet many of them.

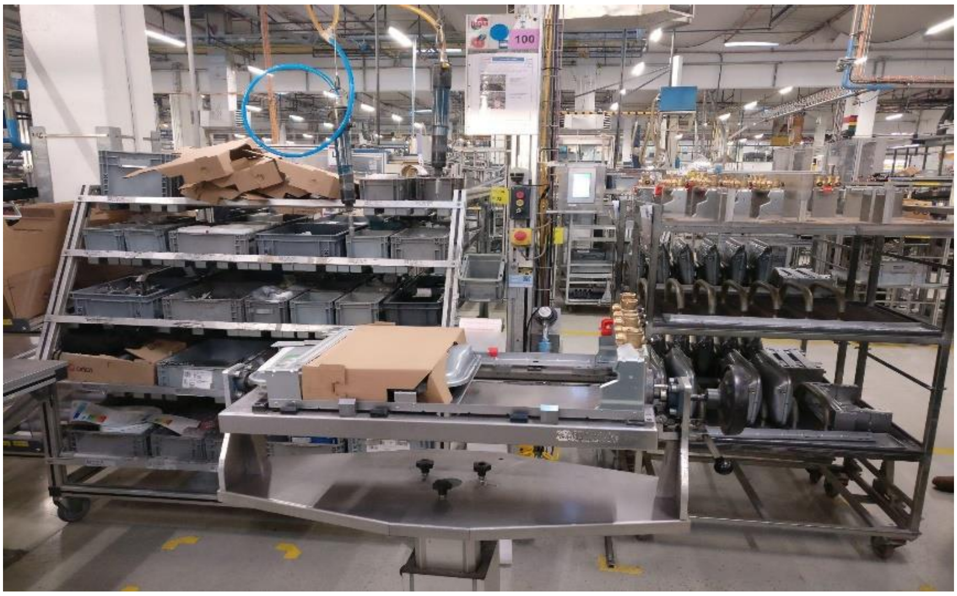


Figure **43** - Workstation "Riveting L7"

IV.4.3. Process Discovery

In this phase, the current state of the relevant processes is documented. BOSCH was visited in order to get to know the process and at the organization, visual observation was performed along with writing of important aspect. Useful documents were also provided, and it was important to also communicate with the operators as these are the people that know the process best. Secondly, the as-is process was mapped in BPMN 2.0. in order to have a clear and visual image of the process and make sure that the process was well comprehended. The as-is model can be seen in Figure **44**, Figure **45** and Figure **46**.

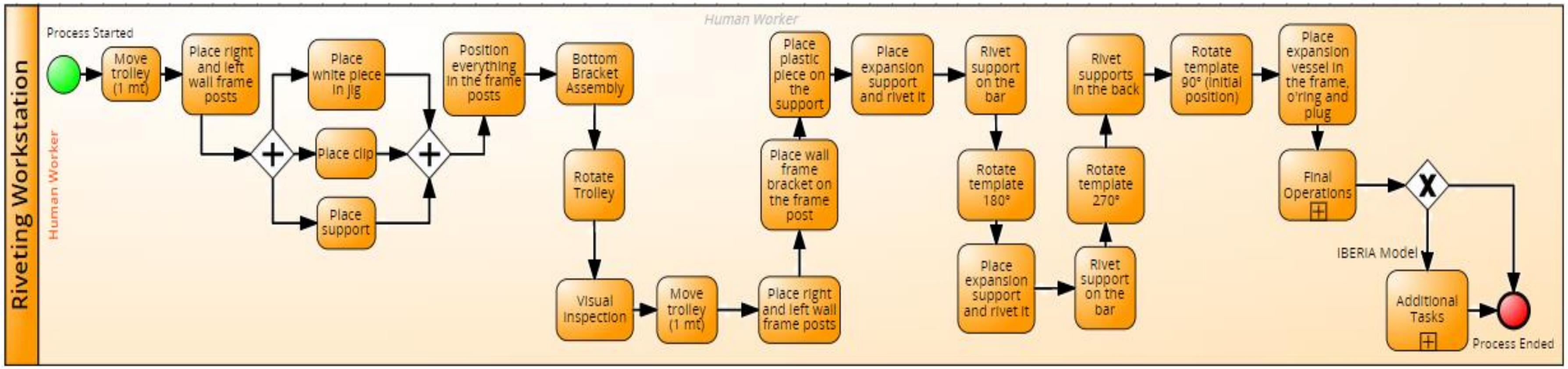


Figure **45** - As Is Process Riveting Workstation at BOSCH

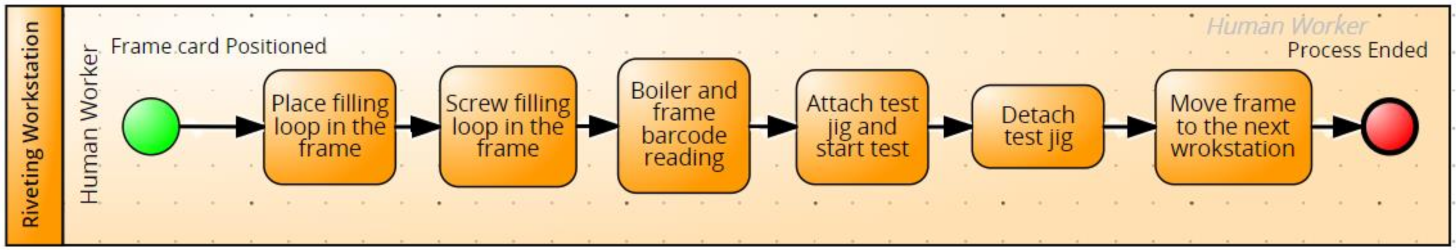


Figure **44** - Additional Tasks for IBERIA Model in As-Is Model

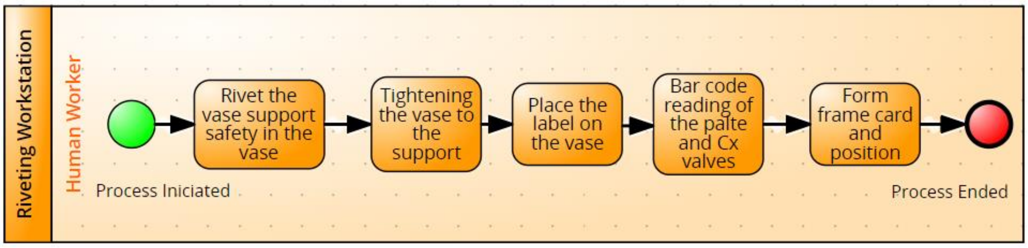


Figure **46** - Final Operations in Riveting Workstation Common to the As-Is and To-Be Models

IV.4.4. Process Analysis and Redesign

In this phase the issues associated with the as-is process are identified as well as the changes that could be implemented in processes in order to help solve the problems identified. Analyzing the current situation, with the implementation of a collaborative robot, it is envisioned that the cobot could be an extremely helpful tool to the human worker as it could place some parts in the necessary order and with the user's configuration in continuous communication with the robot. In this way, the operator does not need to switch so often between the riveting and the manipulation functions because he would have the pieces already placed in his working space. Ultimately, the last piece to be placed (the reservoir), the cobot could hand it directly to the operator who puts it in the final step in a true handover action. One important comment to make regarding this use case is that during the process, the cobot and the operator may communicate. Nevertheless, this process may require an eventual alternative sequencing of the parts, making room for a more elaborate operational communication study.

There are, however, two open questions that need further analysis. The variety of parts may require a more complex clamp, and this can limit or make it impossible for the cobot to handle some parts. In addition, the picking of parts must be ensured, either by palletizing or by another solution already available, commercial, or similar, to make bin picking. This is because the current picking is done manually so there is no indexation of the picking part as it can be seen in Figure **47**. The to-be model can be seen in Figure **48** and Figure **49**.

Figure **47** - Current organization of Picking Parts

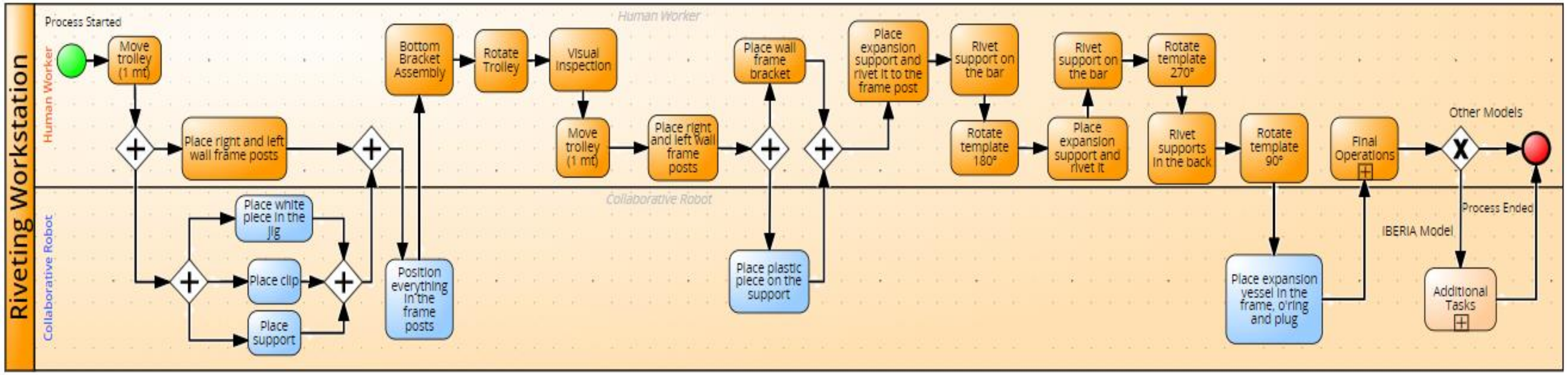


Figure **49** - To-Be Process at Riveting Workstation

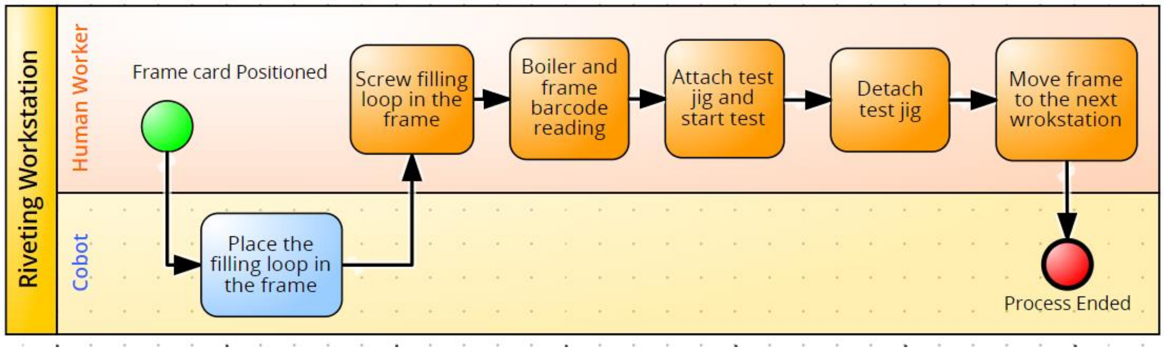


Figure **48** - Additional Tasks for IBERIA Model in the To-Be Model

IV.4.5. Use case analysis and match with the literature

In the use case of BOSCH, it is expected that the cobot will help the human by picking and placing in the workspace specific parts so the human can rivet them. In this way, the human does not have to switch so frequently between rivet and manipulation. In this case, according to Matheson et al. (2019) it is an example of a cooperation scenario because while the cobot picks and places parts, the human operator will rivet them, so each agent focuses on separate tasks. However, there is also the possibility that the cobot could handover the reservoir to the human and in this case, as the cobot reacts in real time to the operator, it is an example of pure collaboration. Therefore, true collaborative tasks can be identified:

- **Pick and Place:** While the cobot picks and places parts, the human operator rivets.
- **Handover:** The cobot handovers the reservoir to the human worker.

IV.5. Case Study of Microplásticos SA

IV.5.1. Presentation of the Organization

Microplásticos was born in Figueira da Foz, Portugal in 1987. This organization is dedicated to the production of plastic components with high precision and high dimensional rigor. Microplásticos is specialist in automatic overmolding processes, expert in different assembly processes, like potting, ultrasonic welding, tampoprint, resistance welding and PCB assembly process. Furthermore, has fully automatic assembly lines, uses artificial vision, individual traceability with laser or inkjet marking and has a great focus in process optimization (Microplásticos, 2015). Microplásticos offers services in engineering, molding, injection, assembly and logistics and its core business is in the automotive, electric and consumer industry.

IV.5.2. Process Identification

Following the BPM Lifecycle as a methodology, and regarding process identification, the use case of Microplásticos focuses on the spring workstation. The final assembled product is presented in Figure **50**.

Figure **50** - Final Product of the Use Case Workstation

Currently, the workstation process is the following:

1) The worker picks the part and in two small springs;
2) Inserts the two small springs;
3) Picks one big spring;
4) Assembles the big spring;
5) Picks another big spring;
6) Assembles the second big spring;
7) Makes a visual inspection;
8) Puts the part to be tested in the visual inspection machine;
9) Packs the part.

IV.5.3. Process Discovery

In this phase, the current state of the relevant processes is documented. Similarly, to the other industrial partners Microplásticos was visited in order to get to know the process and visual observation was performed. Useful documents were also provided, and it was important to also communicate with the operators. Then, the as-is process was mapped in BPMN 2.0. in order to have a clear and visual image of the process and make sure that the process was well comprehended. The as-is model can be seen in Figure **51**.

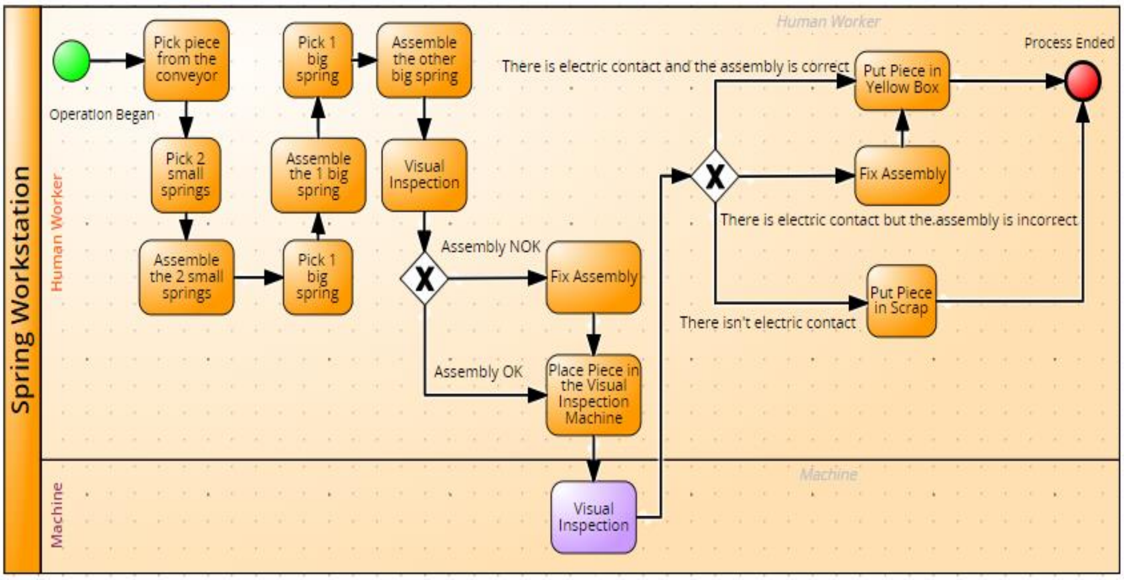


Figure **51** - As-Is Model in Spring Workstation at Microplásticos

IV.5.4. Process Analysis and match with literature

In this phase the issues associated with the as-is process are identified. Analyzing the current situation, the spring workstation is extremely optimized, however, the visual machine it is getting outdated, and the process of visual inspection could be faster. Moreover, some flexibility could be added to the process.

This use case represents a simple case of HRC, as there is no communication between the agents - the worker and the cobot. However, it is still the second highest level of HRI which is cooperation because the human operator and cobot will work in the same workspace at the same time, though each focuses on separate tasks. In fact, while the cobot is performing the last steps of the process, the human worker can start the assembly of a new part. Therefore, there isn't responsive collaboration between the agents.

IV.5.5. Process Redesign

This phase is characterized by identifying the changes that could be implemented in processes in order to help solve the problems identified. Therefore, the desired and possible solution is the implementation of a collaborative robot, in order to substitute the visual machine. Thus, the cobot could also take over some of the tasks that are currently performed by the human worker. The future collaborative workstation is presented in Figure **52**.

