Dissertation

Adaptive Task Sharing Between Humans and Cobots in Assembly Processes

carried out for the purpose of obtaining the degree of Doctor technicae (Dr. techn.), submitted to the Faculty of Mechanical and Industrial Engineering, TU Wien, by

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Affidavit

I, Christina Schmidbauer, declare in lieu of oath, that I wrote this thesis and performed the associated research myself using only literature cited in this volume. If text passages from sources are used literally, they are marked as such.

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Deutsche Kurzfassung

Die (Teil-)Automatisierung manueller Montageaufgaben ermöglicht Wettbewerbsvorteile sowie eine Verbesserung der Arbeitsbedingungen für Montagearbeiter*innen in Produktionsbetrieben. Aufgrund der bisher vorherrschenden Ansätze zur Aufgabenteilung zwischen Mensch und Maschine treten jedoch Nachteile wie unflexible Prozesse, verringerte Lernmöglichkeiten bzw. Kompetenzrückgang, und Monotonie auf. Kollaborationsfähige Roboter (Cobots) werden entwickelt für eine direkte Interaktion mit dem Menschen, und ermöglichen neue Formen der Zusammenarbeit zwischen Mensch und Maschine.

In dieser Arbeit wird eine Methode zur adaptiven Arbeitsteilung zwischen Mensch und Cobot präsentiert. Die Methode besteht im Wesentlichen aus drei Teilen: Erstens, aus einer Aufgabenanalyse, um die Automatisierbarkeit und ergonomischen Aspekte einer Aufgabe zu beschreiben; Zweitens, aus einer Aufgabenzuteilung, welche jedoch nicht alle Aufgaben einem ausführenden Agenten, sondern nur diejenigen zuteilt, die eindeutig einem Agenten zugeteilt werden müssen. Alle weiteren Aufgaben werden als „austauschbar“ (shareable) bezeichnet. Diese können von der/m Werker*in am Mensch–Cobot–Arbeitsplatz, auch nach der Arbeitsplatzdesignphase, dem Cobot oder Mensch zugeteilt werden. Dafür wird im dritten Teil der Arbeit eine Aufgabenvisualisierungsmethode präsentiert. Ein prozessbasiertes Werkerassistenzsystem, welches mit dem Cobot verbunden ist, wurde dafür entwickelt und evaluiert.

Die Methode zur adaptiven Arbeitsteilung zwischen Mensch und Cobot wurde im Zuge mehrerer wissenschaftlicher Iterationen entwickelt und umfangreich, anhand von u.a. zwei Demonstratoren in der Pilotfabrik für Industrie 4.0 der TU Wien, evaluiert. Ergebnisse der Evaluierung zeigten eine potenzielle Verbesserung der ökonomischen Effizienz der Prozesse, durch Kosteneinsparungen durch die Verwendung des Cobots. Die physische Ergonomie der Mitarbeiter*innen kann durch den Einsatz der Cobots verbessert werden, indem unergonomische Aufgaben stets an den Roboter abgegeben werden. Die mentale Ergonomie wird durch die Flexibilisierung der Arbeitsteilung verbessert, da so einer monotonen Arbeitsweise durch erhöhte Aufgabenvielfalt entgegengewirkt wird. Darüber hinaus konnte gezeigt werden, dass die Zufriedenheit der Werker*innen mit der Aufgabenteilung durch die Methode erhöht wird. Zudem kann mittels der Methode auf unterschiedliche Losgrößen flexibel reagiert werden, da je nach Losgröße unterschiedliche Aufgabenteilungen ökonomisch effizient sind.

Deutsche Suchwörter

Arbeitsteilung; Mensch–Roboter Interaktion; Montage; kollaborationsfähige Roboter.

Abstract

The (partial) automation of manual assembly tasks enables competitive advantages as well as an improvement in working conditions for assembly workers in manufacturing industries. However, due to the prevailing approaches for task allocation between humans and machines, disadvantages such as inflexible processes, reduced learning opportunities, decline in competence, and monotony occur. Collaborative robots (cobots) are being developed for direct interaction with humans, enabling new forms of human–machine interaction.

In this thesis, a method for adaptive task sharing between humans and cobots is presented. The method primarily comprises three parts: first, task analysis, which describes the automation potential and ergonomic aspects of a task; second, task allocation, which, however, does not allocate all tasks to an executing agent but only those that must be uniquely assigned to an agent. All other tasks are called "shareables" that can be assigned to the cobot or human by a worker at the human–cobot workplace, even after completing the workplace design phase. For this purpose, a task visualization method is presented in the third part of the thesis. A process-based worker assistance system, which is connected to the cobot, was developed and evaluated for this purpose. The method for adaptive task sharing between humans and cobots was developed over the course of several scientific iterations and was then comprehensively evaluated, using, among others, two demonstrators in the Pilot Factory for Industry 4.0 at TU Wien.

The evaluation results showed a potential improvement of the process' economic efficiency that was achieved through cost savings associated with the cobot use. The physical ergonomics of the workers can be improved using the cobots, i.e., by always handing over unergonomic tasks to the cobot. Mental ergonomics are improved by making task allocation more flexible, as this counteracts the monotonous way of working owing to higher task diversity. Furthermore, the satisfaction of the workers with the task allocation increases when using this method compared to not using this method. In addition, the method can be used to enable flexibility to produce different batch sizes, as different task allocations result in economic efficiency depending on the batch size.

Key Words

Task Sharing; Task Allocation; Task Assignment; Human–Robot Interaction; Assembly; Collaborative Robots.

Acknowledgments

The thesis was written while I, Christina Schmidbauer, was working as a University and Project Assistant in the research unit “Human–Machine Interaction” at the Institute of Management Science (IMW), TU Wien. The thesis was funded by the TU Wien Doctoral College “Trust Robots – Trust in Robots,” the Austrian Research Promotion Agency (FFG), and the Austrian Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology (BMK) through the endowed professorship “Human Centered Cyber Physical Production and Assembly Systems (HCCPPAS)” (FFG-852789) and the “Cobot meets Makerspace (CoMeMak)” project (FFG-871459).

I would like to thank Sebastian Schlund for his consistent and reliable supervision of this work. Without his regular feedback as well as proactive and additional support in the implementation of the thesis, this research would not have been possible. I would also like to thank the whole HCCPPAS research unit at the IMW for the cooperation and exchange. In particular, I would like to thank Tudor B. Ionescu for his support during the development of the basic concept of my thesis. His contributions to the basic considerations led to the development of my thesis. Special thanks go to Tanja Zigart, David Kostolani, and Hans Küffner-McCauley who contributed valuable feedback to this thesis.

I would also like to thank my students, who worked on research topics related to my thesis in the course of their scientific work at TU Wien. In particular, Bernd Hader, who made significant contributions to the implementation of the work presented in thesis during the course of his master's thesis.

Special thanks also go to my colleagues and indirect supervisors from the Doctoral College. The interdisciplinary exchange provided helpful input, and the social cohesion within the college constantly helped me stay motivated and focused. Here, I would like to especially thank Sabine T. Köszegi, Astrid Weiß, Setareh Zafari, and Helena Frijns.

I am very thankful for the cooperation of the involved collaborators, who have made significant contributions to the practical relevance, the demonstrators, and the evaluation of this thesis. Here I would like to thank especially Michael Heiss of Siemens AG Österreich, the employees of TELE Haase Steuergeräte Ges.m.b.H, and Christian Bodor.

Contents

1. INTRODUCTION

This section presents the motivation and relevance, problem statement, research questions, as well as the methodology and design of this thesis.

1.1. Motivation and Relevance

The widely used manual assembly processes and quickly changing market requirements require new methods and tools for manufacturers to stay competitive. Depending on the product, assembly takes 15% to 70% of the total production time: in mechanical engineering, the proportion of assembly time varies with complexity and lies between 20% and 45% and in vehicle construction, it relies on the vertical range of manufacturing and lies between 30% and 50%. The highest proportion of assembly time, 40%–70 %, can be found in electrical and precision engineering (Lotter and Wiendahl, 2012). Therefore, assembly processes have a high potential for time and cost savings (Wang, L. et al., 2019).

To stay competitive, high-wage countries particularly benefit from the use of (partial) automation in manual production areas, such as assembly line. A quantitative study (n = 229) to implement Industry 4.0 concepts in enterprises showed that enterprises primarily want to increase labor productivity and product and service quality as well as cope with workforce shortage (Grenčíková et al., 2020). Coping with workforce shortage is associated with the society and thus the labor force, which depends on demographic changes (Makris, 2021). Furthermore, there exist requirements for small lot sizes and shorter product lifecycles; mass customization has replaced mass production in several areas (Wang and Gao, 2020). These changing requirements push the need for flexible automation systems in assembly lines. In automation, the deployment of machines increases productivity and the quality of standards as well as standardizes and stabilizes processes. However, it also induces inflexibility, which is in contrast to the need for mass customization.

Industrial robots are used to fulfill these needs owing to their unique advantages compared to traditional automation, where specific machines designed for certain tasks are deployed. As per definition, industrial robots are reprogrammable and multipurpose manipulators (DIN EN ISO 10218-1, 2020); thus, they offer a higher flexibility than machines. Industrial robots are established in manufacturing processes and perform monotonous, repetitive, and dangerous tasks, e.g., welding, gluing, or handling heavy parts. However, they have no perception of their environment and must therefore work behind fences or in cells to prevent them from injuring humans or other freely moving agents[1]. This also limits the possible applications of industrial robots because safety fences (cells) occupy large space on the shop floor and the isolation of the robotic cell interrupts processes. The linking of processes leads to new challenges and makes production more complex, static, and inflexible.

Recently, collaborative robots (cobots, also co-bots) (Fast-Berglund and Romero, 2019), which are robotic devices, have been designed and developed with the purpose to manipulate objects in collaboration with a human operator/worker. They have at least a minimal perception of their environment. Cobots are entering industry and introducing new fields of application for manufacturers. Moreover, they offer several advantages in comparison to industrial robots (Makris, 2021; Wang, L. et al., 2019):

1. *Possibility to interact with humans*

Due to safety features of cobots that ensure safe interaction with humans, cobots can work physically next to or directly with humans without harming them. The possibility of a direct human–robot interaction (HRI) introduces new fields of applications of the implementation of cobots that are being researched and developed. The advantages of human workers, such as intuition, flexibility, versatility in problem solving, and sensory skills, as well as of cobots, such as strength, endurance, repeatability, and accuracy, are combined (Wang, L. et al., 2019). However, regionally applicable safety standards limit the theoretical flexibility of cooperation (Brandstötter et al., 2020).

2. *Low costs*

Regarding the investment costs, cobots are usually cheaper than industrial robots. Entering of several manufacturers in the cobot market have resulted in intense competition and better offers for cobot buyers (Ionescu and Schlund, 2019). Moreover, total setup investment costs are low because cobots can be operated without many additional installations, such as fences or cells, to ensure human safety until a certain level of deployment, such as their speed, is attained.

3. *Flexibility in purpose*

Because the end effector of cobots is usually exchangeable, cobots can be used in various ways, ensuring high flexibility. A multitude of tools and grippers are being developed, such as different grippers with two fingers (or more), but grippers or end effectors that use vacuum pressure or specific tools for tasks, such as screwing or gluing (Thallemer et al., 2018). Due to

[1]"*An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators*" Russell and Norvig (2010, p. 34). Humans, robots, other machines, and software can be described as agents, if they correspond the definition.

the use of force sensors in cobots, new areas of application, such as the insertion of a key in a lock (Voigt et al., 2020), have opened.

4. *Flexibility in setup*

As cobots are mostly lightweight and easy to mount on different surfaces, they are often found in mobile platform applications, such as automated guided vehicles or mobile manipulators (Rathmair et al., 2020). This offers the possibility to use cobots not only for one task, but also for further tasks in an assembly line.

5. *High usability*

Manufacturers of cobots focus on high usability of their user interfaces (El Zaatari et al., 2019). Therefore, they are often easier to control and program than industrial robots, which offers the possibility that cobots can also be controlled by nonprofessionals with little training compared to the level of training needed to operate an industrial robot (Schmidbauer, Komenda, Schlund, 2020).

Although there are clear advantages in the use of cobots over traditional industrial robots, the market share of cobots in 2018 and 2019 was 4%–5% (IFR, 2020) and is forecast to increase to 8%–13% by 2022 (Statista, 2021). Statistics showed that about 18,000 cobots were sold in 2019 in comparison to 363,000 traditional industrial robots (IFR, 2020, p. 4). The following data have emerged for one country, Austria, as an example: cobot deployment ratios of 42.0% (n = 88) are observed for manufacturing industries, where deployment ratios are higher for large companies (49.1%) than for small and medium-sized enterprises (SMEs) (28.0%) (Patsch et al., 2021). This is because large companies can invest in future technologies for testing and demonstration purposes without bringing them directly into current production. In the case of SMEs, a direct benefit is necessary because the investment costs must be able to justify the revenue.

In the remainder of this thesis, the terms robot and cobot are used, but the scope of this thesis refers to cobots only due to the advantages described above. In the following section, the challenges that arise from the implementation and use of cobots, and the resulting problem statement of this work are derived.

1.2. Problem Statement and Research Questions

Research on the challenges posed by cobots have been identified by Ranz et al. (2017). The authors presented a study "*to investigate the barriers that impede a stronger prevalence of human–robot applications in industrial environments*". They asked robot manufacturers (n = 15), system integrators (n = 14), and companies using HRI in manufacturing (n = 5) about their perception of the relevance of different challenges (Ranz et al., 2017, p. 183). Two main observations were made: (1) the issues related to HRI safety assessment and planning aspects and (2) the identification of HRI-suitable workstations and the determination of task allocation between humans and cobots.

In reference to the questions posed by Ranz et al. (2017), manufacturers in Austria were asked about their perceived challenges. This time, only potential cobot users (n = 88) were asked, where multiple answers were possible. The results identified the four most important challenges: too high costs or long amortization period (52%), the work planning and task allocation between humans and robots (44%), the safety of humans (36%), and acceptance by the employees (22%) (Patsch et al., 2021, unpublished results). The significance of these results is elaborated below:

1. *High costs/long amortization period*

In contrast to the advantage of cobots, the costs are generally mentioned as a challenge for integrating cobots on the shop floor. This may be because, in addition to the cobot arm investment costs, there are additional costs related to tool(s) and integration, which may not have been anticipated initially. It is also possible that the full potential of the technology cannot yet be realized due to manufacturer's lack of experience in deploying and implementing cobots. In addition, a cobot is not used continuously, and thus, do not achieve the expected or calculated productivity gains or economic efficiency. Automation itself may lead to additional costs and efforts due to the so-called "Ironies of Automation" (Bainbridge, 1983). The use of cobots in assembly applications results in the fragmentation of human tasks, the reduction of learning opportunities, and the additional efforts of handling unforeseen errors, which drive costs upward. The economic efficiency of the use of cobots is elaborated in Sections 2.3.1 and 5.1.4.

2. *Safety of humans*

When interacting with robots, human safety is of utmost importance. Cobots are a relatively new technology and new processes and methods are implemented with it. Thus, the assurance of physical safety as well as privacy and security is an ongoing research topic (Gualtieri et al., 2021). In addition, the newness of cobots results in a complex situation and hinders implementation. Relevant conditions, such as applicable standards, are explained in Section 2.1.2.

3. *Acceptance by the employees*

Acceptance to interact and collaborate with a new technology is a long process with various influencing factors. A reference is made to a technology acceptance model adapted for HRI

(Bröhl et al., 2016). Easy user interfaces of cobots are developed because perceived ease of use predicts acceptance. References for an easy interaction can be found in Section 2.1.1.

4. *Work planning and task allocation between humans and robots*

Task allocation between humans and cobots in manufacturing has been demonstrated in theory and practice, where the implementations can mostly be traced back to two approaches: the leftover and compensatory (Challenger et al., 2013). These will be explained subsequently, followed by an elaboration on the problem statement of this thesis.

The leftover approach of automation describes a work organization in which humans perform feasible tasks left by automation. Tasks that were previously not automated due to high effort or simply because they were not possible to automate will continue to be performed by humans. These remaining tasks are often supervisory tasks, such as monitoring the automated system (Malik and Bilberg, 2019c).

The compensatory approach has its origins in the so-called "Fitts list" (Fitts, 1951). As machine capabilities evolved during the 20th century, the division of tasks between humans and machines became increasingly important in planning work systems. In 1951, Paul M. Fitts and his team presented their work in the field of air-traffic control on the question *"which of these functions should be performed by human operators and which by machine elements"* (Fitts, 1951, p. x). Their results showed that *"humans appear to surpass present-day machines in respect to six abilities which are denoted as (1) detection, (2) perception, (3) improvisation, (4) long-term storage, (5) induction and (6) memory […] present-day machines appear to surpass humans in respect to the following: (1) speed, (2) power, (3) routinization, (4) short-term storage, (5) deduction and (6) performance of simultaneous operations"* (Fitts, 1951, p. x). This task allocation method was transferred to other application areas and resulted in the compensatory approach, i.e., tasks should be allocated to the *"best-fitting"* part. Fitts' work has been cited several hundred times to date, despite massive criticism (Winter and Dodou, 2014).

Both task allocation approaches have their justification in their respective areas of application. However, they cause a rigid and static working system, which was criticized in literature (Lagu and Landry, 2011) and has already led to rethinking in other areas, such as the automation of tasks while piloting airplanes, where dynamic task allocation methods are already deeply researched and applied (Sherry and Ritter, 2002). Dekker and Woods (2002, p. 8) discussed the Fitts list and its related compensatory or substitution-based function allocation methods, and argued that the focus of further discussion should be moved from *"who does what"* to *"how do we make them get along together."* The authors questioned the assumption that humans and machines have fixed strengths and weaknesses and argued that engineers should capitalize on their strengths while eliminating or compensating weaknesses. These arguments were also raised by Bainbridge (1983).

In addition to economic disadvantages that may arise from static task allocation, human factors/ergonomics (HF/E) research argued for more task allocation decision-making authority of humans in HRI (Tausch and Kluge, 2020). Further, researchers identified the disadvantages of static task allocation approaches, such as skill degradation, degraded situation awareness, complacency, problems when reclaiming control, disruption of mental workload, and humans as a last stronghold (Fujimoto and Abril, 1992; Parasuraman, 2000). Moreover, within static task allocation, workers have little opportunity to learn new skills, and if an error occurs in an automated task, humans may be unable to solve the problem, resulting in possibly increased costs (Bainbridge, 1983). The need for the adaptability to tasks by unskilled users and an adaption between different tasks as the manufacturing output shifts between product types is declared in the Multi-Annual Roadmap (Robotics, 2017).

Both industry and academia highlight that humans and robots should be seen as a team that must work together in a complementary work organization (Ansari et al., 2018; Challenger et al., 2013; Kemény et al., 2021; Parasuraman, 2000). For instance, changing the level of collaboration between humans and machines leads to several advantages, such as productivity gains (Malik and Bilberg, 2019c, p. 1547) and HF/E improvements (Tausch et al., 2020). Research on HRI showed that high perceived control is associated with mitigated negative attitudes, which fosters a social relationship between humans and robots (Zafari and Köszegi, 2020). Studies on manufacturing demonstrated achievements in productivity gains through safe HRI in contrast to pure automation using cobots (Komenda et al., 2019). Evjemo et al. (2020) concluded that the achievement for smart factories is, inter alia, an open workspace where humans as well as cobots can collaborate on decisions and actions as well as share autonomy. Because this approach has so far only been tested in practice at demonstration level or test workstations, there is a need for the elaboration and evaluation of this work-sharing approach. The goal is to create a work system that allows a more flexible distribution of tasks on an operational level that fulfills the needs of HF/E and industry, such as economic efficiency. This thesis intends to narrow this research gap.

To establish the problem statement and objective of this work, terminology is established. First, the level of abstraction needs to be defined. To focus on assembly processes and reduce the complexity of the mathematical problem, the highest operational sublevel of performance, namely the task level, is chosen (see Section 2.3.2). Second, similar terms are delineated as follows. Flexible automation systems refer to systems capable of responding to requested changes and maintaining manufacturing goals (Vicentini, Askarpour et al., 2020). Often, the term dynamic task allocation is used (Bruno and Antonelli, 2018; Müller et al., 2017; Riedelbauch, 2020; Sherry and Ritter, 2002), implying a continuous change in the distribution of tasks. This would lead to numerous task allocation decisions that are too complex or unmanageable for humans. However, the system adapts to circumstances and is controllable by a human (Nachtwei, 2011). A distinction can be made between adaptive and adaptable systems. Adaptive systems refer to systems that adapt autonomously to changing environmental conditions (context adaptive) or user characteristics (user adaptive). Adaptable systems refer to a system that can be adapted by the user according to changing environmental conditions (context adaptable) or user properties (user adaptable) (Reinhart, 2017, p. 58). This work does not exclude adaptivity or adaptability, but for the sake of simplicity, only the term *adaptive* is used because this is an established term in the task allocation research (Colim et al., 2020; Rencken and Durrant-Whyte, 1993; Wang, L. et al., 2019).

To distinguish this work from existing work (see Section 3.4) that focuses on either static task allocation to agents or systems that adapt (dynamically) automatically, the term *sharing* is used instead of allocation. This allows one to consider humans as part of the human–robot team and not see them solely as an executor of tasks without any decision-making authority in the task allocation process. Following the previous explanations, the research question of this dissertation is established as follows:

What is an appropriate method to adaptively share tasks in assembly processes between a human and collaborative robot to increase economic efficiency and improve human factors/ergonomics?

This thesis aims to develop a method to adaptively share tasks between a human and cobot in assembly processes. The sequential planning of the scheduling process is not part of this work. A workplace comprising a stationary cobot and worker in a high-mix low-volume production is considered in this work because this thesis intends to increase economic efficiency in mass customization assembly systems.

The challenge is to leverage the economic advantages of using a new technology, i.e., cobots, and avoid the disadvantages of static task allocation approaches. Therefore, hybrid automation is aimed, in which humans are not excluded from either the assembly line or the task allocation decision-making processes. This allows one to exploit the positive effects of task sharing in HF/E.

The development of a method enabling the hybrid automation using cobots is elaborated in three parts, which answer the following three subresearch questions:

I. ***How to analyze tasks for human–robot teamwork in assembly processes?***

II. ***How to assign tasks to the human, robot, or "shared tasks" for human–robot teamwork in assembly processes?***

III. **How to visualize the human–robot tasks for both the human and robot?**

To elaborate on these questions, the following section explains the pursued research methodology and provides an overview of this thesis.

1.3. Research Methodology and Design

To develop the proposed method, an iterative design science methodology was chosen. The main benefit of this methodology is the reintegration of gained knowledge and insights into the research to further develop and improve the method. Based on proven design science methods, an individual procedure was created (Hevner et al., 2004; Hevner, 2007; Nunamaker, JR. et al., 1991; Peffers et al., 2007). Figure 1 shows the adapted and extended research methodology principle based on Nunamaker, JR. et al. (1991). The iterative research process is connected to the so-called body of knowledge, including the knowledge of research methods, research domains, and experiences. Results of the research process contribute to the body of knowledge and vice versa.

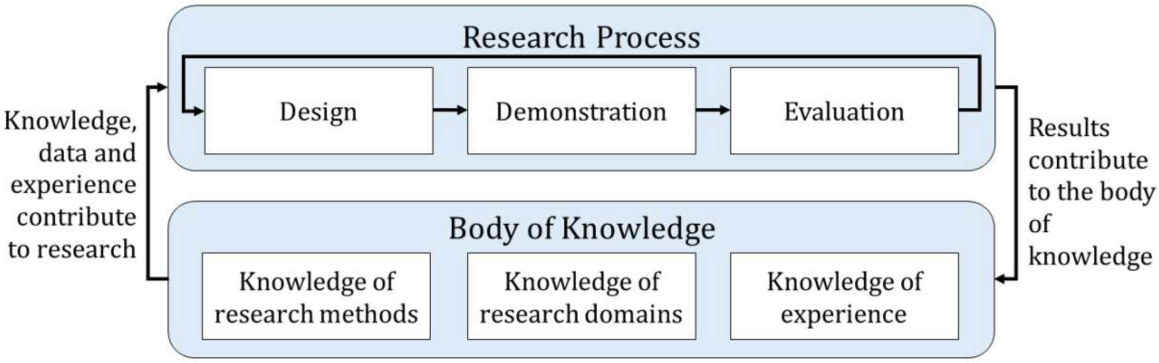

Figure 1 Adapted and extended research methodology based on Nunamaker, JR. et al. (1991).

To develop the proposed adaptive task sharing (ATS) method, the research process consists of five research iterations. These are depicted in Figure 2 and described below:

1. Method concept development

During the first iteration, an initial ATS concept was developed using the setup of a physical demonstrator at the Pilot Factory for Industry 4.0 at TU Wien. A simple manual use-case from the electronics manufacturing industry was analyzed regarding the potential of "cobotization" (automation using the cobot) and its economic implications. Changing lot sizes was considered when the economic efficiency of different task sharing alternatives was calculated. The evaluation of the first demonstration included a comparative analysis of the concept and the derivation of design principles for ATS. The initial concept, demonstration, and evaluation are described and published by Schmidbauer, Schlund et al., (2020). Evaluation results are discussed in Section 6.1.

2. Mockup user interface development

The first draft of task visualization was realized in a mockup user interface for the cobot. The mockup was deployed within a video vignette study about attitudes toward attributed agency and the role of perceived control in HRI (Zafari and Köszegi, 2020). Within the study, the task visualization concept regarding suitability was validated in the sense that the study participants understood the arrangement of tasks in the form of (swim) lanes based on business process model and notation (BPMN) 2.0. The initial task visualization mockup user interface is shown in Section 4.5.

3. Worker assistance system development

During the third iteration, the requirements for the task visualization to enable ATS were developed. These are presented in Section 4.5. Based on the requirements, a worker assistance system for task visualization was developed and evaluated (Hader, 2021; Schmidbauer et al., 2021). The evaluation process involved concept verification and a quantitative evaluation study regarding HF/E and economic efficiency. The task visualization method and evaluation are discussed in Section 5.3 and 6.1.4.2.

4. Method development

In the fourth iteration, the second more complex demonstrator including the worker assistance system was set up. A use-case stemming from the electronics manufacturing industry was realized. With the aid of this use-case, the requirements for the method were refined and methods for task analysis and assignment were selected. To identify suitable task analysis methods, a systematic literature review (SLR) and simulation tests were conducted (Cristea, 2020). The final task analysis methods used are described in Section 5.1. For task assignment, decision-making criteria were defined and implemented in the method to reduce the complexity of task sharing. Thus, the core method for ATS was created. Then, a user study was conducted to validate the ATS concept and verify the requirements. The evaluation results are presented in Section 6.2.4.

5. *Method refinement*

During the final iteration, the methods used for task analysis and sharing as well as the worker assistance system were refined. The results are shown in Section 5. An outlook on further development of the ATS method is presented in Section 7.2.

The body of knowledge used for this thesis comprises the theoretical framework regarding HRI in assembly processes (Section 2.1), HF/E (Section 2.2), and transition methods from manual to hybrid assembly (Section 2.3). Based on this knowledge, different task analysis, allocation, and visualization methods in HRI were identified through a SLR (Section 3). These methods were analyzed, and the most appropriate ones were selected for the ATS method based on the requirement analysis (Section 4). The final ATS method including the subparts task analysis, assignment, and visualization is explained in Section 5. Two example ATS implementations using different assembly use-cases were set up (Section 6). For the evaluations (Section 6), different methods were deployed, including quantitative data collection, analysis, and evaluation methods (Section 6.1.4.2 and 6.2.4), computer simulations (Section 6.1.1.3), laboratory experiments (Section 6.1.4.1), as well as online (Section 6.1.4.2) and physical user studies (Section 6.2.4). A discussion and various limitations are presented (Section 6.3) before the conclusion in Section 7.1 and an outlook in Section 7.2.

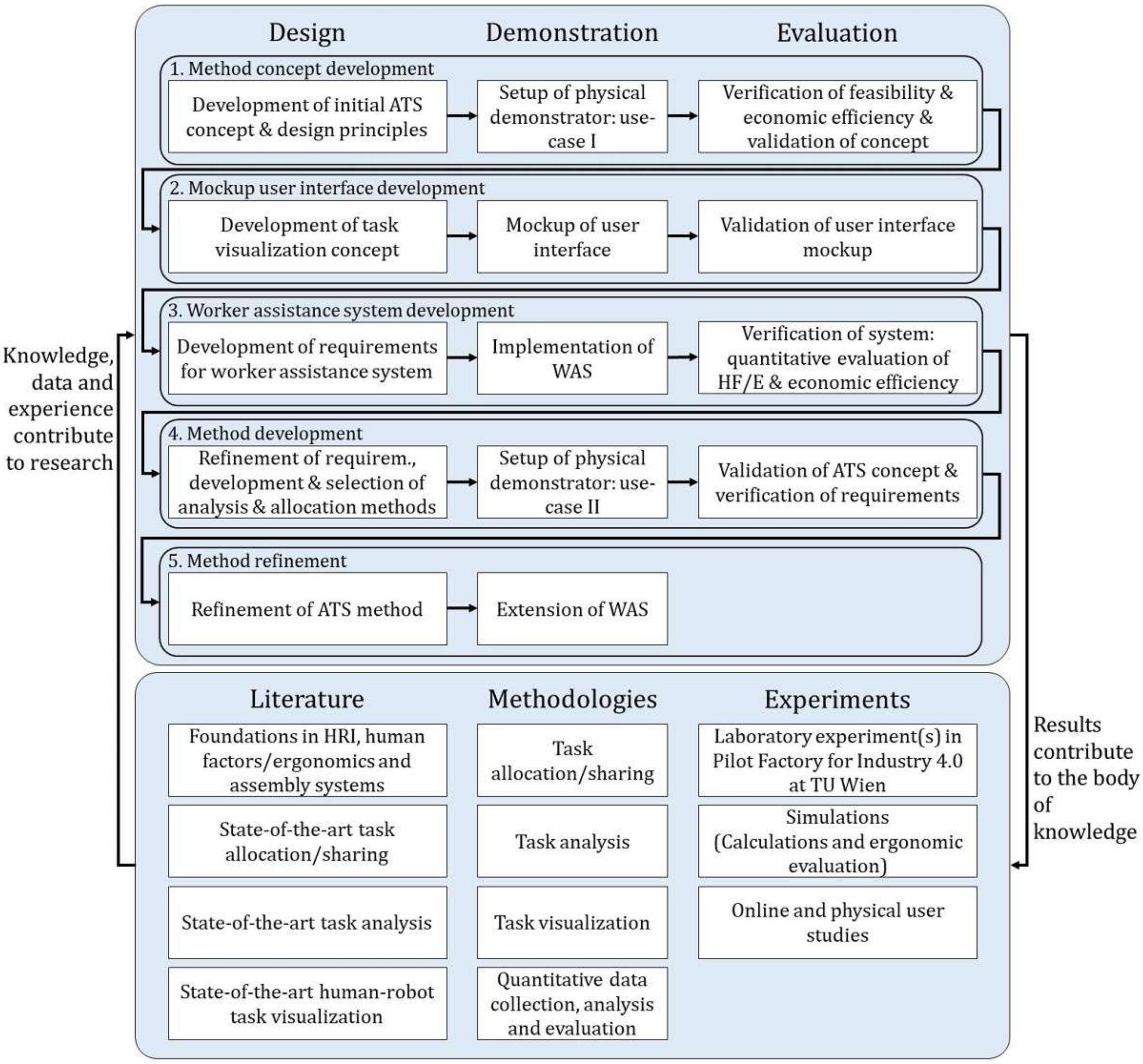

Figure 2 Research methodology to develop a method for adaptive task sharing based on design science (own figure).