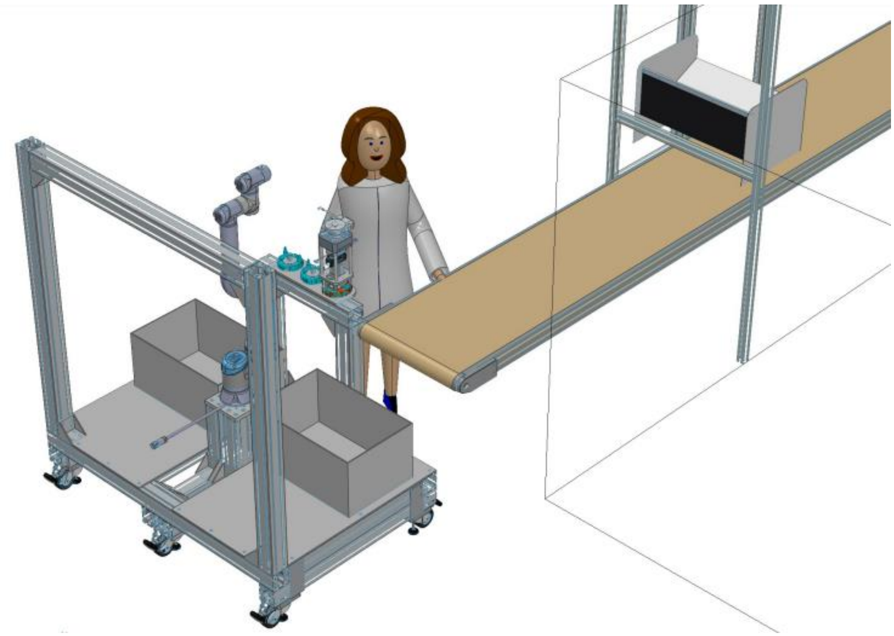


Figure **52** - Future spring post in Microplásticos with one cobot

The interference zones between the cobot and the worker correspond to the position in which the worker is marked as it is represented in Figure **53** and every time the container ends, the zones marked as red represent the location of the full and empty containers. In fact, Microplásticos has already bought the cobot, developed the structure of the collaborative work cell presented in Figure **53** and is already assembling this structure. The outcome of this phase is the model of the future process, therefore, the to-be process is presented modelled in BPMN 2.0 in Figure **54**.

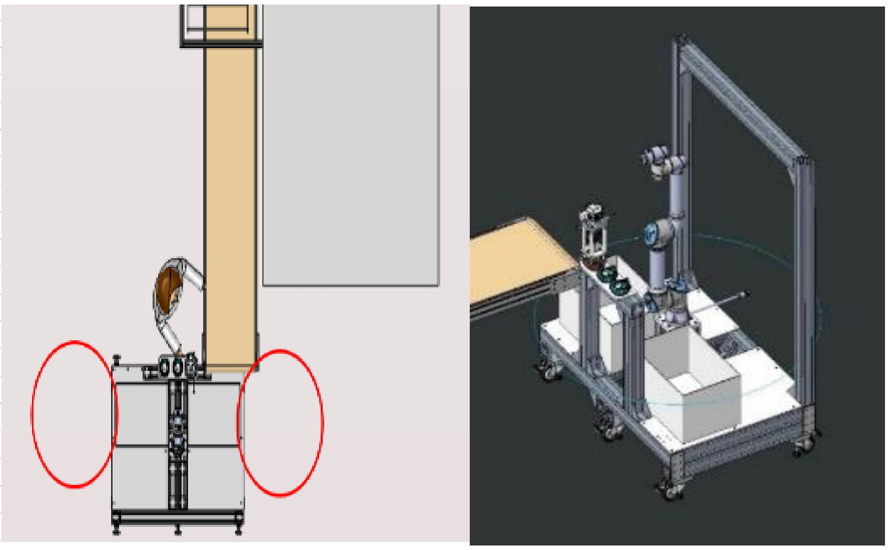


Figure **53** - Upper View of the workstation and structure for the collaborative work cell

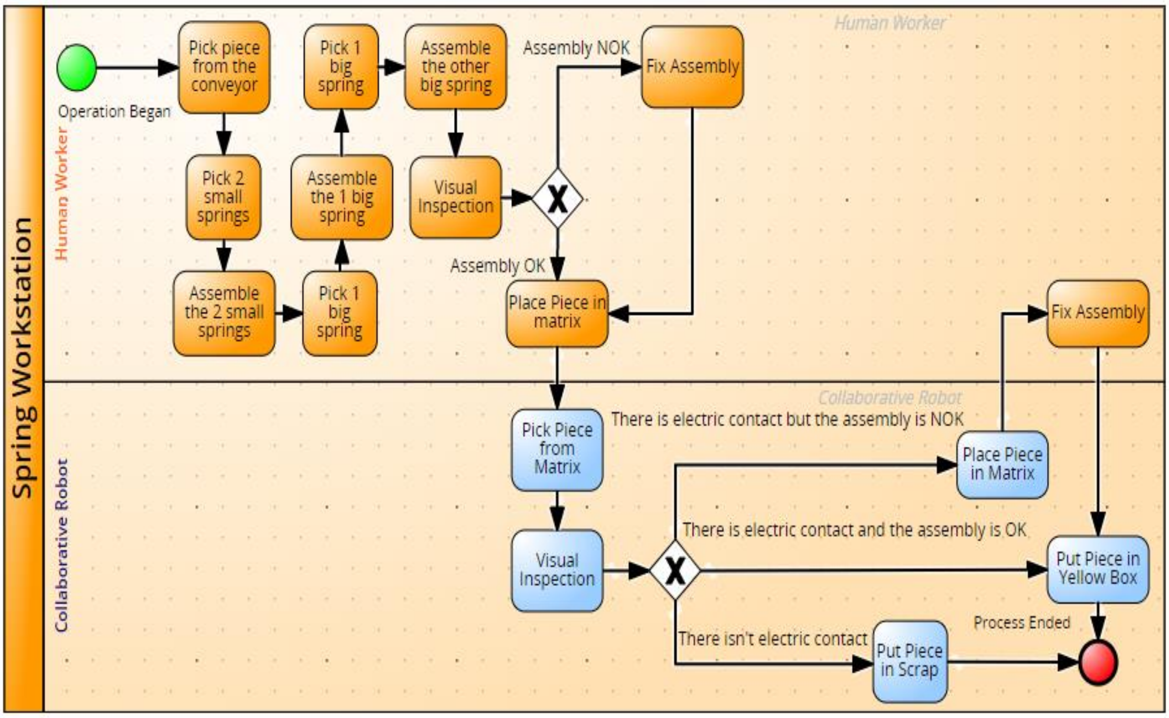


Figure **54** - To Be Model in Spring Workstation in Microplásticos

IV.6. Discussion

The main goal of this chapter was to discover the best workstation to implement a collaborative robot in three different corporations. For that, the BPM lifecycle was followed. Each relevant processes were mapped using BPMN 2.0 so that, the process was fully comprehended and in order of identifying the best workplace for implementing the cobot.

Process modelling can in fact, assist people to specify, understand and document processes more effectively than using text. In addition, having a visual image of the process can also help the emergence of ideas to improve processes. Business process modelling is therefore useful to the understanding of the as-is and to-be processes during all kind of changes such as software development, automation or even restructuration of business processes (Kesari et al., 2003). In this case, the modelling of the process functioned as a common language for the team to communicate and understanding where it would be best to adopt a collaborative work cell. The modelling of the as-is process improves the perception of the actual process and where it would be more advantageous to add a cobot, in terms of minimizing time, minimizing the ergonomic risk for the human worker, where it was possible because of space reasons, etc. However, the modeling of process as its own limitations, so communication, discussion and brainstorming between the team members was crucial for the development of the project.

Regarding the implementation of the collaborative robot, it is difficult to evaluate the advantages of the implementations quantitatively, because in the three case studies the cobot is not fully implemented in the chosen workstations. However, some qualitative analysis can be depicted.

Concerning the Industry in Paços de Ferreira, the cobot will fulfill the main objective which is the gained flexibility. Because of constant changes in demand patterns, the Industry is changing lines and products more frequently. Therefore, compared to traditional robots, cobots have the advantage of being easily transported and moved which enables the flexibility and adaptability necessary to short product lifecycles. However, after its implementation, it would be important to also quantify the ergonomic and time gains.

In regard of BOSCH Thermotechnology Aveiro, the mapping of process help to understand that the adoption of a collaborative robot could enable the parallelization of tasks between the robot and the human which would diminish the cycle time of the studied workstation. Despite the fact that, it was not possible to measure the time gains, because the cobot is not implemented until the present date, this decrease will be critical for the assembly line as the riveting workstation represents a bottleneck in the process.

In concern of Microplásticos, despite the robot being bought it is not implemented in the desired workstation. The adoption of a collaborative robot, substituting the visual inspection machine pretended to add innovation to the shopfloor, which in the automotive industry is extremely important, sector where the corporation in included. In addition, the cobot will also substitute some of the tasks that were assigned to the human worker which will diminish human fatigue. Moreover, it will reduce the number of needed operators in the workstation, since it was almost two. Therefore, costs will be reduced, and human capital can be employed in other tasks.

IV.7. Conclusion and Future Work

BPMN proved to be a powerful tool as it enables the visual representation of a process providing a general and unambiguous vision of processes and making possible the identification of where the process can be improved or automated. Therefore, BPMN helped to identify the best workstation to implement place the cobot and which tasks would be best to be allocated to the human worker and to the collaborative robot. The developed work also helped and contributed to the work presented in Chapter **V** in the development of algorithms to the scheduling of tasks in collaborative robotics because it provided awareness about the process. However, after the real implementation of the cobot, quantitative ergonomic and time improvements should be measured in order to clearly identify the benefits of the collaborative implementation.

Chapter V - Development of an Algorithm for the Assignment and Scheduling of Tasks in Collaborative Robotics

V.1. Introduction

After understanding collaborative robotics, the processes and knowing where and how to implement a collaborative robot it is extremely important to understand how to assign and schedule tasks between a human worker and a robot. In fact, humans and robots have different qualities and limitations therefore, there are tasks which are more suitable for each type of the agents, and others that both can perform. For that, in this chapter an algorithm for the assignment and scheduling of tasks will be developed. The algorithm aims to help engineers to decide the best schedule for a specific job.

The approach to compute task schedules and assignments by considering time and ergonomics to integrate a collaborative robot is presented. Firstly, the terms to describe work at different levels are defined. Secondly, the problem under study is described. Thirdly, the optimization approach is described. Finally, the algorithm is tested using a small-scale problem.

V.2. Objectives and Methodology

This chapter is dedicated to the development of an algorithm to the allocation and scheduling of tasks in collaborative robotics. The methodology followed to the development of the algorithm was an adaptation of the agile software development methodology which is presented in Figure **55**. The main goal of agile methods is the reduction of the overhead in the development process with the ability to adopt changes without risking the overall process and without excessive rework.

Figure **55** - Adopted Agile Software Development Methodology

The adopted agile development software methodology begins with a planning phase, follows with the design towards the development phase, testing, and then the review step. This methodology has characteristics from agile methods such as iterations and incremental interactions throughout the life cycle of the project (Al-Saqqa et al., 2020). Agile methods follow a set of principles such as:

- ❖ People and interactions over processes and tools, in this way, formalities and technicalities as key factors is extremely incorrect. Important factors include communication and interaction.
- ❖ Software over documentation. Documentation is valuable but the amount of time and resources that are given to it must be optimized to not overwhelm the development process.

- ❖ Response to change over following a plan. As the software development process is progressing, all participants in the project will gain more knowledge and a better understanding of the project itself, therefore the addition or the annulation of some requirements may be necessary (Al-Saqqa et al., 2020).

Moreover, agile methods are more adaptive to changes than traditional approaches and there is collaboration between the developers and other participants. However, agile methods are more efficient in small and medium projects than in long term projects. In addition, the planning phase in agile methods is projected in the short term which is easier to be done when comparing with the traditional methods that need a long-term plan (Al-Saqqa et al., 2020). A more detailed comparison between agile methods and other traditional approaches can be seen in Table **10**.

Table **10** - Agile Development vs Traditional Development Methods (Al-Saqqa et al., 2020)

Parameter	Traditional Methods	Agile Methods
Ease of Modification	Hard	Easy
Development Approach	Predictive	Adaptive
Development Orientation	Process Oriented	Customer Oriented
Project Size	Large	Small or Medium
Planning Scale	Long Term	Short Term
Management Style	Command and Control	Leadership and Collaboration
Learning	Continuous Learning while Development	Learning is secondary to Development
Documentation	High	Low
Organization Type	High Revenue	Moderate and low Revenue
Organization's Number of Employees	Large	Small
Budget	High	Low
Number of Teams	Multiple	One
Team Size	Medium	Small

Concerning the present project of developing an algorithm to the task assignment and scheduling of tasks in collaborative robotics, the adopted approach is described below.

Firstly, the first planning phase was characterized by the definition of the problem and the system scope and by capturing the necessary requirements to the development of the algorithm: tasks, duration of each task when it is the robot and the human performing the task, ergonomic risk or strain index value of each task, which tasks can the robot and the human do, which tasks are done in collaboration and precedencies. Secondly, in the design phase it was important to decide what was the solution approach to use and what was the solution pretended, in other words, what the running of the algorithm was going to show. It was decided that the program should return the list of tasks assigned to the human worker, the list of tasks allocated to the robot, in which temporal interval was each task happening, the total makespan of the job, and the maximum and ergonomic risk allowed to the tasks assigned to the human worker.

Then, in the development phase simple inputs were introduced and the algorithm started to be developed. The software used was IntelliJ IDEA Community version, and the algorithm was coded in java. The algorithm inspired in the GRASP metaheuristic started to be developed.

The next phase was dedicated to testing. Firstly, the develop algorithm was tested with created data by the author in order to test all the functionalities of the program and another one with data from Pearce et al. 2018 which will be presented hereafter.

The review phase consisted in making sure that the program enabled all the functionalities pretended such as the parallelization of tasks, collaborative tasks, tasks which cannot be done by the human and the robot etc. In addition, it also focused in solving small errors that would occur.

V.3. Problem Description

The description of the type of problem was inspired by industrial partners' use cases that belong to the activity 3 of the Augmanity Project, where this dissertation is included. In order to test the developed algorithm, it was necessary to choose a type of problem and described it which was based considering the real-world use cases of the Industry in Paços de Ferreira, BOSCH Thermotechnology and Microplásticos. Before the presentation of the problem definition, it is important to firstly clarify some terms that will be used in order to fully understand the problem under study. The definitions were inspired by Radwin et al. (1994).

- A **job**, J, consists of several tasks that may have precedencies between them. Therefore, job J can be divided into a set of N specific tasks, such that:

$$J = \{T1, T2, T3, \ldots, TN\}$$

- Each **task**, T, is an operation that cannot be subdivided like, for example, pick, place, reach, grasp, move, etc.

Considering a single workstation, in other words, a collaborative cell, where two agents, a human operator H and a robot R, have to cooperate during a work shift in order to perform S jobs (J1, . . . , JS). Each job can be split into a set of tasks (T1,…,TN). In the developed algorithm, tasks are assigned and scheduled.

Thus, the allocation and scheduling of tasks between a human and a robot is designed as a multiagent assignment and scheduling problem as Pearce et al., 2018. Each task is associated with an execution time pi(A), where $A \in \{H,R\}$ represents the agent that executes the task. The duration of the tasks will depend on the agent that performs it. Moreover, each task has also a strain value. This parameter is extremely important in order not to allocate tasks that are repetitive, heavy or dangerous to the human worker which can improve the quality of the human job. Precedence relations among tasks, are also considered. Because of the capabilities required for some operations (e.g. analytic skills, visual inspection, or high flexibility) and agent-limited capabilities, only a set of operations can be performed by the robot, and there could also exist tasks that cannot be done by the human. A human and robot can perform different operations simultaneously or collaborate on an operation, in other words there are tasks that can only be executed when the human and the robot work in close collaboration. Each agent can only perform one task at a time (no overlapping) and preemption it is not considered, in other words, for task j to begin, task i has to be finished first, if there is a precedence relation between tasks I and j.

The solution of the scheduling algorithm will be a set of assigned tasks to the human and to the robot, its order, and times, and the total makespan. The objective of the scheduler is to distribute tasks to the agents and determine the sequence of tasks that minimizes the makespan, considering human strain. The ergonomic risk is inputted as a constraint. The input to the scheduler consists of the ergonomic risk for each task along with the time to complete each task for both agents and its precedencies. The scheduler also has a set of constraints that represents which tasks cannot be done by the robot or by the human. A summary of the main characteristics of the studied problem is presented in Figure **56**.

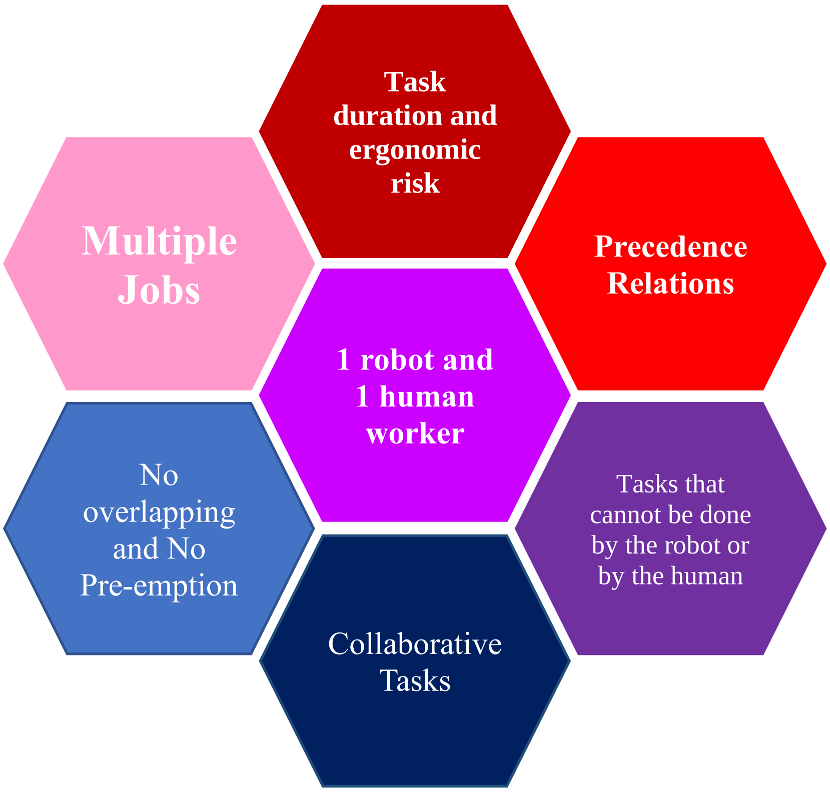


Figure **56** - Main characteristics of the studied problem

V.4. Solution Method

For many years, heuristics have been studied to solve combinatorial optimization problems. By definition, heuristics are search methods that take advantage from the characteristics of the problem to be explored, making it easier to try to find a global minimum in the search space (Blum & Roli, 2003). On the other hand, heuristic procedures are limited since they return the same solution when the beginning point is the same. Therefore, metaheuristics try to solve this issue, by having as their main objective to intelligently explore a research space and find high-quality solutions by moving to unexplored areas. Thus, metaheuristics are search procedures capable of escaping from local minimums, focusing on efficiency and greater exploration of the search space (Blum & Roli, 2003).

Metaheuristics have in common some characteristics among them such as:

- use of strategies to guide the search process
- efficiently exploration of the search space, with the objective of finding an optimal solution
- use of local search to complex learning processes
- having mechanisms that avoid the imprisonment in restricted areas
- use of a specific domain of knowledge with a heuristic for search strategies
- store search experiences (Blum & Roli, 2003).

Most used metaheuristics include Tabu Search, Iterated Local Search (ILS), Variable Neighborhood Search (VNS), Simulated Annealing (SA), Genetic Algorithms (GA), Ant Colony, and Greedy Randomized Adaptive Search Procedures (GRASP), among others. The method chosen to solve the described problem was an algorithm inspired in the metaheuristic GRASP. GRASP is a metaheuristic of neighborhood search which by means of a trade-off between greediness and randomness, is able to escape of local optimums and is easy to compute. It has a constructive heuristic mechanism which can provide a feasible solution for an optimization problem at each step of the algorithm (Resende & Ribeiro, 2018).

The algorithm was inspired in the GRASP metaheuristic because of its potential and because it has an especially appealing characteristic which is the ease of implementation in which few parameters are needed. Also, from our literature search no application of this method to the problem under consideration was found, making it a potentially good contribution to literature. In fact, GRASP has two main parameters: the stopping criterion and the quality of the elements in the restricted candidate list. The stopping criterion is usually determined by the number of iterations. The total computation time increases linearly with the number of iterations, by consequence, the larger the number of iterations, the larger the computation time and the better the solution found (Resende & Ribeiro, 2018).

V.4.1. Greedy Randomized Adaptive Search Procedure

The following description of GRASP will follow Resende and Ribeiro (2018) guidelines. An algorithm is called greedy if at a given step selects the best available solution. However, trying to select the best solution at a given step can prejudice the overall final result. A greedy algorithm can generate a solution of good quality, but it does not guarantee the optimal solution. In fact, research have shown that greedy algorithms can get stuck at local optimums. Therefore, GRASP can establish a trade-off between greediness and randomness. GRASP is a multi-start metaheuristic for combinatorial optimization problems, in which each iteration includes the following two phases: solution construction and local search. The construction step builds a feasible solution. Then, during the local search phase, the neighborhood of the initial solution is investigated until a local minimum is found

The pseudo-code of the method is presented in Figure **57** which represents the main blocks of a GRASP aiming for the minimization and in which the term “Seed” is used as the initial seed for the pseudo-random number generator and “Max_Iterations” are performed.

```
procedure GRASP(Max_Iterations, Seed)
    Read_Input();
    for k = 1,...,Max_Iterations do
        Solution ← Greedy_Randomized_Construction(Seed);
        if Solution is not feasible then
            Solution ← Repair(Solution);
        end;
        Solution ← Local_Search(Solution);
        Update_Solution(Solution, Best_Solution);
    end;
    return Best_Solution;
end GRASP.
```

Figure **57** - GRASP pseudo code

GRASP consists in multiple local search applications, each starting from a different solution. The initial solutions are generated by a greedy random construction and the algorithm stores the best solution(s) found. In the construction phase, at each iteration, a set of candidates are formed. The selection of these candidates is determined by a greedy evaluation function. The greedy function represents the increase in the minimization function with the incorporation of an element into the solution under construction. The evaluation of the elements leads to the creation of a Restricted Candidate List (RCL) formed by the best elements, in other words, those whose incorporation to the actual solution results in the smallest incremental costs or time or etc. The RCL is created with an α factor, which represents a percentage of the possible elements to include in the RCL.

The value of α has influence in the quality and diversity of the generated solution in the construction phase. On the one hand. low values for α generate greedy high-quality solutions but with a lower diversity. On the other hand, high values for α generate solutions with a higher diversity but with lower quality. Low quality solutions make the local search process slower. Then, the element to be incorporated is randomly selected from those in the RCL and then the candidate list is updated. In Figure **58** the pseudo-code of the construction phase is presented.

To the calibration of the α value, the following strategies can be adopted:

- use of a fixed value
- use of a random value chosen in a uniform Distribution, for instance, in each iteration, generate an α between 0 and 1
- use of a random value of an empiric distribution, for instance between 0 and 0,75
- reactive strategy (Paris & Ribeiro, 2000) which usually provide better results

Normally, the use of a fixed value for α incurs in worst results because the algorithm retards the process of obtention of better solutions. The reactive strategy consists of choosing the value for α according to a probability distribution, which is dynamically updated in a selective manner, in other words, it's generated during the GRASP iterations.

```
procedure Greedy_Randomized_Construction(Seed)
    Solution ← ∅;
    Initialize the set of candidate elements;
    Evaluate the incremental costs of the candidate elements;
    while there exists at least one candidate element do
        Build the restricted candidate list (RCL);
        Select an element s from the RCL at random;
        Solution ← Solution ∪ {s};
        Update the set of candidate elements;
        Reevaluate the incremental costs;
    end;
    return Solution;
end Greedy_Randomized_Construction.
```

Figure **58** - Pseudo-code of the construction phase

The local search phase tries to improve the constructed solution. The local search algorithm works iteratively by replacing the current solution with a better solution in its neighborhood. It finishes when no better solution is found. The pseudo-code of a local search algorithm is presented in Figure **59**.

```
procedure Local_Search(Solution)
    while Solution is not locally optimal do
        Find s' ∈ N(Solution) with f(s') < f(Solution);
        Solution ← s';
    end;
    return Solution;
end Local_Search.
```

Figure **59** - Pseudo-code for the local search step

The neighborhood search can be implemented using a best-improving or a first-improving strategy. In a best-improving strategy, all neighbors are investigated, and the current solution is replaced by the best neighbor. In a first-improving strategy, the current solution moves to the first neighbor which is better than the current solution.

Advantages of this metaheuristic include the fact that it is less dependent of parameters than other algorithms because it only needs two parameters; its computational implementation is extremely easy; because of its greedy randomly construction it makes it easier to construct feasible solutions. The only limitation is the lack of memory during the search process because it does not acquire the knowledge obtained from previous iterations. To conclude, GRASP is one of the most robust metaheuristics to solving combinatorial optimization problems and its construction phase can be used in other metaheuristics such as genetic algorithms.

V.5. Presentation and Description of the Algorithm

The algorithm was coded in java in the software of IntelliJ IDEA Community version counting a total of 2218 lines of code which can be found in https://github.com/JoanaPereira99/GRASP-algorithm-for-the-assignment-and-scheduling-of-tasks-in-collaborative-robotics/tree/main. Because of the complexity of the program, it was created an initial menu as it can be seen in Figure **60** in order to make it easier for all users to use the program. This menu has 3 options, to list the already created jobs, to create a new job and to exit which will terminate the program.

```
# ---------------------------------------------------------------------------- #
1 - List created Jobs
2 - Create new Job
0 - Exit
# ---------------------------------------------------------------------------- #
What is the selected option? |
```

Figure **60** - Initial Menu

The program enables the creation of multiple jobs, each job consisting of a distinct set of tasks and a specific maximum desired value for the ergonomic risk. As it can be seen, in Figure **61**, choosing option 1 from the initial menu will return the list of the available jobs to run. However, the program can only run one job at a time.

```
Available Jobs:
1 - Job 1
2 - Job 2

0 - Return
Enter a value |
```

Figure **61** - List of created Jobs

Then, choosing option 1 (Job 1), the program will retrieve all the information about that job as it can be seen in Figure **62**: the groups, the dependencies, the tasks, and the maximum defined ergonomic risk, which in this case, means that tasks with a higher value than 5 of ergonomic risk cannot be assigned to the human worker. Then, it also shows the menu of jobs which enables the creation of a new group, list already created groups, run the schedule for the selected job, modify the maximum value for the ergonomic risk, modify the dependencies, delete a job or change the name of the job. Then choosing option 2, to list created groups and then selecting one of the created goups, the program will return all the information about that group and other relevant options as it can be seen in Figure **63**

Figure **63**.

```
Name: Job 1
Groups: [C, B, A, D, E]
Actual Dependencies: C,B;A;D,E
Tasks (10): [Task 5, Task 6, Task 3, Task 4, Task 1, Task 2, Task 7, Task 8, Task 9, Task 10]
Maximum Ergonomic Risk: 5

1 - Create new Group
2 - List created Groups
3 - Run schedule of the Job.
4 - Establish the maximum value for Ergonomic Risk.
5 - Establish Dependencies (Ex.: [A-B-C,D-E-F]).
6 - Delete selected Job
7 - Change the name of the selected Job
0 - Return
Enter a value: |
```

Figure **62** - Information of Job 1 and options of the Job Menu

```
Name of group: C
Total of tasks: 2
Tasks: [Task 5, Task 6]
1 - Change the name of the Group
2 - List created Tasks
3 - Create new Tasks
4 - Delete selected group
0 - Return
Enter a value: |
```

Figure **63** - Options of the Task Menu

Groups were created in order to deal with precedencies between tasks. This entity enables one task to have more than one dependency, for example, task 4 can have task 1 and task 3 as dependents. This was the approach taken, whereas there could be other methods to deal with this matter such as the creation of acyclic graphs, however the adopted approach seemed to be simpler. In case the created groups are only separed by commas (,), for example: A,B,C it means that the tasks of each group can be executed at the same time, in other words, there are no precedencies between the tasks between groups. Within the same group, if it has more than one task, the program assumes that the tasks entered will have to be done by the order of entry. For instance, as it can be seen in Figure **63**, group C has Task 5 and Task 6, therefore, Task 5 will have to be performed before Task 6 can be scheduled. If groups are separed by a dash (-), by a semmi-comma (;) or by a greater than symbol (>) it means that the groups have precedencies, for instance if the dependencies entered were A-B it means that the tasks of group A must be concluded pior to start the tasks of group B, in other words, group B depends on group A. Afterwards, choosing option 2 to list the created tasks and then choosing Task 5, for instance, the program will show all the information of that task and the menu as it can be seen in Figure **64**.

```
Name of task: Task 5
Time of human performance: 18 seconds
Time of robot performance: 16 seconds
Ergonomic risk of task: 2
Is the task collaborative? true
1 - Change name of task
2 - Edit ergonomic risk for task
3 - Edit task human time.
4 - Edit task robot time.
5 - Edit collaborative task time
6 - Delete selected task.
0 - Return
Enter a value: |
```

Figure **64** - Options in the Group Menu

Regarding the way of working of the algorithm its main steps can be described as followed:

1) Firstly, the algorithm, begins with the greedy construction function where it will order all tasks taking into consideration its duration, in other words, the tasks will be ordered increasingly by duration, considering the robot time and the human time. In case there are tasks with equal duration, the algorithm takes into account the difference between the human's time and the robot's time, and it will prefer tasks with a smaller difference.

2) Secondly, the algorithm will create a RCL, with 80% of the fastest tasks. However, this parameter can also be modified according to the trade-off between greediness and randomness pretended. In addition, it is important to state that the approach to define α was to use a single fixed value for matters of simplicity and because Resende and Ribeiro (2018) stated that this approach presents the shortest average computation times. After the creation of the set of candidate tasks, one task will be chosen randomly.

3) Thirdly, the chosen task will be assigned randomly to one of the agents (to the robot or to the human worker) but taken into consideration if each agent can indeed perform the task and if the task can be assigned to the human, in other words if the ergonomic risk of the task is not higher than the maximum defined. Once the selected task is incorporated into the partial solution, the RCL is updated and the incremental costs (in this case the tasks duration) are reevaluated which is the adaptive aspect of the algorithm. This process will be repeated until all tasks are assigned to an agent. The process of selecting another task to be assigned works as following described: the algorithm will always look for the task with the lowest duration, taking into consideration both durations (the human and the robot). The best task represents the one which will increase less the makespan. The selection of the next task for incorporation is determined by the evaluation of all candidate tasks according to a greedy evaluation function, which represents the incremental increase in the minimization time function due to the incorporation of the task into the solution under construction. The incremental costs in time will be updated after each assignment. A feasible solution for the job schedule is constructed. The solution will always be feasible as the constraints of capability matters and ergonomic risk and precedencies are already considered when assigning each task, so there is no need to apply a repair procedure to achieve feasibility.

4) The process will be repeated 100 times which is the number of iterations defined, whereas this parameter can also be modified. Finally, after iteration number 100, the best solution, in other words the solution which respecting all the constraints, has the lowest makespan, is kept as the result.

The main reason the developed algorithm does not work as the GRASP metaheuristic is because the presented algorithm does not have the local search process which builds an initial solution and tries to improve it. Conversely, the presented algorithm builds a new solution at each iteration and does not consider the initial solution. Regarding the limitations, the program has a greater focus on optimizing time, and ergonomics is only considered as a constraint. For future work it would be interesting to rebuilt the main function as a trade-off between ergonomics and time where each component would have a weight and the user could decide the pretended weight for each component. Moreover, when there is a task that cannot be executed by the robot and that has a higher ergonomic risk than the maximum defined, the task will be assigned to the human anyway, because the program is built in order that all tasks that are inputted must be made. However, when this happens the program shows a message informing that a task that shouldn't be allocated to the human was assigned anyway as it can be seen in Figure **65**. Finally, other limitation that can be identified is the use of a fixed value for alpha. In fact, Prais and Ribeiro (2000) as cited in Resend and Ribeiro (2018) showed that using a single fixed value for α can hinder from finding a high-quality solution. A better strategy would be the reactive approach in which α is periodically modified depending on the quality of the solutions obtained along the search however, at the cost of computation times (Resende & Ribeiro 2018).

```
Warning: The human worker was forced to perform a task with a higher ergonomic risk than it is supposed to.
```

Figure **65** - Message in case the human is assigned a task with a higher value of ergonomic risk in case the robot cannot perform the task

In addition, the ergonomic risk is only counted when the task is assigned to the human. When the task is collaborative, it is supposed that the robot will be the agent which is doing the most effort therefore, in this case the ergonomic risk is also not counted. Another supposition that was also made regarding collaborative tasks is that its duration will be the higher value between the duration time of the task when it is performed by the robot and the duration time when it is assigned to the human, for instance, if the time for the human worker is 20 seconds and the time for the robot is 22 seconds, the time of the collaborative tasks will be 22 seconds. For future work it would be important to have a specific time for the collaborative task which is what happens in a real situation.