2. THEORETICAL FRAMEWORK

Implementation of cobots in human workspaces depends on several considerations. For instance, Gualtieri et al. (2020) considered technical, ergonomic, quality, and economic factors. Bauer et al. (2016) added safety, acceptance, as well as the development of work content and work organization. Study results (n = 88) supported the considerations and identified the four most important challenges when implementing a cobot on the shop floor: (1) too high costs or long amortization period (52%), (2) work planning and task allocation between humans and robots (44%), (3) human safety (36%), and (4) employee acceptance toward the cobots' implementation (22%) (Patsch et al., 2021, unpublished results). This section discusses these important factors, beginning with an introduction and the delineation of cobots and their applications, safety considerations, and the implications for interaction scenarios in assembly processes. The next section provides an overview of HRI relevant HF/E, including physical, mental, and organizational aspects. The section ends with an overview of transition methods from manual to hybrid or automated assembly.

2.1. Human–Cobot Interaction in Assembly Processes

Due to the progressive development of industrial collaborative robotic arms, several terms and definitions evolved regarding the interaction forms between humans and cobots in manufacturing. This section provides an insight into the theoretical foundations and framework conditions for task sharing between humans and cobots. In the following section, the term cobot will be defined including its areas of application. Moreover, safety and security aspects, as well as different interaction forms are discussed.

2.1.1. Collaborative Robots

Industrial robots are defined as *"automatically controlled, reprogrammable multipurpose manipulator(s) (3.6), programmable in three or more axes (3.16), which can be either fixed in place or mobile for use in industrial automation applications"* (DIN EN ISO 10218-1, 2020, p. 4). This is applicable to cobots as well. In addition, cobots are designed for direct physical interactions with humans (Fast-Berglund and Romero, 2019, p. 683).

The term "cobot" was introduced by Colgate et al. (1995, p. 1) as a *"robotic device which manipulates objects in collaboration with a human operator."* In 1999, the possible positive effects of the use of cobots as intelligent assistive devices in assembly applications on the human worker were proposed by Akella et al. (1999). These included ergonomics, productivity, quality, and safety issues. Although the initial presented idea of cobots does not resemble cobotic arms today, the original purpose is still valid. Photographs of different cobots are shown in Figure 3.

In comparison to industrial robots, cobots work at lower speeds and forces to fulfill the safety requirements (DIN ISO/TS 15066, 2016) and can be used more flexibly due to several reasons, including the relatively high reconfigurability of processes (Makris, 2021). In addition, cobots have at least one inherent safety feature, such as force control (DIN ISO/TS 15066, 2016). Cobots are force sensitive and detect unexpected forces to stop immediately to prevent collisions with humans and other physical objects. Efforts have been made to make cobots mobile and flexible by mounting them on existing mobile platforms. However, these applications are still demonstration use-cases and not market ready (Brandstötter et al., 2020; D'Souza et al., 2020). Furthermore, developers and companies have equipped cobots with social features or cues, including a tablet with a face or eyes to increase the usability, user experience, and user acceptance toward the technology (Rethink Robotics, 2020). In summary, a cobot can be defined as follows:

"A cobot is a compliant, reprogrammable, multipurpose robotic arm designed for a physical interaction with humans that can flexibly be used stationary or mobile."

Figure 3 Photographs of different cobots used in the TU Wien Pilot Factory for Industry 4.0 in Vienna, Austria. (a) Bosch APAS, (b) Universal Robot UR5, (c) Fanuc CR-7iA, and (d) Franka Emika Panda (own figure).

Different modalities were developed to interact with a cobot (El Zaatari et al., 2019; Schmidbauer, Komenda, Schlund, 2020). The primary means of interaction is the representation of a cobot program displayed on either a connected computer screen or a handheld device.

All modalities are summarized as user interfaces (UIs)[2] and serve different purposes, such as programming, controlling, and maintaining.

Some interaction modalities are listed by Schmidbauer, Komenda, Schlund (2020):

- Visual UIs: signal lamps, projectors, and displays
- Acoustic UIs: sounds and speech
- Haptic UIs: keyboard, mouse, teaching pendants, buttons, and smart surfaces, such as sensory skins or safety mats

Detailed information on different interaction types, in particular on controlling (programming) cobots, can be found in the studies by El Zaatari et al. (2019) and Hader (2021). A deeper insight into the usability and heuristics regarding cobot UIs can be found in the studies by Schmidbauer, Komenda, Schlund (2020) and Frijns and Schmidbauer (2021).

2.1.2. Safe Human–Cobot Interaction

The physical safety in HRI plays an important role in real implementations and workplace design. The aim is to protect the humans "*from the consequences of unexpected and unwanted collisions between human body parts and robot systems and/or workspaces elements by maintaining proper performance of production systems at the same time*" (Gualtieri et al., 2021, p. 17). To enable safe working with humans, cobots are limited in their speed (DIN ISO/TS 15066, 2016). Moreover, the maximum force that can be applied by a cobot is limited. Biomechanical constraints must be maintained in every possible interaction with humans. If cobots are operated separate from a human workspace, they can exceed these limits carry heavy loads, and deploy at high speeds. Because cobots are partly complete machines (Machinery Directive 2006/42/EC, 2016), when designing a workstation, not only the cobotic arm but also its tool, the workpiece, all fixtures, and other physical conditions must be considered.

The applicable safety standards are as follows:

- DIN EN ISO 10218-1:2020: Robotics – Safety requirements for robot systems in an industrial environment – Part 1: Robots (Draft)
- DIN EN ISO 10218-2:2020: Robotics – Safety requirements for robot systems in an industrial environment – Part 2: Robot systems, robot applications and robot cells integration (Draft)
- DIN ISO/TS 15066:2016 Robots and robotic devices - Collaborative robots

[2]A user interface is defined as *"all components of an interactive system that provide information and controls for the user to accomplish specific tasks with the interactive system"* (DIN EN ISO 9241-110 (2019, p. 3).

To ensure human safety, four collaborative safety features are foreseen in the standard (DIN ISO/TS 15066, 2016) and presented in Figure 4:

- “Safety-monitored stop” means that a cobot is not moving when there is a human in the workspace. This safety function will be delisted from collaborative modes, as it is a transition state and stopping condition and not an interaction mode (Vicentini, 2020).
- “Hand guiding” should not be misunderstood with programming by hand guiding or walkthrough programming and the manual operation of a tool (Vicentini, 2020). In this context, “hand guiding” refers to when the cobot is only moving when the human is actively guiding the cobot during execution.
- In “speed and separation monitoring,” the system is constantly monitoring the motion of the human in the workspace, which means that when the human is in too close proximity to the cobot, the system changes into a safe state (Vicentini, 2020). To ensure monitoring, the cobot system depends on sensors, that are often not included in the cobot itself. External sensors, e.g., laser scanners or light barriers, connected with the cobot’s software are necessary to ensure this interaction mode.
- “Power and force limiting” describes that power and force of the cobot are limited so as not to exceed the maximum acceptable forces in the possible event of a collision. This interaction mode is often included via internal sensors in cobotic arms. Most UIs of cobots allow the adjustment of different limits for speed and force.

As the human safety relates to the system’s security, associated aspects should not be underestimated (DIN EN ISO 10218-1, 2020; Hollerer et al., 2021).

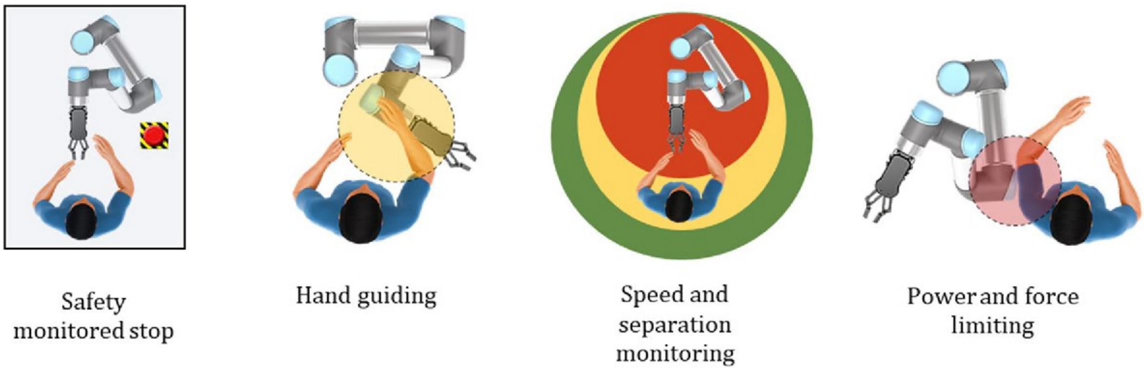

Figure 4 Human–robot interactions based on DIN ISO/TS 15066:2016 (Malik and Bilberg, 2019c, p. 1546).

Literature provides different notations for HRI constellations including human–agent–robot–teamwork (Bradshaw et al., 2012), human–robot teaming (Shah et al., 2011), physical human–robot interaction (Johannsmeier and Haddadin, 2017, p. 41), or symbiotic human–robot assembly (Wang et al., 2020). The interaction is often divided into different subgroups. One attempt to refine these interaction subgroups or levels is presented by Aaltonen et al. (2018, p. 95):

- No coexistence: physical separation
- Coexistence: human works in (partially or completely) shared space with the cobot with no shared goals or direct contact between them
- Cooperation: human and cobot work towards a shared goal in (partially or completely) shared space without any direct contact between them
- Collaboration (HRC): human and cobot work simultaneously on a shared object in a shared space. *"A collaborative human–robot workspace is defined as a shared space within the operating space where the robot system, including the workpiece, and a human can perform tasks concurrently during a production operation"* (Fast-Berglund and Romero, 2019, p. 683)

Wang et al. (2020) added HRI to the classification of human–robot relationships and referred to a relationship in which the workspace and tasks are shared but only sequentially. The cobot and human communicate through, e.g., UIs.

Orlandini et al. (2020, p. 240) stated four interaction modalities in task allocation development:

- Independent: humans and cobots operate on separate workpieces without collaboration
- Synchronous: humans and cobots operate components of the same workpiece sequentially, i.e., one starts and other finishes
- Simultaneous: humans and cobots simultaneously operate on separate tasks on the same workpiece
- Supportive: humans and cobots work cooperatively to complete the processing of a single workpiece/simultaneously on the same task

Malik and Bilberg (2019c) referred to a study (Bauer et al., 2016) for investigating the state-of-the-art and state-of-the-practice lightweight cobots. They distinguished five interaction levels (Bauer et al., 2016) (Figure 5).

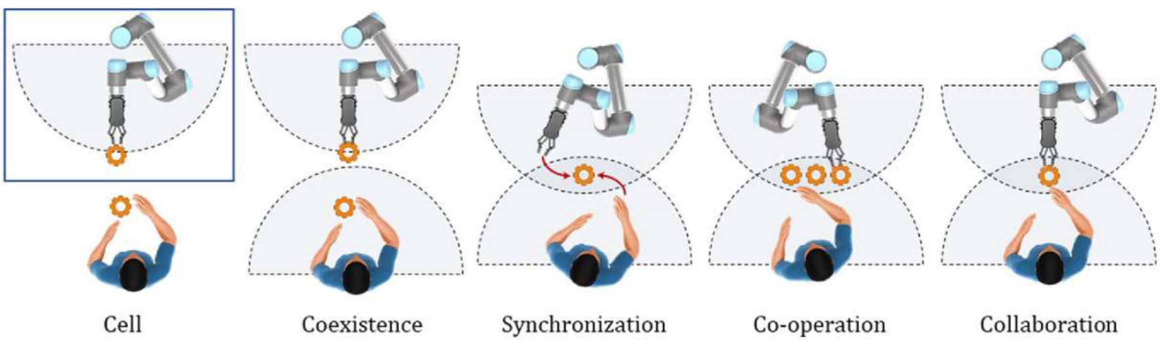

Figure 5 Engagement levels between a human and robot based on time and space sharing (Malik and Bilberg, 2019c, p. 1545).

2.1.3. Cobot Skills and Applications in Assembly Processes

Within the safe HRI framework, explained in Section 2.1.2, the cobot's skills play an important role in defining its tasks and application areas. Skills refer to *"the ability to use one's knowledge effectively and readily in execution or performance"* and *"[...] coordination especially in the execution of learned physical tasks" (Merriam-Webster, 2021).* In terms of cobot's skills, the second part of the definition explains the primary purpose of a robotic manipulator, whereas the first part relates more to software applications (integrated in a robotic system). Meanwhile, various researchers refer to the term "functions" instead of skills (Challenger et al., 2013; Hancock and Scallen, 1996; Janssen et al., 2019). Ameri et al. (2019, p. 249) described tasks as "*an ordered sequence of skills aiming to achieve a specific goal".*

2.1.3.1.Cobot Skills

The favorable skills and limitations of robots based on Fitts (1951) paper are stated in a study by Schröter (2018). Examples for favorable skills are the handling of heavy parts, precision, repeatability, and integrated process control possibilities. The limitations mentioned are possible failures, the necessary provision of parts, and the rigid processing of tasks due to part properties. In addition, the adherence to tolerances partly requires external sensors.

Primarily, cobotic arms can perform mechanical actions. They can sense some environmental variables, such as physical obstacles. They can process the collected data to, e.g., calculate paths and make decisions or stop in case of a collision. In some cases, they can actively communicate visually or by voice with their human operators (Schmidbauer, Komenda, Schlund, 2020). However, cobots are mainly made to take over physical tasks from humans, but this statement does not apply to every physical task, as cobots operation is limited in terms of spatial range, maximum payload, maximum speed, etc. Additional capabilities of cobots are often implemented with the help of tools or external sensors to enhance its usability and user experience. In several tasks, custom tools and devices are built to allow the cobot to perform the certain task.

A favorable characteristic of robots is routinization. Compared to a human, a robot has negligible wear and tear associated with repetitive tasks. Besides, an advantage of cobots over other machines is their flexibility (Makris, 2021), as cobots can be moved relatively quickly from one workstation to another and programmed easily for a new task. Algorithms are being developed to equip cobots with additional capabilities such as grasping parts with uncertain shapes, using machine learning and the feedback of force sensors (Lundell et al., 2019). When enhancing cobot capabilities with machine learning, the *"Proposal for a Regulation laying down* *harmonised rules on artificial intelligence (Artificial Intelligence Act)"* (European Commission, 2021) should be considered.

2.1.3.2.Cobot's Applications

Bauer et al. (2016) examined companies' first experiences with lightweight robots. They collected and analyzed 25 example use-cases in Germany. Most use-cases were found in the automotive (40%) or electrical engineering (36%) sector. Most applications were implemented in production lines (68%), but some were in a demonstration (24%) or testing (8%) phase. About 72% of the use-cases were implemented in the assembly area, 24% in parts manufacturing, and 4% in logistics. Most of the lightweight robots used were cobots such as the UR5 (24%), Kuka iiwa (28%) or Bosch APAS (28%). 60% of the robots were operated in coexistence with human coworkers, and 16% of the robots were synchronized with human coworkers in a shared workspace. 12% of the robots were cooperating and 8% were collaborating with human coworkers. The authors classified the applications and found that the most common tasks (multiple answers were possible) were as follows: grip a part (13/25), mount or join (11/25), quality control (10/25), pick & place (9/25), grip multiple parts (8/25), or load a machine (8/25).

In a study on manufacturing work in Austria, Patsch et al. (2021) asked 88 production companies about their deployment of cobots. Most study participants indicated that they use cobots in parts of their production (29.5%) or in pilot cases (12.5%) and 14.8% stated they are planning to use cobots. The main reasons to use cobots were increasing economic efficiency (36.1%), improving HF/E (26.9%), testing the technology (25.9%), or increasing flexibility (11.1%).

Fast-Berglund and Romero (2019) summarized common applications of cobots in their work "*Strategies for Implementing Collaborative Robots for the Operator 4.0.*" Their results are presented in Table 1, where pre-assembly and final assembly were merged to one application "assembly". The wording "inspection robots" or "joining robots" does not suggest that a separate robot is needed for each of these tasks. Tools, devices, and the programming of the robots vary, but the robotic arm remains the same.

Table 1 Common applications of cobots (Fast-Berglund and Romero, 2019, p. 685).

Application	Description
Assembly	Assembly robots assemble parts and components into subassemblies (part handling, high-speed picking, and assembly), freeing up the operators to do more value-added tasks at the assembly line.
Inspection	Inspection robots evaluate the conditions of a part or product in a short time with high accuracy using computer vision when compared with humans' vision.
Kitting	Kitting robots combine their coordinated computer vision with their picking & placing capabilities to identify individual parts or products and assemble them in specific kits (assortments).
Joining	Joining robots hold a welding torch or a glue gun and use their precision capabilities to deposit material at a constant rate and in a fixed path.
Packing	Packing & palletizing robots use their handling capabilities for shrink-wrapping, box assembly and loading, and box collating or placing onto a pallet for shipping.
Pick & place	Pick & place robots use their part handling and high-speed picking capabilities to place a part in a different location. Manual pick & place is one of the most repetitive tasks performed by human workers today.

2.2. Human Factors/Ergonomics

HF/E[3] comprises three dimensions of research including physical, mental, and organizational factors, which are relevant in an assembly setting considering HRI. The aim of HF/E in HRI is to support the humans "*in the reduction of work-related biomechanical and cognitive overload without introducing new hazards for the health and safety of the operator*" (Gualtieri et al., 2021, p. 23).

The standard DIN EN ISO 6385, 2016 describes principles of ergonomics in the form of basic guidelines for the design of work systems and defines the relevant fundamental terms. In particular, if the work design cannot be ensured to meet ergonomic design principles, the changing of activities (job rotation) should be enabled or the set of tasks should be extended (job enlargement or enrichment). The difference between job enlargement and enrichment is that enrichment aims at empowering the human by, e.g., assigning more responsibilities to the human and enlargement (only) diversifies the set of tasks by adding other but similar tasks.

[3] *"The word ergonomics — "the science of work" is derived from the Greek ergon (work) and nomos (laws). Ergonomics (or human factors) is the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimize human well-being and overall system performance (ratified by the IEA Council, 2000). The terms ergonomics and human factors are often used interchangeably or as a unit (e.g., human factors/ergonomics HF/E or E/HF), a practice that is adopted by the IEA"* (2020).

Fujimoto and Abril (1992) presented human factor considerations in the implementation of flexible automatic production systems. The authors considered flexibility in the focal point of the discussion and identified capabilities and possible problems of human–computer interaction within flexible manufacturing systems. They criticized that humans are an "afterthought" and should compensate the incapacities of the automation system. The identified problems were, inter alia, the centralized expertise, variability among humans' experiences, the lack of skilled labor force, and skill loss (if humans are no longer in charge of a function).

Based on these considerations, the following sections provide profound and HRI specific information about the three dimensions of HF/E. Before that, the human's skills in relation to HRI in assembly processes are discussed.

2.2.1. Human Skills

Based on Fitts (1951), Schröter (2018) summarized favorable skills and limitations of humans. Humans' limitations mentioned are unreliability in terms of process control, ergonomic aspects, lack of precision, as well as their desire for demanding tasks. In contrast, the advantages of humans are their high availability, their handling of complex components, and their reliability in terms of complex operations. In addition, they do not require strict part provisioning and are flexible in terms of task variety. Human operators usually adapt to new equipment, to sudden failures of equipment, or the occurrence of unique and unforeseen problems.

Humans have high sensory capabilities to detect and perceive their environment. In comparison to robots or machines, these comprehensive and complementary senses are unique. However, through the targeted development of sensors, specific machines and robots can be developed that far surpass the senses of humans for a certain use-case, e.g., quality control. The state-of-the-art is such that the cobots always need to be trained for a few tasks, and so far, they have not been very successful in coping with new tasks. The development of machine learning is expected to expand such possibilities in the next years.

Gombolay et al. (2015, p. 297) summarized the human skills and competencies as follows: *"Humans are intelligent agents capable of advanced reasoning, dexterous manipulation, and multi-modal communication".* Intelligence is a quality particularly attributed to human beings (Jensen, 1989). The basis of intelligence is to be able to gather information (perceive), store and retrieve this information (memorize), and use this information to learn. Humans can gather knowledge, learn, be creative, and form strategies. Creativity refers to making new connections and using new tools to solve a problem. Further, critical thinking and sharing knowledge over generations are core capabilities that make humans successful (Godden, 1969).

Induction, i.e., learning from experience or data, is a skill where humans surpass machines in general. This is highly important because new technologies require new skill sets of humans. *"Top emerging skills are (1) technology use, monitoring and control, (2) critical thinking and analysis, (3) active learning and learning strategies, (4) leadership and social influence, (5) analytical thinking and innovation, (6) reasoning, problem-solving and ideation, (7) complex problem solving, (8) service orientation, (9) resilience, stress tolerance and flexibility as well as (10) technology design and programming"* (Komenda et al., 2021, p. 2; WEF, 2020, p. 62).

The use of nonhumanoid robots is mentioned as the third most relevant technology adopted in industry (WEF, 2020, p. 62). More insights on skill and competency development of humans in relation to HRI can be found in the studies by Komenda et al. (2021) and Schmidbauer, Komenda, Schlund (2020).

Limitations of human skills in terms of monitoring complex automatic machines and taking over if machines break down should not be neglected. Bainbridge (1983) introduced the ironies of automation with the assumption that the human operator is seen as unreliable and inefficient and should therefore be eliminated from the work system. The ironies are (1) design errors can be a major source of operating problems and (2) the designer still leaves the operator to do the tasks, which the designer cannot automate. These tasks include manual skills that deteriorate when they are not used or trained and cognitive tasks that can be forgotten after some time or that are hard to grasp in a short amount of time. Imagine a worker who starts their shift and needs to get an overview of the things that happen while they were absent. The worker will need some time to be able to decide on next steps even if there was a shift handover. Another prominent human task is monitoring the automated system. Situation awareness and vigilance problems are likely to occur. The irony is that the automation is introduced to make the work more effective and efficient than the human does, but then the human is asked to monitor that the automation is working effectively. Despite extensive and regular training, this will be challenging for the human operator as the amount of data exceeds their abilities. Simulators can help to reduce these problems. It is ironic that the most reliable automation systems require the highest training effort because day-to-day operations provide little opportunity to get acquainted with the system. Conversely, unreliable systems require low training effort because considerable manual intervention is required. Another irony related to automation is the incongruous pay differentials. Workers that previously executed accountable and important manual tasks, adding to the value chain directly, had a high pay level. They continuously insisted on high pay as a symbol of status, despite the changed job content. Bainbridge (1983) presented some ideas on solutions for the problems focusing on interaction design between the automation and human, e.g., alarm systems are important but often confuse the operators. Training and simulators can help reduce knowledge and skill degradation. Work design should be human-centered as humans are impressive problem solvers when they are not pressured under time constraints. Another factor that influences human capabilities is stress, which will be discussed in the following section.

2.2.2. Stress-Strain-Model

Stress is the *"total of all assessable influences impinging upon a human being from external sources and affecting the person [...]"* (DIN EN ISO 10075-1, 2017, p. 6). Mental and physical work always imposes stress, which is in principle neither good nor bad. However, stress induces processes of increasing or decreasing strain within humans depending on the human preconditions (DIN EN ISO 10075-1, 2017). In other words, the effect of the workload (the stress) on the individual highly depends on the individual's characteristics, abilities, skills, and needs (Reinhart, 2017). Therefore, the strain on the individual can be different, although the load (the stress) is the same. If the (mis)strain is too high, physiological (e.g., back/shoulder pain and cardiovascular disease) and psychological illnesses (e.g., emotional exhaustion/burnout) can occur. This shows that workers need to be individually supported in their work to keep stress levels low (Schlund et al., 2018).

2.2.3. Physical HF/E

Physical HF/E aims at the human's anatomical characteristics, such as anthropometric, physiological, and biomechanical, related to physical activity. The postures while working and repetitive movements are considered. The safety and health of the human body must be maintained. The standard DIN 33402-2, 2020 provides average body dimensions as a basis for physical ergonomic considerations.

Physical work causes physical stress that affects the worker's body. However, routine work achieves positive effects, such as muscle building and learning. Negative effects are fatigue or physical disorders, such as back and neck pain. The standard ISO 11226, 2000 recommends static working postures and its limits. It states that *"work tasks and operations should provide sufficient physical and mental VARIATION. This means a complete job, with sufficient VARIATION of tasks (for instance, an adequate number of organizing tasks, an appropriate mix of short, medium and long task cycles, and a balanced distribution of easy and difficult tasks), sufficient autonomy, opportunities for contact, information and learning. Furthermore, the full range of* *workers possibly involved with the tasks and operations should be considered, in particular their body dimensions*" (ISO 11226, 2000, p. 2).

2.2.3.1.Physical HF/E in HRI

Rücker et al. (2019, p. 134) investigated ergonomics in HRI and compiled relevant human factors. This list includes general ergonomic factors such as physical environment, working postures, materials handling, repetitive movements, work-related musculoskeletal disorders, safety, and health. Furthermore, the listed robot-related factors include the type, anatomy, behavior, dependability, reliability, predictability, proximity, personality, adaptability of the robot and the level of automation, failure rates, false alarms, transparency of actions, and anthropomorphism. The authors include biomechanical factors such as dimensions, kinematics, and contact forces. Their work showed the complexity of HF/E in HRI.

2.2.3.2.Exemplary Physical HF/E Evaluation Methods

Several evaluation methods for physical HF/E were developed. These methods are either pen and paper methods or simulations of the manual work in the design phase or for further evaluation purposes. The enumeration is not intended to represent a comprehensive state-of-the-art ergonomic evaluation method. More methods such as NIOSH (national institute for occupational safety and health) to estimate the maximum load in load handling operations, and OWAS (Ovako working posture assessment system) to assess work situations on the basis of postures, are presented in the studies by Bullinger-Hoffmann and Mühlstedt (2016).

- *RULA: Rapid Upper Limb Assessment*

The rapid upper limb assessment (RULA) is a method to assess the need for ergonomic-related adaptions in a workplace. It provides quick assessment of the postures of the neck, trunk, and upper limbs along with muscle function and the external loads experienced by the body (McAtamney and Corlett, 1993). Table 2 summarizes the interpretation of the assessment results as well as derived procedure and actions. RULA is especially applicable for quick first analyses of workplaces.

Table 2 Interpretations of results obtained by RULA.

Score	Derived Procedure & Actions
1–2	Current state is acceptable and no changes needed
3–4	Changes should be undertaken
5–6	Changes should be undertaken soon
7	Changes are needed immediately

- *EAWS: European Assembly Worksheet or Ergonomic Assessment Worksheet*

The European assembly worksheet or ergonomic assessment worksheet (EAWS) method investigates different types of stress, such as action forces, load handling, postures, and repetitive activities. The method is based on other methods, e.g., the OWAS, key indicator method (KIM), RULA, and occupational repetitive actions (OCRA), and focuses on process evaluation rather than static ergonomic evaluations (Schaub et al., 2013). "*EAWS focuses especially on existing CEN and ISO standards, which consider physical workload in terms of working postures, action forces, manual materials handling and repetitive loads of the upper limbs*" (Schaub et al., 2012, p. 14). The result of EAWS is classified into three categories (Table 3). EAWS is applicable when detailed analyses are needed.

Table 3 Interpretation of results obtained by EAWS.

Score	Derived Procedure & Actions
0–25	Low risk: no need for adaption
25–50	Medium risk: need for adaption
>50	High risk: urgent need for adaption

2.2.4. Mental HF/E

Mental ergonomics aims at factors affecting the human's mental health. The DIN EN ISO 10075-1 (2017, p. 10) clearly states *"any activity – even a predominantly physical one – can impose mental stress".* Mental stress (or mental workload) refers to cognitive, informational, and emotional processes in the human body. These processes are not separated for analysis, as it is hardly possible. Similar to physical stress, mental stress can have positive effects, such as motivation, practice, and learning, and negative effects, such as fatigue. Mental strains are caused by stress within the individual depending on their preconditions. Moreover, there are long-term effects such as the advancement of competences and in negative cases, burnout. Mental stress can lead to errors in human performance, like inability to perform work well. Therefore, it is important that workplaces, tasks, and tools including machines and its UIs, are designed to avoid mental overload. A summary of positive (facilitating) and negative (impairing) effects, given by DIN EN ISO 10075-1, 2017, is presented in Table 4.

Table 4 Effects of mental stress according to DIN EN ISO 10075-1, 2017.

Facilitating effects with short-term potential	Facilitating effects with long-term potential	Impairing effects with short-term potential	Impairing effects with long-term potential
Warming-up effect	Competence development	Mental fatigue	Burnout
Activation		Fatigue-like state	
Learning		Monotony	
Practice effect		Reduced vigilance	
		Mental satiation	
		Stress response	

2.2.4.1.Mental HF/E in HRI

Relevant mental factors in HRI summarized by Rücker et al. (2019, p. 134) include mental workload, skilled performance, human reliability, work stress, training, attention capability, and expertise. In addition, competency, prior experiences, demographics, personality traits, attitude towards robots, comfort with robots, self-confidence, propensity to trust, decision-making time, decision accuracy, vigilance, awareness, and human error are mentioned. Endsley and Kiris (1995) showed that situation awareness and the response time after the automation fails correlate with the automation level based on the results of a user study. It took the participants much longer time to respond in a fully automated system than in a manual system. The authors concluded that the methods should be implemented to minimize the negative effects while maintaining the benefits of automation.