V.6. Experiments and Results

In order to test the algorithm a small instance was created, consisting of one job, eight tasks, a human worker and a robot. The tasks between groups were supposed to not have precedencies, in other words, there can be paralleliztion of tasks between groups. Inside the groups there is a precedence, for instance, task 2 (T2) can only start when task 1 (T1) finishes. To test all the functionalites of the algorithm, there is one task which is collaborative (T5) and task 7 (T7) and task 8 (T8) cannot be assigned to the human and to the robot, respectively. Firstly, the problem was solved without constraining the ergonomic risk. Despite being a problem inspired by the industrial partners that belong to the activity 3 of the Augmanity project, in this instance, the classification of the ergonomic risk did not follow any specific method, so further on, the values for ergonomics will be designated as ergonomic risk (ER). The higher the value for the ergonomic risk the higher the physical strain for the human worker. The best solution found by the algorithm inspired by GRASP resulted in a total makespan of 82s, the solution is presented in Figure **66**.

Secondly, in order to understand the influence of the ergonomic risk in the total makespan, the ergonomic risk was decreased, step by step. Along with the reduction in the maximum accepted ergonomic risk it is expected that the human worker will be assigned to fewer tasks. One important comment to state is that, no matter the maximum value for the ergonomic risk, task 8 (T8) will always be assigned to the human worker, because the robot is not able to executed it, however the message in Figure **65** is showed to the user as a warning.

```
- A:
  - T1:
      Ergonomic Risk: 6
      Time for Human: 14
      Time for Robot: 17
      Timelapse: [0,14]
      Is the task collaborative? False
      Chosen: Human
  - T2:
      Ergonomic Risk: 7
      Time for Human: 19
      Time for Robot: 25
      Timelapse: [14,39]
      Is the task collaborative? False
      Chosen: Robot
- B:
  - T3:
      Ergonomic Risk: 5
      Time for Human: 15
      Time for Robot: 20
      Timelapse: [14,29]
      Is the task collaborative? False
      Chosen: Human
  - T4:
      Ergonomic Risk: 6
      Time for Human: 13
      Time for Robot: 14
      Timelapse: [29,42]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T5:
      Ergonomic Risk: 3
      Time for Human: 10
      Time for Robot: 12
      Timelapse: [42,54]
      Is the task collaborative? True
      Chosen: Human and Robot
  - T6:
      Ergonomic Risk: 7
      Time for Human: 16
      Time for Robot: 14
      Timelapse: [54,68]
      Is the task collaborative? False
      Chosen: Robot
- D:
  - T7:
      Ergonomic Risk: 15
      Time for Human: -1
      Time for Robot: 10
      Timelapse: [0,10]
      Is the task collaborative? False
      Chosen: Robot
  - T8:
      Ergonomic Risk: 2
      Time for Human: 10
      Time for Robot: -1
      Timelapse: [54,64]
      Is the task collaborative? False
      Chosen: Human
```

Figure **66** - Solution for the created problem without constraining the ergonomic risk and with ER=6

In Table **11** it can be seen the different information of the job for each value of the ergonomic risk, the total makespan, the sequence of tasks and allocations, the number of tasks assigned to the human and to the robot, parallel tasks and human and robot idle time. As it can be depicted in Table **11**, makespan will increase along with the reduction of the maximum accepted value for the ER until ER=3. For ER equal to 2 and 0 the makespan stagnated. For ER=15, a higher importance is being given to makespan, whereas for ER=0 a higher importance is being given to ergonomics. For values in between, the solutions present a trade-off between makespan and ergonomics. In this example, the robot worker represents a cobot, therefore by its nature usually a collaborative robot is slower than a traditional robot because of safety reasons. Thus, it can be seen in Figure **66** that for the majority of tasks the human worker is faster than the cobot. In Figure **68** and Figure **69** presented in the Appendix, the schedules for the job are presented considering other values for the ergonomic risk constraint. For this reason, it is understandable that the solution with the best makespan is the one where more tasks were assigned to the human worker. Consequently, the human idle time will increase with the reduction of the maximum allowed value for ER. In contrast, along with the reduction of ER, more tasks will be assigned to the robot because in that way, the ER value for the tasks is not accounted. Therefore, robot idle time will decrease with the reduction of the maximum allowed value for ER. In addition, it can be also seen, that solution with a smaller makespan, will have more parallel tasks which provide a better makespan.

Table **11** - Schedule information for First Job

Ergonomic Risk	**15**	**6**	**5**	**3**	**2**	**0**
Makespan	68s	68s	102s	122s	122s	122s
Sequence of Tasks	T1, T7-T2, T3 -T4-T5-T6, T8	T1, T7-T2, T3 -T4-T5-T6, T8	T1, T3-T2-T4 -T5-T6 -T7-T8	T1-T2-T3-T4-T5-T6 -T7-T8	T1-T2-T3-T4-T5-T6 -T7-T8	T1-T2-T3-T4 -T5-T6 -T7-T8
Sequence of Allocations	H, R-R, H-H-H&R -R, H	H, R-R, H-H-H&R -R, H	R, H-R-R-H&R-R-R-H	R-R-R-R-H&R-R-R-H	R-R-R- R -H&R-R-R-H	R-R-R-R-H&R-R-R-H
H**uman** Tasks	4	4	2	1	1	1
Robot Tasks	3	3	5	6	6	6
Parallel Tasks	T1, T7 and T6, T8	T1, T7 and T6, T8	T1, T3	0	0	0
Human idle time	5.9%	5.9%	63.7%	82%	82%	82%
Robot idle time	10.3%	10.3%	9.8%	8.2%	8.2%	8.2%

Besides the previous example, the algorithm was also tested using adapted data from Pearce et al., (2018) in order to understand the performance of the algorithm and to enable the analysis of the results. Six real-world based processes that, were executed by human workers were considered, including three observed during a visit at Steelcase, Inc., a furniture manufacturer bases in the USA and three chosen from the NIOSH video database developed (Pearce et al., 2018). The three processes from Steelcase included a quality-control process (Job 1), a packaging process (Job 2), and an assembly process (Job 3). The other three processes from NIOSH database consist of a stocking process (Job 4), a parts-assembly process (Job 5), and a metal-cutting process (Job 6) (Pearce et al., 2018). The approach will be to analyze the effect on the total makespan with the changing of the maximum limit allowed for the ergonomic risk.

In Figure **67** the solution of the algorithm can be seen for Job 1 when there is no constraint to the ergonomic risk. The solutions for the different values for the ergonomic risk and for the other jobs can be seen in Appendix from Figure **70** to Figure **92**.