2.2.4.2.Exemplary Mental HF/E Evaluation Methods

To measure mental stress, several methods were developed. An overview is given by Stanton et al. (2013), and two exemplary methods are presented in the following.

- *NASA-raw-TLX: National Aeronautics and Space Administration raw Task Load Index*

The national aeronautics and space administration task load index (NASA-TLX) (Hart and Staveland, 1988) is often used to assess the perceived workload (Endsley and Kiris, 1995). The assessment includes a superficial consideration of physical demand, although this is not sufficient as an evaluation method for physical workload in most assembly workplaces because the causes of physical strain are not assessed. The NASA-raw-TLX comprises a version of the NASA-TLX. The difference between them lies in the number of questions assessing each variable. Moreover, the NASA-TLX considers a weighting of the questions. The assessment of the NASA-raw-TLX comprises six variables that are evaluated through a single question for each variable (Hart and Staveland, 1988; Stanton et al., 2013):

1. Mental demand: how mentally demanding was the task?

2. Physical demand: how physically demanding was the task?
3. Temporal demand/stress: how hurried or rushed was the pace of the task?
4. Performance: how successful were you in accomplishing what you were asked to do?
5. Effort: how hard did you have to work to accomplish your level of performance?
6. Frustration: how insecure, discouraged, irritated, stressed, and annoyed were you?

The results are measured on a scale ranging from 1 (very low) to 5 (very high). The developed method is used to evaluate and compare different types of tasks or work settings.

- *CLAM: Cognitive Load Assessment for Manufacturing*

Thorvald et al. (2019) developed a method to assess cognitive work load in manufacturing, particularly in assembly processes. The assessment consists of several task-based (1–5) and workstation (6–11) factors, which are given below:

1. Saturation
2. Variant flora
3. Batching of variants level of difficulty
4. Difficulty in tool use
5. Level of attention required
6. Number of available tools
7. Workstation mapping
8. Parts identification
9. Quality of instruction
10. Information cost
11. Poke-a-Yoke and constraints

Each factor is rated on a scale from 0 (no), 1 (very low), 2 (low), 3 (moderate) to 4 (high cognitive load) (Table 5). The factors and assessment are explained in detail in the CLAM handbook (Thorvald and Lindblom, 2019).

Table 5 Interpretation of the results of CLAM (Thorvald and Lindblom, 2019).

Score	Derived Procedure & Actions
0	Not a problem with high cognitive load at all
1	Only a trivial problem with high cognitive load, which does not need to be reduced unless extra resources are available
2	Minor problem with high cognitive load, and reducing this should be given low priority
3	Major problem with too high cognitive load, and it is important to reducing it and should be given high priority
4	Catastrophic problem with too high cognitive load, and it is of major importance to immediately reduce, and fix this problem with high priority

In the following, the topics of monotony and learning are explained in more detail due to their relevance to this thesis.

2.2.5. Monotony and Task Diversity

According to DIN EN ISO 10075-1 (2017, p. 5) monotony describes a *"slowly developing state of reduced activation, which is mainly associated with drowsiness, tiredness, decrease and fluctuations in performance, reductions in adaptability and responsiveness, as well as an increase in variability of heart rate".* Similar in effects is reduced vigilance, which describes a *"slowly developing state with reduced activation and detection performance in monitoring tasks offering only little variation"* (DIN EN ISO 10075-1, 2017, p. 5). The latter is mostly known from jobs where workers are monitoring data on a screen or inspecting physical parts for defects or impurities, whereas monotony appears when a worker has to execute long, uniform, and repetitive tasks, such as assembly tasks. Both states are impairing effects with short-term potential of mental strain and have different causes; however, the effects are identical.

Richter (2000, p. 49) showed short-term and long-term effects of monotony:

- Short-term effects
    - The average performance is dropping.
    - The frequency of errors increases compared to that in less monotonous work situations.
    - The reaction times to signals from the activity and additional stimuli are extended. The changeover time to suddenly occurring new requirements is longer. Reliability is thus impaired.
    - The eye lid closure is increased.
    - The entire body musculature slackens.
- Long-term effects
    - The unlearning of some qualifications that are not used or are used infrequently.
    - Deterioration, in particular, of intellectual performance in the sense of avoidable premature age-related reduction.
    - The satisfaction drops below average with the risk of demotivation.
    - The level of active and creative leisure activities drops below average.
    - The impairments of well-being, abuse of medication, and probability of depressive and anxious moods increase.
    - Sickness rates increase.

To reduce and prevent monotony, design guidelines are presented as follows. All measures expand the scope of attention. To reduce and avoid the development of monotonous conditions, a scheduled change of activity and the creation of mixed activities or group work are useful. However, the most effective measure is the creation of complete activities, i.e., the activities should be designed to include execution, processing, preparation, organization, and control. This makes it possible for work activities to contain requirements necessary for regulating mental activities at different levels. Such activities contain (Richter, 2000, p. 50):

- Scope for decision-making and action-taking
- Information about the task (including "higher" level information)
- Feedback about the results

After the effectiveness of the design measures, the following points must be observed in order of priority (Richter, 2000, p. 50):

- Function allocation between humans and machines
- Work organization (task allocation among humans)
- Qualification
- Working environment

In summary, task diversity and function/task allocation are of high relevance for human well-being.

2.2.6. Learning

One of the rewards of workload is learning. The importance of learning new skills and competencies for a manufacturing worker is a prominent research topic (Komenda et al., 2021). Qualifications and competencies are the result of the learning process (Schlick et al., 2018). In contrast, physical workload helps workers build muscles and be trained for work-related movements, which can be retrieved when they are needed. Meanwhile, mental workload explicitly aims at competence development through practice. Performance improves with time in the learning process (learning curve). This also implies that practice is required to perform a task with good quality. Contrarily, monotony leads to the unlearning of some qualifications that are not or used seldom.

However, learning is highly relevant in an increasingly technological world of work. Because machines and software took over, new tasks and competencies are thus demanded from human workers. Buxbaum et al. (2020, p. 568) claimed that HRI design requires a competence-focused work design: "*The technical possibilities should allow an individualized solution, which allows to assign tasks to the human being according to the current skill level*".

Ansari, Hold et al. (2018) elucidated the barriers and challenges of learning within smart factories. These include the decreasing diversity of processes to be mastered because of high system automation levels, few learning opportunities because of automation of several routine tasks, and the uncertain role of human work in human–machine interaction. The authors focused on mutual learning "*a bidirectional process involving reciprocal exchange, dependence, action or influence within human and machine collaboration on performing shared tasks, which results in creating a new meaning or concept, enriching the existing ones or improving skills and abilities*" (Ansari, Erol, Sihn, 2018, p. 119). To facilitate mutual learning as well as increase total knowledge in the system, the authors divided tasks into human, machine, and shared tasks (Figure 6). Humans should learn from their machine counterparts and machines should be enabled to learn from their human colleagues through cognitive computing capabilities. Deeper insights into the learning capabilities of machines, particularly robots, can be found in Wang, W. et al. (2019).

A human worker can learn a task by performing it; however, in routine activities, it can lead to unlearning of other tasks. Thus, learning can be promoted through the shared tasks concept where tasks are not statically allocated to one agent (human or robot) but are in a pool of tasks where both agents can take over. This enables the assignment of tasks to different agents.

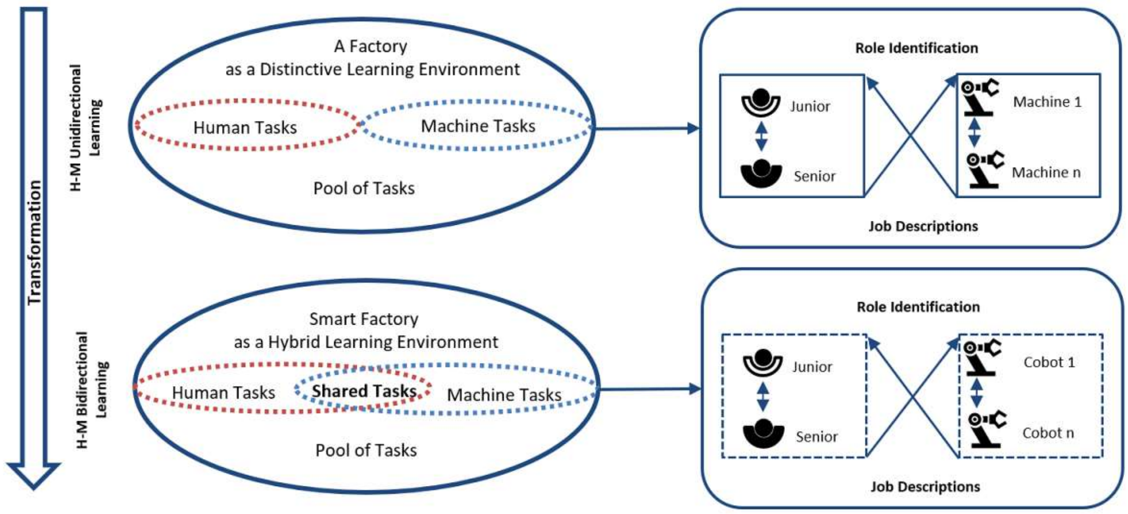

Figure 6 Division of tasks and its impact on human–machine learning (Ansari, Hold et al., 2018, p. 63).

2.2.7. Organizational HF/E

Organizational ergonomics concerns the optimization of socio-technological systems, including organizational structures, rules, and processes. The division and combination of labor (task allocation) influence the work system's requirements that arise from and determine the order and execution conditions, work requirements, regulation forms, and work activity structure. Task allocation thus corresponds to the wholeness (completeness and task identity) or fragmentation (partialization) of the work activities (Hacker and Sachse, 2014).

The degree to which tasks are divided among different entities or are combined to form one or a few entities determines the necessary and possible cooperation and communication between them. It defines the content, wholeness, task variety, and structure of the work activity of each individual entity. After optimizing the human–machine task allocation, it is important to investigate and further optimize the division and combination of tasks. Hacker and Sachse (2014) outlined the characteristics of "well-designed work" for a human worker (Table 6).

Table 6 Characteristics of a "well-designed work" for a human worker (adapted and translated from Hacker and Sachse (2014, p. 24).

	Characteristics of a "well-designed work" for a human worker
1	Holistic, complete, and meaningful work content
2	Significant contribution to the work system that is recognizable to workers
3	Appropriate diversity of skills and abilities, avoiding repetitive and one-sided tasks
4	Scope for action (in terms of working speed, sequence, and procedure)
5	Sufficient and meaningful feedback on task performance
6	Consideration of the knowledge, experience, skills, and abilities of the worker (no over-/under-qualified)
7	Possibility to use and develop existing knowledge, experience, skills, and abilities or to acquire new ones
8	Avoid socially isolated work

2.2.7.1. Organizational HF/E in HRI

Rücker et al. (2019, p. 134) mentioned that relevant organizational ergonomics in HRI including workplace layout, communication, crew resource management, work design, design of working times, teamwork, participatory design, task type and complexity, multitasking requirement, mutual allocation and safe methods of operation. Owing to its relevance, the foundations of task allocation are discussed in detail in the following.

HF/E research discusses the limitations of static task allocation and raises the idea of a dynamic and adaptive allocation (Hancock and Scallen, 1996) as well as an adaptive automation, focusing primarily on applications in aviation and shipping, e.g., air traffic control (Sheridan and Parasuraman, 2005). In this context, changes in allocation should be based on the performance level of the human operator. Sheridan and Parasuraman (2005) also discussed possible issues related to automation, such as threatened or actual unemployment, erratic mental workload and dissatisfaction with work, centralization of management control and loss of worker control, desocialization, deskilling, intimidation from large aggregations of interconnected automation, technological illiteracy, mystification and misplaced trust, sense of not contributing, abandonment of responsibility (false assumption that automation is responsible), and blissful enslavement. The authors questioned what should not be automated and responded that this question should be asked as early as possible before something is automated. Even if it would be exciting to automate a challenging process, the question whether it should be automated should not be ignored.

Sheridan and Parasuraman (2005) discussed the role of humans in automation and summarized some criteria for a human-centered automation and reasons to question them (Table 7). The compilation shows the conflicting goals and challenges in human–machine interaction.

Table 7 Some criteria of human-centered automation and reasons to question them (Sheridan and Parasuraman, 2005, p. 95).

No.	Criteria of Human-centered Automation	Reasons to question them
1	Tasks best suited to humans should be allocated to them. Tasks best suited to automation should be automated.	Unfortunately, there is no consensus on how to do this nor there is any allocation policy, which may be fixed or depend on the related context.
2	Keep the human operator in the decision-and-control loop.	This is good for only intermediate-bandwidth tasks. The human operator is too slow for high-bandwidth tasks and may fall asleep if bandwidth is too low.
3	Maintain the human operator as the final authority over the automation.	Humans are poor at monitoring, and in some decisions; thus, it is better not to trust them; they are also poor decision makers under time pressure and in complex situations.
4	Make the human operator's job easier, more enjoyable, or more satisfying through friendly automation.	Operator's ease, enjoyment, and satisfaction may be less important than system's performance.
5	Empower or enhance the human operator to the greatest extent possible through automation.	Power corrupts.
6	Support trust by the human operator.	The human may come to over-trust the system.
7	Give the operator computer-based advice about everything they want to know.	The amount and complexity of information are likely to overwhelm the operator at exactly the worst time.
8	Engineer the automation to reduce human error and minimize response variability.	A built-in margin for human error and experimentation helps the human to learn and not become a robot.
9	Make the operator a supervisor of subordinate automatic control systems.	Sometimes straight manual control is better than supervisory control.
10	Achieve the best combination of human and automatic control, where best is defined by explicit system objectives.	Rarely a mathematical objective function does exist.

Parasuraman et al. (2000) classified tasks into four groups: information acquisition, information analysis, decision and action selection, and action implementation. Within decision and action selection, the authors identified 10 levels of automation varying from no assistance to fully autonomous decision and action selection, see Table 8. Regarding the question what should be automated, the authors presented several evaluation criteria, including mental workload, situation awareness, complacency (over-trust), skill degradation (out-of-the-loop unfamiliarity), automation reliability, decision cost, and action outcomes. Later, the authors focused on situation awareness, mental workload, and trust in automation as viable constructs to predict human performance in human–automation interaction (Parasuraman et al., 2008).

Table 8 Levels of automation of decision and action selection (Parasuraman et al., 2000, p. 287).

HIGH	10.	The computer decides everything, acts autonomously, ignoring the human.
	9.	The computer informs the human only if it decides to.
	8.	The computer informs the human only if asked.
	7.	The computer executes automatically, then necessarily informs the human.
	6.	The computer allows the human a restricted time to veto before automatic execution.
	5.	The computer executes that suggestion if the human approves.
	4.	The computer suggests one alternative.
	3.	The computer arrows the selection down to a few.
	2.	The computer offers a complete set of decision/action alternatives.
LOW	1.	The computer offers no assistance: human must take all decisions and actions.

An important contribution to function allocation research has been made by Challenger et al. (2013). The authors identified three different approaches of function allocation:

- Compensatory approach or function allocation by substitution: tasks are assigned to the agent more capable of performing the task effectively (Parasuraman et al., 2000).
- Leftover approach: automate as many functions as possible and only the leftover should be done by humans.
- Complementary approach: humans and machines should be considered as a team with complementary abilities that should be exploited to the full.

The authors argued that function allocation should not only be a HF/E and micro-ergonomics problem but should be discussed early in the design process on a macro-ergonomics level for designing effective and successful systems (Challenger et al., 2013). Nevertheless, a compensatory approach with a strict division of tasks according to capabilities brings many disadvantages, such as little learning opportunities, low flexibility, and a rigid work system. Besides, other risks such as low workload, complacency and the related safety issues, deskilling, vigilance decrements, and the inability to intervene successfully in unpredictable situations are considered by Parasuraman et al. (2000). These disadvantages with even more intense consequences can also occur in systems with a leftover approach.

Bradshaw et al. (2012) presented the concept of human–agent–robot–teamwork to compile research and applications of human–machine collaboration. They necessitated on *"modest efforts to understand and develop capabilities that would allow the participation of humans as first-class citizens in collaboration with autonomous systems"* (Bradshaw et al., 2012, p. 5). Since then, technology, such as collaborative robots, has further developed, which allows realizing the proposed form of complementary collaboration. Other researchers referred to complementary approaches as symbiotic human–robot collaboration (Shaffer et al., 2018; Wang, L. et al., 2019), dynamic task allocation (Sherry and Ritter, 2002), and shared tasks (Michalos et al., 2018). The proposed advantages of human–robot teams include the reduction in negative effects of static compensatory or leftover approaches on HF/E and introduction of new positive effects, such as learning opportunities of the worker, increased economic efficiency, and high flexibility (Ansari, Hold et al., 2018; Bradshaw et al., 2012; Ender et al., 2019; Wang, L. et al., 2019).

The collaboration of humans and robots as a team affects worker's job satisfaction due to factors such as decision-making authority/autonomy. The following method introduces this perspective to evaluate organizational HF/E. Afterward, research on workers' job satisfaction is described.

2.2.7.2. Exemplary Organizational HF/E Evaluation Method

- *WDQ: The Work Design Questionnaire*

The work design questionnaire (WDQ) was developed by Morgeson and Humphrey (2006) to assess job design and the nature of work. The questionnaire covers the organizational aspects of work design and aspects such as physical demands. The items listed in Table 9 are used in the WDQ. All items are evaluated using a 5-point "strongly disagree" to "strongly agree" scale. The underlying research shows that task and knowledge work characteristics correlate with and predict the satisfaction of the worker significantly (Morgeson and Humphrey, 2006). In addition, the interaction outside the organization, ergonomics, and work conditions correlated significantly with the worker' satisfaction. This research underlines the importance of the work autonomy, additional tasks, and knowledge characteristics.

Table 9 Items of the work design questionnaire (Morgeson and Humphrey, 2006).

Characteristics/Context	Items
Task	Work scheduling autonomy, decision-making autonomy, work methods autonomy, task variety, task significance, task identity, and feedback from job
Knowledge	Job complexity, information processing, problem solving, skill variety, and specialization
Social	Social support, initiated and received interdependence, interaction outside organization, and feedback from others
Work	Ergonomics, physical demands, work conditions, and equipment use

2.2.8. Job Satisfaction and Workers' Preferences

Job satisfaction is a widely used term with various definitions. Research on job satisfaction is of high interest as several correlations with economic factors, such as performance, absenteeism, commitment, fluctuation, and productivity, are assumed (Schlick et al., 2018). The delineation and evaluation of job satisfaction are not clear, and thus, several different measurement methods have emerged. Some of them, e.g., the job diagnostic survey, can be found in Schlick et al. (2018).

Zafari and Köszegi (2020) conducted a user study (n = 102) to examine the attitude toward robots by addressing the role of perceived control when working together with a cobot. Their results showed that high attributed agency of robots is associated with negative attitudes toward the robot. This indicated that participants prefer having control when collaborating with robots. The results presented by Zafari and Köszegi (2020) correspond to the model on the psychological effects of task allocation in HRI developed by Tausch et al. (2020). The authors recommended a dynamic "ad hoc" task allocation process, where the human is given the authority to assign tasks to the agents. The model consists of the allocation decision process with the following three steps: (1) allocation criteria definition, (2) influence on allocation, and (3) allocation communication. Allocation criteria, such as work costs and production time, computational effort, and competence retention must be appropriate. The influence on the allocation decision refers to, inter alia, the 10 levels of automation (Parasuraman et al., 2000) and the respective decision autonomy of the human vs. the machine. This influence is relevant to the perceived autonomy, process satisfaction, related mental effort, and process control. Allocation communication describes that workers need to be provided with information about the cooperation. Here, informational fairness and trust in the allocation agents are important. The resulting allocation influences the task identity as well as the allocation satisfaction and acceptance, and further execution influences the flow experience, execution satisfaction, and self-efficacy of the worker. The completion of the task affects the individual goal attainment, result satisfaction, and internal attribution (Tausch et al., 2020). The authors supported their model (Figure 7), with results of a user study (*n* = 151) and showed that satisfaction with the allocation process, solution and result of the work process was higher when participants were given authority over the allocation decision (Tausch and Kluge, 2020).

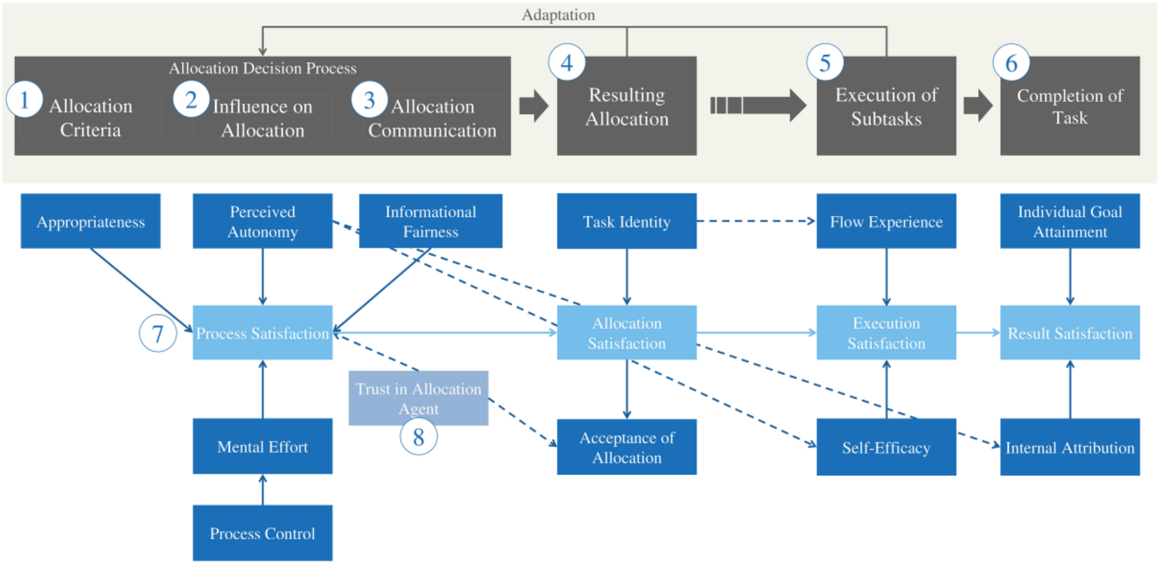

Figure 7 Psychological effects of the “ad hoc” task allocation process by Tausch et al. (2020, p. 8).

In case workers have the authority over the decision-making of task allocation, the questions arise which tasks workers prefer to delegate to a machine/robot and which tasks workers take over themselves. These questions are addressed in more detail in the following paragraphs. Prior to this, a method is discussed that allows preferences to be set when planning work.

Mioch et al. (2018) presented an ontology for work agreements in HRI. Work agreement is a tool that provides the human a certain level of authority over system decisions. Preferences concerning task allocation and execution can be made to increase the trust of the human in the system and allow the human to improve the performance of the system (Mioch et al., 2018). The concept is well known from the setting of apps on smartphones, e.g., “Do not send me nonurgent notifications between 8 pm and 8 am,” and could be applied to manufacturing automation work settings, such as “Do assign handling tasks to the robot, when only one worker is executing value adding tasks.”

Workers’ preferences are discussed and studied by Gombolay et al. (2015; 2017). The authors conducted HRI experiments focusing on the effects of workers’ preferences. The pilot study revealed that statistically significant subjects prefer working with a robot that considers their preferences rather than ignoring or scheduling the opposite of the preference. The results further revealed that participants were more satisfied when the robot assigned the tasks on its own or at least remaining tasks that the participants did not want to take over in comparison to when participants had to assign all the work to themselves or the robot and another human assistant. Participants preferred to give the control authority to the robot and were more likely to assign a disproportionate number of tasks to themselves when working with a robot rather than human teammates. The authors concluded that *"providing workers with a role in the allocation of tasks to their robotic counterparts may not be an effective method of improving worker satisfaction"* (Gombolay et al., 2015, p. 310). Conversely, the authors showed that workers prefer to give the decision-making authority of task allocation to the robot, which indicated that they prefer working with highly autonomous robots. On the other hand, participants in the underlying study were students or young professionals, not manufacturing workers. The authors pointed out that the results might be different if workers were targeted as they are more involved in the working process and are dependent on their jobs. These results would be congruent with studies on HF/E, such as the work by Hacker and Sachse (2014, p. 24), who characterized well-designed work, inter alia, with a scope for action regarding working speed, sequence, and procedure. Future study in which manufacturing workers are surveyed is proposed by Gombolay et al. (2015).

Another study on workers' preferences and human decisions in HRI concluded that *"many participants showed contradictory strategies and an inconsistent perception of their decisions"* (Klaer and Wibranek, 2020, p. 297). The setup included four different transport or measurement tasks. In four rounds, the participants ($n = 12$) had to assign the tasks to the robot or themselves. The authors conducted interviews that showed that participants who stated that they prefer giving measurement tasks to the robot, assigned the task with the least measurements to the robot. Limitations of the study include the little physical demands of the tasks and the academic background of the participants who were engineering students. A long-term study with professionals in a more elaborated experimental setup is proposed by Klaer and Wibranek (2020).

2.3. Hybrid Assembly

If cobots take over tasks at a workplace to achieve advantages of the organization and individual human being, the tasks that are to be automated must be defined. By means of cobot, some basic conditions must be considered in the direction of economic efficiency of automation. This section gives an overview of the relationship between hybrid assembly and economic efficiency. In the end, transition methods from manual to hybrid and automatic manufacturing are referred.

2.3.1. Economic Efficiency and Hybrid Assembly

Lotter and Wiendahl (2012) compared the categorization into manual, hybrid, and automatic manufacturing/assembly in the area of tension between variety of variants, flexibility, quantity/lot size, and throughput/productivity, shown in Figure 8. Depending on these conditions, manual, hybrid, or automatic assembly is the most cost- or time-efficient. The constellation is also presented in Bruno and Antonelli (2018) with a slight difference that hybrid manufacturing is denoted as "collaborative production."

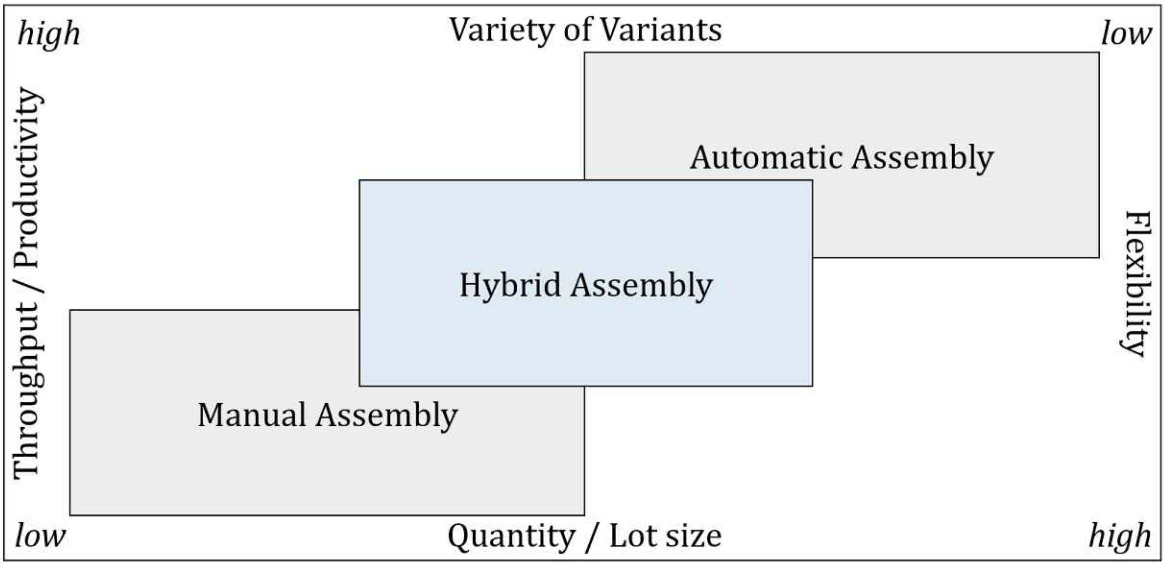

Figure 8 Applications of manual, hybrid, and automated assembly concepts (adapted and translated after Lotter and Wiendahl (2012, p. 168)).

Komenda et al. (2019) presented effects of HRI modes' task allocation patterns on safety and productivity. The authors referred to DIN ISO/TS 15066, 2016 that defines the four HRI modes (safety-rated monitored stop, hand guiding, speed and position monitoring, as well as power and force limiting by design and control). Different HRI modes were presented in executing the same task and the HRIs (exposures) and cycle (process execution) times were evaluated. The results showed that the fastest task allocation variant had the most exposures to the cobot. In one variant, the speed limit of the cobot was not restricted, which restricted the human's possibilities to work in the cobot's workspace, and so this cycle time was the highest.

Another case study shows that cobots can be deployed to partly substitute its human coworker and compensate for the productivity loses after a certain amount of time or lot size is produced. In addition, changeover time and effort must be considered. The calculations and results are shown by Hjorth et al. (2022). It is indicated that economic efficiency is primarily determined by the size of the order.

2.3.1.1. Quantity/Lot size

Lot/batch/order size (quantity) describes how many identical components are produced at a given time. If a customer orders 1000 pieces of an identical product, the lot size corresponds to 1000 pieces. For very large batch sizes, full automation is the best option regarding economic considerations because investment costs are amortized over a quantity of products to be produced.

However, the developments on the demand side show a need for smaller lot sizes and a high degree of individualization (Wang and Gao, 2020). The variety of products desired by the market makes it difficult to (completely) automate production processes because this is not cost effective and limits the flexibility of the processes. For very small order sizes, it is advisable to save the effort of (partial) automation and proceed with manual production. Humans can work much more flexibly with their skills than cobots or machines.

2.3.1.2. Throughput/Productivity

High levels of automation in assembly processes are only possible under certain conditions, which are high lot sizes and simple assembly tasks. Substeps are easy to automate and often bundled in an interlinked system to increase the degree of automation and efficiency. This procedure is only cost effective for a high number of identical components. Otherwise, the investment and implementation costs for such a system are too high. With large order sizes, the benefit of the high number of parts can compensate for high automation efforts.

In terms of throughput, it is advisable to automate production for large order sizes and to have a human perform the tasks for small order sizes. Applications of HRI in assembly processes are classified into hybrid or collaborative assemblies between manual and automatic assemblies. Comparison between the economic efficiency of automatic, hybrid, and manual assembly processes in relation to quantities that are produced is depicted in Figure 9. The figure displays the three different cost functions starting at different levels of investment for the production process. Full automation is characterized by high investment and low unit costs; manual production by low investment costs, such as assembly fixtures, and high unit costs. Hybrid assembly realized by a human worker and cobot lies in the middle. The horizontal axis shows the size of quantities.

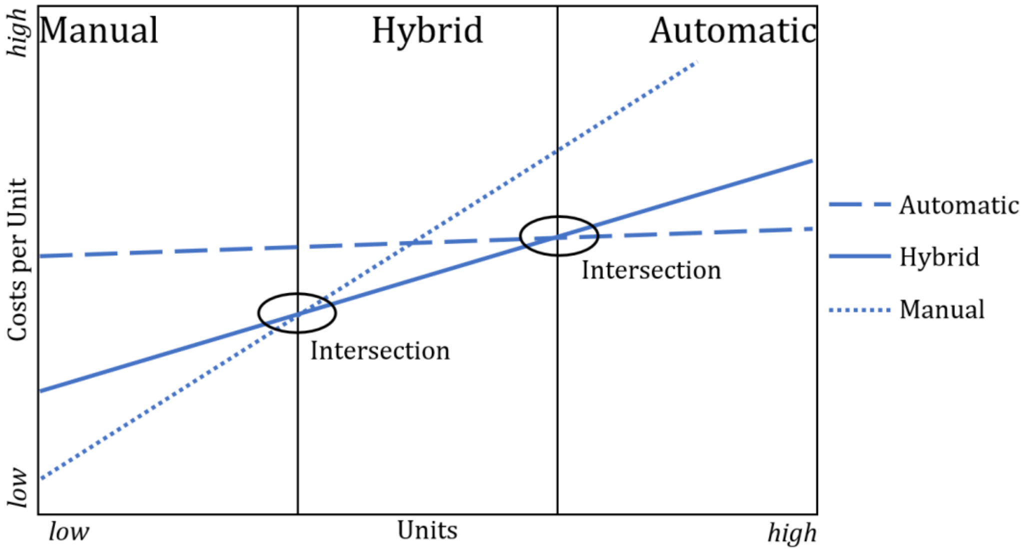

Figure 9 Comparison of the economic efficiency of the three process designs (manual, hybrid, and automatic) including the two intersection points after which another design becomes more cost-efficient (own figure).

2.3.1.3.Variety of Variants

Full automation is realized by performing individual subtasks by machines and robots. These are usually linked to make the process efficient. The linked automated system is optimized for one or a few variants of a product to be processed. Examples of this can be found in the process industry, where the process units perform all the work steps and humans are only responsible for monitoring and maintaining the machines. Parts of automotive production, such as body shop or painting, are also fully automated. If individualization or varieties of variants are given, the design of the systems is not flexible enough to be able to realize this variety. Mass customization describes that products can be configured by a customer with a large but finite number of possibilities (Reinhart, 2017). To enable mass customization, manual assembly is primarily used.

2.3.1.4.Flexibility

The variability of manufacturing processes refers to requested changes in the production system, such as parts, processes, tools, and materials (Vicentini, Pedrocchi et al., 2020). To respond to these requested changes and maintain manufacturing goals, the system needs to be flexible. Human workers usually offer the highest flexibility as they can quickly adapt to new system variants. Fully automated machines, on the other hand, are usually optimized for one or a few variants and therefore, they cannot cover this flexibility. Some features, such as certain reconfigurability, might to be able to respond to some predefined changes through, for instance, tool changes.

Flexibility is not only related to the lot size or the individualization of the products (mass customization), but also to the flexibility when errors or unforeseen situations occur—resilience describes a system's ability to recover from such situations (Heinicke, 2014; Zhang and van Luttervelt, 2011). In a fully automated system, predictive measures should prevent errors that are not foreseen. If one such error occurs, troubleshooting is often costly. These systems usually have to be analyzed by experts, which usually require production stoppage. The consequences of this inflexibility are additional costs, delays, etc. Therefore, a high degree of automation severely restricts the flexibility of production. The goal of hybrid manufacturing is, inter alia, to combine the automation of a few work steps with the flexibility of human labor.

2.3.2. Transition methods

Beumelburg (2005, p. 26) presented different methods and systems that support the transition from manual to hybrid or automatic processes. The following common approach is usually followed: first, the manual processes are decomposed into different (sub)levels of performance, see Table 10, and then, these decomposed processes are evaluated to identify which tasks should be taken by the human or robot. Therefore, chosen parameters are valued quantitatively or qualitatively.

The levels of performance (or planning in production systems) are divided into operational, tactical, and strategic levels (Kemény et al., 2021). The operational level focuses on the execution of processes in an instance-by-instance basis, whereby the horizon of attention focuses mostly on the respective process and not on the other processes. The tactical level considers more than one process and includes the relations between them. Thus, process parameters and execution decisions can be adjusted to meet goals or preferences. The strategic level considers wider horizons in time and organizational structures. The validity of process models and model structures is surveyed (Kemény et al., 2021).

A definition and evaluation on a tactical or strategic level would concern general decisions of a manufacturer and a less concrete allocation of assembly tasks within HRI. Therefore, the operational level of performance is chosen to guarantee a hybrid work environment in which shared goals, such as an increase in economic efficiency, an improvement in HF/E, and high flexibility can be achieved. A task, skill/function, or motion level can be evaluated. An evaluation of a motion or skill/function level would be abstract and unclear as the context is mostly missing. Even if further time could be saved through high granularity, e.g., on the motion level (Nikolakis et al., 2018), the complexity of the mathematical problem would also increase. This would make it difficult for the worker to control the task assignment. To reduce this complexity, the highest operational sublevel of performance "task" is chosen for the evaluation.

Table 10 (Sub)Levels of performance.

Level of Performance	Sublevel of Performance	Example
Strategic	Mission	Satisfy customers' needs
Tactical	Job	Manufacturing
Operational	Task	Assembling
	Skill/function	Pick & place
	Motion	Moving

Schoen et al. (2020) presented four technical challenges when translating manual tasks into human–robot task plans:

1. Representing tasks for the agents
2. Developing an intuitive and effective authoring channel
3. Matching tasks with skills
4. Supporting across different robot platforms

The first and second points aim at enabling the active human integration and effective HRI, for which tasks must be represented or visualized (Schoen et al., 2020). To enable skill matching, tasks and agents must be known. The prior analysis is often referred to as task analysis. The resources, referred to as agents, need to be evaluated. Then, the resources can be (pre)allocated to the tasks. The fourth challenge deals with the universality and generalization of the method. The transition process from manual to collaborative assembly operation is also described by Mateus et al. (2018, p. 408).

Based on these works, three main steps for the design of a human–cobot assembly are proposed that form the core of this thesis. These steps also provide the framework for the structure of the next sections:

- Human–robot task analysis
- Human–robot task allocation/assignment
- Human–robot task visualization

3. STATE-OF-THE-ART

In this section, relevant preliminary work regarding frameworks and methods of task allocation between humans and robots is presented. The focus lies on task allocation methods between humans and cobots, but if applicable, frameworks and methods of task allocation between humans and other (industrial) robots were considered, although the interaction design is different (Malik and Bilberg, 2019c).

This section is structured as follows: first, the methods, procedure, and quantitative analysis of the SLR are presented. Second, methods and approaches in human–robot task analysis, visualization, and allocation are described. Third, a summary and conclusion as well as further elaboration of the research gap are presented.

3.1. Literature Review

To minimize the potential for bias within the literature review, three comprehensive SLRs were conducted to identify relevant previous works. The results of the SLRs were continuously supplemented by additional research publications from other sources to comprehend the state-of-the-art methods for this thesis.

3.1.1. Systematic Literature Review

The procedure of the SLR is based on studies by Booth et al. (2016) and Denyer and Tranfield (2009), and the scope of the SLR was to identify relevant previous publications on task allocation in HRI. The primary research question for the search is as follows: What methods and techniques exist to allocate tasks between a human and robot? The reference to assembly or manufacturing was not explicitly used in the search, as it would have limited the results too much. For the SLR, the Scopus, SpringerLink, and IEEE Xplore® databases were employed.

First, the databases were searched for specific keywords. Different keywords per database were used because the databases provide unique results based on their different scientific focuses. Then, the results were collected and imported into a reference management and knowledge organization tool.[4] After that, all titles were analyzed to see if they were relevant to the topic. The same process was performed for the abstracts of the publications. Subsequently, all remaining publications were read, and further analysis was performed.

[4] Citavi (6.10.0).

For the analysis of the relevant publications on SpringerLink, the keywords "task allocation," "human," and "collaborative robot" were searched. The search[5] resulted in 46 publications, from which 29 titles sounded relevant to the manufacturing application area. In the end, there were 25 abstracts, but only 22 publications were relevant for this thesis. All the analyzed publications dealt with HRI in a manufacturing setting and most of them focused on a flexible and complementary task sharing. Publications not relevant were partly overview papers or dealt with other aspects of HRI but not with task allocation.

To identify the relevant publications published by IEEE, all metadata, including the abstract, index terms, and bibliographic citation data (title, author, etc.) were searched for the keywords. To analyze the relevant IEEE publications, it was necessary to use different terms for the search than for SpringerLink. For IEEE, the best fitting keywords were "task allocation," "human," and "robot" in combination with exclusion terms "mobile robot,"[6] "humanoid robot," and "multi robots." The search[7] resulted in 63 publications. In the next step, the titles were reviewed. Papers with a strong focus on service robots, teleoperated robots, and unmanned space missions were excluded because of the missing context. Papers that present new algorithms, software, or devices for HRI without a strong focus on task allocation were excluded too. This resulted in remaining 26 papers, of which the abstracts were reviewed. After this process, 19 papers remained, which were analyzed further regarding the relevance to this work. In the end, 15 papers were identified as the most relevant state-of-the-art.

To identify the relevant publications published by Elsevier, the database Scopus was employed. Scopus covers not only Elsevier publications but also others, e.g., IEEE, ACM, Taylor & Francis, and Emerald. The search function was used to search titles, abstracts, and keywords as follows: ("Task allocation" AND human AND robot AND NOT "mobile robot" AND NOT "humanoid robot" AND NOT "multi robots" AND NOT swarm AND NOT unmanned AND NOT rescue) AND PUBYEAR > 1989. 98 papers were preselected in Scopus,[8] where 5 papers had to be excluded because there was no author information available. The rest 93 publications contained 18 duplicates from the previous SpringerLink and IEEE SLR, resulting in 75 publications that were then reviewed if the title suited the topic of this work. 33 publications remained. A subsequent abstract review resulted in 28 publications. Exclusions were made mainly because of a missing context, e.g., if the abstract mainly dealt with space or household

[5] The search on SpringerLink was conducted on the 19th of August 2020.
[6] The term "mobile robot" was not excluded by default, as mobile robots could also fit into a manufacturing context. However, the search including "mobile robot" did not yield any additional useful results in the field.
[7] The search on IEEE was conducted on the 18th of September 2020.
[8] The search on Scopus was conducted on the 19th of November 2020.

applications. After reviewing the 28 publications, 3 had to be excluded because of the missing relevance. The search ended up with 25 publications. An overview of the quantitative results of the SLR is shown in Figure 10.

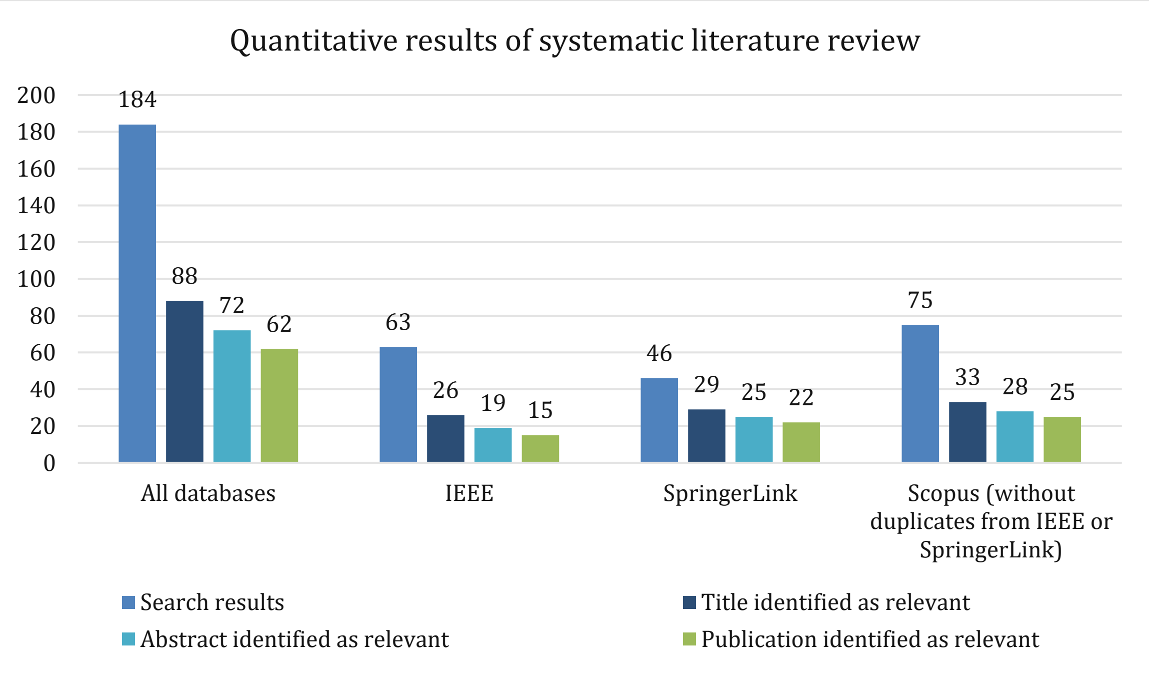

Figure 10 Quantitative results of systematic literature review (own figure).

3.1.2. Meta-Analysis

All 62 relevant publications were read and analyzed. The point of view was identified, where three different viewpoints were distinguished:

- Humanistic: trendsetting preliminary work for the development of methods of task allocation, e.g., in terms of researching the effects of different levels of automation on the human
- Organizational: design of methods as preliminary work for the development of algorithms for task allocation
- Mathematical: development of algorithms based on methods for task allocation

The analysis of the publications regarding the three viewpoints, that reflects the different focus of the databases, is shown in Figure 11. To structure the publications, the key aspects, such as task allocation (71.0%), task analysis (12.9%), interaction design (6.5%), task visualization (4.8%), safety (4.8%), and human factors (4.8%) were explored. While reviewing the publications, focus was laid on the identification of relevant design methods or decision criteria. In addition, the application area, if applicable, was noted. 48 publications focused explicitly on manufacturing applications. Other publications focused on space missions (3), humanoid robots (1), rescue robots (1), whereas 9 had no specific application focus. If applicable, the task allocation approach was distinguished between static (45.2%) and flexible (41.9%), and between compensatory (46.8%), complementary (33.9%), and leftover (1.6%).

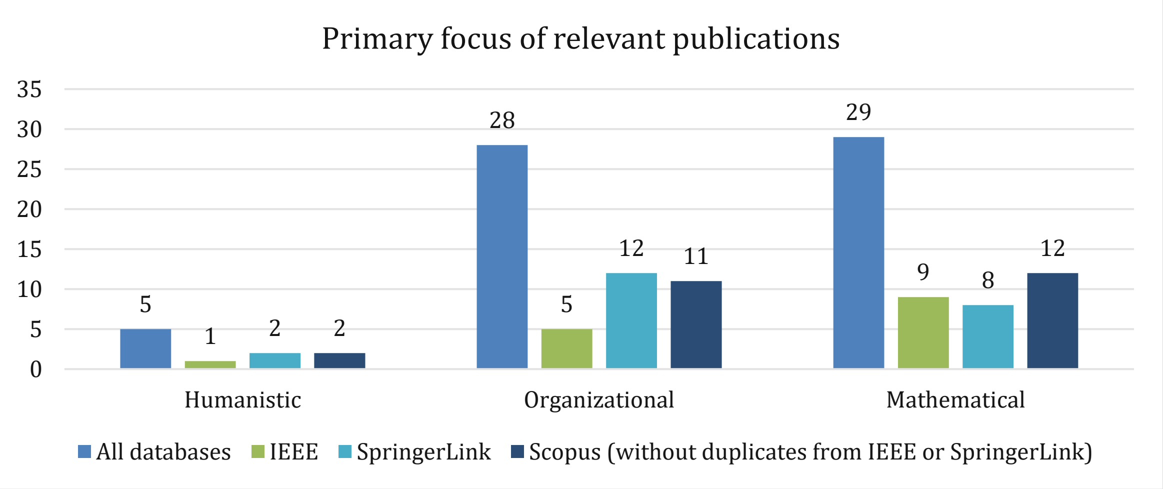

Figure 11 Primary focus of relevant publications (own figure).

In the following, qualitative research analysis and synthesis are undertaken. Besides the 62 relevant publications, other resources were used to draw a comprehensive picture of the state-of-the-art. The qualitative results are divided into three parts:

- Human–robot task analysis to identify suitable tasks for the agents
- Human–robot task allocation to allocate tasks to the agents
- Human–robot task visualization to enable the HRI and task sharing

3.2. Human–Robot Task Analysis

Task analysis methods are used to record and evaluate all tasks of a process. *“Task analysis is conducted to identify the details of specified tasks, including the required knowledge, skills, attitudes, and personal characteristics required for successful task performance”* (Guiochet et al., 2003, p. 3212). The analysis includes “*identifying tasks, collecting task data, analyzing the data so that tasks are understood and then producing a documented representation of the analysed tasks*” (Stanton et al., 2013, p. 39). It is a part of the work design process and is often used for evaluating tasks and processes. There are several task analysis methods, notation techniques, and terminologies in the literature (Sørensen et al., 2018; Stanton et al., 2013). Stanton et al. (2013) provided an overview and described some methods, such as the hierarchical task analysis (HTA), task decomposition, the subgoal template method, and the tabular task analysis. All these methods can be implemented relatively easy using pen and paper or recording equipment. As they all have certain disadvantages, such as they are time-consuming or provide only descriptive information, they can only act as an upstream method before a more structured method is used.

Another method to describe tasks is the primary secondary analysis (Schüppstuhl et al., 2019), which primarily evaluates tasks based on whether they are value or nonvalue adding activities. Similar to the analysis, specifications on how to describe or record these tasks are not given.

Van der Waa et al. (2020, p. 208) divided tasks into direct and indirect works, where the former is everything "*that aims at reducing the distance to the team goal"* and the latter *"aims at making the team more effective or efficient at achieving the team goal, but does not move the team closer to its goal*" (van Diggelen and Johnson, 2019). Direct work includes acting, sensing, and decision-making, and indirect work includes standing by, handovers, and supervision (van der Waa et al., pp. 208–209; van Diggelen and Johnson, 2019). The authors focused on moral decision-making, i.e., whether decisions made have a moral dimension (something is "right," "wrong," or in between).

The following task analysis methods are presented below in detail:

1. Hierarchical task analysis
2. Task terminology standards
3. Predetermined time method systems (PTMS)
4. Task evaluation by capability and human factors assessment

3.2.1. Hierarchical Task Analysis

In human factors, HTA is a generic technique to describe task activities, where tasks and their goals are documented in a hierarchical way. The HTA procedure and examples are presented by Stanton et al. (2013, pp. 40–47).

Shah et al. (2007) developed a framework to engineer human–robot systems for space exploration tasks and stated that nearly all surveyed task allocation methods used a hierarchical task network planning technique. The framework included specification of tasks, generation of the human–robot system architecture, allocation of the functions to the agents in the system, and evaluation. The authors identify common metrics to compare different human–robot systems including "*productivity/effectiveness; reliability of successfully completing the task(s); risk to humans in the system; resources required to support system design, implementation, and operations; and flexibility/robustness of the system to changes in task functions or environment states*" (Shah et al., 2007, p. 790). Although their work was developed for space missions, the criteria are applicable to manufacturing as well. The authors identified the following further research topics: "A *method to quantify uncertainties associated* *with task specification; a formal representation of human–robot systems; a framework to enumerate and evaluate task allocations; and methods to carry through the evaluation of different human–robot system for the proposed metrics*" (Shah et al., 2007, p. 792).

Mateus et al. (2018; 2019) deployed an HTA by decomposing the assembly operation into subassemblies, subassemblies into assembly tasks, assembly tasks into functions, and functions into elementary motions.

3.2.2. Task Terminology Standards

There are two important standards to describe and classify the manufacturing processes. One is the DIN 8580, 2020 that divides manufacturing processes into six main groups:

1. Primary shaping
2. Forming
3. Separating
4. Joining
5. Coating
6. Changing material property

Assembly processes can be found in the group "joining" (DIN 8593-0, 2003). Wiendahl et al. (2015, p. 129) described "joining" according to the DIN 8593 as follows: "*Joining is durably connecting or otherwise bringing together two or more geometrically defined workpieces or the same kind of workpiece with a shapeless substance. The cohesion is applied locally and increased in the whole respectively.*" Joining as one of the main manufacturing processes is again divided into nine subcategories, which are described in detail in DIN 8593-0, 2003 (Figure 12).

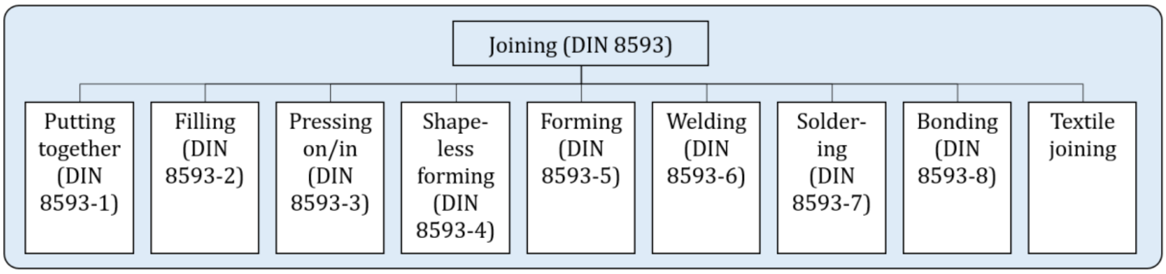

Figure 12 Classification of the main manufacturing process "joining" based on DIN 8593-0, 2003 and Wiendahl et al. (2015).

The difference between joining and assembly is that assembly also includes handling and auxiliary operations, including measuring or testing. On the other hand, joining includes manufacturing processes that are not used in connection with assembly, e.g., sheathing and vulcanization. According to the norm, assembly is currently a not clearly defined collective term for joining processes, particularly from group 1 (putting together), see Figure 13, and group 3 (pressing on/in), see Figure 14, group 4 (shapeless forming), and group 8 (bonding) (DIN 8593-0, 2003).

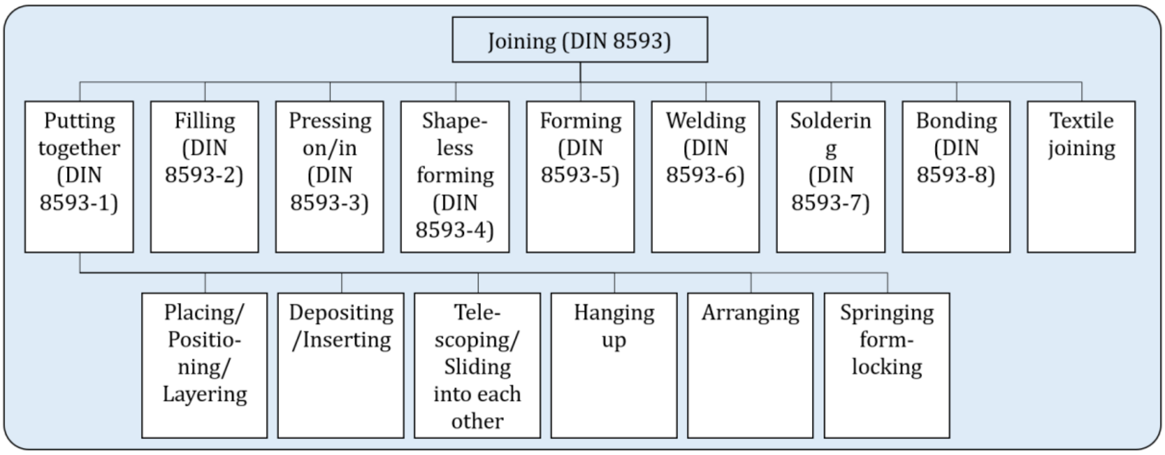

Figure 13 Classification of "putting together" based on DIN 8593-1, 2003 (own translation from German to English).

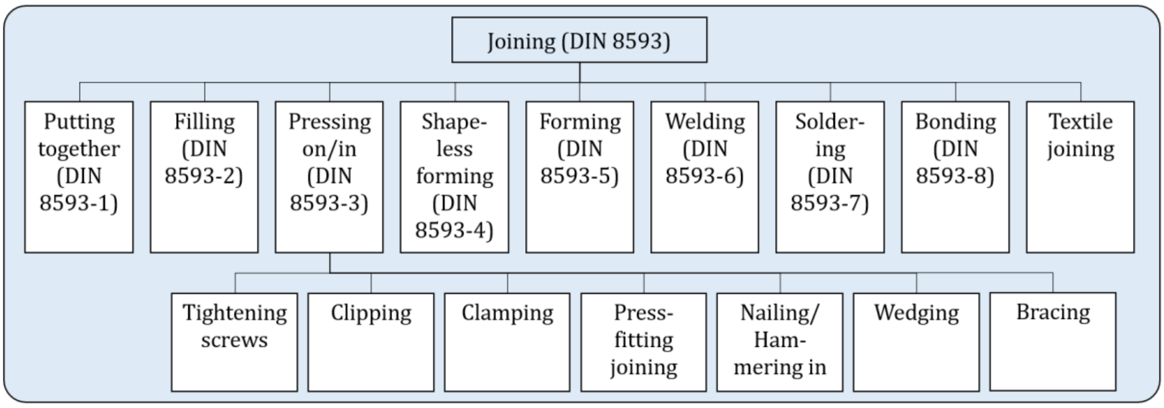

Figure 14 Classification of "pressing on/in" based on DIN 8593-3, 2003 (own translation from German to English).

DIN 8580, 2020 is often used to develop an individual ontology. One example is the product model ontology and its use in capability-based matchmaking by Järvenpää et al. (2018), which is based on the manufacturing resource capability ontology model. Assembly is structured from the product and parts side of view, e.g., "PickAndPlace," which is then again structured in "Picking," "Transporting," and "Placing." On that level, it is then matched with the process requirements, such as for "Picking"—the capability requirement is a specific accuracy.

Tasks that are not described by DIN 8593-0, 2003 are covered by VDI 2860, 1990, which was withdrawn without replacement. According to the withdrawn VDI 2860 (1990, p. 2), "*handling is the creation, defined modification or temporary maintaining of a given spatial arrangement* *of geometrically defined bodies in a reference coordinate system*".[9] Further conditions such as time, quantity, or movement path can be specified. The norm divides handling into five subfunctions: storing, changing quantities, moving, saving, and checking. It provides 43 symbols for functions that can be used to illustrate task dependencies similar to process descriptions such as BPMN 2.0. VDI 2860, 1990 provides a generic level to describe handling functions. Seven elementary functions were defined (illustrated in Figure 15), which can be used to describe all other handling functions such as the function "positioning," and the combined elementary functions "checking position" and "moving."

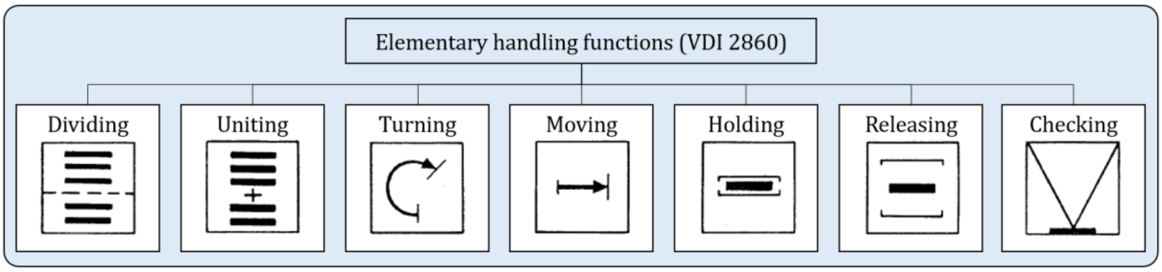

Figure 15 Elementary handling functions based on VDI 2860, 1990 (own translation from German to English).

DIN 8580 describes the joining functions and VDI 2860 describes handling functions. This implies that they should be merged into a single ontology. Lotter and Wiendahl (2012) combined parts of the standards and added tasks called special operations to the ontology shown in Figure 16. The authors used five subfunctions and distinguished between testing and measuring when checking. In addition, six distinctions were made when adjusting. The authors take out some operations and put them separately in the group "special operations," which makes the description of these functions easier and more defined, e.g., deburring instead of describing how the burrs are removed from the part in detail.

[9] Translated from German to English.