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [0,5]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 6
      Time for Robot: 19
      Timelapse: [5,11]
      Is the task collaborative? False
      Chosen: Human
 - C:
   - T3:
       Ergonomic Risk: 1.5
       Time for Human: 5
       Time for Robot: 14
       Timelapse: [0,14]
       Is the task collaborative? False
       Chosen: Robot
 - D:
   - T4:
       Ergonomic Risk: 1.5
       Time for Human: 5
       Time for Robot: 12
       Timelapse: [11,16]
       Is the task collaborative? False
       Chosen: Human
- E:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 2
      Time for Robot: -1
      Timelapse: [16,18]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 7
      Time for Robot: 26
      Timelapse: [18,25]
      Is the task collaborative? False
      Chosen: Human
  - T7:
      Ergonomic Risk: 2.25
      Time for Human: 4
      Time for Robot: -1
      Timelapse: [25,29]
      Is the task collaborative? False
      Chosen: Human
  - T8:
      Ergonomic Risk: 1
      Time for Human: 4
      Time for Robot: 10
      Timelapse: [29,33]
      Is the task collaborative? False
      Chosen: Human
```

Figure **67** - Schedule for Job 1 without constraining the SI

In Table **12** and similarly to Table **11** the information for all jobs along with the restriction of the maximum value for the SI can be depicted. Similarly, to what happened in the previously example, overall, the same conclusions can be made:

- Makespan increases along with the reduction of the maximum value for SI;
- Human idle time will increase with the reduction of the maximum value for SI while robot idle time will decrease.

However, some exceptions can be seen, for jobs with: SI=1.5 and SI=0.75 the makespan did not increase, contrarily, the algorithm found even better solution in terms of makespan. This happened because without the restriction of SI (SI=2.25) the algorithm was not able to enable the parallelization of tasks as it happened for SI=1.5 and SI=0.75. One justification that can be made for this to happen is that the greedy part of the algorithm, made the algorithm get stuck in a local optimum.

Table **12** - Information of job schedules with different SI

	SI	**2.25**	**2**	**1.5**	**1**	**0.75**	**0.25**	**0**
Job 1	**Makespan**	33s	52s	52s	62s	68s	96s	96s
	Sequence of Allocations	H,R-H-H-H-H-H-H	H,R-H-H-H-R-H-H	H,R-H-H-H-R-H-H	H,R-H-R-H-R-H-H	H,R-H-R-H-R-H-R	R-R-R-R-H-R-H-R	R-R-R-R-H-R-H-R
	Human Tasks	7	6	6	5	4	2	2
	Robot Tasks	1	2	2	3	4	6	6
	Parallel Tasks	T1,T3	T1,T4	T1,T3	T1,T3	T1,T3	0	0
	Human idle time	0%	50%	50%	66.1%	75%	93.8%	93.8%
	Robot idle time	57.6%	26.9%	23.1%	16.1%	8.8%	6.3%	6.3%
	SI	**11**	**10**	**2**	**0.75**	**0.5**	**0.375**	**0.25**

Job 2	**Makespan**	24s	24s	24s	39s	50s	50s	50s
	Sequence of Allocations	H,R-H-H-H-H-H	H,R-H-H-H-H-H	H,R-H-H-H-H-H	H,R-H-R-H-H-H	H,R-R-R-H-H-R	H,R-R-R-H-H-R	H,R-R-R-H-H-R
	Human Tasks	6	6	6	5	3	3	3
	Robot Tasks	1	1	1	2	4	4	4
	Parallel Tasks	T1 with T3	T1 with T3	T1 with T3	T1 with T2	T1 with T2 T6 with T7	T1 with T2 T6 with T7	T1 with T2 T6 with T7
	Human idle time	0%	0%	0%	56.4%	70%	70%	70%
	Robot idle time	58.3%	58.3%	58.3%	23.1%	0%	0%	0%
Job 3	**SI**	**0.375**	**0.28125**	**0.1875**	**0.125**	**0.09375**	**0.0625**	**0**
	Makespan	46s	46s	48s	59s	59s	59s	59s
	Sequence of Allocations	H-H-H-H-H,R-H-R-H-H	H-H-H-H-H,R-H-R-H-H	R-H-H-H-H,R-H-R-H-H	R-R-H-H-H,R-H-R-H-H	R-R-H-H-H,R-H-R-H-H	R-R-H-H-H,R-H-R-H-H	R-R-H-H-H,R-H-R-H-H
	Human Tasks	8	8	7	5	5	5	5
	Robot Tasks	2	2	3	5	5	5	5
	Parallel Tasks	T5 with T7	T5 with T7	T5 with T7	T5 with T7	T5 with T7	T5 with T7	T5 with T7
	Human idle time	21.7%	21.7%	35.4%	53.4%	53.4%	53.4%	53.4%
	Robot idle time	60.9%	60.9%	47.9%	25.4%	25.4%	25.4%	25.4%
Job 4	**SI**	**2.25**	**1.5**	**0.75**	**0.25**	**0**	**-**	**-**
	Makespan	422s	416s	413s	541	637s	-	-
	Sequence of Allocations	H-H-H-H-H-H	H,R-H-H-H-H	H-H,R-H-H-H	R-H,R-H-H-H	R-H,R-R,H-H	-	-
	Human Tasks	6	5	5	4	3	-	-
	Robot Tasks	0	1	1	2	3	-	-
	Parallel Tasks	0	T5 with T1,T2,T3 and T4	T2 with T3	T2 with T3	T2 with T3 and T4 with T5	-	-
	Human idle time	0%	17.3%	0%	32.5%	54.9%	-	-
	Robot idle time	100%	25%	89.1%	59.1%	16.3%	-	-
Job 5	**SI**	**10.125**	**2.25**	**2**	**0.5**	**0.25**	**0**	**-**
	Makespan	38s	41s	52s	52s	61s	64s	-
	Sequence of Allocations	H-H-H-H-H	H,R-H-H-H	H,R-H-H-R	H,R-H-H-R	R-R-H-H-R	R-R-R-H-R	-
	Human Tasks	5	4	3	3	2	1	-
	Robot Tasks	0	1	2	2	3	4	-
	Parallel Tasks	0	T1 with T2	T1 with T2	T1 with T2	0	0	-
	Human idle time	0%	14.6%	36.5%	36.5%	54.1%	60.9%	-
	Robot idle time	100%	85.4%	53.8%	53.8%	45.9%	39.1%	-
Job 6	**SI**	**2.25**	**2**	**0.5**	**0.375**	**0.28125**	**0.25**	**0**
	Makespan	58	58	57	57	57	57	57
	Sequence of Allocations	H,R-H-H-R,H	H,R-H-H-R,H	R-H,R-H-R,H	R-H,R-H-R,H	R-H,R-H-R,H	R-H,R-H-R,H	R-H,R-H-R,H
	Human Tasks	4	4	3	3	3	3	3
	Robot Tasks	2	2	3	3	3	3	3
	Parallel Tasks	T2 with T3 and T5 with T6	T2 with T3 and T5 with T6	T2 with T3 and T5 with T6	T2 with T3 and T5 with T6	T2 with T3 and T5 with T6	T2 with T3 and T5 with T6	T2 with T3 and T5 with T6
	Human idle time	3.4%	3.4%	19.3%	19.3%	19.3%	19.3%	19.3%

Robot idle time	62.1%	62.1%	45.6%	45.6%	45.6%	45.6%	45.6%

Despite Pearce et al., (2018) used a different method to analyze the trade-off between time and ergonomics it is still interesting to compare the results because the authors referred that the solution of theirs had a gap to optimality of 1%, Therefore, it can be inferred how close the algorithm was from the optimum solution. Thus, the values obtained for makespan for the six processes when a higher importance is given for the time can be seen in Table **13**. The comparison between the values when a higher importance is given to ergonomics will not be made because Pearce et al., (2018) studies ergonomics as a component in the main function, and the developed algorithm uses ergonomics as a constraint, therefore, the results are not comparable.

Table **13** - Values of makespan for jobs for Pearce et al. (2018) and the developed algorithm

	Baseline	Pearce et al. (2018)	Developed algorithm
Job 1	38s	28s	33s
Job 2	25s	25s	24s
Job 3	55s	36s	46s
Job 4	422s	370s	413s
Job 5	38s	38s	38s
Job 6	65s	57s	57s

The baseline values represent the solution when all tasks are performed by the human worker. Analyzing Table 13, for jobs 5 and 6, the best solutions when a higher importance is given to time, the developed algorithm managed to reach the values of Pearce et al. (2018). On the other hand, for jobs 1,4 and 5, the solution of the presented algorithm is near, but it was not able to reach the near-optimum solution, however, for job 2 the algorithm could even find a better solution than Pearce et al. (2018) , probably the optimal solution.

V.7. Discussion

This section aims to explore the key results from this research discuss the overall promise of the approach followed. Finally, the limitations of the method are also recognized.

Regarding the six real-world jobs studied in Pearce et al. (2018) and taking into consideration the baseline values that are presented in Table **13**, with the exception of job 5, all the other jobs benefit from the application of the algorithm inspired by the GRASP metaheuristic, it always returned a better solution regarding the total makespan. However, it was also possible to see that job 5 do not benefit from the approach, as the best value for time was equal to the baseline value.

Concerning limitations, the main one is that the developed algorithm gives always a higher importance to the time component and the ergonomic component is in the background. This happens because the main objective function aims to optimize time and ergonomics is introduced as a constraint. Furthermore, one limitation regarding the method for constraining the ergonomic risk is that it does not take into account the cumulative fatigue that the human worker is expose to in a real scenario.

The flexibility of the approach is that many assignment and scheduling options are presented so that it is possible to choose from them. However, it is unrealistic to expect that time and ergonomics to be the only factors considered when designing and analyzing a process, but it is also unfeasible to attempt to consider all possible factors. Therefore, having a set of schedules enables engineers to select the ideal and pretended that suit the process goals.

V.8. Conclusions and Future work

In this chapter, it is proposed and demonstrated an approach that considers time and ergonomics for integrating a collaborative robot to a set of manufacturing processes. A variation of the ergonomic risk for the "first job" instance and the SI for the jobs presented by Pearce et al., (2018), as a measure of human physical stress in a task and use its values along with task times to generate a schedule. Trade-off between time and ergonomics are discussed by modifying the constraint of the maximum value for the ER or SI allowed. The resulting set of schedules enable process engineers to balance these parameters in the most convenient way for the organization. Overall, the development of the algorithm showed to be successful as good results were found to the jobs presented in Pearce et al., (2018).

The developed algorithm showed to be effective. However, there are some improvements that could be made in the future. To deal with the limitation of the ergonomic part be seen with the same weight of the time component, it would be interesting to resemble the method of Pearce et al., (2018), in other words to have a main function with the two components: time and ergonomics, where it would be possible to give the pretended weight to each component. In addition, it would be interesting to improve the graphics to the program when the user is introducing all the necessary inputs in order to make it more appellative. Moreover, one limitation of the program is that the algorithm does not take into consideration the human fatigue over time which could influence the performance when executing certain tasks, in other words the simulated environment is considered to be ideal when in a real situation, there are pauses for the human worker and the robot could even stop working. Also, it will be interesting to explore in the future some improvements to the RCL list, namely, including the study of alternative approaches to the inclusion of the alfa parameter and also the study of alternative incremental costs. Finally, in order to have a fully working GRASP algorithm a local search procedure will have to be developed.

Discussion, Final Considerations and Future Work

The present dissertation had as major purpose looking for foundations that help to answer the question of how to assign and schedule tasks in collaborative robotics. The research procedure started with the development of a theoretical background which permitted the creation of a theoretical basis to relevant topics and concepts that needed to be discussed.

In the third chapter, a systematic literature review was developed, as a way of exploring and studying systematically and methodologically the field of collaborative robotics and allocation and scheduling of tasks. This chapter enabled the comprehension of the field, get to know specific and important terms, and to explore the work that has already been done in this field. In addition, it represents an added value to the literature since in the best knowledge of the author of this research there is not a SLR or taxonomy in assigning and scheduling tasks in collaborative robotics. Therefore, the content of the chapter is present in a paper which was already submitted to a special issue of a journal.

In the fourth chapter, in order to help understand the best context to implement a collaborative robot, the processes of the three industrial partners of the Augmanity project were mapped in BPMN 2.0. The mapping helped to create a visual image to understand which tasks were best to attribute to the robot and which to assign to the human robot.

In the fifth chapter an algorithm inspired in the GRASP metaheuristic was developed which enables the assignment and scheduling of tasks between a robot and a human. The algorithm aims to minimize the total makespan of a job and has the ergonomic risk as a constraint. In addition, collaborative tasks are also possible, in other words, there are tasks that could be performed simultaneously by the human worker and by the collaborative robot. Firstly, the algorithm was tested in a fictitious problem to test all the functionalities of the program, Then, the algorithm was tested using the data from Pearce et al., (2018) which enabled the analysis of the performance of the algorithm as the solutions of the referred authors were 1% near optimality.

As future work, besides the already presented suggestions for further developments, regarding the case studies in the three industries, it would be interesting to develop some instances to test the algorithm inspired in the GRASP metaheuristic and to measure the ergonomic and time gains after the implementation of the collaborative robot.

As final considerations, this project was the most challenged adventure of my academic career as it made me leave my comfort zone exponentially as the project went along. In addition, it provided me knowledge in a field I did not even know exits before it.

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Appendix

Table **14** – Studies included in the sample for analysis

Paper	Environment	Problem	Characteristics	Objective	Method	Driver
(Bogner et al., 2018)	Assembly of printed circuit boards	Single Board Problem and Sequences of Board Problem	The problem is a simplification of the multi-mode resource constrained scheduling problem, and the computational evaluation is based on a real-world use case.	Minimize the makespan	Heuristic and Mathheuristic	Flexibility
(Bruno & Antonelli, 2018)	Assembly	Task Assignment Problem	This paper addresses the task assignment problem by proposing a method for the classification of tasks starting from the hierarchical decomposition of activities.	Minimizing production times and costs	Task Assignment Procedure: 1.º Task Indicators, 2.º Task Classification with Decision Trees Algorithm, 3.º Task Assignment	Risks and Ergonomics
(Casalino, Mazzocca, et al., 2019)	Assembly of a clock and a torch	Dynamic Scheduling	A scheduling approach for dealing with human uncertainty is proposed. Experiments include a dual arm robot and a human.	Minimize human waiting time	Fuzzy Timed Petri Nets	Managing human uncertainty
(Casalino, Zanchettin, et al., 2019)	Assembly of USB/microSD adapter	Scheduling Problem	The proposed method allows to schedule tasks based on the knowledge acquired during runtime.	Maximize the throughput (minimizing cycle time)	Timed Petri Nets	Flexibility
(Chatzikonstantinou et al., 2019)	Disassembly of WEEE devices in recycling factories	Task assignment and scheduling problem	The concept of an Adaptive work cell, (aCell), is proposed which becomes the basis for the proposed search approach.	Minimization of makespan and disassembly costs	High-level global metaheuristic search and adaptative greedy operation assignment	Cost Reduction
(Coltin et al., 2011)	Office	Scheduling Problem	A mobile cobot is deployed to accomplish user-requested actions.	Minimize the total difference in time from the start of the scheduling window	Mixed Integer Programming	Study Purposes

(Dalle Mura & Dini, 2019)	Assembly	Assembly line balancing problem	A genetic algorithm to approach ALBP in HRC to establish a proper task assignment to combine robot productivity with human flexibility is proposed.	Minimization of assembly line cost, the number of skilled workers in the line and the energy load variance among workers	Genetic Algorithm	Efficiency and Ergonomics
(Ferreira et al., 2021)	Theoretical	Multimode Multiprocessor Task Scheduling Problem	The tasks may be executed by a human, a robot or by both simultaneously	Minimizing the Makespan	Constraint Programming and Genetic Algorithm	Performance Analysis
(Gjeldum et al., 2021)	Assembly of Gearbox	Task Allocation Problem	To a proper task allocation in HRC a decision support is presented.	Reduction of the cycle time, investment cost, increase of workspace layout and worker effort reduction	Heuristic and HUMANT algorithm	Automation
(Gombolay et al., 2015)	Assembly	Scheduling Problem	A human-subject experiment investigating how a robotic teammate should incorporate the preferences of humans into the team's schedule is studied.	General objective function of minimization (e.g., minimization of makespan)	Dynamic scheduling algorithm called Tercio	Increase Productivity
(Hari et al., 2020)	Unmanned Systems	Task Allocation, Sequencing and Scheduling Problem (TASSP)	Each target has a specific task that needs to be performed collaboratively between a robot and a human operator.	Minimization of the maximum mission time robots	Approximation Algorithm and a Greedy Heuristic	Not specified
(Kinast et al., 2021)	Disassembly of electric vehicle batteries	Job shop scheduling problem	It is assumed, that cobots can be installed on all workstations. And the problem focuses on the assignment of cobots.	Minimization of the production cost and the makespan	Metaheuristic - Genetic Algorithm	Reduction of costs and risks
(Koltai et al., 2021)	Assembly of power inverters	Assembly line balancing problem	The models allow for three possibilities: 1) only workers are assigned to the workstations. 2) a worker or a robot is assigned; 3) both are assigned.	Minimization of the number of stations and cycle time	Linear and constraint Programming	Automation and reduction of risks and health problems
(L. Zhang et al., 2021)	Not specified	Task assignment problem	A human-robot task assignment method under the IF environment based on the three-way decision theory is proposed.	Minimization of costs	TOPSIS	Turn the traditional 2-way decision problem into a 3-way (robot, man, robot, and man)

(Lamon et al., 2019)	Assembly	Task Allocation Problem	Agent characteristics that should be considered in the task allocation problem are investigated.	Minimization of costs	Heuristic	Ergonomics And safety
(Liau & Ryu, 2020)	Mold Assembly	Task Allocation	The collaborative cell simulated has one worker and two cobots.	Minimize the operation cycle time and maximize the agent capability	Analytic Network Process (ANP) and GA	Ergonomics
(M. Zhang et al., 2021)	Cable assembly	Task scheduling problem	The results suggest that integrating micro-breaks compared with rest breaks between job cycles, outperforms in job-cycle performance in most cases.	Minimize the job cycle time	Genetic Algorithm	Trade-off between Job cycle and human fatigue
(Maderna et al., 2020)	Assembly	Multiagent coordination problem with temporal and spatial constraints	The goal of the MILP scheduler is to allocate objects to workers such that time and human physical stress are minimized. A set of constraints are added such as the capabilities of the robot.	Minimization of costs (trade-off between performance and ergonomics)	Online scheduling algorithm in mixed integer linear programming	Reduction of operator's effort and increase productivity
(Maderna et al., 2022)	Assembly of emergency button	Scheduling Problem	A dynamic scheduler that adapts to the system variability, is presented. The human and the robots work parallelly.	Minimization of costs	Model Predictive Control Approach-Timed Petri Nets and AND/OR graph	Flexibility
(Mokhtarzadeh et al., 2020)	Printed Circuit Boards Assembly	Single Board Problem and Sequence of Boards Problem	Tasks are divided into three categories: tasks can be performed only by humans; tasks can be performed only by robots; tasks can be performed by human or robot.	Minimize the makespan	Constraint Programming and Mixed Integer Linear Programming	Flexibility
(Nikolakis et al., 2018)	Assembly of a turbocharger	Dynamic Scheduling	For a given task, there may be one or more suitable resources. The suitability of the resources is decided upon their skills.	Maximization or Minimization of utility value depending of the nature of the implemented criteria	Multicriteria: total weight, total duration of human tasks, production rate and operating cost	Flexibility and adaptability
(Pearce et al., 2018)	Diverse Factories	Multiagent Coordination Problem with temporal and spatial constraints	The proposed framework generates tasks assignments for a human-robot team aiming to improve time and ergonomics.	Minimize the makespan and physical strain	Mixed Integer Linear Programming	Time and Ergonomics

(Pupa, Landi, et al., 2021)	Assembly	Dynamic Scheduling	A 2 layers architecture for task allocation and scheduling is proposed. The 1.º solves the task allocation problem and the 2.º adapts online the sequence of tasks.	Minimization of the job execution time and maximization of the parallelism	Multi-objective Mixed Integer Linear Program	Achieve efficient HRC
(Pupa, van Dijk, et al., 2021)	Assembly	Multi-agent task allocation problem	A two-layered architecture for task allocation and dynamic scheduling is proposed considering job quality.	Minimization of the job makespan optimizing job quality	Mixed Integer Linear Programming, coded in Python, solved in Gurobi solver	Job quality
(Raatz et al., 2020)	Automotive Assembly	Flexible Job Shop Scheduling Problem	Industrial use case of gearbox assembly in which to set the objectives, the user selects his goals: ergonomics, quality, etc. Two schedules were tested, one aimed to increase production volume and the second aimed to increase ergonomics.	Multi-objective optimization (ergonomics, safety, quality and technical automatability)	Time Measurement Method and Genetic Algorithm	Productivity and Flexibility
(Sadik & Urban, 2017)	Assembly of centrifugal pump:	Two Stage Flow Shop Scheduling Problem	The simplest case-study of a collaborative work cell is studied: one cobot in cooperation with one worker.	Minimize the makespan	First-Come-First-Served and Johnson Algorithm	Agility and flexibility
(Sadik et al., 2017)	Pump Manufacturing	Two-Stage Flow Shop Scheduling Problem	The case study is developed in a collaborative work cell with one cobot in cooperation with two workers.	Minimize the makespan	Johnson's Algorithm	Flexibility and Productivity
(Seyyedhasani et al., 2020)	Agriculture	Scheduling Problem	Harvest-aid robots that transport empty and full trays during manual harvesting of specialty crops such as strawberries are used to increase harvest efficiency	Reduce pickers' walking increase harvest efficiency	Simulation and Heuristic	Automation/ Augment efficiency
(Shannon et al., 2016)	UAV (Unmanned Aerial Vehicles)	Task Allocation Planning Problem	Fast algorithms that integrate humans into the planning problem to allocate human-robot teams are developed.	Maximization of scores	Heuristic and simulation	Unspecified

(Smith et al., 2020)	Assembly	Task Allocation	A framework to allow HRC based on cost functions that quantify capabilities and performance is developed. Each worker separately performs the tasks.	Minimization of costs considering human fatigue and agent performance	Dynamic Cost Functions	Autonomously controlling task allocation
(Stadnicka & Antonelli, 2019)	Snowplow mill Assembly	Task Assignment and Scheduling	The process of task assignment and scheduling is incorporated in the proposed methodology for HRC design.	Performance Analysis and Minimize the maximum completion time.	Hierarchical Task Analysis, UML, Activity Diagram, and a Gant chart	Ergonomics and Safety
(Stecke & Mokhtarzadeh, 2021)	Assembly	Assembly line balancing problem with operation assignment and scheduling problems	Regression lines were developed that can help managers determine how many and what types of robots are best for a line.	Minimize cycle time, ergonomic risk and maximize the number of operations allocated to their preferred resources	MILP model, CP model and Bender's decomposition algorithm	Optimize cycle time and reduce ergonomic risk
(Tsarouchi, Matthaiakis, et al., 2017)	Assembly of hydraulic pump.	Task Allocation Problem	A decision-making method that allows human-robot task allocation is proposed. The focus is given to the human–robot coexistence for the execution of sequential tasks,	Increase automation level in manual or hybrid assembly lines.	Procedure: 1.º Resource suitability 2.º Resource availability 3.º Operation time	Automation
(Vieira et al., 2021)	Automotive Assembly	Planning and scheduling optimization problem	The proposed approach optimizes production plans while satisfying scheduling constraints, such as robots' allocation in collaborative tasks.	Minimization of the operational costs and makespan	Recursive Optimization-Simulation Approach (ROSA)	Provide effective decision-support for integrated planning and scheduling
(X. Wang et al., 2015)	Multi-agent systems	Multiagent Scheduling problem	Time-series human agent mutual trust models based on known results from human factors engineering is proposed.	Provide effective real-time scheduling of the human multi-agent collaboration while ensuring proper mutual trust.	MATLAB Simulations	Mutual trust
(Weckenborg et al., 2020)	Assembly	Assembly line balancing and scheduling problem	Humans and robots can simultaneously execute tasks at the same workpiece either in parallel or in collaboration.	Minimize cycle time	Metaheuristic-MIP and Hybrid genetic algorithm	Productivity gains
(Wilcox et al., 2012)	Assembly of airplane spars	Simple Temporal Problem with Preferences	A dynamic robotic scheduling is developed that adapts to the changing preferences of a human.	Maximize the global preference function	Adaptive Preferences Algorithm with non-linear programming	Economic and Ergonomic

(Li et al., 2019)	Disassembly of a gear pump	Sequence Planning	A task allocation and sequencing method is proposed considering human fatigue. The approach is experimented on MATLAB.	Minimize the total disassembly time	Bee Algorithm	Human Fatigue and Efficiency of Production
(Bänziger et al., 2018)	Automotive Assembly	Task Allocation Problem	Case study at Volkswagen Assembly line	Minimize waiting times and walking distances	Simulation tool and Genetic Algorithms	Ergonomics and Efficiency
(Ranz et al., 2017)	Assembly and Kitting	Task Allocation	The proposed approach determines task allocation considering the capabilities of humans and robots aiming at improving work quality.	Multicriteria: Process Time, Additional Invest and Process Quality	Heuristic Procedure	Work Quality
(Makrini et al., 2019)	Assembly of Gearbox	Task Allocation	The paper proposes a novel framework for tasks allocation considering capabilities and ergonomic aspects.	Minimize Human Workload	1.ºTask Decomposer, 2.º Capability evaluator, 3.º Ergonomic Evaluator, 4.º Task Allocation	Ergonomics
(Michalos et al., 2018)	Automotive Assembly	Layout planning and Task Assignment	A multicriteria method along with a search algorithm is proposed. The method is implemented in the form of a planning tool – Task Planner.	Multicriteria: Ergonomics, Saturation Level, Fatigue, Operation Cost, Operation Time. Floor Space Payload	Search Algorithm	Ergonomics and Productivity
(Singer & Akin, 2010)	Space Missions	Task Allocation and Scheduling	The author reviews a methodology from Singer and Akin, (2008) to characterize the effect of the robot in the overall team performance.	Minimize the overall completion time and the waiting time between agents	1.º Task Decomposition 2.º Task Allocation 3.º Task Scheduling	Productivity/ Efficiency
(Tsarouchi, Michalos, et al., 2017)	White goods industry and automotive industry	Workplace design and Task Allocation	Two case studies are addressed where alternative scenarios for the workplace design are studied as well as the task planning aspect.	Multicriteria: Shop floor utilization, total completion time, investment cost, ergonomics, and robot reachability	A multicriteria decision-making framework and simulation	Efficiency and Ergonomics
(Chen et al., 2011)	Industrial Power Supply Module Assembly	Task Allocation and Scheduling	A dual Generalized Stochastic Petri Net model is studied theoretically. The authors aim at solving the persistent growing cost	Minimize time and costs	Task Decomposition, Monte Carlo Simulation and Multiple-Objective optimization	Costs

(Rahman & Wang, 2018)	Assembly of center console and the front fender and Assembly of LEGO	Task Allocation	Human´s trust in the robot and robot's trust in the human is considered which is measure in real-time.	Minimize costs	Two-level feedforward optimization strategy	Automation
(Tsarouchi et al., 2016)	Automotive Assembly	Task Planning and Sequencing	This study presents a task planning method where humans and robots perform tasks according to their capabilities, The case studies 2 robots in collaboration with a human.	Multicriteria: Resource Average Utilization and Mean Flowtime	Multicriteria Approach	Automation and Reduce Complexity
(Dianatfar et al., 2019)	Assembly of diesel engine components	Task Allocation	The case study is implemented in three different interaction levels: shared workplace without shared task; shared workplace with shared task without physical interaction and shared workspace with shared task "handing-over".	Multicriteria: task complexity, ergonomics, payload and repeatability	1.º Task Decomposition 2.ºClassification of Task Allocation 3.º Task Allocation based on factors	Productivity and Flexibility
(Pini et al., 2020)	Additive Manufacturing	Scheduling Problem	This paper suggests a design method to identify the best scheduling of human-robot collaborative tasks with considering a required safety level.	Identify the best scheduling of human robot collaborative operations considering a safety level.	Simulation	Human Safety
(Fechter et al., 2020)	Waste Electrical and Electronic Equipment	Task Assignment and Scheduling Problem	The paper proposes a two-stage approach to orchestrate large HRC teams: 1.º a topological and task assignment problem is solved; 2.º the result is used to initialize a constrained search for a schedule	Orchestrating Large Human-Robot Collaborative Teams	Variable Neighborhood Search and Computation	Efficiency
(Pellegrinelli et al., 2017)	Assembly	Task Scheduling and Assignment	The paper introduces an innovative and integrated motion planning and scheduling methodology.	Minimize cycle time	Heuristic	Productivity and Efficiency
(Chen et al., 2014)	Electronic Assembly	Scheduling Problem and task assignment	A mathematic method to describe a discrete-event system is developed considering the tradeoff between assembly time and payment cost.	Minimize assembly time and payment cost	Genetic Algorithm	Productivity

(Hu & Chen, 2017)	Re-Assembly	Optimal Task Allocation Problem	A Linear Programming approach is developed to optimally solve the task allocation Problem. The Problem is modelled with Petri Nets and human fatigue is also modeled.	Find an optimal task allocation such that an average joint-cost considering human and process performance are minimized	Model in Petri Nets, Linear Programming and Simulation	Human Fatigue and Performance
(Müller et al., 2016)	Aircraft Industry	Task Assignment	The approach is based on a detailed analysis of the skills of humans and robots,	skills-oriented assembly sequence planning	Skills-based Task Allocation Procedure (Extended version of Müller et al.)	Customized Automation
(Takata & Hirano, 2011)	Assembly	Task Allocation	A human and robot allocation planning method for hybrid assembly systems is proposed and analyzed	Minimize the total production cost	Heuristic and Computation	Changeability and Efficiency
(Tan et al., 2009)	Cable Harness Assembly	Task Allocation and Analysis	The production operation is modeled into hierarchical task analysis (HTA)	model the collaboration between human worker and robot	HTA	Innovation
(Howard, 2006)	Space Missions	Task Allocation	The proposed methodology consists of either the human or the machine is allocated to a task, incorporating the concept of task switching.	Minimize mental workload while maximizing task performance.	Genetic Algorithm and Simulation	Performance
(Rahman et al., 2015)	Assembly of LEGO	Optimal Subtask Allocation	The authors derive dynamics models for human's trust in the robot and robot's trust in the human.	Minimize the variations between human and robot speeds and maximize trusts.	A two-level feedforward optimization strategy	Productivity and Flexibility

Table **15** - Tasks studied in the scheduling topic in HRC

<table>
<tr><th>Paper</th><th>Task</th><th>Human(s) Tasks</th><th>Cobot(s) Tasks</th><th>Type of Collaboration</th></tr>
<tr><td>(Liau & Ryu, 2020)</td><td>Cavity of mold sub-assembly</td><td>2.º Pick and place component
3.º Insert small component
5.º Pick and place component
6.º Insert small component
7.º Pick, place and insert screw
9.º Pick and place component
10.º Pick, place and insert screw
12.º Pick, place and insert screw</td><td>1º Both cobots lift and position plate
4º Both cobots lifts and positions plate
8º A cobot tightens screw
11º A cobot tightens screw
13º A cobot tightens screw</td><td>Synchronized</td></tr>
<tr><td>(Raatz et al., 2020)</td><td rowspan="2">Assembly of Gearbox</td><td colspan="2">Two alternatives:
1.º The robot builds the core shaft from two gears, the shaft, and some spacer rings. The assembled core is then transferred to the human. While the robot assembles the next core, the worker inserts the transferred core into the housing and checks the backlash.
2.º The robot only assists in the assembly of the core. Instead, the robot helps the worker in preparing the housing (step 5) and applies the thread locker (step 23).</td><td>Cooperation</td></tr>
<tr><td>(Gjeldum et al., 2021)</td><td colspan="2">Not specified</td><td>Collaboration</td></tr>
<tr><td>(Coltin et al., 2011)</td><td>User requested actions</td><td>The user only interacts with the cobot to request a service.</td><td>The cobot can perform 3 tasks: GoToRoom, Telepresence or Transport</td><td>Coexistence with minimal interaction</td></tr>
<tr><td>(Ferreira et al., 2021)</td><td>Not specified</td><td colspan="2">Not specified</td><td>Cooperation</td></tr>
<tr><td>(Pearce et al., 2018)</td><td>T1- Quality control
T2-Packaging
T3-Assembly
T4-Stocking
T5-Parts-assembly
T6-Metal-cutting</td><td colspan="2">In current days, all tasks are performed manually, but the performance was tested with the introduction of a cobot. The subtasks are not specified.</td><td>Coexistence</td></tr>
<tr><td>(Sadik et al., 2017)</td><td>Customized Pump Manufacturing</td><td>2.º Then, the results of the cobot's work are sent to the workers, who work in parallel, for post-processing.</td><td>1.º Perform initial processing of the product or just pick and place operation.</td><td>Synchronized</td></tr>
<tr><td>(Wilcox et al., 2012.)</td><td>Assembly of airplane spars</td><td>2.º Place and torque the fasteners,</td><td>1.º Apply sealant to each hole</td><td>Synchronized</td></tr>
</table>

(Casalino, Mazzocca, et al., 2019)	Assembly of a clock	2.º Insert the hands.	1.º Assemble the clock dial with the engine 3.º Insert the glass into the frontal frame and add the dial with the engine and the bottom part of the clock.	Cooperation
	Assembly of a torch	2.º The human screws the frontal part with the body of the torch. 4.º The human assembles the batteries of the torch. 6.º The human finalizes the torch screwing the bottom part and archive the finite product	1.º The robot assembles the frontal part of the torch with the light inside. 3.º The robot moves the body of the torch to assembly station A. 5.º Inserts the batteries into the body of the torch.	Cooperation
(Bogner et al., 2018)	Assembly of printed circuit boards	For each component to be inserted onto the blank board, 4 tasks must be fulfilled: 1.º The adjacent wire of each component is bent into the right position. 2.º The component is placed onto the PCB 3.º. Solder the pins 4.º Excess wire is cut off. (The authors do not refer which tasks are allocated to each agent)		Synchronized
(Mokhtarzadeh et al., 2020)		Inserting and mounting	Inserting and mounting	Synchronized
(Stadnicka & Antonelli, 2019)	Snowplow Mill Assembly	1.ºThe human setups workplace and components 2.º Collaboratively, the base and headstock are positioned 3.º The human performs the internal blade bending, the brackets placements and then the welding 4.º Parallelly, the human does the external disk welding and the robot does the external blade bending 5.º The human mount the holder 6.º Parallelly, the robot performs the headstock welding to outer disk and the robot does the central support bending and grinding 7.º Collaboratively, the spacer is assembled 8.º Collaboratively, the grinder and the outer ring are assembled 9.º the human performs the holder unmount		Collaboration
(Bruno & Antonelli, 2018)		There are a lot of tasks which some of them are performed collaboratively such as: pick and place, grinding, etc.		Collaboration
(Kinast et al., 2021)	Disassembly of electric vehicle batteries	Not specified.		Not specified.
(Koltai et al., 2021)	Assembly of power inverters	Not specified.		Synchronized

(Maderna et al., 2020)	Kitting	The human is instructed to change the completed kit before starting a new one. Meanwhile, the robot starts picking. When the human has positioned the new empty box and pressed the button to communicate the end of the task, he/she receives information about the next object to be picked. Then, both start to work in parallel coordinating their movement until the kit is completed. Finally, the operator changes the completed box with an empty one so that a new kit can start.	Cooperation
(Hari et al., 2020)	Inspection, classification, or data collection	A human operator remotely and collaboratively works with a robot on a task at a target location; after the task is completed, the robot travels to its next destination without the aid of the human, and the operator is available to work on other tasks with other robots.	Collaboration
(Pupa, Landi, et al., 2021)	Assembly job	The assembly job consists of storing 4 plastic shapes, fixing 3 little PCBs, and positioning a big PCB and a wooden bar. It can be divided into Pick & Place or screw task which some are performed sequentially, and others performed at the same time. The human can communicate with the robot.	Collaboration
(M. Zhang et al., 2021)	Cable assembly	1.º Picking and laying operations can be done either by a robot or human. 2.º Checking and Shaping sub harness are performed by the human. 3.º Anchoring the right end is done by a robot and a human. 4.º Installing buckle operations can be done either by a human or a robot. 5.º Releasing the right end is done by a human. 6.º Removing harness from the platform can be done by a robot or a human.	Collaboration
(Vieira et al., 2021)	Assembly of Automotive parts	Not specified	Collaboration
(Lamon et al., 2019)	Assembly of aluminum profile	1.º While the cobot picks the corner joint, the human inserts the nuts in the profile. The gesture triggers the release of the corner joint from the gripper. 2.º The human can start screwing and meanwhile, the cobot picks the long profile. 3.º Then the cobot holds the profile in gravity compensation, while the worker easily aligns it to the mounted piece.	Collaboration
(Chatzikonstantinou et al., 2019)	Disassembly of WEEE devices	Not specified.	Coexistence
(Nikolakis et al., 2018)	Pick and place, screwing and sensing	Different scenarios are considered. A shared task could include a human placing a screw and holding while the robot starts screwing. Also, both resources could be screwing something on the same part having to share the same space for a certain period.	Collaboration
(Sadik & Urban, 2017)	Assembly of centrifugal pump	The cobot is responsible for the pick and place operations while the worker assembles the handled products.	Cooperation
(Smith et al., 2020)	Bolt tightening	Each agent performed each task separately. 1.º Pick up the bolt from a holder and screw the bolt into a 3D printed fixing;	Coexistence
(Smith et al., 2020)	Pick and Place	1.º Pick up four 3D printed nuts from a holder in sequential order and place each nut in one of four predefined placement positions. To add complexity to the task and simulate high mix production, the position for each bolt is randomly selected from the four predefined.	Coexistence
(Pupa, van Dijk, et al., 2021)	Pick and Place	The cobot executes pick and place tasks while the human is packing USB keys. The human can communicate with the cobot and delegate tasks.	Cooperation
(Maderna et al., 2022)	Assembly of emergency button	1.º Start new product: 1.º YuMi Start new product 2.º YuMi Assemble Top 2.º IRB Clamp product & assemble Top	Cooperation

		2.º Clamp product for IRB task 3.º Complete product from YuMi 3.º Complete product from IRB 4.º Change full box	2.º IRB Assemble Top 4.º IRB Store finished product in box	
(Stecke & Mokhtarzadeh, 2021)	Assembly of Balance Shaft Module	1.º Balance shaft 1 is assembled by a cobot. 2.º Balance shaft 2 is assembled by a human. Then a BSET is precisely attached collaboratively. 3.º Screws are put in the holes by the robot while the human assembles the second shaft). 4.º Tightening the screws is done by the robot. 5.º Placing a screw in the balance shaft hole and screwing the pulley can be performed by the human while the robot tightens the balance enclosure screws. Then the shafts are braced, and the pulley screw is tightened by a human.		Collaboration
(L. Zhang et al., 2021)	Not specified	Not specified		Not specified
(Shannon et al., 2016)				Cooperation
(Weckenborg et al., 2020)				Cooperation
(Wang et al., 2015)				Collaboration
(Seyyedhasani et al., 2020)	Transport	The humans perform harvesting.	The robots transport full or empty trails.	Coexistence
(Gombolay et al., 2015)	Assembly of Lego	The human can fetch and build	The robot can fetch.	Cooperation
(Dalle Mura & Dini, 2019)	Assembly of scooter chassis	Not specified		Collaboration
(Tsarouchi et al., 2017)	Assembly of hydraulic pump	There are 3 alternatives presented. This is alternative 1: 1.º The human places the pump, 4.º The human moves the pump	2.ºThe robot 2 attaches the pump, 3.º The robot 1 releases the pump 4.º The robot 1 performs a second movement	Coexistence
(Li et al., 2019)	Disassembly of Gear Pump	Not specified		Cooperation
(Bänziger et al., 2018)	Assembly of Automotive Parts	2.º Then the worker picks screws from the moveable table to fix the prepositioned body protection part. 3.º Then the worker can check the fixation.	1.º The robot picks the body protection part and positions it in the tire area 2.º Meanwhile the robot screws the air pipe fixation in the motor block area 3.ºAt the same time, the robot collects three clips from the table to assemble them to the car	Coexistence

(Ranz et al., 2017)	Assembly	Pick and Place tasks.		Coexistence
	Kitting	Not specified		
(Makrini et al., 2019)	Assembly of Gearbox (workload limit of 0.75)	The human and the dual arm robot work at the same time in the same gearbox. There are 34 tasks that for simplicity reasons won't be described. The tasks consist of pick and place operations, insertion, and screwing.		Collaboration
(Michalos et al., 2018)	Automotive Assembly	4.º Assembly of right cable on axle	1.ºLoading of the axle	Synchronized
		2.ª Assembly of the right brake drum on axle (could be done by the human or the robot) 3.ºAssembly of screw on right drum (could be done by the human or by the robot)		
(Singer & Akin, 2010)	Tasks from a Space Mission	Robot and Human work in parallel.		Cooperation
(Tsarouchi, Michalos, et al., 2017)	Rear Axle Assembly	8.º Pick screwdriver 9.º Pick screws 10.º Install screws 1.º Concurrently with the Task 12 of the robot, Install screws	1.ª Load Gripper 1 2.º/3.º Pick and Place Axle 4.º Unload Gripper 1 5.º Load Gripper 2 6.º Hold wheel 1 7.º Hold wheel 1 11.º Pick wheel 2 12.º Hold wheel 2	Cooperation
	Sealing Path	1.º /2.º Pick and Place Polionda 3.º Fix Polionda 4.º Guide Robots	5.ºSimultanously to task 4 of Humans, seal Paths	Collaboration
(Chen et al., 2011)	Module Assembly	1.º Pick and Insert connector C1 2.º Pick and Insert connector C2 3.º Pick and Insert C3	2.º Meanwhile the robot assembles C2 3.º Meanwhile the robot assembles C3	Cooperation
(Rahman & Wang, 2018)	Assembly of center console and the front fender	Not specified		Not specified
	Assembly of LEGO	1.º Move red part 3.º Attach the first green part to the red part 5.º Attach the second green part to the red part 7.º Attach the third green part to the red part 9.º Attach previous assembles to blue part 10.º Move white parts	2. º Move the first green part 4.º Move the second green part 6.º Move the third green part 8.º Move blue part 12.º Move final product	Collaboration

		11.º Attach previous assembly to ehite part		
(Tsarouchi et al., 2016)	Dashboard Assembly	19.º-21.º Pick, Assembly and Install Operations	1.º-18.º Pick, Place and Install Operations	Synchronized
(Dianatfar et al., 2019)	Assembly of diesel engine components	Human and Robot assemble rocker shaft		Cooperation
(Pini et al., 2020)	Post-processing of parts produced by laser powder bed fusion	Not Specified		Synchronized and Cooperation
(Fechter et al., 2020)	Device dismantling in a recycling process	Open Cover, Extract Panel, Extract Capacitor and Extract PCB.	Open Cover and Extract Panel.	Cooperation
(Pellegrinelli et al., 2017)	Assembly	4.º Change the robot tool in 5.º Screw a component 6.º Take to part in P2 and mount 7.º Unscrew the part in P10	1.º Reach P4 for the tool change 2.º Reach P3 for a quality check T1 3.º Move the part from P13 to P14	Cooperation
		Human or Robot: 8.º Move the part from P1 to 9.º Quality check on 10.º Check the raw part 11.º Quality check on part 12.º Move the part from P10 in P9		
(Chen et al., 2014)	Power Module Box Assembly	Diverse Scenarios are tested but tasks are from the following types: Place or Mate the connector;		Synchronized and Cooperation
(Hu & Chen, 2017)	Four-Part Assembly	Not Specified		Not Specified
(Müller et al., 2016)	Assembly of aircraft fuselages.	1.º Plasma Activation (done with the robot in the synchronized scenario); 3.º Joining the component;	2.º Adhesive Bonding. 4.º Inspection and documentation	Coexistence and Synchronized
(Takata & Hirano, 2011)	Assembly	Not Specified		synchronized
(Tan et al., 2009)	Cable Harness Assembly	3.º Arrange cables on marking board	1.º Prepare parts kits	Coexistence
		2.º Assisted cooperation by robot manipulator to hold the connector and indicate assembly po3.ºints while human worker insert the cable contacts 4.º Assisted cooperation by robot manipulator to hold the terminal and indicate assembly points while human worker insert the cable ends		Collaboration

		5.º Assisted cooperation by robot manipulator to hold the metal plate while human worker fasten the cables with cable ties	
(Howard, 2006)	Space Missions	Not specified	Coexistence
(Rahman et al., 2015)	Assembly of LEGO	Equal to the previous mentioned at (Rahman & Wang, 2018)	Collaboration