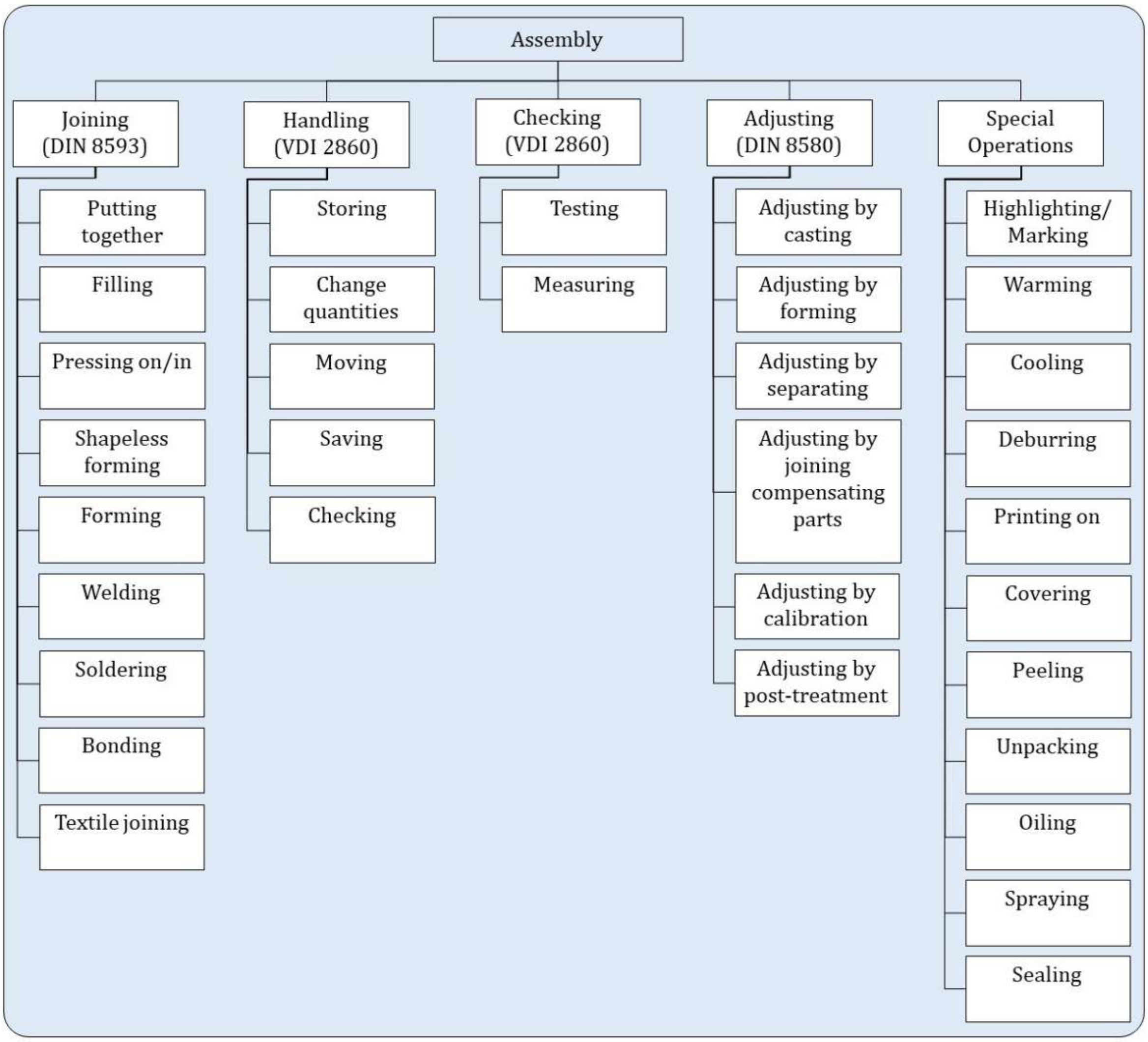

Figure 16 Assembly functions according to Lotter and Wiendahl (2012) (own translation from German to English).

Sørensen et al. (2018) provided an overview of classification schemes and taxonomies. Because the authors were not satisfied with the existing publications, they developed a method to classify manufacturing as well as handling processes. It resulted in a classification scheme with four process categories (manufacturing, material handling, test & inspection, and control & planning), which were subdivided into 16 process families (e.g., shaping, forming, separating, and joining), 53 process classes (e.g., adhesive bonding, assembly, brazing, and fastening) and 232 process subclasses (e.g., hang, insert & put in, lay & put on, and nesting and reset) (Sørensen, 2021). An excerpt of the classification is shown in Figure 17.

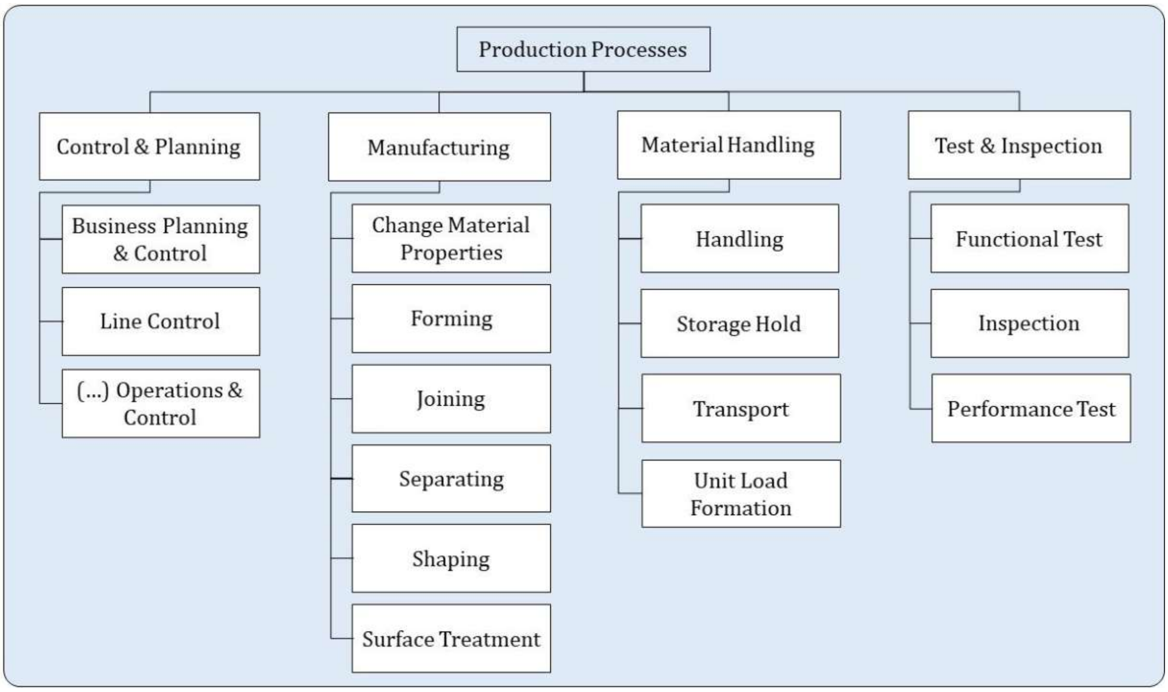

Figure 17 Excerpt of the class hierarchy adapted based on Sørensen et al. (2018).

3.2.3. Predetermined Time Method Systems

The completion time/makespan of a product is relevant for calculating costs and meeting delivery dates. To achieve these cost and time targets, the individual times of a task must be known. Historically, different methods were developed starting with the concept by Taylor (1911) who proposed task and scientific management. Time studies were undertaken, and tasks and all tools connected with the work as machines and tools were standardized. Tasks were divided into subtasks, called "motions", and were assigned to workers. For the sake of the prosperity of companies, the efficiency of work increased and there was free time to develop new methods to be more efficient and effective. Back then, Taylor's systematic methodology had positive effects on the economic success of organizations. Later, critics found that this creates a work system where workers get exploited like machines without any feedback and further developed the methodology including behavioral science to create a more motivational and supportive work environment (Uddin and Hossain, 2015). One must consider the time in which scientific management was developed, the difference in the society and the idea that workers, particularly in the Western world, have usually completed a (basic) education and practical training, which cannot be assumed in Taylor's time; therefore, the expectations of a worker were much lower back then. In addition, the level of automation was much lower. It is therefore easier to understand why this methodology was developed in this way. Since then, PTMS were developed further that resulted in three predominant methods (Lotter and Wiendahl, 2012):

- Methods time measurement (MTM)
- Work factor (WF)
- Maynard operations sequence technique (MOST)

MTM is a bottom–up approach of recording tasks and times of a specific process and is used as a tool in the planning process of several corporates. Because MTM was released, several variations have been developed, e.g., MTM-1 which allows a high granularity of the analysis and MTM-universal analyzing-system (UAS) for series production (Finsterbusch and Kuhlang, 2015). The advantage of MTM is that a certain terminology is already used for recording the so-called "motions." An HRI extension for MTM was developed by Schröter (2018). With the method and respective tool, human–robot assembly processes can be calculated. The author incorporated the safety measures according to the respective standards, and achieved experimental validation results with an accuracy of 93.1% and 95.3% compared to real process times (Schröter, 2018).

WF is closely related to MTM-1 in terms of the structure and level of details are similar (Seifermann et al., 2014). MOST is used primarily in industrial settings to set the standard time in which a worker should perform a task. There are three forms of MOST, the BasicMOST which is mainly used, the MiniMOST for short-cycle and high-repetitive operations, and the MaxiMOST for long-cycle-time processes (Seifermann et al., 2014; Zandin, 2003).

Seifermann et al. (2014) compared different work measurement concepts, including predetermined time standards like MTM, WF, and MOST. The authors applied the concepts on a cellular manufacturing line and found that MTM-1 results were very close to reality. It was the most detailed result after the WF analysis and MTM-2. The authors stated that the effort exerted for WF and MTM-1 analysis was the highest. In comparison, least effort was required to perform the BasicMOST, MiniMOST, and MTM-UAS methods.

3.2.4. Task Evaluation by Capability and Human Factors Assessment

Tasks can be analyzed with the goal of a capability-based task allocation to either the human or a machine/robot. A predefined set of criteria can be applied. Beumelburg (2005) deployed different criteria to analyze tasks considering the assembly process, ergonomics, the part to be assembled, and the feeding systems. The criteria include, for instance, the possibility of hooking during joining and for process control, if sensory skills are needed. In terms of ergonomics, the author referred to harmful (e.g., exposure to pollutants in the air or hot/cold temperatures) and unhealthy (e.g., physiological continuous human load during heavy dynamic muscle work) criteria. The author provided 22 criteria with its different characteristics. Most criteria are applicable on human–cobot assembly processes and have been addressed by other authors later.

The characteristics of the whole HRI application, such as the process, parts or components, and workspace, play a role in the decision-making of task allocation (Malik and Bilberg, 2019b). For instance, the weight, size, and flexibility (regarding the shape) of a part (Bruno and Antonelli, 2018; Michalos et al., 2018) must be considered. Malik and Bilberg (2019b) mention part feeding as an element of the evaluation. The presentation and refilling are important features to consider when evaluating the feeding. The process, including the mounting and joining, and if there is a certain insertion direction or resistance, should be considered; refer to the critical issues described by Gualtieri et al. (2020). The evaluation of the workspace focuses on the HRI safety and potential risks. Such evaluations refer to the capabilities of the agents.

Task indicators such as the weight of the parts, the accuracy requirements or the dexterity requirements, and the displacement are considered by Bruno and Antonelli (2018). Gualtieri et al. (2020) included in their set technical, ergonomic, quality, and economic evaluation criteria. For the technical evaluation, the authors set up a list of critical issues concerning the feeding, handling, and assembly of the parts. These critical issues could arise if the components are magnetic, sticky, fragile, or they provide resistance to insertion, etc. For the ergonomic evaluation, the authors proposed the RULA method, and for the quality evaluation, they calculated the process variability through the coefficient of variation. For the economic evaluation, they assessed if the task is value adding or not. Nonvalue adding tasks should be executed by the robot (Gualtieri et al., 2020). The related task allocation approach is presented in Section 3.4.1.

It must be considered that task analysis by capability assessment is often a qualitative process with freedom within the evaluation left to the assessor. Criteria, such as part specification, can be calculated and evaluated exactly. Considering other criteria, such as insertion resistance and fragility, the evaluation becomes vague.

The task evaluation by human factors analysis is strongly related to the capability assessment. Gualtieri et al. (2021) gave an overview of emerging research fields in safety and ergonomics by presenting results of a SLR. The results covered articles dealing with physical and mental HF/E in HRI. Exemplary applications and assessments are discussed in the following. Weckenborg and Spengler (2019) considered ergonomics to reduce overall costs in assembly line balancing in HRI. Makrini et al. (2019) focused on the integration of physical HF/E in their task allocation method using results of a rapid entire body assessment (REBA) evaluation. Tasks that are above a certain REBA limit (maximum allowable REBA score) should be allocated to the robot. Similar approach is used by Gualtieri et al. (2020) who employed the RULA method. This method was also used by other authors such as Mateus et al. (2019), who also considered the strain index. The strain index was also deployed by Pearce et al. (2018). Castro et al. (2019) assessed physical ergonomics using the RULA method and compared simulation results with motion capture recordings. Tsarouchi, Michalos et al. (2017) considered the average human muscle strain percentage calculated through simulations. Michalos et al. (2018) included the level of physical fatigue of the human operator based on the work duration.

In terms of mental HF/E, situation awareness was assessed by Endsley and Kiris (1995). The authors showed that low situation awareness correlates with the level of control in automation. Results indicated that the shift from active to passive interaction is responsible for decreased situation awareness under automated conditions. Gombolay et al. (2015) worked on incorporating workers' preferences, see Section 2.2.8. Liu et al. (2020) presented a resource coordination algorithm incorporating the relative strengths and learning abilities of the human.

3.3. Human–Robot Task Visualization

Human–robot task visualization methods are important to enable task sharing. Van Rhijn and Bosch (2017, p. 144) stated that "*if there is a (flexible or adaptive) level of automation, the remaining (inspection or manual) tasks of the operator require up to date information for the operator to perform his/her tasks properly.*"

Mostly, proprietary UIs of robots do not consider the human agent. To indicate human tasks in robot workflows, placeholders, such as "wait," are used. An extensive overview of robot programming interfaces was presented by Hader (2021). Examples of process modeling languages can be looked up in the study by Schlick et al. (2018).

Stöhr et al. (2018) presented an approach for adaptive work instructions for workers with different abilities, disabilities, and preferences. The authors considered different user types, such as people with disabilities or elderly people, and mentioned that the state-of-the-art task allocation methods do not consider their needs. The authors provided an approach wherein the users can override the preferences to further customize the user profile. Thus, work instructions are adapting to the users' needs and preferences. Mioch et al. (2018) presented a framework and software for work agreements in HRI.

Relevant methods for human–robot task visualizations are elaborated in the following sections:

- Unified modeling language (UML) activity diagrams

- Business process model and notation
- Event driven process chains (EPC)
- Petri nets or place/transition nets
- AND/OR graphs
- Precedence graphs
- Behavior trees

3.3.1. Unified Modeling Language Activity Diagrams

UML is an object-oriented business modeling method developed by the Object Management Group (OMG, 2021) and is mainly used in software development. Activity diagrams are used to visualize how a system realizes a particular behavior. Action elements are connected with control flow elements; however, the granularity is not defined, so the definition of an action element is vague (Froschauer and Lindorfer, 2019). The benefit of UML diagrams is that they show all interactions between the agents in the sociotechnical system to guarantee consistency of information between the different stakeholders (engineers and other interaction partners of the robot). A visualization method of task allocation using UML was presented by Guiochet et al. (2003). UML use-case diagrams were used that enabled to visualize more agents and roles (human and robot) in the system. A medical robot use-case scenario was employed to exemplify the approach.

3.3.2. Business Process Model and Notation

BPMN is a business modeling method developed by the Object Management Group (OMG, 2021). A standard set of elements is used to model a process including its activities (tasks and subprocesses), events (start, intermediate, and end events), data objects, gateways (decisions), connections (sequence or message flow), and authority distributions. Authority distributions between the elements can be displayed via (swim) lanes and pools. A pool represents the major participants in a process and normally contains one or more lanes. Lanes are used to represent one role or function in the process. This role is responsible for the contained activities and events in the lane. BPMN is a widely accepted standard and understandable for all involved parties (Froschauer and Lindorfer, 2019). It can be used intuitively for modeling processes (Lang et al., 2020). BPMN engines enable the execution of the process in automated systems. The BPMN engine by Camunda (2021) provides the possibility to distinguish between user tasks for humans and service tasks for robots or machines (Vanderfeesten et al., 2019).

Froschauer and Lindorfer (2019) compared different modeling languages for HRI and deployed BPMN for workflow-based programming for collaborative assembly stations. Pauker et al. (2018) presented a BPMN-based modular manufacturing system called “centurio.work.” The solution covered not only the representation of the processes but also the possibility of connecting and controlling different machines.

3.3.3. Event Driven Process Chains

EPCs serve as a method to represent business and work processes from the perspective of business information systems. They are often used for the analysis of processes at departmental level and for computer-aided optimization (Schlick et al., 2018). EPCs focus on the visualization of events that trigger functions, which generate output events (Froschauer and Lindorfer, 2019). In EPC functions, event and logical connectors are used to model the process chain. It is an easy method, but due to the simplicity, it also leaves room for interpretation (Froschauer and Lindorfer, 2019). Another limitation is that it is used to model the process chain for one role (human or robot) and does not focus on the visualization of different functions or roles (human and robot).

3.3.4. Petri Nets

Petri nets or place/transition nets are formal methods for the mathematical modeling of systems to describe and visualize distributed systems. Casalino et al. (2019) described their approach using Petri nets to model HRI scheduling problems. First, tasks were specified by modeling the Petri nets. In the beginning, the robot has a token, which will be consumed if the robot decides to start the action. Inactivity (waiting) is related with costs, which should be minimized. This can be related to the necessary preconditions, that need to be met before an action can occur.

Chen et al. (2011) deployed a dual generalized stochastic Petri net to model the assembly task for human–robot coordination. This Petri net can be used to model and visualize places (circles) and transitions (immediate transitions are black and timed transitions are white rectangular bars) to describe distributed systems, see Figure 18. A place can also be seen as a state, such as “human is ready,” “robot finishes,” or “part is inserted,” and a transition as a task that has to be executed such as “human inserts” or “robot handles.” The authors incorporated the possibility that agents make mistakes.

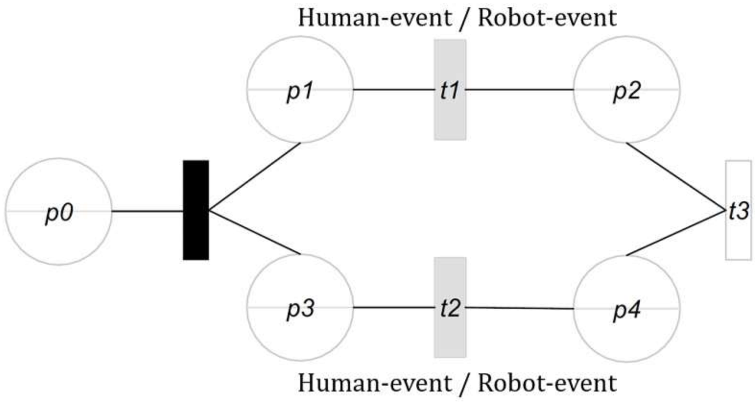

Figure 18 A dual generalized stochastic Petri net model demonstration for HRI (Chen et al., 2011, p. 492).

Petri nets are robust and adaptive methods to visualize events/tasks. The representation is less descriptive compared to other modeling languages, but the formal description well suits the simulation of complex work processes (Schlick et al., 2018). For nonprofessionals, the graphs are not easy to read. Petri nets are less suitable if one wants to allow a large number of shifts/rescheduling. An additional interface would be necessary so that the human coworkers can understand the processes and tasks.

3.3.5. AND/OR Graphs

AND/OR graphs are a form of decision graphs or trees that solve or decompose a problem. AND/OR graphs represent procedures and logic relationships among the subproblems that are part of the graph. This method was used by several authors (Darvish et al., 2018; Johannsmeier and Haddadin, 2017; Karami et al., 2020; Lamon et al., 2019; Murali et al., 2020).

Johannsmeier and Haddadin (2017, p. 43) deployed AND/OR graphs "*because of their ability to explicitly facilitate parallel execution of assembly actions, as well as the time independence of parallelly executable actions*" to allocate tasks on a team level. A distinction between humans and robots is not made explicitly at team level. Karami et al. (2020) used AND/OR graphs on their task representation level. The authors used the graphs in combination with a breadth-first search algorithm to search the graph with the minimum costs, thus, optimizing the execution time.

3.3.6. Precedence Graphs

Precedence graphs, also conflict graphs, are directed acyclic graphs used to show the execution level of a process in an operating system. The nodes represent the processes, and the edges represent the execution flow.

Riedelbauch and Henrich (2017) mentioned a shared task representation to achieve a common understanding of the process and tasks (a shared mental model) using, e.g., precedence graphs or AND/OR-Graphs. The authors used precedence graphs to illustrate the tasks for the algorithm.

3.3.7. Behavior Trees

Behavior trees are a formal, graphical modeling language used in systems and software development. They are used to model and plan execution paths in computer science, robotics, control systems, and video games. Behavior trees consist of control nodes, leaf nodes and transitions, and are executed vertically from top to bottom and back up again (Csiszar et al., 2017).

First industrial research applications showed that behavior trees combine good readability and navigation features through their abstraction level and offer a wide functional range to cover different scenarios. It was reported that behavior trees are easy to learn and understand. A skill library could facilitate their usage, thereby improving the global data handling. The skills should have an interface definition to make them reusable (Csiszar et al., 2017). A huge disadvantage of behavior trees is that human's tasks are not implemented in the visualization.

3.4. Human–Robot Task Allocation

In the following section, human–robot task allocation approaches and methods are presented. Beumelburg (2005) provided an overview of existing task allocation methods and programs. In addition, the author gave an insight into the discussion about the feasibility of automation of tasks. Traditionally, manufacturing systems are planned top–down using enterprise resource planning and/or manufacturing execution system solutions. "*These systems are intended to provide a smooth production by explicitly defining the tasks that each system, including robots has to do. Everything is defined in a centralized manner. Usually the task allocation is defined by a human designer and put into the system. This approach is good enough if nothing changes in the task and system itself. Still, whenever a new situation occurs due to new production task or new configuration of the system, the whole production just stops until the designer designs new production plan.*" (Nikitenko et al., 2018, p. 372).

Various approaches for task allocation are presented by Chen et al. (2014). The authors gave the following examples:

- Resource-constrained project scheduling problems
- Resource investment project scheduling problems
- Multi-objective optimization problem

- Traditional salesman problem
- Max-plus algebra model
- Heuristic approach based on genetic algorithm

Other examples, including the dynamic vehicle routing problem and optimization techniques, such as mixed-integer linear programming solvers or dynamic programming, are mentioned by Ponda et al. (2010).

All these approaches follow specific algorithms, that provide work instructions for an agent that are generally valid, executable (uniquely defined), and finite (Rimscha, 2014). Algorithms can be deterministic, "*if the next state of the environment is completely determined by the current state and the action executed by the agent*" (Russell and Norvig, 2010, p. 43), or stochastic, if the environment is too complex to be described. Machine learning plays a special role when the algorithm is not fully created by a human programmer and is thus partly created by the software itself.

Algorithms can also be distinguished as static and dynamic, based on the environment (Russell and Norvig, 2010, p. 44). If an algorithm can adapt to changing, i.e., dynamic, environments, this is referred to as a dynamic algorithm — if not — it is a static algorithm. Further classifications of algorithms can be found in the study by Russell and Norvig (2010). Due to the large number of task allocation approaches, they are divided into deterministic, heuristic, and machine learning.

3.4.1. Deterministic Approaches

In this approach, the current state of information and the chosen action of an agent solely define the next state. There is no possibility that the intended goal state will not be reached with the appropriate action (Russell and Norvig, 2010).

Rencken and Durrant-Whyte developed "*a decision-making human-computer interface capable of adapting to the human's changing performance with time*" (Rencken and Durrant-Whyte, 1990, p. 148). The multiple-resource pool model was used to model the algorithm, which considered the human's performance, estimated task arrival, and service rates. The model was tested using a human-controlled surveillance system. The system enhanced the human's performance during periods of high mental workload. Tasks were classified as encoding (receive external stimuli/signals), central processing (act on the perceived stimuli), and response (employ when acting) task groups (Rencken and Durrant-Whyte, 1993, p. 1074). These two papers by Rencken and Durrant-Whyte focused on solving a queuing problem using a dynamic decision-making human–computer interface. Even though no robot in the conventional robotic arm sense was considered, the method used is relevant for human–robot task allocation. The underlying problem is similar to task allocation between humans and robots when it is assumed that both agents can execute the tasks. For this reason, a queuing model that could be implemented by both agents could be used to solve the task allocation problem.

Based on the modeled Petri nets and a combined calculation of all possible variants of task allocation, the task finish time and payment cost can be calculated using the Monte Carlo method (Chen et al., 2011). Monte Carlo algorithms are used for problems that are difficult or impossible to solve exactly. Samples, simulations, and experience data are used to create these algorithms. From one iteration to the next, the Monte Carlo algorithm learns and gets better results. A multiple-objective optimization is then performed to identify the best solution with the objective of minimizing costs and time. Using this method enables allocating tasks to the robot or human in a cost- and time-optimal way. The approach is described rather practical and is validated by simulation and lab experiment.

Constraint programming is an approach to solve discrete problems. In this approach, a problem is formulated as a constraint satisfaction model and is solved using general solvers. Mokhtarzadeh et al. (2020) deployed a constraint programming approach to solve the task allocation between humans and robots. The objective function minimizesd the completion time of all tasks.

Tsarouchi et al. (2016; Robo-Partner, 2020) developed a decision-making framework for HRI within the project "*ROBO-PARTNER – seamless human–robot cooperation for intelligent, flexible, and safe operations in the assembly factories of the future.*" The authors optimized the workplace layout and task allocation between a human and a robot. Criteria included in their optimization were the occupied floor space, the robot's reachability, ergonomics, and investment costs. Based on the resources, tasks and workplace, task allocation alternatives are generated and evaluated. The optimization problem was solved by maximizing a utility value (Tsarouchi, Michalos et al., 2017). The solution was implemented in a simulation tool[10] to allow the work designer to check the satisfaction requirements.

Tsarouchi et al. (2017; XACT, 2020) presented a hierarchical decision-making framework to allocate tasks according to the capabilities of the agents. Capabilities included in the decision-making were resource suitability, availability, and operation time. The three steps, shown in Figure 19, were conducted sequentially to identify the suitable agent(s). A scheduling algorithm was designed to identify the different variants of task allocation, and subsequently,

[10] Tecnomatix Process Simulate.

an evaluation identified the best allocation regarding minimized operation time. The authors implemented their work in the robot operation system framework. Their method was based on a complementary approach of task allocation aimed at minimizing operation time; however, the method lacked the possibility of parallel tasks.

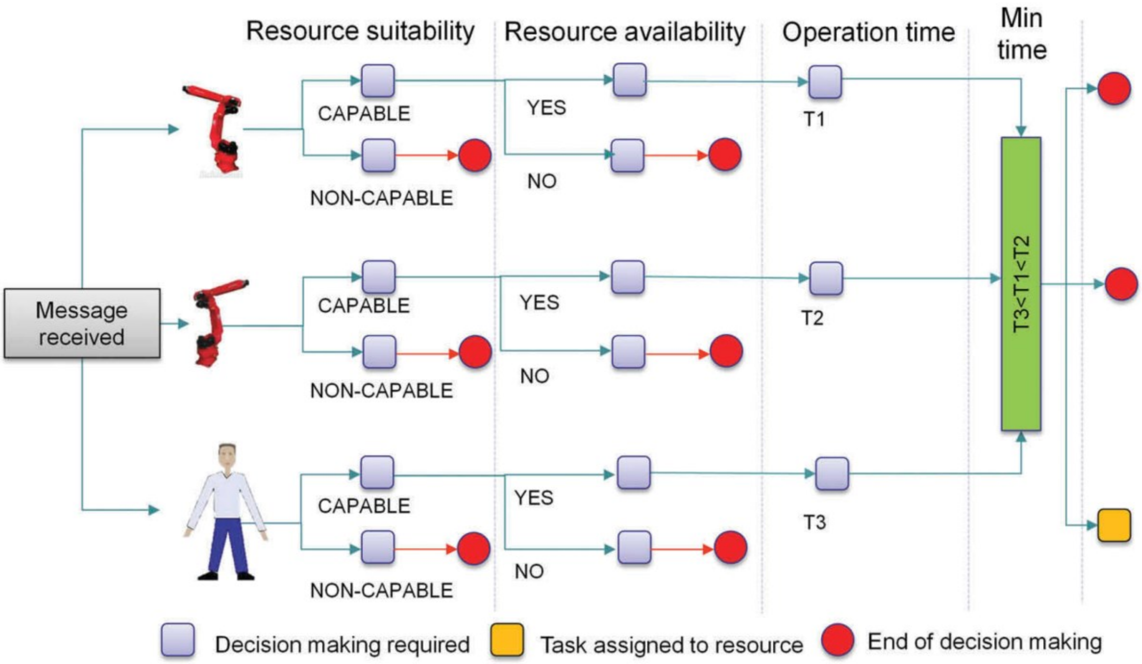

Figure 19 Visualization of the human and robot consideration in the task allocation (Tsarouchi, Matthaiakis et al., 2017, p. 582).

Axiomatic design, a method to derive functional requirements of a system from the customer's requirements, was deployed to allocate tasks in HRI by Fechter et al. (2016). The authors considered the work of Beumelburg (2005) and derived the automation assessment of different assembly tasks with axiomatic design: the design properties are the assembly jobs, such as "move parts to buffer," and the functional requirements are the assembly tasks, such as "buffer parts." All considered tasks were in a database based on descriptions from VDI 2860 and DIN 8593-0. A task analysis was undertaken to characterize the tasks using handling time estimation via MTM and part geometry, material property, and ergonomics aspects. With this information, the axiomatic design matrix was built. Functional requirements were then agglomerated based on their automation level and related technologies in cluster for robotic and manual tasks. The method was applied in an industrial use-case.

Ranz et al. (2017) proposed a compensatory task allocation method. In this method, first, the process was defined and broken down to process sequences. Then, a knockout list helped match the process attributes with capabilities and defined the tasks that were unquestionably allocated to one of the agents. The remaining tasks, that could be executed by both agents, called "variable tasks," were then evaluated using capability indicators, such as process time, additional invest, and process quality. The authors calculated the average of the three criteria for the human capability indicator. The robot indicator was calculated by subtracting one from the human indicator. Then, the sum of all capability indicators for all tasks was weighted and the evaluation facilitated decision-making; the output is a human–robot execution plan.

Malik and Bilberg (2019b) followed a capability-based approach of task allocation. The authors developed an assessment of task potential for HRI. Several criteria or attributes for task analysis were identified and each attribute was rated with a score (Malik and Bilberg, 2019a) similar to Ranz et al. (2017). Attributes were based on the physical characteristics of the part or components, the process of mounting, assembling, joining, and the human–robot safety. Attributes included, inter alia, the (graspability of) parts, feeding mechanism, and mounting, insertion, and fastening requirements. The score was then used for evaluating automation potential (score 0 = no automation potential and score 1 = highest automation potential). It was stated that the final task assignment must consider the working time and availability of each resource. The authors also presented a software application to facilitate the task evaluation (Malik and Bilberg, 2019b).

Müller et al. (2017) introduced the compensatory approach of task allocation. Based on the products' requirements and the humans' and robots' skills, the manufacturing process was analyzed. The authors clarified the approach by stating that attention to a task and performance level of a human can vary throughout the day, which is not the case for robots. Humans have an automatic sense of touch (sensitivity), whereas robots need to be equipped with sensors to perceive their environment, which cannot yet reach the abilities of a human. Another positive aspect of humans is their mobility and adaptability in the workspace. Nevertheless, robots can work with high accuracy. The weight of the assembly parts highly depends on the robot; however lightweight cobots are mostly not designed for lifting heavy parts with more than 2–5kg, whereas industrial robots can easily lift hundreds of kilograms. In the welding applications by Müller et al., humans outperformed robots when it comes to hardly inaccessible areas or complex shapes of parts, which would consume more time for programming a robot. In addition, trained humans are capable of inspecting welding seams and spots visually. These considerations were made when allocating the tasks to the agents. The authors developed a simple UI for the HRI based on computer aided design (CAD) data. A digital projector, highlighting the parts at the workspace, was used to support the worker (Müller et al., 2017).

Liu et al. (2018) applied game theory to solve the task allocation problem. The authors began with the assumption that the procedure decomposition problem in a one–human–one–robot setup is a typical substantive bilateral cooperative game and the procedure allocation is a typical clan cooperative game. First, all possible permutations of task allocation were calculated. Then, the Nash axiom for cooperative games was applied. A cost function (time, energy costs, etc.) was formulated. Afterward, the sequence was calculated using the Weber set of cooperative game. The approach was verified by simulating the assembly of a roller bearing.

Dondo and Cerdá (2006) and Pearce et al. (2018) deployed a mixed-integer linear problem framework. The approach used by Dondo and Cerdá (2006) to solve a dynamic vehicle routing problem with time windows was also suitable to solve a human–robot task allocation problem as well. Pearce et al. (2018) used an optimization software tool[11] to optimize human–robot teaming and aimed to improve time and ergonomics. The authors incorporated an HTA approach to describe the tasks.

Schoen et al. (2020) developed the end-to-end task authoring environment "Authr" to assist engineers in translating manual tasks into human–robot task plans. A shared representation for human–robot work using a task analysis method called "Therbligs" was created. For the task allocation, a breadth-first search algorithm was deployed to identify possible traces and compare the resulting traces regarding time and costs. Task plans were implemented into a cobot by deploying MoveIt based on the robot operating system. The system's web-based interface was divided into three modes: setup, plan, and simulate.

The assessment methodology was applied by Dianatfar et al. (2019) to identify the suitable agent for task execution. Criteria such as task complexity, ergonomics, payload, and repeatability were considered, and tasks were rated with positive and negative assessments. The resource with fewer negative points was selected for the respective task. However, if there were equal points, the task was allocated to both agents. The approach was applied to an HRI workstation.

Krä et al. (2020) presented a skill-based task allocation approach for production planning in hybrid teams. The authors examined different strategies for prioritizing orders to schedule production including the "shortest manufacturing time", "smallest number of cooperation groups", and "least feasible order first". A combination of the "smallest number of cooperation groups" and "least feasible order first" showed the shortest duration of schedule and the lowest number of average delays. The work is related to the project FORobotics.

Mateus et al. (2020) developed an algorithm for the identification of assembly task precedence considering resource capabilities, workplace design, and safety. The algorithm used a liaison matrix, collision matrix, CAD base part, and subassembly content as input. The base part was

[11] IBM CPLEX Optimizer

the part with the highest fitness value regarding the surface, volume, and number of liaisons. Starting with the base part, all subassembly tasks connecting other parts were analyzed. Their methodology, shown in Figure 20, is based on four steps (Mateus et al., 2019):

- Information extraction and processing from CAD model
- Work disaggregation
- Resource capability assessment
- Identification of HRC workplace building blocks

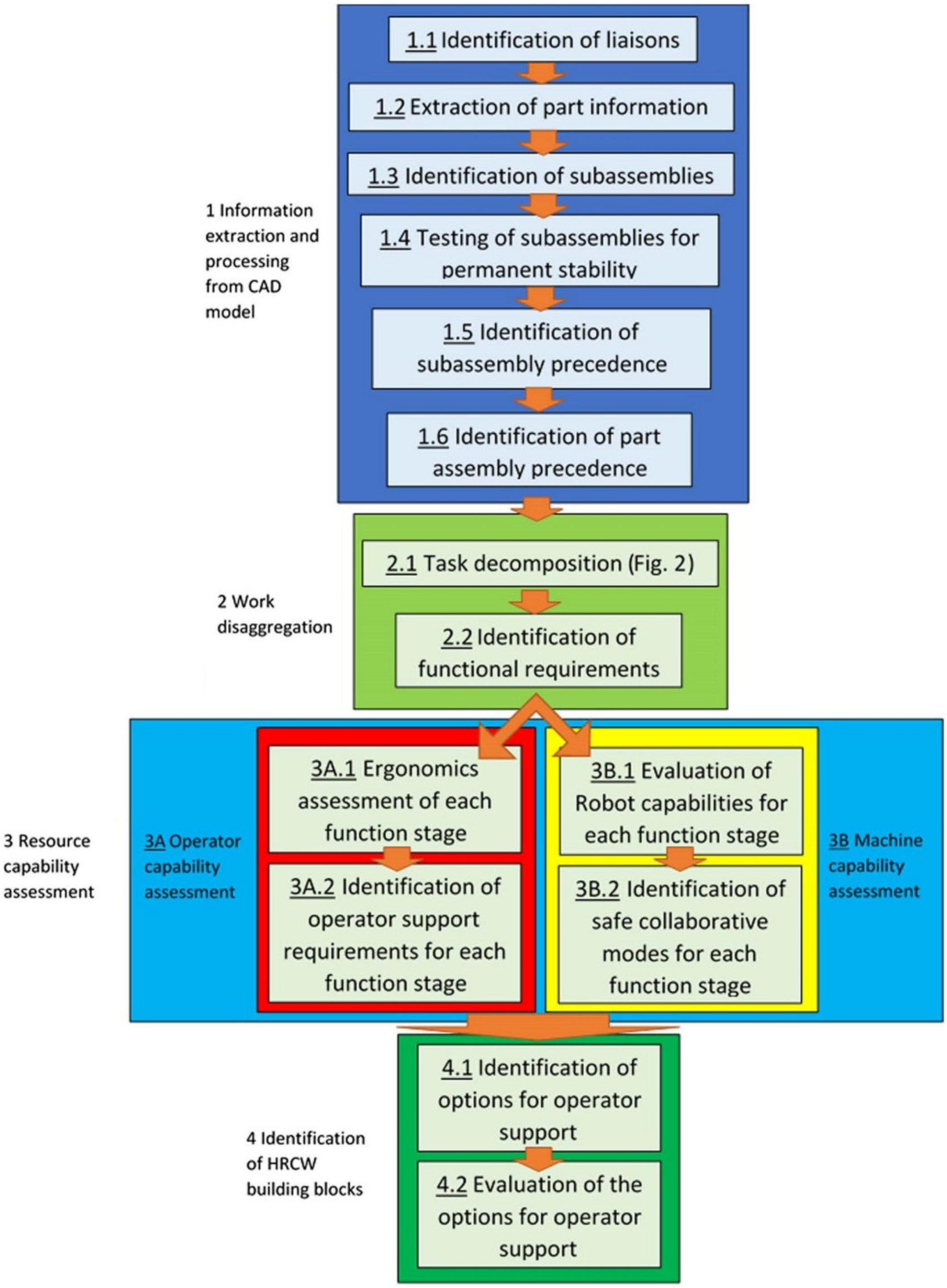

Figure 20 Methodology diagram by Mateus et al. (2019, p. 2667).

Gualtieri et al. (2020) presented a capability-based approach of task allocation that includes four task evaluation and decision levels:

- Technical evaluation level (is the task automatable from a technical point of view?)
- Ergonomics evaluation level (does the task lead to biomechanical stress?)
- Quality evaluation level (does the task require quality improvements?)
- Economics evaluation level (does the task provide value to the final customer?)

If the task is not automatable, then the human should take over. The author's work was based on a compensatory approach, where the humans should do activities, such as reasoning, interpretation, responsibility, flexibility, and value adding and the robots should take over feasible tasks that provide biomechanical stress to the human, require quality improvements and do not add value to the final customer. Other tasks should be allocated to either the human or robot. "Human or robot tasks" are combined so that few handovers must take place. The authors applied their approach and the results concluded that *"[...] a system where the operator can choose in real time and indiscriminately which task will be the next one according to his/her needs and wants could significantly improve cognitive ergonomics conditions, operators' psychological well-being, and production flexibility. [...] this would be the perfect implementation of a human-centered design in the Industry 4.0 context*" (Gualtieri et al., 2020, p. 370).

Dhungana et al. (2020) presented an allocation algorithm based on skill or capability matching called producibility check. They focused not on HRI but on the general assignment of jobs or tasks to workstations, machines, or factories. Through a constraint satisfaction technique, which was suited for combinatorial problems. Constraints were, inter alia, the skill matching, the start of the process execution must be before the end of the process execution, the process must be serialized, the same materials must be used, and a material transport must exist between two workstations that work on the same material. The authors considered production and transportation (shipping) costs. The algorithm worked in two phases: first, an optimal selection of factories was computed to minimize costs and second, execution graphs for all intra-factory subparts were computed.

3.4.2. Heuristic Approaches

In contrast to deterministic approaches that specify an exact decision path of an algorithm, heuristics are used to solve a task allocation problem approximately. These are often used, as they attain a solution quickly, which is not guaranteed to be optimal. Heuristic approaches use experience data to solve a problem and are often represented using decision graphs or trees, such as AND/OR graphs, precedence graphs, or behavior graphs.

WeBuild is a task distribution system that deploys a greedy algorithm (Fraser et al., 2017). The algorithm adapts if one or more agents become available and incorporates two parameters: task diversity and group priority. Task diversity refers to the variety of tasks one agent should perform. High diversity leads to high work engagement, more quality work, and prevents repetitive strain. In contrast, low diversity has high learning effects on certain tasks and can increase efficiency in short term. Group priority refers to tasks where more than one worker is working. When team building is important, group priority should be high, and when requiring a high focus of one worker, individual work is prioritized. WeBuild deploys a Node.js (JavaScript) application running on a local server (Fraser et al., 2017). The system enables an interaction with mobile devices, where the work instructions can be viewed.

Johannsmeier and Haddadin (2017) proposed a hierarchical HRI planning framework, which is also applicable to scenarios with multiple robots. Their method was structured in three levels:

- Team-level assembly task planner
- Agent-level skill planning
- The real-time skill execution level

In the first level, i.e., the team level, the assembly process was planned offline from the view of a fore(wo)man. Furthermore, information about the parts location, agents, and other resources was necessary. The authors deployed an A* graph search algorithm, which aims to find an allocation of agents to tasks that is optimized with respect to a cost function (Johannsmeier and Haddadin, 2017). In A* algorithms, a problem is conceived as a graphical branching problem. First, an initial and a target state (node) were defined, following which the possible branches/paths leading to the target node were examined (Russell and Norvig, 2010, p. 93).

Different objectives for the cost functions are mentioned as suitable candidates for their approach (Johannsmeier and Haddadin, 2017, p. 46):

- Overall or local execution time
- Resource costs, such as energy consumption or peak power
- Risk factors, such as danger to human, workload amplitude, and frequency or ergonomic factors
- Assumptions about the human worker, including attention level, general experience level, and reliability

On the second level, i.e., the agent level, process interruptions (e.g., collisions), handovers (from human to robot and vice versa), pick-ups (end-effector adjustments to pick up a part), and assemble actions (concrete assembling of part) are included in the planning. The third level, i.e., the real-time (online) level, is responsible for the trajectory planning, but is not detailed in their work. In the experiments, the authors considered the human workload, which results in an execution scheme, where the robots work in parallel, and the human is doing what the robots are not capable of executing. Their approach describes a dynamic compensatory allocation of tasks, which is dynamic in terms of unforeseen and possible faulty events, e.g., collisions.

Lamon et al. (2019) presented a modular capability-aware solution with a focus on the physical characteristics of the agents to allocate tasks between a cobot and human in fast-reconfigurable industrial scenarios. Three layers were identified to model the capability-based task allocation problem: the agent, team, and assembly layer, where the assembly task decomposition and assignment was handled by the latter. The authors used AND/OR graphs to illustrate the assembly plan (refer to Johannsmeier and Haddadin (2017)). Decision-making primarily relies on the physical capabilities of both agents according to Michalos et al. (2018) and Tsarouchi et al. (2016). The authors defined the indices of task complexity, agent's dexterity or kinematic reachability, and agent's effort or human and robot fatigue. Agent dexterity and effort were introduced to resolve situations where more agents were suitable for the same task. All indices were combined to a weighted sum to formulate a reasonable heuristic for a search algorithm. The model worked as follows: "*First, the agent execution cost for each action is computed. Second, the role allocation algorithm assigns the actions to the agents in the team through a cost-minimisation principle. Finally, the task is executed by the agents relying on the algorithm results.*" (Lamon et al., 2019, p. 3379) Johannsmeier and Haddadin (2017) deployed an A* algorithm to set up the cost function. Their approach was evaluated in an experiment, and the obtained results showed improved performance and intuitiveness-of-use.

The system architecture of a dynamic task planner was presented by Darvish et al. (2018). The architecture was entitled "FlexHRC" and was later extended for a concurrent task allocation and execution and was called "ConcHRC" (Karami et al., 2020). The three levels of the architecture consisted of the following:

- Perception level (object and scene perception, human action recognition, knowledge base)
- Action level (robot execution manager, controller, and simulator)
- Representation level (task representation and planner)

On the perception level, the human activities, product defects, and whole scene were considered (Karami et al., 2020). Product defect detection and scene perception provided the knowledge base for the task allocation framework using a camera. The human activity recognition was done by data from wearable sensors worn by the humans. On the action level, the robot execution manager received commands from the task planner and mapped and communicated them to the controller or simulator (Karami et al., 2020). The representation level consisted of the task presentation deploying the AND/OR graphs, task planner, and knowledge base. A cost function was developed to find the graph with the minimum costs. The planner selected the AND/OR graph with the minimum defined costs by deploying a breadth-first search algorithm that simulates all possible branches of the graphs. The optimization was done based on execution time. The planner module combined a set of parameters, such as the capabilities, preconditions, and action effects (such as the state features, temporary conditions, and agents). The authors' approach was verified through a laboratory use-case experiment. However, the A* algorithm method must know all attainable combination states, which requires an increased computational effort. The framework was deployed and evaluated by Murali et al. (2020). The partly significant results showed that the fluency of the teamwork improved, as the idle time minimized. The flexibility, comfort, and success increased, and physical and mental efforts decreased in comparison to a manual execution of the process.

Riedelbauch and Henrich (2017) strived for a complementary approach of task allocation and mentioned several properties to achieve symbiotic collaboration. First, they deployed precedence graphs to illustrate the tasks for the algorithm. Second, they created a dynamic team setup to attain easy task switching if, e.g., the human gets distracted. Third, they executed a dynamic plan, which means both agents can decide quickly. This approach relates to the robot plan execution system called "Chaski," as demonstrated by Shah et al. (2011), which uses insights from human–human teaming to make HRI more natural and fluid. Further, decision autonomy was shared, i.e., each agent can decide for the next operation based on the decisions previously taken and communicated. Fourth, Riedelbauch and Henrich (2017) mentioned equal partners' collaboration and limited their work to only shareable tasks. Their task–sharing framework considered the world context in terms of the perception of the agents and tasks with their superordinate structure. Their task coordination mechanism considered the readiness and success of an operation instance (subtask). The algorithm had two phases: the execution and monitoring phases. Task choosing was shown to each agent by putting the human hand or robot gripper over or in front of the necessary part. Although their complementary approach where the human and robot were working as a team is promising, it is hard to implement in existing shop floors because all tasks must be executable by both agents, a reliable image recognition is crucial, and the human needs to know the content and sequence of tasks. In addition, the human is immanently observed by the robot that could raise privacy issues. The human behavior is modeled by the variable certainty that will decrease over time depending on how likely the world model will be modified by humans. A trust factor is implemented describing the correspondence between the world model and robot memory (Riedelbauch and Henrich, 2019). The authors applied the concept on experiments simulating different scenarios. Best results in terms of fast execution times were measured in a cooperative scenario, where the human and robot can work in parallel (Riedelbauch and Henrich, 2019).

Fechter et al. (2019) used a heuristic approach to optimize task allocation. If multiple resources fulfill the requirements of a <product, process, resource>, two approaches are useful: full combination (Cartesian product) and heuristic search algorithm with associated fitness function to shorten the search time and effort. The function aims to achieve a minimum cycle time. For the latter, two different algorithms were used: greedy algorithm and a combination of simulated annealing and the basic idea of evolutionary algorithms (single-crossover and multi-crossover). The application of the algorithms showed that the single-crossover hybrid algorithm performed best for a short example use-case.

Anima et al. (2019) developed a method for dynamic task allocation by means of a tree structure that consists of sequential, non-ordering, and alternative paths of execution. The robot monitored the human's hand-by-hand recognition. To ensure that the human and robot do not work on the same task component and to coordinate the cooperation, a continuous peer node message was passed between the task representations. They evaluated their method via a laboratory use-case with overlapping and nonoverlapping subtasks between a human and cobot.

Beumelburg (2005) presented a genetic algorithm to allocate tasks to a human or robot by deploying a compensatory capability-based approach. The peculiarity of a genetic algorithm is that it should be able to adapt and mutate as per its environment and environmental effects over time (like evolutionary genetics). The author calculated a capability indicator or score for the automation of an assembly operation. The capability indicators mapped the three corporate goals of time, cost, and quality by aggregating takt time, additional investment, process safety, and work quality on a weighted basis (Beumelburg, 2005). The results indicated a suitability level, ranging from zero to one, for the robot and human. Beumelburg compared and evaluated different optimization approaches, including the genetic algorithm, simulated annealing, tabu search, branch and bound, and threshold acceptance. According to Beumelburg, the best fitting approach for the human–robot task allocation problem was the genetic algorithm.

Howard (2006) focused on the problem of maximizing the system performance in HRI by incorporating the concept of task switching. Influencing factors were capabilities, repetitive workload, and stress. "*Task switching is defined as the process of alternating or switching attention between tasks when responding to a sequence of stimulus presentations*" (Howard, 2006, p. 3588). The author presented a genetic algorithm to minimize the mental workload while maximizing task performance required for achieving HRI scenarios. The heuristic was implemented in a manner that at first, random allocations were selected as possible allocations. Then, the fitness of each allocation was computed. The vectors with the highest fitness value were selected, and the offspring was reproduced for the next generation, etc. The field of application of the algorithm concerned space missions and differed strongly from manufacturing because space missions were characterized by activities, some of which could often not be performed by humans only or were very complex. This means that the individual criteria, like minimizing mental workload, are not necessarily appropriate for this thesis, but the basic approach of a genetic algorithm might be applicable. Solution paths must already exist for developing the genetic algorithm. Without existing solution strategies, this method cannot be used meaningfully (Russell and Norvig, 2010).

Chen et al. (2014, p. 1067) present the resource-constrained project scheduling problems algorithm for hybrid assembly systems. Parallel and sequential task scheduling between humans and several robots was realized considering the assembly time and payment costs. A genetic algorithm was deployed. Four different algorithms (idle time first, switch load first, fixed priority selection, and dynamic priority selection) were compared to solve the task allocation problem. The dynamic priority selection algorithm was the most efficient one with the lowest task finish time and the distribution of tasks to the human and robot was most balanced (difference in operation times was lowest).

Bänziger et al. (2018) deployed a genetic algorithm to assign and sequence tasks. Based on standardized work descriptions using MTM, different task sequences of a given distribution were evaluated using a simulation tool. Criteria included in the simulation were task progress, waiting time, and traveled distance. The simulated experiment data was validated by comparing with real recorded data from an assembly line.

Weckenborg et al. (2020) deployed a genetic algorithm to solve the problem of balancing and scheduling assembly lines with cobots. The authors incorporated ergonomic aspects and minimized the cost function of task allocation (Weckenborg and Spengler, 2019).

Liu et al. (2020) introduced a heuristic approach of task allocation by incorporating the learning curve of a human worker. The approach aimed to minimize the makespan based on the individual's learning curve and the respective duration of task execution.

3.4.3. Machine Learning Approaches

Task allocation between humans and robots in unstructured environments is a challenging endeavor. As presented in previous sections, most aforementioned works simplified the problem by assuming exact knowledge about the environment including the human. Real scenarios can hardly be described or mapped because of involved uncertainties (Lin and Nguyen, 2016). Different machine learning approaches based on a selection of data from which an agent independently derives generally valid rules (Rimscha, 2014) are discussed in this section. The idea of these approaches is the generation of knowledge using the collected experiences. Notably, the rules defined by machine learning can only be as good as the sample data provided. In some intelligent systems, the robotic agent autonomously performs sample data retrieval.

Roncone et al. (2017) proposed a transparent task planner for a human–cobot interaction. Using the Markov decision process (MDP) framework (Figure 21), the authors modeled the optimization of the robot's actions. The model of a MDP can be considered as a graphical branching problem. MDP framework solves a method to solve a sequential decision problem for a fully observable, stochastic environment with a Markovian transition model and additive rewards. It comprises a set of states, actions, a transition model, and a reward function (Russell and Norvig, 2010, p. 647). Besides, MDP comprises of a decision-making agent, i.e., the robot, which is observing its environment regarding specific states. The agent decides its actions based on the different states of its actions. The agent also receives numerical rewards for its actions, thus, enabling the system to learn from previous decisions.

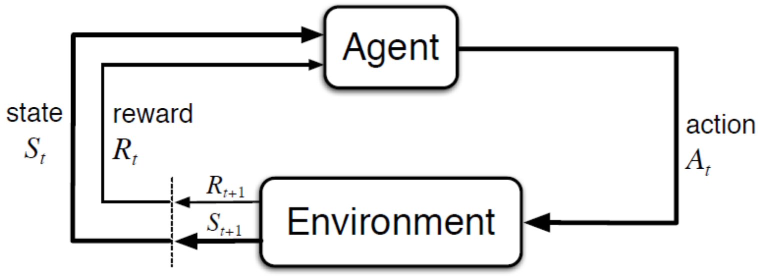

Figure 21 Agent–environment interaction in a Markov decision process (Sutton and Barto, 2017, p. 38).

Roncone et al. (2017) used an automated technique, which is able to transform task-level hierarchical task models, e.g., robot operation system services, into low-level partially observable Markov decision processes. The authors evaluated their approach and showed an improvement in completion time and a reduction in cognitive workload for the human. The transparent role assignment and HRI were enabled through a multi-model interaction system including a web interface that enables bi-directional communication, a text-to-speech system, and safety buttons. In terms of the changing status, the method of the presented task allocation is dynamic, which the robot can observe. The human was constantly informed about the intentions of the robot and intervened in the decision-making, if necessary, through multi-model interaction methods. Partially observable MDPs were deployed in similar collaborative human–robot scenarios (Lin and Nguyen, 2016; Taha et al., 2011).

Srivastava et al. (2014) presented a dynamic queue with latency penalty and posed the problem in a MDP framework. An approximate solution in the certainty-equivalent receding horizon optimization framework was proposed. The authors derived performance bounds for the suggested solution and proposed guidelines for choosing the mean arrival rate for the queue. For future work, they planned to incorporate human feedback and study closed loop policies that are jointly optimal for the human operator as well as the automation. Majji and Rai (2013) developed a task and attention allocation solution for multiple operators with appropriate performance measures based on the work of Srivastava et al (2014). They referred to single operator optimal attention allocation problems, which are modeled as scheduling problems in a queuing framework. The objective was modeled as reward maximization problem, and the primary decision variable defined the sequence of tasks allocated to the operator.

Ponda et al. (2010) presented an approach to solve the problem of task allocation in human–robot team (space) missions using the consensus-based bundle algorithm. This algorithm was developed to solve task allocation problems in a multi-agent environment with a finite number of tasks to be accomplished. It was a polynomial-time algorithm and provided a decentralized decision architecture. The authors aimed to achieve an optimum for each agent task completion. The algorithm consisted of two phases: in the first phase, the tasks are assigned and in the second phase, the consensus of tasks is regulated. In phase one, the tasks are allocated with the help of an integrated queue. In phase two, the agents compared the completion of all tasks and submitted task offers. The task offer comprised of the workload of the individual agents as well as their abilities to complete a task. A reallocation of tasks in the queue from agents to agents is possible. Ponda et al. (2010, p. 4) defined the heterogenous task allocation problem as "*a stochastic combinatorial optimization problem, for which the objective is non-stationary and nonlinear.*" The authors aimed to allocate tasks to different agents without conflicts and to maximize the global reward. The human and robot were incorporated in the algorithm based on their availability and their workload. The robot was rewarded for arriving at a task but discounted by delay times and a fuel penalty due to travel distance. The human part was modeled using the inverse Yerkes–Dodson law, which describes the empirical relationship between arousal (or stress) and performance of a human. This indicates that the human should not be stressed (overutilized) too much and bored (underutilized). The authors tested their approach using simulations and observed improved mission performance with efficiently distributed workload among the agents.

Wu et al. (2017) presented a method to model the human trust by deploying a MDP algorithm. The human trust in relation to the robot's actions and performance was considered in the optimization problem. The MDP counted possible robot failures and uncertainties in the human worker's response, such as fatigue and trust. The desired optimal task allocation showed minimal expected average costs for each cycle of the tasks and maximum probability for satisfying linear temporal logic specifications. Linear temporal logic is a popular logic, which was used by the authors to specify their desired system properties in the HRI. Using atomic propositions, *true*, *false*, Boolean and temporal operations, e.g., □ for always true, ◊ for eventually true, ◯ for next true, U for until true, R for release, W for weak until, and M for strong release, linear temporal logic can be used to create a formula that should be optimized. The authors evaluated their model using a case study and showed the effectiveness and benefits of the proposed trust based HRI.

Regarding the uncertainty of situations, Bayesian decision-making or Bayesian networks were used in literature (Liao et al., 2017; Rahman et al., 2016). Bayesian decision-making is based on a network with graphs through which the dependencies of different variables are clearly displayed. This enables an exact determination of the probability distribution between different influencing variables. In addition, Bayesian network is a visualization option (Russell and Norvig, 2010, p. 511). The approach provides decisions based on the expected value criterion, which is particularly useful in uncertain situations. The human uncertainty in decision-making can be described by the regret theory. Both approaches were combined by Rahman et al. (2016) and Liao et al. (2017).

Pellegrinelli et al. (2017) presented a motion and scheduled planning framework consisting of a motion planner, task planner, and plan executive. The authors began with an analysis of the process, the resources (agents), and the relations among the tasks. Using a machine learning approach, they aimed to minimize lead (cycle) time and maximize system performance while considering human unpredictability and robot temporal uncertainty.

Wicke and Luke (2017) proposed the concept of bounty hunting for multirobot cooperation and HRI, describing a complementary task allocation approach. The approach described that a task should be distributed to the "first" agent. The agents were incentivized by the completion of tasks. If an agent cannot complete one task, another agent takes over. The idea is similar to an MDP approach through incentives (bounties). However, the authors argued that existing MDP approaches use a decentralized optimization method or a centralized planner rather than a multiagent algorithm. In addition, they argued that their approach does not exclude any agents.

3.5. Summary of the State-of-the-Art and Research Gap

To answer the research question regarding the SLR (what methods and techniques exist to allocate tasks between a human and robot), the following summary is given. Afterward, the research gap of this thesis is discussed.

3.5.1. Quantitative Summary of the State-of-the-Art

A summary of the state-of-the-art is discussed during the qualitative engagement with the literature. 49% (44/90) of the sources were identified directly by the SLR and the remaining sources resulted from forward and backward searches of the found sources. The most relevant 90 state-of-the-art literature sources are summarized in Table 11.

Table 11 Summary of the state-of-the-art references.

No.	Authors	Year	Main Focus on Task				SLR
			Analysis	Allocation	Visualization	Context	
1	Taylor	1911	x	x		x	No
2	Rencken and Durrant-Whyte	1990		x			Yes
3	Rencken and Durrant-Whyte	1993		x			Yes
4	Endsley and Kiris	1995	x			x	No
5	Guichoet et al.	2003	x		x		Yes
6	Zandin	2003	x			x	No
7	Beumelburg	2005	x	x			No
8	Dondo and Cerdá	2006		x			No
9	Howard	2006		x			Yes
10	Shah et al.	2007	x	x			Yes
11	Ponda et al.	2010		x			Yes
12	Russel and Norvig	2010		x		x	No
13	Chen et al.	2011		x	x		Yes
14	Shah et al.	2011		x			Yes
15	Taha et al.	2011		x			No
16	Lotter and Wiendahl	2012	x			x	No
17	Stanton et al.	2013	x			x	No
18	Majji and Rai	2013		x			No
19	Seifermann et al.	2014	x				No
20	Chen et al.	2014		x			Yes
21	Rimscha	2014		x		x	No
22	Srivasatva et al.	2014		x			No
23	Wiendahl et al.	2015	x				No

Table 11 Summary of the state-of-the-art references (continued).

No.	Authors	Year	Main Focus on Task				SLR
			Analysis	Allocation	Visualization	Context	
24	Finsterbusch and Kuhlang	2015	x				No
25	Gombolay et al.	2015	x	x			No
26	Uddin and Hossain	2015	x				No
27	Tsarouchi et al.	2016		x			No
28	Fechter et al.	2016		x			Yes
29	Lin and Nguyen	2016		x			No
30	Rahman et al.	2016		x			Yes
31	Tsarouchi et al.	2017	x	x			Yes
32	van Rhijn and Bosch	2017			x		No
33	Johannsmeier and Haddadin	2017		x	x		Yes
34	Riedelbauch and Henrich	2017		x	x		Yes
35	Csiszar et al.	2017			x		No
36	Tsarouchi et al.	2017		x			Yes
37	Ranz et al.	2017		x			Yes
38	Müller et al.	2017		x	x		Yes
39	Fraser et al.	2017		x			No
40	Roncone et al.	2017		x			Yes
41	Sutton and Barto	2017		x		x	No
42	Wu et al.	2017		x			Yes
43	Liao et al.	2017		x			Yes
44	Pellegrinelli et al.	2017		x			Yes
45	Wicke and Luke	2017		x			Yes
46	Sørensen et al.	2018	x				No
47	Mateus et al.	2018	x				No
48	Järvenpää et al.	2018	x				No
49	Schröter	2018	x	x			No
50	Michalos et al.	2018	x	x			No
51	Bruno and Antonelli	2018	x				Yes
52	Pearce et al.	2018	x	x			No
53	Stöhr et al.	2018			x		Yes
54	Schlick et al.	2018			x	x	No
55	Pauker et al.	2018			x		No
56	Darvish et al.	2018		x	x		Yes
57	Nikitenko et al.	2018		x			No
58	Liu et al.	2018		x			Yes
59	Bänziger et al.	2018		x			Yes
60	Mioch et al.	2018			x		Yes
61	Schüppstuhl et al.	2019	x				No
62	Mateus et al.	2019	x				Yes

Table 11 Summary of the state-of-the-art references (continued).