```
  - A:
    - T1:
        Ergonomic Risk: 6
        Time for Human: 14
        Time for Robot: 17
        Timelapse: [0,17]
        Is the task collaborative? False
        Chosen: Robot
    - T2:
        Ergonomic Risk: 7
        Time for Human: 19
        Time for Robot: 25
        Timelapse: [17,42]
        Is the task collaborative? False
        Chosen: Robot
- B:
  - T3:
      Ergonomic Risk: 5
      Time for Human: 15
      Time for Robot: 20
      Timelapse: [0,15]
      Is the task collaborative? False
      Chosen: Human
  - T4:
      Ergonomic Risk: 6
      Time for Human: 13
      Time for Robot: 14
      Timelapse: [42,56]
      Is the task collaborative? False
      Chosen: Robot
- C:
  - T5:
      Ergonomic Risk: 3
      Time for Human: 10
      Time for Robot: 12
      Timelapse: [56,68]
      Is the task collaborative? True
      Chosen: Human and Robot
  - T6:
      Ergonomic Risk: 7
      Time for Human: 16
      Time for Robot: 14
      Timelapse: [68,82]
      Is the task collaborative? False
      Chosen: Robot
- D:
  - T7:
      Ergonomic Risk: 15
      Time for Human: -1
      Time for Robot: 10
      Timelapse: [82,92]
      Is the task collaborative? False
      Chosen: Robot
  - T8:
      Ergonomic Risk: 2
      Time for Human: 10
      Time for Robot: -1
      Timelapse: [92,102]
      Is the task collaborative? False
      Chosen: Human
```

Figure **68** - Schedule for the problem when the maximum ergonomic risk is 5