No.	Authors	Year	Main Focus on Task				SLR
			Analysis	Allocation	Visualization	Context	
63	Malik and Bilberg	2019	x	x			Yes
64	Weckenborg and Spengler	2019	x	x			No
65	Makrini et al.	2019	x	x			Yes
66	Castro et al.	2019	x				No
67	Froschauer and Lindorfer	2019			x		No
68	Vanderfeesten et al.	2019			x		No
69	Casalino et al.	2019		x	x		No
70	Lamon et al.	2019		x	x		Yes
71	Malik and Bilberg	2019		x			Yes
72	Dianatfar et al.	2019		x			Yes
73	Riedelbauch and Henrich	2019		x			Yes
74	Fechter et al.	2019		x			Yes
75	Anima et al.	2019		x			Yes
76	van d. Waa et al.	2020	x				Yes
77	Gualtieri et al.	2020	x	x			Yes
78	Weckenborg and Spengler	2020		x			Yes
79	Lang et al.	2020			x		No
80	Karami et al.	2020		x	x		Yes
81	Mokhtarzadeh et al.	2020		x			No
82	Schoen et al.	2020	x	x	x		No
83	Krä et al.	2020		x			Yes
84	Mateus et al.	2020		x			Yes
85	Dhugana et al.	2020		x			No
86	Murali et al.	2020		x	x		No
87	Liu et al.	2020	x	x			No
88	Buxbaum et al.	2020		x		x	Yes
89	Gualtieri et al.	2021	x			x	No
90	Hader	2021			x		No

3.5.2. Qualitative Summary of the State-of-the-Art

Most human–robot task analysis approaches focus on task evaluation via capability and HF/E assessments. This approach is usually identical, i.e., a certain number of criteria are selected to evaluate the possible executing agents. The criteria range from feasibility criteria to cost and quality, to ergonomics metrics, and workers' preferences.

Human–robot task visualization methods are described using different approaches. Some of these methods are not intended for HRI, in which the human can actively intervene in the system but only serve to describe tasks for the robot, such as in Petri nets.

In terms of human–robot task allocation approaches, various algorithms and procedures were identified. The described approaches have in common that the task allocation is conducted in the work design process phase and is completed before the work begins. Approaches where monitoring of the workers and environment in the work system allows to dynamically reallocate tasks presuppose a perception of the robot, e.g., a camera system and machine learning for image and event recognition. Often, authors aim at a complementary approach and develop algorithms to make the robot adaptive to all situations.

An overview of the identified approaches is summarized in Table 12. There are overlaps between the individual methods, as some authors have used combinations of different methods. Note that, some authors are not listed in case the publication was an overview article or context literature, such as a fundamentals book.

Table 12 Summary of identified task allocation approaches.

Main Approach	**References**
A* graph search algorithm	Gombolay, 2015; Johannsmeier and Haddadin, 2017; Lamon et al., 2019
AND/OR graphs algorithm	Darvish et al., 2018
Assessment method	Dianatfar et al., 2019
Axiomatic design	Fechter et al., 2016
Bayesian decision-making	Rahman et al., 2016; Liao et al., 2017
Bounty hunting	Wicke and Lucke, 2017
Breadth-first search algorithm	Schoen et al. 2020; Karami et al., 2020
Capability indicators evaluation/matching	Beumelburg, 2005; Müller, 2017; Ranz et al., 2017; Schröter, 2018; Makrini et al., 2019; Malik and Bilberg, 2019b; Gualtieri et al., 2020b; Krä et al., 2020; Mateus et al., 2020
Consensus-based bundle algorithm	Ponda et al., 2010
Constraint programming/resource-constrained project scheduling problems	Chen et al., 2014; Mokhtarzadeh et al., 2020; Dhungana et al., 2020
Deterministic queuing model	Rencken and Durrant-Whyte, 1990; Rencken and Durrant-Whyte, 1993
Game theory	Liu et al. 2018
Genetic algorithm	Beumelburg, 2005; Howard, 2006; Chen et al., 2014; Bänziger et al., 2018; Fechter et al., 2019; Weckenborg and Spengler, 2020
Greedy algorithm	Fraser et al., 2017; Fechter et al., 2019
Heuristic approach	Liu et al., 2020

Table 12 Summary of identified task allocation approaches (continued).

Main Approach	References
Hierarchical task network/tree-structures	Shah et al., 2007; Anima et al., 2019
Machine learning	Pellegrinelli et al., 2017
Markov-decision process	Taha et al., 2011; Majji and Rai, 2013; Srivastava et al., 2014; Lin and Nguyen, 2016; Roncone et al., 2017; Wu et al. 2017
Maximizing of a utility value/minimizing costs	Dondo and Cerdá, 2006; Tsarouchi, 2016; Tsarouchi, 2017; Johannsmeier and Haddadin, 2017; Fraser et al., 2017; Pearce et al., 2018; Michalos et al., 2018; Lamon et al., 2019; Fechter et al., 2019; Karami et al., 2020; Murali et al., 2020
Monte Carlo method	Chen et al., 2011
Petri nets	Casalino et al., 2019
Precedence graphs	Riedelbauch and Henrich, 2017; Riedelbauch and Henrich, 2019; Weckenborg and Spengler, 2019

3.5.3. Research Gap

Although research in the field of HF/E recommends active integration of the worker in the decision-making process (see Section 2.2), this is rarely foreseen or implemented (Mioch et al., 2018). The engineering researchers also recommend that the flexibility of the process can be increased through flexible re-organization of tasks, when necessary (Buxbaum et al., 2020, p. 576). Van Rhijn and Bosch (2017, p. 143) explicitly stated that "*there is a need for a more flexible/dynamic task allocation model in which the division between robots and humans can be considered continuously (on the fly), based on human-oriented parameters of workload (physical, cognitive, psychosocial load), safety, flexibility and performance criteria (quality, costs, productivity).*"

To reduce this research gap, this thesis focuses on the research question:

What is an appropriate method to adaptively share tasks in assembly processes between a human and collaborative robot to increase economic efficiency and improve human factors/ergonomics?

The following section focuses on the selection of appropriate methods based on a requirements analysis.

4. ANALYSIS OF REQUIREMENTS

A comprehensive analysis of requirements is necessary to connect the problem of this thesis to the solution. Besides the feasibility of the method that is to be developed, functional requirements for the design, implementation, and running the system are defined. To explain how these requirements will be fulfilled, design parameters for all the method's parts are derived from the requirements. Relevant factors, such as technical, ergonomic, quality, and economic factors, as well as work content, organization, and acceptance (Bauer et al., 2016; Gualtieri et al., 2020) are explained in Section 2. Regarding the research methodology followed in this thesis, the functional requirements and respective design parameters were elaborated iteratively.

4.1. Requirements for the Method

To derive the functional requirements, the research question of this thesis is decomposed. The two descriptive characteristics of the research question are the terms "appropriate" and "adaptively share."

The term "appropriate" refers to the feasibility of the method and the improvement of economic efficiency through the method. The first implies both the basic compliance with law and standards as well as the feasibility in terms of skills. The implications (subrequirements) of this requirement "appropriateness" are elaborated in the section "Task Analysis." The consideration of the safety aspects in terms of safety certified for HRI workplaces and security is beyond the scope of this work. References to current literature on these subjects can be found in Section 2.1.2.

Sharing adaptively involves the ability of the system to adapt to changing environmental conditions (the user or context). Moreover, to improve HF/E, the method should allow its adaptability by the user. To enable the adaptive sharing of tasks between the human and cobot, the tasks need to be visualized by both the agents. The implications (subrequirements) of the requirement "adaptiveness" are elaborated in the section "Task Visualization."

The two objectives, i.e., increasing economic efficiency and improving HF/E, should be achieved by the method. The calculation and visualization of the economic and ergonomic effects of the task sharing are described through task analysis and visualization. The context and implications of the task sharing need to be discussed separately in the Section "Task Assignment." In this case, a task is not considered individually, but the effects of the assignment of a task on the process, which consists of several tasks, are considered. In terms of flexibility, the method should allow adaptiveness regarding fluctuating order sizes and product variations to cope with the markets' mass customization needs. The eight general requirements for the ATS method are summarized in Table 13.

Table 13 General requirements for the adaptive task sharing method.

No.	Requirements for ATS
1	Apply the method in the planning of assembly systems.
2	Apply the method during human–robot interaction.
3	Enable the identification of tasks clearly assigned to humans or robots.
4	Enable the identification of task that could be performed by humans or robots.
5	Increase economic efficiency of the process.
6	Allow flexibility of the assembly system in terms of fluctuating order sizes.
7	Allow flexibility of the assembly system in terms of product variations.
8	Improve human factors/ergonomics.

4.2. Design Principles for the Method

Based on a first proof-of-concept of the method to share tasks adaptively, six design principles were identified to fulfill the eight general requirements for ATS (Schmidbauer, Schlund et al., 2020). During the first iteration of the iterative design science methodology of this thesis, the initial approach of task sharing was demonstrated using an industrial use-case. At this point, the tasks and robot program were only visualized but there was no connection. The preassignment of tasks did not follow an elaborated procedure. To enhance this initial concept, the following six design principles were identified (Schmidbauer, Schlund et al., 2020, pp. 547–548):

1) *"Participatory design: When designing a shared task assembly application, the workers should be explicitly involved in the process to promote motivation and learning at work, and foster acceptance.*
2) *Scaling on demand: The share of human tasks can be flexibly increased or decreased depending on the lot size – with different lot sizes entailing a different task allocation between humans and cobots (i.e., very small and very high but transient lot sizes requiring more manual instead of, or in addition to, automated assembly).*
3) *Dynamic division of tasks: In the case of multi-model or multi-variant assembly processes, workers can flexibly take over tasks that distinguish themselves from one model to another. This helps to simplify and standardize robot tasks while diversifying human tasks.*
4) *Loose coupling between tasks: Workpiece handovers should occur at predefined locations in the assembly workspace. This allows for a more effective bundling of robotic and human tasks to increase productivity.*
5) *Reusable robot tasks: Certificates for applications should be focused on reusable robot tasks, which can be flexibly embedded in a multitude of product variants.*
6) *Robot programming by non-experts: Workers and assembly planners should be involved in the programming of robots in human–robot applications supported by suitable safeguards."*

The mapping of the requirements and design principles are summarized in Table 14. It should be noted that one design principle supports several requirements, for instance, the design principle "reusable robot tasks" supports the planning process of the assembly application and the economic efficiency, as setup costs can be reduced to a minimum. Reusable robot tasks also support classifying tasks in terms of their assignment to the human, robot, or both as a shareable task.

Table 14 Requirements and design principles for the adaptive task sharing method.

No.	Requirements for ATS	Design Principles for ATS
1	Apply the method in the planning of assembly systems.	Reusable robot tasks and loose coupling between tasks
2	Apply the method during human–robot interaction.	Robot programming by non-experts
3	Enable the identification of tasks clearly assigned to humans or robots.	Reusable robot tasks and loose coupling between tasks
4	Enable the identification of task that could be performed by humans or robots.	
5	Increase economic efficiency of the process.	
6	Allow flexibility of the assembly system in terms of fluctuating order sizes.	Scaling on demand
7	Allow flexibility of the assembly system in terms of product variations.	Dynamic division of tasks
8	Improve human factors/ergonomics.	Participatory design

In the following the requirements are elaborated in detail to answer the subresearch questions.

4.3. Requirements and Design Parameters for Task Analysis

In reference to the subresearch question of this work "How to analyze tasks for human–robot teamwork in assembly processes?," the focus lies on defining the individual criteria needed for the task analysis for ATS. To answer the question as whether one task is suitable as a shared task or whether this task should be clearly assigned to the human or robot, different criteria are considered. This leads to the following question: "Which criteria are required to analyze and describe a task sufficiently to identify if it is a shared task or it should be assigned to the human or robot?"

First, the tasks need to be identified for the analysis. The basic requirements of a task must be specified. This includes comprehensiveness (task coverage), ease of use, precision (descriptive power), use in task organization and clarification, and use in task discovery (as a generative method), whereby descriptive power and comprehensiveness were commonly found in literature (Kerracher and Kennedy, 2017). In accordance with the design principle of reusable tasks, similar tasks should be named similarly.

A task evaluation method is proposed that covers technical, ergonomic, and economic aspects. The proposed quality evaluation through an analysis of process variability given by Gualtieri et al. (2020) is presented but not used. If necessary, the method can be included additionally. Table 15 shows the connection of the design parameters for task analysis to the requirements for the method.

Table 15 Requirements and design parameters for task analysis.

No.	Requirements for ATS	Design Parameters for Task Analysis
1	Apply the method in the planning of assembly systems.	Descriptive power and comprehensiveness of definition, simplicity of analysis, and reuse of definitions and evaluations
3	Enable the identification of tasks clearly assigned to humans or robots.	Holistic evaluation of a task in terms of matching skills
4	Enable the identification of task that could be performed by humans or robots.	
5	Increase economic efficiency of the process.	Consideration of economic aspects
8	Improve human factors/ergonomics.	Consideration of ergonomic aspects

4.4. Requirements and Design Parameters for Task Assignment

The subresearch question "how to assign tasks to the human, robot, or "shared tasks" for human–robot teamwork in assembly processes?" is directly related to the task analysis. All aspects from the task analysis, including appropriate skill matching, the economic efficiency of an application and HF/E, such as physical and mental strains, monotony, learning, and job satisfaction aspects should be considered. Part of the tasks needs to be statically assigned based on the task analysis results. However, the goal is to assign most of the tasks on the sharing basis to remain as flexible as possible. To enable loose task coupling and the reconfigurability of the task assignment, tasks should not be aggregated to task groups. Workpiece handovers must be designed during the workplace design phase. Scaling on demand should be enabled by indicating the optimal order/lot size for specific task assignments. The requirements and design parameters for the task assignment are shown in Table 16.

Table 16 Requirements and design parameters for task assignment.

No.	Requirements for ATS	Design Parameters for Task Assignment
1	Apply the method in the planning of assembly systems.	Preassignment of tasks only for those that are not suitable for sharing
2	Apply the method during human–robot interaction.	Calculation of effects of task sharing
6	Allow flexibility of the assembly system in terms of fluctuating order sizes.	
7	Allow flexibility of the assembly system in terms of product variations.	
8	Improve human factors/ergonomics.	Preassignment of tasks only for those that are not suitable for sharing

4.5. Requirements and Design Parameters for Task Visualization

To enable human–robot teamwork, tasks need to be transparent to both agents. The subresearch question “how to visualize the human–robot tasks for both the human and robot?” needs to be answered. The main functionality is, therefore, the visualization of the tasks for all agents. The allocation of tasks to one agent should be visualized, and the sequence of tasks is a necessary function. In the course of the research process, a first mockup of the UI was developed. This UI displayed the functions (Figure 22) but was not connected to the robot, which would have resulted in extra work and high synchronization effort.

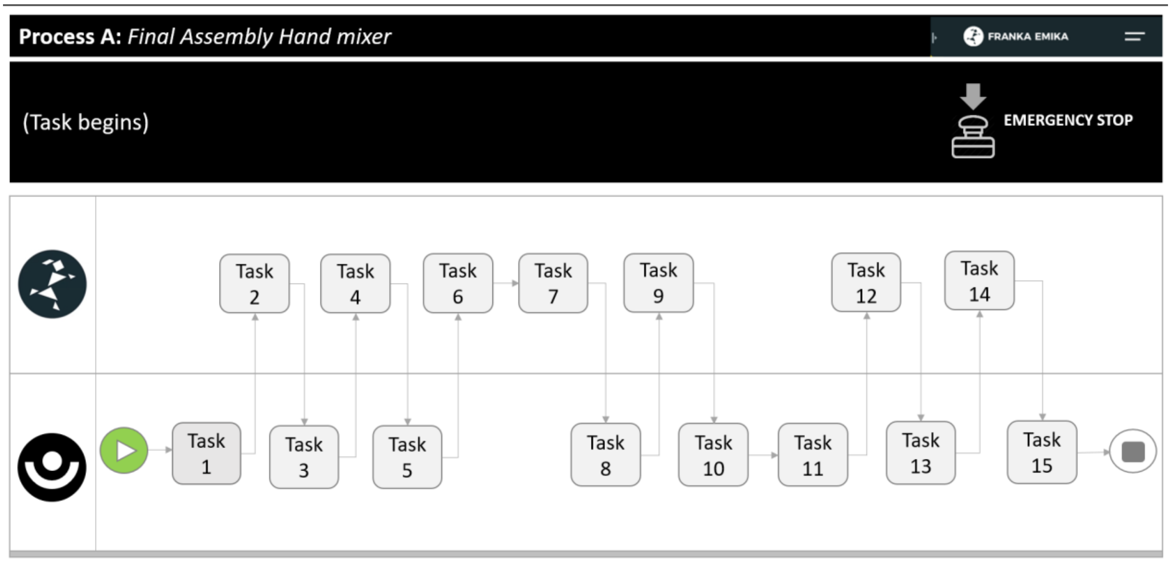

Figure 22 First draft of UI visualizing human–robot tasks for ATS (own figure).

Therefore, one requirement for the task visualization interface is that it should be connected online to the robot’s software. In addition, the method should provide high usability as well as easy and fast implementation. To enable participatory design and robot programming by non-experts, the method should be easy to use and should not unnecessarily increase the workload of workers. In other words, the method should assist the workers, not hinder them. The five design parameters for the task visualization method are shown as follows (Schmidbauer et al., 2021, p. 2):

1) *"Visualization of the ATS model – visualize the human, robot, and shareable tasks,*
2) *Visualization of sequence of tasks,*
3) *Online connection to robot software,*
4) *Positive productivity impact – easy and fast to implement, and*
5) *Human factors – easy to understand and useful for non-professionals."*

Table 17 shows the connection of these design parameters for task visualization to the requirements for ATS.

Table 17 Requirements and design parameters for task visualization.

No.	Requirements for ATS	Design Parameters for Task Visualization
2	Apply the method during human–robot interaction.	Visualization of the human, robot, and shareable tasks, visualization of the sequence of tasks, and online connection to robot software
5	Increase economic efficiency of the process.	Easy and fast implementation
8	Improve human factors/ergonomics.	Easy to understand and high usability for non-professionals

4.6. Summary of Requirements and Design Parameters

This section shows the requirements for the methods according to design parameters and a reference to the method's part (Table 18). In the next section, the ATS method is described considering the elaborated requirements and design parameters.

Table 18 Requirements and design parameters of the adaptive task sharing method.

No.	Requirements for ATS	Part	Design Parameters for ATS
1	Apply the method in the planning of assembly systems.	Analysis and assignment	Descriptive power and compre-hensiveness of definition, simplicity of analysis, reuse of definitions and evaluations. Preassignment of tasks only for those that are not suitable for sharing.
2	Apply the method during human–robot interaction.	Assignment and visualization	Calculation of effects of task sharing, visualization of the human, robot, and shareable tasks, visualization of the sequence of tasks, and online connection to robot software.
3	Enable the identification of tasks clearly assigned to humans or robots.	Analysis	Holistic evaluation of a task in terms of matching skills.
4	Enable the identification of task that could be performed by humans or robots.		
5	Increase economic efficiency of the process.	Analysis and visualization	Consideration of economic aspects and easy and fast implementation.
6	Allow flexibility of the assembly system in terms of fluctuating order sizes.	Assignment	Calculation of effects of task sharing.
7	Allow flexibility of the assembly system in terms of product variations.		
8	Improve human factors/ ergonomics.	Analysis, visualization, and assignment	Consideration of ergonomic aspects, preassignment of tasks only for those that are not suitable for sharing, easy to understand, and high usability for non-professionals.

5. ADAPTIVE TASK SHARING

In this section, the ATS method is described. The procedure of the method (Figure 23), frames the following explanations and consists of three main parts with eight substeps. The sequence of the procedure must be followed. Each part is described with its substeps in the next sections.

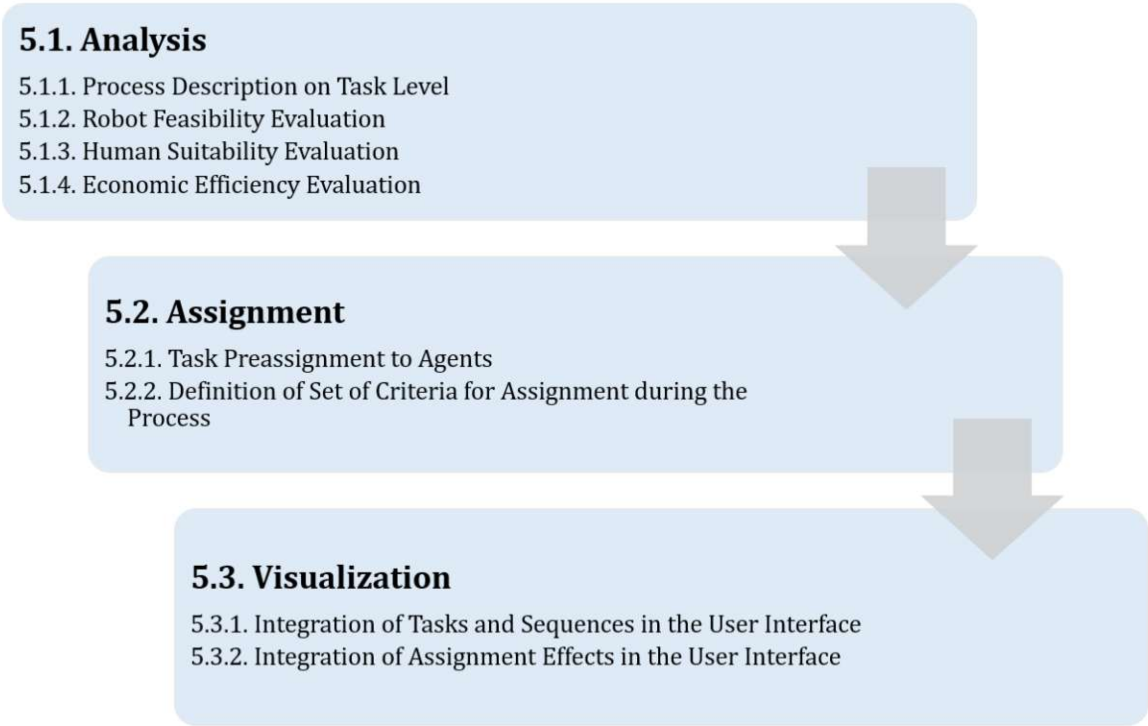

Figure 23 Procedure of the adaptive task sharing method (own figure).

5.1. Task Analysis for ATS

The first part of the ATS method is the task analysis. As presented in Section 3.2, there are different methods to analyze and evaluate assembly tasks:

1. Hierarchical task analysis
2. Task terminology standards
3. Predetermined time method systems
4. Task evaluation by capability and human factors assessment

Prior to the evaluation, the process must be defined and described with its tasks. Afterward, the tasks are analyzed considering their feasibility of automation by means of a cobot. Then, a human suitability evaluation regarding the HF/E is investigated. Finally, an economic efficiency evaluation of the possible assignments of the task to a human or cobot is analyzed. All substeps of the task analysis are described in the following.

5.1.1. Process Description on Task Level

First, the assembly process must be recorded. Different methods are available to record processes; however, this is not within the scope of this work. The process recordings and documentations are the input for further task analysis. Ideally, the processes are mapped using MTM-UAS that allows using this documentation for further analysis.

To describe a task, the method proposed by Lotter and Wiendahl (2012) is selected because it covers different standards and provides descriptive power and comprehensiveness by a large population. The terminology combines three respected standards, the DIN 8580 for manufacturing processes, the DIN 8593-0 for joining functions, and the VDI 2860 for handling functions and additional tasks called special operations. Moreover, the method can be easily applied on a suitable level of detail. In comparison, the method by Sørensen et al. (2018) provides a great depth of detail, which is not necessary to enable ATS, and requires more effort in the definition phase; thus it is not applied.

5.1.2. Robot Feasibility Evaluation

It is assumed that the process can be performed by a human. First, criteria concerning the feasibility of a robotization F must be considered. Gualtieri et al. (2020) elaborated the main feeding, handling, and assembly critical issues based on the guidelines by Boothroyd et al. (2010). Gualtieri et al. (2020) listed and assessed 25 critical issues that are summarized in Table 19. Because the list given contains 25 issues, the evaluation is time-consuming. To enable a fast and less expensive evaluation process, these criteria are summarized into three questions that can be answered with Yes/No. The following questions can be asked to evaluate the robot feasibility:

1. Are there any unsolvable issues while picking or grasping the part with the robots' gripper or tool? (Graspability g)
2. Are there any unsolvable issues while manipulating (moving, releasing, assembling etc.) the part with the robot? (Critical issues u)
3. Are there any unsolvable issues with the spatial reachability of the robot? Can the task not be completed in the working zone of the robot? (Spatial reachability r)

Table 19 Summary of critical issues in cobot automation by Gualtieri et al. (2020).

	The component ...
Feeding	Is magnetic, sticky, a nest or tangle.
Handling	Has no symmetry axis, is fragile, delicate, flexible, very small/big, too light, or slippery.
Assembly	Has no reference surface or base part, cannot be easily oriented, does not self-align, cannot be located before release, provides resistance to insertion, does not provide chamfers or tapers to guide and position the parts in correct position, and cannot be assembled from directly above.

In addition, two questions need to be answered. The first question covers the maximum payload of a robot, which is not directly covered by the questions presented by Gualtieri et al. (2020). Michalos et al. (2018) added the criterion weight, which is critical for cobots, because it is a technical restriction that must be met. The following question can be asked:

4. Is the part heavier than the maximum payload of the robot? (Payload p)

Another question regarding the feasibility is the human safety. The criterion safety is introduced, although safety is a separate topic in HRI, standardized by the DIN ISO/TS 15066, and is not comprehensively considered in this work. Malik and Bilberg (2019a) raised two questions regarding the additional risk of tools (sharp edged and pointed tools) and collisions in the head/neck area. The question aimed at whether, when an HRI workspace is implemented, the task could introduce new risks that are not covered by the existing measures. If this is the case, the tasks should be taken over by a human:

5. Does the robot's execution of the task raise risks of collision with the human? (Safety y)

These five questions can be answered with Yes (1)/No (0) (binary variables). If a question is answered as Yes (1), the robotization feasibility cannot be ensured and the task should be assigned to the human worker H. If the question is answered as No (0), the task should be assigned to the shareable/shared tasks B, which means that the task can be assigned later in the process. All decision criteria for the robot feasibility evaluation are shown in Table 20.

Table 20 Decision criteria for robot feasibility evaluation.

Decision Criteria	Explanation	Unit	Symbol
Robot feasibility check	If one of the values is below 1, the task is assigned to the human *H*, otherwise it is a shared task *B*.	0–5 (0: shared tasks, ≥ 1: human)	F
(Spatial) Reachability	If the task can be completed in the robot's working zone, the value is 0, otherwise 1.	0, 1 (0: shared tasks, 1: human)	r
Payload	If the part to be handled is lighter than the maximum payload of the robot, the value is 0, otherwise 1.	0, 1 (0: shared tasks, 1: human)	p
Graspability	If the part to be handled has a suitable contact surface to be picked up (grasped) and moved by the robot, the value is 0, otherwise 1.	0, 1 (0: shared tasks, 1: human)	g
Critical issues	If the part can be manipulated (moved, released, and assembled) by the robot, the value is 0, otherwise 1.	0, 1 (0: shared tasks, 1: human)	u
Safety	If the task, despite safety measures, raises no risk of collision with a human this value is 0, otherwise 1.	0, 1 (0: shared tasks, 1: human)	y

5.1.3. Human Suitability Evaluation

A basic feasibility of the task by a human is assumed; however, the suitability E must be described. One chosen criterion is the physical ergonomics, which is mentioned and evaluated by several authors in the literature. A simplified version is provided by Michalos et al. (2018), who introduced the part's weight limit of 23 kg that should not be exceeded. A more comprehensive evaluation of physical ergonomics is pursued. The quality of a physical ergonomics evaluation highly depends on the available data. If no simulations or actual evaluations on the living object are available, a simple evaluation can be performed using RULA. RULA is particularly well suited for tasks at assembly workplaces. For other tasks, another method might be more suitable; see Section 2.2.3.

RULA evaluation results in a score ranging from 1 to 7 (1–2: current state is acceptable, 3–4: change should be undertaken, 5–6: change should be undertaken soon, and 7: changes are needed immediately). It can be assumed that tasks with scores equal to or higher than 5 should be assigned to the robot (or should be changed otherwise). Here, a maximum of 5 is the threshold for a RULA assessment. Other maximum thresholds can be applicable (Table 21).

Available data must also be considered regarding cognitive ergonomics. A simple assessment is the NASA-raw-TLX, which consists of six questions. However, it is usually used to evaluate existing processes within user studies. These user studies are rarely feasible for single tasks. Similar limitations are applicable to CLAM. The focus of the cognitive ergonomics evaluation should therefore lie on the incorporation of variables to reduce monotony and increase job satisfaction and learning opportunities. To promote motivation and learning at work and foster acceptance, one of the design requirements is participatory design. This requirement can be enabled by the workers themselves, thus, retaining the decision-making power over the task assignment process. The system should transparently inform the workers about the feasibility as well as the effects on the physical ergonomics and economic efficiency of the tasks to provide assistance in decision-making. This should also avoid cognitive overload or unreasonable decisions.

Table 21 Decision criteria for human suitability evaluation.

Decision Criteria	Explanation	Unit	Symbol
Physical Ergonomics	If the score is higher or equal than the threshold, the task is assigned to the robot *R*, otherwise it is a shared task *B*.	Score	E

5.1.4. Economic Efficiency Evaluation

Referring to scaling on demand, economic efficiency needs to be calculated for different quantities of parts to be produced. Different cost factors affect the economic efficiency. The following calculations are simplified and do not include interests or opportunity costs.