```
- A:
  - T1:
      Ergonomic Risk: 6
      Time for Human: 14
      Time for Robot: 17
      Timelapse: [0,17]
      Is the task collaborative? False
      Chosen: Robot
  - T2:
      Ergonomic Risk: 7
      Time for Human: 19
      Time for Robot: 25
      Timelapse: [17,42]
      Is the task collaborative? False
      Chosen: Robot
- B:
  - T3:
      Ergonomic Risk: 5
      Time for Human: 15
      Time for Robot: 20
      Timelapse: [42,62]
      Is the task collaborative? False
      Chosen: Robot
  - T4:
      Ergonomic Risk: 6
      Time for Human: 13
      Time for Robot: 14
      Timelapse: [62,76]
      Is the task collaborative? False
      Chosen: Robot
- C:
  - T5:
      Ergonomic Risk: 3
      Time for Human: 10
      Time for Robot: 12
      Timelapse: [76,88]
      Is the task collaborative? True
      Chosen: Human and Robot
  - T6:
      Ergonomic Risk: 7
      Time for Human: 16
      Time for Robot: 14
      Timelapse: [88,102]
      Is the task collaborative? False
      Chosen: Robot
- D:
  - T7:
      Ergonomic Risk: 15
      Time for Human: -1
      Time for Robot: 10
      Timelapse: [102,112]
      Is the task collaborative? False
      Chosen: Robot
  - T8:
      Ergonomic Risk: 2
      Time for Human: 10
      Time for Robot: -1
      Timelapse: [112,122]
      Is the task collaborative? False
      Chosen: Human
```

Figure **69** - Schedule for the problem when the maximum for the ergonomic risk is 3, 2 or 0

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [0,5]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 6
      Time for Robot: 19
      Timelapse: [5,11]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 14
      Timelapse: [11,16]
      Is the task collaborative? False
      Chosen: Human
- D:
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 12
      Timelapse: [0,12]
      Is the task collaborative? False
      Chosen: Robot
- E:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 2
      Time for Robot: -1
      Timelapse: [16,18]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 7
      Time for Robot: 26
      Timelapse: [18,44]
      Is the task collaborative? False
      Chosen: Robot
- T7:
    Ergonomic Risk: 2.25
    Time for Human: 4
    Time for Robot: -1
    Timelapse: [44,48]
    Is the task collaborative? False
    Chosen: Human
- T8:
    Ergonomic Risk: 1
    Time for Human: 4
    Time for Robot: 10
    Timelapse: [48,52]
    Is the task collaborative? False
    Chosen: Human
```

Figure **70** - Schedule for Job 1 when maximum SI=2

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [0,5]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 6
      Time for Robot: 19
      Timelapse: [5,11]
      Is the task collaborative? False
      Chosen: Human
 - C:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 14
      Timelapse: [0,14]
      Is the task collaborative? False
      Chosen: Robot
 - D:
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 12
      Timelapse: [11,16]
      Is the task collaborative? False
      Chosen: Human
- E:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 2
      Time for Robot: -1
      Timelapse: [16,18]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 7
      Time for Robot: 26
      Timelapse: [18,44]
      Is the task collaborative? False
      Chosen: Robot
 - T7:
     Ergonomic Risk: 2.25
     Time for Human: 4
     Time for Robot: -1
     Timelapse: [44,48]
     Is the task collaborative? False
     Chosen: Human
 - T8:
     Ergonomic Risk: 1
     Time for Human: 4
     Time for Robot: 10
     Timelapse: [48,52]
     Is the task collaborative? False
     Chosen: Human
```

Figure **71** - Schedule for Job 1 when maximum SI=1.5

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [0,5]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 6
      Time for Robot: 19
      Timelapse: [5,11]
      Is the task collaborative? False
      Chosen: Human
 - C:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 14
      Timelapse: [0,14]
      Is the task collaborative? False
      Chosen: Robot
 - D:
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 12
      Timelapse: [14,26]
      Is the task collaborative? False
      Chosen: Robot
- E:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 2
      Time for Robot: -1
      Timelapse: [26,28]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 7
      Time for Robot: 26
      Timelapse: [28,54]
      Is the task collaborative? False
      Chosen: Robot
 - T7:
     Ergonomic Risk: 2.25
     Time for Human: 4
     Time for Robot: -1
     Timelapse: [54,58]
     Is the task collaborative? False
     Chosen: Human
 - T8:
     Ergonomic Risk: 1
     Time for Human: 4
     Time for Robot: 10
     Timelapse: [58,62]
     Is the task collaborative? False
     Chosen: Human
```

Figure **72** - Schedule for Job 1 when maximum SI=1

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [0,5]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 6
      Time for Robot: 19
      Timelapse: [5,11]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 14
      Timelapse: [0,14]
      Is the task collaborative? False
      Chosen: Robot
- D:
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 12
      Timelapse: [14,26]
      Is the task collaborative? False
      Chosen: Robot
- E:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 2
      Time for Robot: -1
      Timelapse: [26,28]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 7
      Time for Robot: 26
      Timelapse: [28,54]
      Is the task collaborative? False
      Chosen: Robot
- T7:
    Ergonomic Risk: 2.25
    Time for Human: 4
    Time for Robot: -1
    Timelapse: [54,58]
    Is the task collaborative? False
    Chosen: Human
- T8:
    Ergonomic Risk: 1
    Time for Human: 4
    Time for Robot: 10
    Timelapse: [58,68]
    Is the task collaborative? False
    Chosen: Robot
```

Figure **73** - Schedule for Job 1 when maximum SI=0.75

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [0,9]
      Is the task collaborative? False
      Chosen: Robot
- B:
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 6
      Time for Robot: 19
      Timelapse: [9,28]
      Is the task collaborative? False
      Chosen: Robot
- C:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 14
      Timelapse: [28,42]
      Is the task collaborative? False
      Chosen: Robot
- D:
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 5
      Time for Robot: 12
      Timelapse: [42,54]
      Is the task collaborative? False
      Chosen: Robot
- E:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 2
      Time for Robot: -1
      Timelapse: [54,56]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 7
      Time for Robot: 26
      Timelapse: [56,82]
      Is the task collaborative? False
      Chosen: Robot
- T7:
    Ergonomic Risk: 2.25
    Time for Human: 4
    Time for Robot: -1
    Timelapse: [82,86]
    Is the task collaborative? False
    Chosen: Human
- T8:
    Ergonomic Risk: 1
    Time for Human: 4
    Time for Robot: 10
    Timelapse: [86,96]
    Is the task collaborative? False
    Chosen: Robot
```

Figure **74** - Schedule for Job 1 when maximum SI=0.25 or SI=0

```
  - A:
    - T1:
        Ergonomic Risk: 10.125
        Time for Human: 7
        Time for Robot: -1
        Timelapse: [0,7]
        Is the task collaborative? False
        Chosen: Human
  - B:
    - T2:
        Ergonomic Risk: 0.5
        Time for Human: 4
        Time for Robot: 13
        Timelapse: [7,11]
        Is the task collaborative? False
        Chosen: Human
- C:
  - T3:
      Ergonomic Risk: 0.25
      Time for Human: 1
      Time for Robot: 10
      Timelapse: [0,10]
      Is the task collaborative? False
      Chosen: Robot
- D:
  - T4:
      Ergonomic Risk: 2
      Time for Human: 4
      Time for Robot: 17
      Timelapse: [11,15]
      Is the task collaborative? False
      Chosen: Human
- E:
  - T5:
      Ergonomic Risk: 2.25
      Time for Human: 7
      Time for Robot: -1
      Timelapse: [15,22]
      Is the task collaborative? False
      Chosen: Human
- F:
  - T6:
      Ergonomic Risk: 0.375
      Time for Human: 1
      Time for Robot: -1
      Timelapse: [22,23]
      Is the task collaborative? False
      Chosen: Human
- G:
  - T7:
      Ergonomic Risk: 0.75
      Time for Human: 1
      Time for Robot: 10
      Timelapse: [23,24]
      Is the task collaborative? False
      Chosen: Human
```

Figure **75** - Schedule for Job 2 without constraining SI

```
  - A:
    - T1:
        Ergonomic Risk: 10.125
        Time for Human: 7
        Time for Robot: -1
        Timelapse: [0,7]
        Is the task collaborative? False
        Chosen: Human
  - B:
    - T2:
        Ergonomic Risk: 0.5
        Time for Human: 4
        Time for Robot: 13
        Timelapse: [0,13]
        Is the task collaborative? False
        Chosen: Robot
- C:
  - T3:
      Ergonomic Risk: 0.25
      Time for Human: 1
      Time for Robot: 10
      Timelapse: [7,8]
      Is the task collaborative? False
      Chosen: Human
- D:
  - T4:
      Ergonomic Risk: 2
      Time for Human: 4
      Time for Robot: 17
      Timelapse: [13,30]
      Is the task collaborative? False
      Chosen: Robot
- E:
  - T5:
      Ergonomic Risk: 2.25
      Time for Human: 7
      Time for Robot: -1
      Timelapse: [30,37]
      Is the task collaborative? False
      Chosen: Human
- F:
  - T6:
      Ergonomic Risk: 0.375
      Time for Human: 1
      Time for Robot: -1
      Timelapse: [37,38]
      Is the task collaborative? False
      Chosen: Human
- G:
  - T7:
      Ergonomic Risk: 0.75
      Time for Human: 1
      Time for Robot: 10
      Timelapse: [38,39]
      Is the task collaborative? False
      Chosen: Human
```

Figure **76** - Schedule for Job 2 with maximum SI=0.75

```
- A:
  - T1:
      Ergonomic Risk: 10.125
      Time for Human: 7
      Time for Robot: -1
      Timelapse: [0,7]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T2:
      Ergonomic Risk: 0.5
      Time for Human: 4
      Time for Robot: 13
      Timelapse: [0,13]
      Is the task collaborative? False
      Chosen: Robot
- C:
  - T3:
      Ergonomic Risk: 0.25
      Time for Human: 1
      Time for Robot: 10
      Timelapse: [13,23]
      Is the task collaborative? False
      Chosen: Robot
- D:
  - T4:
      Ergonomic Risk: 2
      Time for Human: 4
      Time for Robot: 17
      Timelapse: [23,40]
      Is the task collaborative? False
      Chosen: Robot
- E:
  - T5:
      Ergonomic Risk: 2.25
      Time for Human: 7
      Time for Robot: -1
      Timelapse: [30,37]
      Is the task collaborative? False
      Chosen: Human
- F:
  - T6:
      Ergonomic Risk: 0.375
      Time for Human: 1
      Time for Robot: -1
      Timelapse: [40,41]
      Is the task collaborative? False
      Chosen: Human
- G:
  - T7:
      Ergonomic Risk: 0.75
      Time for Human: 1
      Time for Robot: 10
      Timelapse: [40,50]
      Is the task collaborative? False
      Chosen: Robot
```

Figure **77** - Schedule for Job 2 for SI=0.5, SI=0.375, SI=0,25, and SI=0

```
- A:
  - T1:
      Ergonomic Risk: 0.28125
      Time for Human: 5
      Time for Robot: 7
      Timelapse: [0,5]
      Is the task collaborative? False
      Chosen: Human
  - T2:
      Ergonomic Risk: 0.1875
      Time for Human: 5
      Time for Robot: 13
      Timelapse: [5,10]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T3:
      Ergonomic Risk: 0.0625
      Time for Human: 5
      Time for Robot: -1
      Timelapse: [10,15]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T4:
      Ergonomic Risk: 0.125
      Time for Human: 5
      Time for Robot: -1
      Timelapse: [15,20]
      Is the task collaborative? False
      Chosen: Human
- D:
  - T5:
      Ergonomic Risk: 0.125
      Time for Human: 6
      Time for Robot: -1
      Timelapse: [20,26]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 0.09375
      Time for Human: 4
      Time for Robot: -1
      Timelapse: [26,30]
      Is the task collaborative? False
      Chosen: Human
- E:
  - T7:
      Ergonomic Risk: 0.0625
      Time for Human: 5
      Time for Robot: 8
      Timelapse: [20,28]
      Is the task collaborative? False
      Chosen: Robot
- F:
  - T8:
      Ergonomic Risk: 0.375
      Time for Human: 15
      Time for Robot: 10
      Timelapse: [30,40]
      Is the task collaborative? False
      Chosen: Robot
  - T9:
      Ergonomic Risk: 0.0625
      Time for Human: 3
      Time for Robot: -1
      Timelapse: [40,43]
      Is the task collaborative? False
      Chosen: Human
  - T10:
      Ergonomic Risk: 0.1875
      Time for Human: 3
      Time for Robot: 6
      Timelapse: [43,46]
      Is the task collaborative? False
      Chosen: Human
```

Figure **78** - Schedule for Job 3 when SI is not constrained and SI=0.28125

```
- A:
  - T1:
       Ergonomic Risk: 0.28125
       Time for Human: 5
       Time for Robot: 7
       Timelapse: [0,7]
       Is the task collaborative? False
       Chosen: Robot
  - T2:
       Ergonomic Risk: 0.1875
       Time for Human: 5
       Time for Robot: 13
       Timelapse: [7,12]
       Is the task collaborative? False
       Chosen: Human
 - B:
   - T3:
       Ergonomic Risk: 0.0625
       Time for Human: 5
       Time for Robot: -1
       Timelapse: [12,17]
       Is the task collaborative? False
       Chosen: Human
 - C:
   - T4:
       Ergonomic Risk: 0.125
       Time for Human: 5
       Time for Robot: -1
       Timelapse: [17,22]
       Is the task collaborative? False
       Chosen: Human
- D:
  - T5:
       Ergonomic Risk: 0.125
       Time for Human: 6
       Time for Robot: -1
       Timelapse: [22,28]
       Is the task collaborative? False
       Chosen: Human
  - T6:
       Ergonomic Risk: 0.09375
       Time for Human: 4
       Time for Robot: -1
       Timelapse: [28,32]
       Is the task collaborative? False
       Chosen: Human
- E:
  - T7:
       Ergonomic Risk: 0.0625
       Time for Human: 5
       Time for Robot: 8
       Timelapse: [22,30]
       Is the task collaborative? False
       Chosen: Robot
- F:
  - T8:
       Ergonomic Risk: 0.375
       Time for Human: 15
       Time for Robot: 10
       Timelapse: [32,42]
       Is the task collaborative? False
       Chosen: Robot
- T9:
     Ergonomic Risk: 0.0625
     Time for Human: 3
     Time for Robot: -1
     Timelapse: [42,45]
     Is the task collaborative? False
     Chosen: Human
- T10:
     Ergonomic Risk: 0.1875
     Time for Human: 3
     Time for Robot: 6
     Timelapse: [45,48]
     Is the task collaborative? False
     Chosen: Human
```

Figure **79** - Schedule for Job 3 when maximum SI=0.1875

```
- A:
  - T1:
       Ergonomic Risk: 0.28125
       Time for Human: 5
       Time for Robot: 7
       Timelapse: [0,7]
       Is the task collaborative? False
       Chosen: Robot
  - T2:
       Ergonomic Risk: 0.1875
       Time for Human: 5
       Time for Robot: 13
       Timelapse: [7,20]
       Is the task collaborative? False
       Chosen: Robot
 - B:
   - T3:
       Ergonomic Risk: 0.0625
       Time for Human: 5
       Time for Robot: -1
       Timelapse: [20,25]
       Is the task collaborative? False
       Chosen: Human
 - C:
   - T4:
       Ergonomic Risk: 0.125
       Time for Human: 5
       Time for Robot: -1
       Timelapse: [25,30]
       Is the task collaborative? False
       Chosen: Human
- D:
  - T5:
       Ergonomic Risk: 0.125
       Time for Human: 6
       Time for Robot: -1
       Timelapse: [30,36]
       Is the task collaborative? False
       Chosen: Human
  - T6:
       Ergonomic Risk: 0.09375
       Time for Human: 4
       Time for Robot: -1
       Timelapse: [36,40]
       Is the task collaborative? False
       Chosen: Human
- E:
  - T7:
       Ergonomic Risk: 0.0625
       Time for Human: 5
       Time for Robot: 8
       Timelapse: [30,38]
       Is the task collaborative? False
       Chosen: Robot
- F:
  - T8:
       Ergonomic Risk: 0.375
       Time for Human: 15
       Time for Robot: 10
       Timelapse: [40,50]
       Is the task collaborative? False
       Chosen: Robot
- T9:
     Ergonomic Risk: 0.0625
     Time for Human: 3
     Time for Robot: -1
     Timelapse: [50,53]
     Is the task collaborative? False
     Chosen: Human
- T10:
     Ergonomic Risk: 0.1875
     Time for Human: 3
     Time for Robot: 6
     Timelapse: [53,59]
     Is the task collaborative? False
     Chosen: Robot
```

Figure **80** - Schedule for Job 3 when maximum SI=0.375 or 0.28125 or 0.1875 or 0.125 or 0

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 48
      Time for Robot: 176
      Timelapse: [0,48]
      Is the task collaborative? False
      Chosen: Human
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 96
      Time for Robot: -1
      Timelapse: [48,144]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 9
      Time for Robot: 45
      Timelapse: [144,153]
      Is the task collaborative? False
      Chosen: Human
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 87
      Time for Robot: -1
      Timelapse: [153,240]
      Is the task collaborative? False
      Chosen: Human
- D:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 78
      Time for Robot: 312
      Timelapse: [240,318]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 104
      Time for Robot: -1
      Timelapse: [318,422]
      Is the task collaborative? False
      Chosen: Human
```

Figure **81** - Schedule for Job 4 when SI is not constrained

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 48
      Time for Robot: 176
      Timelapse: [0,48]
      Is the task collaborative? False
      Chosen: Human
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 96
      Time for Robot: -1
      Timelapse: [48,144]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 9
      Time for Robot: 45
      Timelapse: [144,153]
      Is the task collaborative? False
      Chosen: Human
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 87
      Time for Robot: -1
      Timelapse: [153,240]
      Is the task collaborative? False
      Chosen: Human
- D:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 78
      Time for Robot: 312
      Timelapse: [0,312]
      Is the task collaborative? False
      Chosen: Robot
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 104
      Time for Robot: -1
      Timelapse: [312,416]
      Is the task collaborative? False
      Chosen: Human
```

Figure **82** - Schedule for Job 4 when maximum SI=1.5

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 48
      Time for Robot: 176
      Timelapse: [0,48]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 96
      Time for Robot: -1
      Timelapse: [48,144]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 9
      Time for Robot: 45
      Timelapse: [48,93]
      Is the task collaborative? False
      Chosen: Robot
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 87
      Time for Robot: -1
      Timelapse: [144,231]
      Is the task collaborative? False
      Chosen: Human
- D:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 78
      Time for Robot: 312
      Timelapse: [231,309]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 104
      Time for Robot: -1
      Timelapse: [309,413]
      Is the task collaborative? False
      Chosen: Human
```

Figure **83** - Schedule for Job when maximum SI=0.75

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 48
      Time for Robot: 176
      Timelapse: [0,176]
      Is the task collaborative? False
      Chosen: Robot
- B:
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 96
      Time for Robot: -1
      Timelapse: [176,272]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 9
      Time for Robot: 45
      Timelapse: [176,221]
      Is the task collaborative? False
      Chosen: Robot
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 87
      Time for Robot: -1
      Timelapse: [272,359]
      Is the task collaborative? False
      Chosen: Human
- D:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 78
      Time for Robot: 312
      Timelapse: [359,437]
      Is the task collaborative? False
      Chosen: Human
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 104
      Time for Robot: -1
      Timelapse: [437,541]
      Is the task collaborative? False
      Chosen: Human
```

Figure **84** - Schedule for Job 4 when maximum SI=0.25

```
- A:
  - T1:
      Ergonomic Risk: 0.75
      Time for Human: 48
      Time for Robot: 176
      Timelapse: [0,176]
      Is the task collaborative? False
      Chosen: Robot
- B:
  - T2:
      Ergonomic Risk: 0.75
      Time for Human: 96
      Time for Robot: -1
      Timelapse: [176,272]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T3:
      Ergonomic Risk: 1.5
      Time for Human: 9
      Time for Robot: 45
      Timelapse: [176,221]
      Is the task collaborative? False
      Chosen: Robot
  - T4:
      Ergonomic Risk: 1.5
      Time for Human: 87
      Time for Robot: -1
      Timelapse: [272,359]
      Is the task collaborative? False
      Chosen: Human
- D:
  - T5:
      Ergonomic Risk: 0.25
      Time for Human: 78
      Time for Robot: 312
      Timelapse: [221,533]
      Is the task collaborative? False
      Chosen: Robot
  - T6:
      Ergonomic Risk: 2.25
      Time for Human: 104
      Time for Robot: -1
      Timelapse: [533,637]
      Is the task collaborative? False
      Chosen: Human
```

Figure **85** - Schedule for Job 4 when maximum SI=0

```
- A:
  - T1:
      Ergonomic Risk: 10.125
      Time for Human: 3
      Time for Robot: 11
      Timelapse: [0,3]
      Is the task collaborative? False
      Chosen: Human
- B:
  - T2:
      Ergonomic Risk: 0.5
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [3,8]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T3:
      Ergonomic Risk: 0.25
      Time for Human: 3
      Time for Robot: 6
      Timelapse: [8,11]
      Is the task collaborative? False
      Chosen: Human
  - T4:
      Ergonomic Risk: 2
      Time for Human: 25
      Time for Robot: -1
      Timelapse: [11,36]
      Is the task collaborative? False
      Chosen: Human
- T5:
    Ergonomic Risk: 2.25
    Time for Human: 2
    Time for Robot: 13
    Timelapse: [36,38]
    Is the task collaborative? False
    Chosen: Human
```

Figure **86** - Schedule for Job 5 when SI is not constrained

```
- A:
  - T1:
      Ergonomic Risk: 10.125
      Time for Human: 3
      Time for Robot: 11
      Timelapse: [0,11]
      Is the task collaborative? False
      Chosen: Robot
- B:
  - T2:
      Ergonomic Risk: 0.5
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [0,5]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T3:
      Ergonomic Risk: 0.25
      Time for Human: 3
      Time for Robot: 6
      Timelapse: [11,14]
      Is the task collaborative? False
      Chosen: Human
  - T4:
      Ergonomic Risk: 2
      Time for Human: 25
      Time for Robot: -1
      Timelapse: [14,39]
      Is the task collaborative? False
      Chosen: Human
  - T5:
      Ergonomic Risk: 2.25
      Time for Human: 2
      Time for Robot: 13
      Timelapse: [39,41]
      Is the task collaborative? False
      Chosen: Human
```

Figure **87** - Schedule for Job 5 when maximum SI=2.25

```
- A:
  - T1:
      Ergonomic Risk: 10.125
      Time for Human: 3
      Time for Robot: 11
      Timelapse: [0,11]
      Is the task collaborative? False
      Chosen: Robot
- B:
  - T2:
      Ergonomic Risk: 0.5
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [0,5]
      Is the task collaborative? False
      Chosen: Human
- C:
  - T3:
      Ergonomic Risk: 0.25
      Time for Human: 3
      Time for Robot: 6
      Timelapse: [11,14]
      Is the task collaborative? False
      Chosen: Human
  - T4:
      Ergonomic Risk: 2
      Time for Human: 25
      Time for Robot: -1
      Timelapse: [14,39]
      Is the task collaborative? False
      Chosen: Human
- T5:
      Ergonomic Risk: 2.25
      Time for Human: 2
      Time for Robot: 13
      Timelapse: [39,52]
      Is the task collaborative? False
      Chosen: Robot
```

Figure **88** - Schedule for Job 5 when maximum SI=2 or 0.5

```
- A:
  - T1:
      Ergonomic Risk: 10.125
      Time for Human: 3
      Time for Robot: 11
      Timelapse: [0,11]
      Is the task collaborative? False
      Chosen: Robot
- B:
  - T2:
      Ergonomic Risk: 0.5
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [11,20]
      Is the task collaborative? False
      Chosen: Robot
- C:
  - T3:
      Ergonomic Risk: 0.25
      Time for Human: 3
      Time for Robot: 6
      Timelapse: [20,23]
      Is the task collaborative? False
      Chosen: Human
  - T4:
      Ergonomic Risk: 2
      Time for Human: 25
      Time for Robot: -1
      Timelapse: [23,48]
      Is the task collaborative? False
      Chosen: Human
  - T5:
      Ergonomic Risk: 2.25
      Time for Human: 2
      Time for Robot: 13
      Timelapse: [48,61]
      Is the task collaborative? False
      Chosen: Robot
```

Figure **89** - Schedule for Job 5 when maximum SI=0.25

```
- A:
  - T1:
      Ergonomic Risk: 10.125
      Time for Human: 3
      Time for Robot: 11
      Timelapse: [0,11]
      Is the task collaborative? False
      Chosen: Robot
- B:
  - T2:
      Ergonomic Risk: 0.5
      Time for Human: 5
      Time for Robot: 9
      Timelapse: [11,20]
      Is the task collaborative? False
      Chosen: Robot
- C:
  - T3:
      Ergonomic Risk: 0.25
      Time for Human: 3
      Time for Robot: 6
      Timelapse: [20,26]
      Is the task collaborative? False
      Chosen: Robot
  - T4:
      Ergonomic Risk: 2
      Time for Human: 25
      Time for Robot: -1
      Timelapse: [26,51]
      Is the task collaborative? False
      Chosen: Human
  - T5:
      Ergonomic Risk: 2.25
      Time for Human: 2
      Time for Robot: 13
      Timelapse: [51,64]
      Is the task collaborative? False
      Chosen: Robot
```

Figure **90** - Schedule for Job 5 when maximum SI=0

```
- A:
  - T1:
       Ergonomic Risk: 0.28125
       Time for Human: 10
       Time for Robot: 9
       Timelapse: [0,10]
       Is the task collaborative? False
       Chosen: Human
- B:
  - T2:
       Ergonomic Risk: 0.5
       Time for Human: 1
       Time for Robot: -1
       Timelapse: [10,11]
       Is the task collaborative? False
       Chosen: Human
- C:
  - T3:
       Ergonomic Risk: 0.25
       Time for Human: 3
       Time for Robot: 16
       Timelapse: [10,26]
       Is the task collaborative? False
       Chosen: Robot
- D:
  - T4:
       Ergonomic Risk: 2
       Time for Human: 41
       Time for Robot: -1
       Timelapse: [11,52]
       Is the task collaborative? False
       Chosen: Human
- E:
  - T5:
       Ergonomic Risk: 2.25
       Time for Human: 6
       Time for Robot: 6
       Timelapse: [52,58]
       Is the task collaborative? False
       Chosen: Robot
- F:
  - T6:
       Ergonomic Risk: 0.375
       Time for Human: 4
       Time for Robot: -1
       Timelapse: [52,56]
       Is the task collaborative? False
       Chosen: Human
```

Figure **91** - Schedule for Job 6 when maximum SI=2.25 or 2

```
- A:
  - T1:
       Ergonomic Risk: 0.28125
       Time for Human: 10
       Time for Robot: 9
       Timelapse: [0,9]
       Is the task collaborative? False
       Chosen: Robot
- B:
  - T2:
       Ergonomic Risk: 0.5
       Time for Human: 1
       Time for Robot: -1
       Timelapse: [9,10]
       Is the task collaborative? False
       Chosen: Human
- C:
  - T3:
       Ergonomic Risk: 0.25
       Time for Human: 3
       Time for Robot: 16
       Timelapse: [9,25]
       Is the task collaborative? False
       Chosen: Robot
- D:
  - T4:
       Ergonomic Risk: 2
       Time for Human: 41
       Time for Robot: -1
       Timelapse: [10,51]
       Is the task collaborative? False
       Chosen: Human
- E:
  - T5:
       Ergonomic Risk: 2.25
       Time for Human: 6
       Time for Robot: 6
       Timelapse: [51,57]
       Is the task collaborative? False
       Chosen: Robot
- F:
  - T6:
       Ergonomic Risk: 0.375
       Time for Human: 4
       Time for Robot: -1
       Timelapse: [51,55]
       Is the task collaborative? False
       Chosen: Human
```

Figure **92** - Schedule for Job 6 when maximum SI=0.5, 0.375, 0.28125, 0.25, 0