First, the human costs of task execution need to be known. If these are not known, they can be calculated simply by multiplying the hourly cost rate (c_H) and execution time in seconds (t_H). The cost rate is estimated from the total costs of an average worker in relation to time, usually expressed in 1 year or 1 hour. The average labor costs in manufacturing are € 38.04/h (Labour Cost Index Austria, 2019). Depending on the industry, country, and company, this amount may vary. In addition, costs for extra shifts should be considered. The execution time can be calculated via MTM-UAS. MTM-UAS corresponds most closely to the definition of the tasks, and therefore, it can be used as a calculation method. The costs per part (c_{PH}) are calculated as follows (1 h = 3600 s):

$$c_{PH} = \frac{c_H * t_H}{3{,}600}$$

Then, the costs of robotization must be calculated. The hourly cost rate of a cobot c_R includes the yearly depreciation of the investment and operating costs (power consumption, maintenance costs, etc.) (Cohen et al., 2021). Assuming the purchasing cost of a robot is € 100,000 and if it runs in two shifts of 8 h/day, 240 days/year, for 5 years, the robot's hourly cost is € 5.21. Additional, average electricity costs result in a sample hourly cobot cost rate of € 6. The execution time in seconds t_R can be determined through methods such as MTM for HRI (Schröter, 2018), within robot simulations of the task, or using time stopping. Time stopping can be applied in cases where the cobot task is already implemented and programmed. In all cases, path and speed optimization must be considered because they significantly influence the execution time. In addition, robot costs must include setup costs (c_{setup}) for the specific task setup, such as the programming time of the robot for task execution and other direct task-specific costs, e.g., required provision of a specific tool.

To break down these setup costs, the repetition rate f of a task is needed. The repetition rate is, for instance, the lot/order/batch size and should be determined by asking "how often will this task be needed?" A division can be used to determine the proportional setup costs. The costs per part (c_{PR}) are calculated as follows:

$$c_{PR} = \left(\frac{c_R * t_R}{3600}\right) + \frac{c_{setup}}{f}$$

To identify the most time-efficient task execution t_{opt}, the different execution times per task are compared. If t_R is bigger than t_H, the task should, from a temporal point of view, be assigned to the human or vice versa. The sum of all minimal execution times t_H and t_R of all tasks from $i = 1$ to n is calculated as follows:

$$t_{opt} = \sum_{i=1}^{n} \min(t_{H,i}, t_{R,i})$$

To identify the most cost-efficient task execution c_{opt}, the different costs per part are compared. If c_{PR} is higher than c_{PH}, the task should, from an economic point of view, be assigned to the human vice versa. The sum of all minimal execution costs c_H and c_R of all tasks from $i = 1$ to n is calculated as follows:

$$c_{opt} = \sum_{i=1}^{n} \min(c_{H,i}, c_{R,i})$$

As the costs highly depend on the variable f, the turning point f_{opt} at which the most cost-efficient task execution agent changes should be identified. This optimal repetition rate is calculated as follows:

$$f_{opt} = \frac{3600 * c_{setup}}{t_H * c_H - t_R * c_R}$$

All variables related to the economic efficiency are summarized in Table 22.

Table 22 Variables for economic efficiency calculation.

Variable	Explanation	Unit	Sym.
Hourly costs human	An average hourly cost of human work should be taken, if the real numbers are not available.	€	c_H
Hourly costs robot	An average hourly costs of robot usage should be taken, if the real numbers are not available.	€	c_R
Execution time human	The durations of the execution are calculated or recorded.	s	t_H
Execution time robot	The durations of the execution are calculated or recorded.	s	t_R
Setup costs	If, in addition to the robot and standard gripper, other tools, or fixtures are required, the costs must be estimated/calculated. Setup costs also include the programming/hand guiding time of the robot, if the task is not already available as a reusable task.	€	c_{setup}
Repetition rate	The repetition rate must be known (e.g., lot size), calculated or estimated. The question to be answered is "how often will this task be needed?"	con-stant	f
Setup costs/repetition rate	The setup costs must be set in relation to the repetition rate.	€	c_{setup}/f
Costs per part human	The cost of one part produced by human.	€	c_{PH}
Costs per part robot	The cost of one part produced by robot.	€	c_{PR}
Fastest, most time-efficient process	The sum of all optimal execution times, i.e., the shortest process execution time yielded by either a human or robot.	s	t_{opt}
Cheapest, most cost-efficient process	The sum of all optimal task execution costs, i.e., the most cost-efficient process execution costs yielded by either a human or robot .	€	c_{opt}
Lot size from which robotization is more cost-efficient	The repetition rate from which robotization of this task is more cost-efficient than a manual execution.	con-stant	f_{opt}

Based on this comprehensive task analysis, tasks are preassigned to the agents. This is explained in detail in the following section.

5.2. Task Assignment for ATS

Humans H and robots R are agents A in the work system. The objective of the task assignment in the process design phase is to provide the human a maximum number of shareable tasks to ensure high flexibility. Not all tasks n should be left to humans to assign to an agent. This would involve a great effort as possible variations are calculated through the formula:

$$A^n$$

For example, if six tasks have to be assigned to the two agents, there are 64 possibilities ($2^6 = 64$). Because some task allocation variants are not feasible, a preassignment of tasks to the agents is foreseen.

5.2.1. Task Preassignment to Agents

One task *i*, which is evaluated regarding its robot feasibility *F*, is preassigned to either the human agent *H* or the so-called shareable task set *B*. The consideration of the robot feasibility *F* evaluation with its five subcriteria (*r, p, g, u,* and *y*) can be depicted in the following algorithm:

$$\boldsymbol{IF}$$

$$r \ == 0 \ \boldsymbol{AND} \ p \ == \ 0 \ \boldsymbol{AND} \ g \ == 0 \ \boldsymbol{AND} \ u \ == 0 \ \boldsymbol{AND} \ y \ == 0$$

$$\boldsymbol{THEN}$$

$$B$$

$$\boldsymbol{ELSE}$$

$$H$$

$$\boldsymbol{ENDIF}$$

After that first preassignment, shareable tasks can be preassigned to the robot if the human suitability evaluation reveals insufficient results in terms of ergonomics. The human suitability evaluation is considered by means of the following algorithm:

$$\boldsymbol{IF}$$

$$E \ \geq \ threshold$$

$$\boldsymbol{THEN}$$

$$R$$

$$\boldsymbol{ELSE}$$

$$B$$

$$\boldsymbol{ENDIF}$$

All remaining tasks are seen as shareable tasks in the task set *B*.

5.2.2. Definition of Set of Criteria for Assignment during the Process

The criteria aim to present decision proposals for the worker. They support the worker in the decision-making process by reducing the decision space. However, the suggestions of the system are not binding, i.e., the worker can also decide against the suggestions. Based on the requirements for the ATS method, criteria aimed at improving human factors are selected for assignment.

5.2.2.1. Learning

In the context of assembly processes, the learning objectives generally consist of fast and correct (error-free) execution of a task. The learning or training duration to achieve the performance in terms of task execution time is described by the learning curve (Jeske et al., 2014). The learning curve describes a reference or a limit value *c* to be achieved for the execution time of a task (Figure 24). The specified reference value must be greater than the execution time according to MTM-UAS because this is the limit value of the mathematical model. A company-specific or task-specific acceptance level (*xc*) must be defined individually. The number of iterations, i.e., the training necessary to achieve this performance, depends on several factors. Jeske et al. (2014) identified these factors as the influence of the work task (such as complexity), the influence of the learning method (such as the method of instructions), and the influence of the worker (such as previous experience). A method and tool used for predicting learning times based on information-theoretical entropy are presented by Jeske et al. (2014).

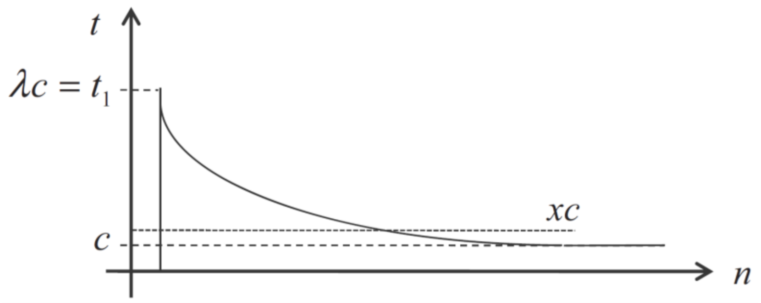

Figure 24 Learning curve with the initial execution time t_1 as multiple λ of the limit value c, the learning rate k, and acceptance level xc (Jeske et al., 2014, p. 180).

The ATS method considers the learning ability of a worker: When a new task is introduced to a worker, they should first perform the task until they reach the reference value xc. This means that if a task is new to a worker, it automatically becomes a human task and only becomes shareable after the worker's training phase. This should enable workers to know how to execute new tasks. The consideration of the learning aspect of the human workers is depicted in the following algorithm:

$$\boldsymbol{IF}$$

$$t_H \geq \mathrm{xc}$$

$$\boldsymbol{THEN}$$

$$H$$

$$\boldsymbol{ELSE}$$

$$B$$

$$\boldsymbol{ENDIF}$$

5.2.2.2. Task Diversity

Learning new skills and building knowledge are based on monotonous task execution. However, monotony has negative effects on the human worker (Section 2.2.5). Therefore, task diversity is of high relevance for the human wellbeing (Hacker and Sachse, 2014). Literature presents questionnaires asking about task diversity, for example, the WDQ by Morgeson and Humphrey (2006) asks, inter alia, the following four questions:

1. The job involves a great deal of task variety.
2. The job involves doing a number of different things.
3. The job requires the performance of a wide range of tasks.
4. The job involves performing a variety of tasks.

However, such questions are asked during or after the task execution. Holism and task diversity are recommended (Hacker and Sachse, 2014), but there are no instructions or precise specifications. For instance, the relationship between repetition rate, task variety, and job duration is not mathematically described. Therefore, a suggestion system is proposed for the implementation of this aspect. After the worker has fulfilled the criteria "learning" and reached the respective execution time, the worker is asked whether the existing task assignment is considered pleasant, or it should be changed. Depending on what occurs first, e.g., every 15 min or after 10 iterations, the Yes/No question "*Does the task variety of the current task assignment correspond to your desired way of working?*" is shown as a pop up on the worker assistance system's UI. If the worker clicks on "*Yes*," the assignment remains. If the worker clicks on "*No*," a prompt box "*Please reassign the tasks*" pops up. Then, the worker can reassign the tasks. This should serve as a reminder for the worker. But the worker can also change the task assignment without this pop up, as described in the next section.

5.2.2.3. Job Satisfaction and Workers' Preferences

Human factors research sees a correlation between self-determined work content and job satisfaction. Particularly, work scheduling and decision-making autonomy correlate significantly with workers' satisfaction (Hacker and Sachse, 2014; Morgeson and Humphrey, 2006). Tausch et al. (2020) showed a model of the psychological effects of the self-determined decision-making of task allocation (Section 2.2.8). Results of studies in which participants were allowed to assign tasks to either themselves or a robot have not revealed naturally preferred allocation solutions. Participants tend to assign more tasks to the robot, than to themselves, but other patterns were not identified (Gombolay et al., 2015; Tausch and Kluge, 2020; Wiese et al., 2021).

Therefore, the ATS method does not give recommendations in terms of task assignment but leaves this decision open to the human worker. The workers can assign tasks to themselves or to the robot according to their preferences. In this way, individual preferences and individual development opportunities can be applied. Tasks that workers do not like to do themselves can be delegated to the robot. This option is provided in the worker assistance system's UI.

5.3. Task Visualization for ATS

Fulfilling the task visualization requirements, this section describes how tasks, sequences, and assignment effects are integrated and visualized in a digital worker assistance system's UI. A digital worker assistance system is a tool that helps the worker concentrate on their essential core competencies (Hader, 2021).

5.3.1. Integration of Tasks and Sequences in the User Interface

To develop the visualization method, existing approaches were presented in Section 3.3. In the following section, a suitable method for task sharing is selected. One important requirement of the method is that all tasks, including human and shareable tasks, can be visualized. EPC, AND/OR graphs, precedence graphs, and behavior trees lack this functionality of representing different agents in an appropriate way. Therefore, the methods are not applicable for human–robot task sharing. Petri nets are difficult to understand for non-professionals and require a long training period. Thus, an additional interface is necessary, so that the human coworkers can understand the processes and tasks. Therefore, the method is not suitable. Nevertheless, UML is primarily useful for modeling software systems. Although it is also possible to model different agents, visualization lacks clear assignment of tasks. In contrast, BPMN is process-oriented and provides a framework to visualize assignments of tasks to different agents and the sequence of tasks clearly.

Table 23 shows the comparison of the degree of fulfillment of the design parameters for the methods. The comparison reveals that BPMN is the best applicable method, enabling the implementation of all design parameters of task visualization.

Table 23 Degree of fulfillment of design parameters for the methods in comparison (0 = not fulfilled, 1 = fulfilled, and 2 = well fulfilled).

Method	**Visualization of human, robot, and shareable tasks**	**Visualization of sequence of tasks**	**Online connection to robot software**	**Easy and fast implementation**	**Easy to understand and high usability**	**Sum**
UML	2	1	2	1	1	7
BPMN	**2**	**2**	**2**	**2**	**2**	**10**
EPC	0	1	2	1	1	5
Petri nets	1	1	2	1	0	5
AND/OR graphs	0	1	2	0	0	3
Precedence graphs	0	1	2	0	0	3
Behavior trees	0	2	2	1	1	6

The implementation of the method in a worker assistance system was enabled through a four-part system architecture (Figure 25). For BPMN representation, the open source BPMN engine by Camunda (2021) was deployed. The engine was connected to the web-based proprietary UI called “Desk” of the cobot Panda by Franka Emika via REST API (representational state transfer application programming interface). This approach is generally applicable to other robots that are accessible via an external Node.js task client. The design and functions of the worker assistance system are described in detail by Hader (2021). The UI consists of three areas: first, the work area with a tool palette to model the tasks and processes; second, the settings for service (robot) tasks and instructions for user tasks; and third, the start and stop button (Figure 26).

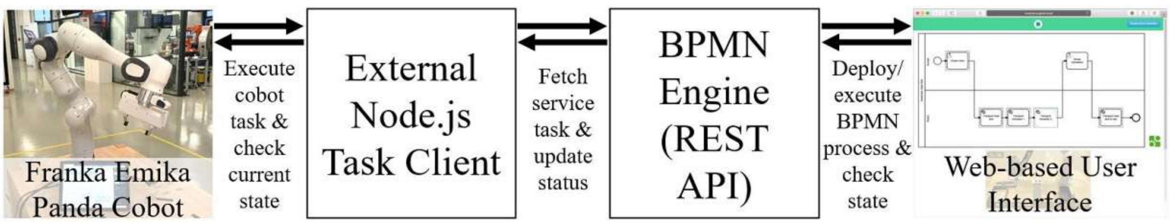

Figure 25 System architecture (Schmidbauer et al., 2021, p. 3).

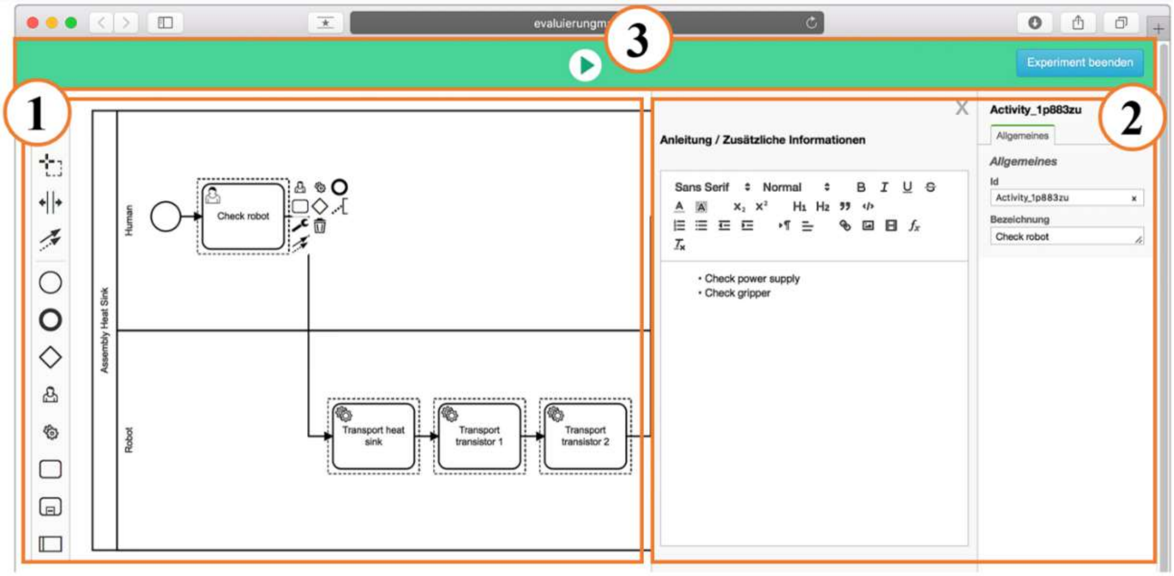

Figure 26 UI with its three areas: (1) work area with tool palette, (2) settings for service tasks and instructions for user tasks, and (3) start and stop button (Schmidbauer et al., 2021, p. 3).

Figure 26 shows two lanes for both human and robot tasks. The final UI was extended with a third lane "Human or Robot" for the shareable tasks (Figure 27). In the beginning of a process, all tasks that are preassigned to one agent are in the respective lane and all others are in the lane "Human or Robot." These shareable tasks must be assigned to one of the other lanes before the process execution can start. The assignment is enabled via a simple drag and drop function, i.e., a task can be easily moved from one lane to another. The control (software) of the robot is connected to the system via so-called service tasks. The robot cannot be programmed via the UI, but the individual robot programs can be run via service tasks.

The play button on the top triggers the first task of the process. If the first task of the process is a robot (service) task, the robot starts executing the task immediately after the worker clicks on the play button. The play button functions as a stop button during the process.

A green frame highlights the active task. In this way, the worker knows the task in the process they are working on. In the case of handovers, i.e., when the worker has finished a task and the robot is to continue, the worker has to click on the task to indicate it is completed. The robot then continues.

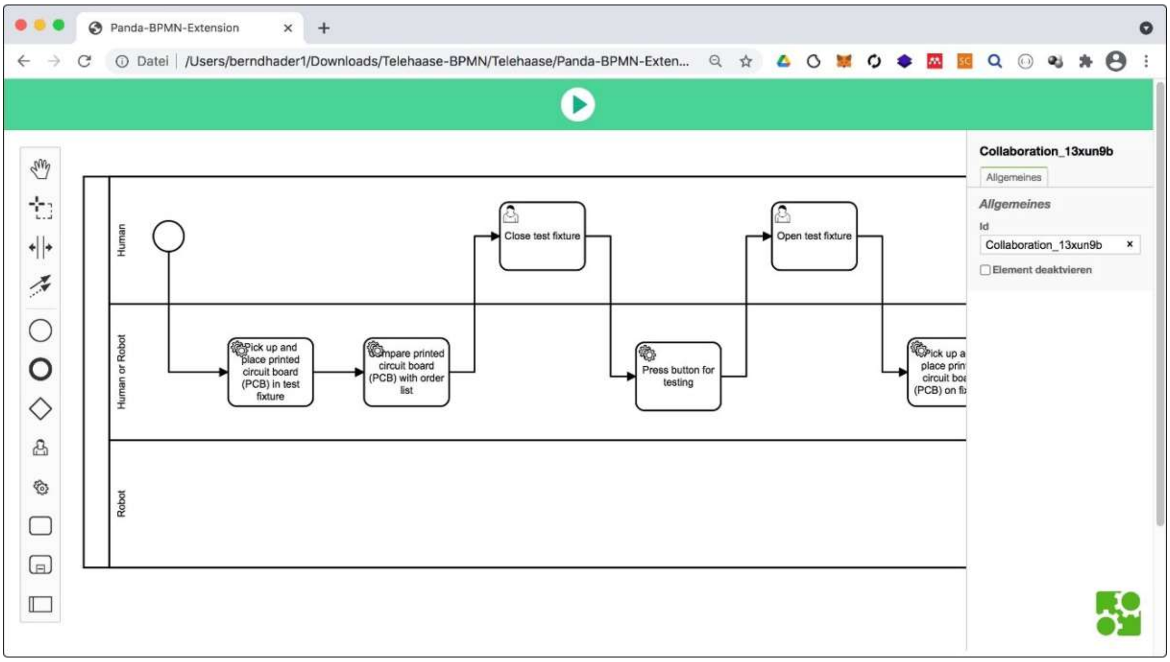

Figure 27 UI of worker assistance system with extended work area consisting of three lanes (own figure).

5.3.2. Integration of Assignment Effects in the User Interface

To support the human in the decision-making process, some tasks are preassigned. For the other tasks, key performance indicators (KPIs) are visualized on a dashboard on the worker assistance system's UI to make the effects of the assignment apparent. These KPIs refer to the economic efficiency, particularly, the required process time and costs as well as the ergonomic effects.

Regarding the economic aspects, the process time of the human, robot, and total process time are displayed on the dashboard. These can be compared with the most cost- and time-efficient process variants. This allows the worker and the management to have an overview of the process time and costs of the selected task allocation.

Regarding the ergonomic aspects, it is beneficial to know the physical stress caused by the individual tasks and total process. In this way, unfavorable strains can be reduced.

In practice, changes due to the assignment of a task are automatically calculated and displayed on the UI. Thus, calculations from the task analysis are implemented in the worker assistance system (Figure 28). In this way, the worker can keep an overview of the effects of their decisions.

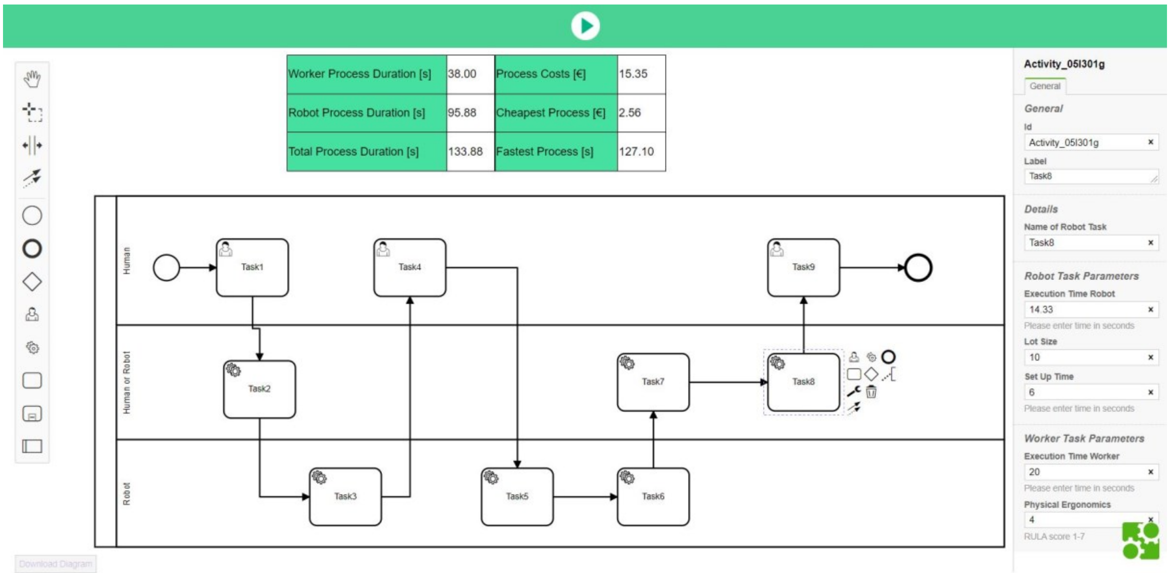

Figure 28 UI of worker assistance system including dashboard for key performance indicators (own figure).

In the following section, the implementation and evaluation of the described method and worker assistance system are discussed.

6. IMPLEMENTATION AND EVALUATION

During the method development, example use-cases from the electronics manufacturing industry were used for demonstrations and evaluations. As the highest proportion of assembly time can be found in the electrical and precision manufacturing, use-cases from the electronics industry were used to exemplify the potential of human–cobot interaction (Lotter and Wiendahl, 2012). To investigate a variety of tasks on the one hand and to get closer to a generalization of the method on the other hand, two different use-cases were selected and evaluated. The considerations for the method development were not limited to electronics manufacturing but extended to other manual assembly workplaces. The evaluations presented are each explained, summarized, and discussed. This section ends with a discussion of the ATS method including its limitations.

6.1. Use-Case I: Assembly of a Heat Sink

The first industrial example use-case is the assembly of a heat sink. The heat sink is one component of a power supply unit for standard applications. It is developed and produced by SIMEA—an electronics manufacturing division of Siemens AG in Austria. The manual assembly process was transferred to a hybrid human–cobot assembly demonstrator in the Pilot Factory for Industry 4.0 at TU Wien (Figure 29). A Franka Emika Panda cobot was used. The demonstrator was deployed to verify the feasibility of the explained concept and investigate the effects on productivity and profitability. Moreover, the task visualization approach was evaluated using the use-case as an example for modeling the process. All results deploying the use-case are published by Schmidbauer, Schlund et al. (2020) and Schmidbauer, Hader, Schlund (2021).

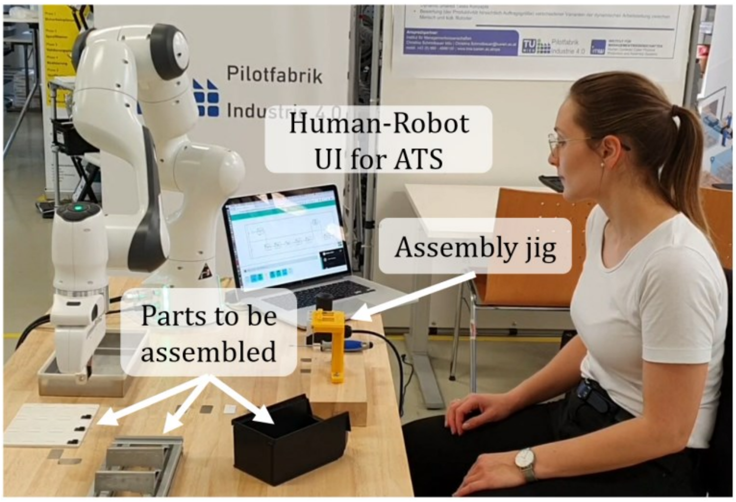

Figure 29 Use-case I "assembly of a heat sink" demonstrator in Pilot Factory for Industry 4.0 at TU Wien (based on Schmidbauer, Schlund et al. (2020)).

6.1.1. Task Analysis

Task analysis performed for use-case I is explained below.

6.1.1.1.Process Description on Task Level

The sample process consists of a few simple steps. The objective is to assemble four transistors (Figure 30-II) on a complex shaped metal heat sink (Figure 30-I) by means of four screws. Figure 30 shows the process steps in a picture story, where the last picture (Figure 30-VI) shows the result. Due to the shape of the heat sink, an assembly jig or fixture is necessary for convenient assembling.

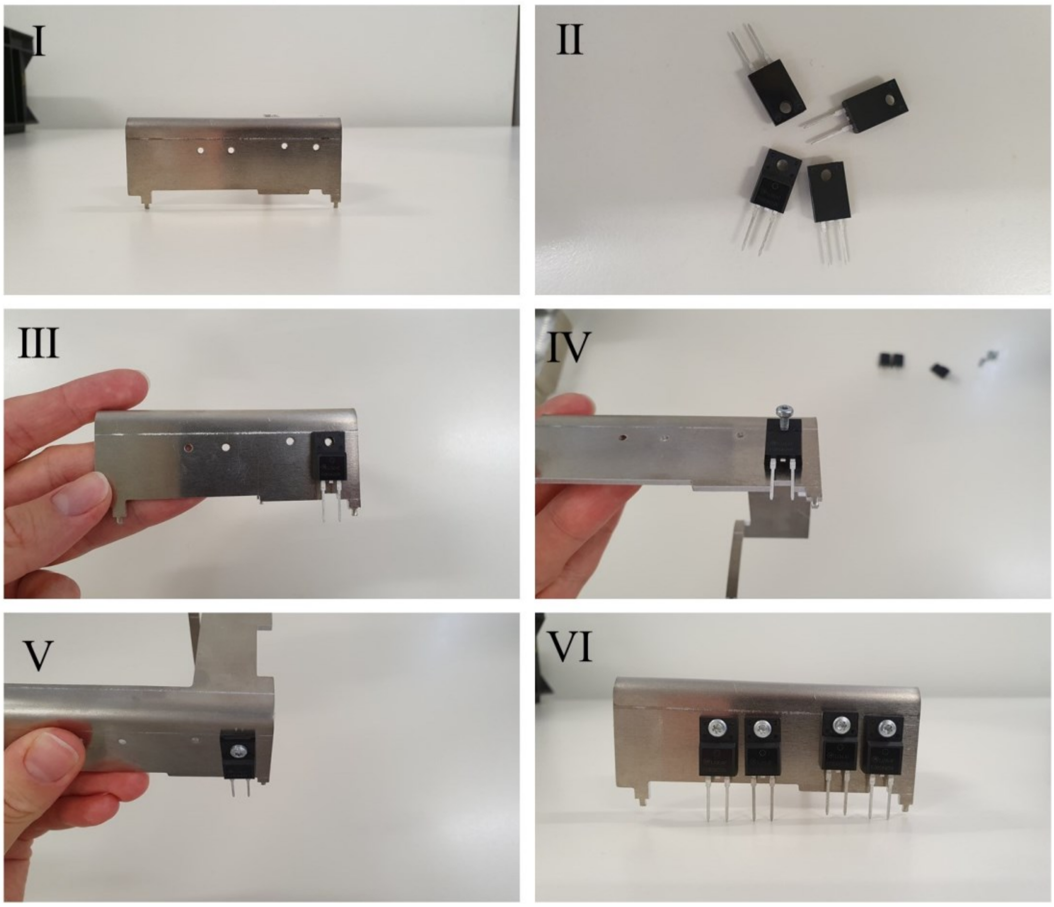

Figure 30 Steps to assemble a heat sink in a picture story I–VI (own figure).

Table 24 shows the assembly functions by Lotter and Wiendahl (2012) applied to the example. Some functions were combined because they are executed in one go without additional handover.

Table 24 Assembly functions applied to use-case I "assembly of a heat sink."

No.	Task	Assembly Function	Function specified
1	Moving heat sink to assembly jig & putting together heat sink and assembly jig	Handling & joining	Moving & putting together
2	Close assembly jig	Handling	Moving
3	Moving transistors to heat sink & putting together transistors and heat sink	Handling & joining	Moving & putting together
4	Moving screws to transistors & putting together screws and transistors	Handling & joining	Moving & putting together
5	Move screwdriver to assembly jig	Handling	Moving
6	Pressing transistors to heat sink (screw bolt to join transistor and heat sink)	Joining	Putting together
7	Move screwdriver to holder	Handling	Moving
8	Opening assembly jig	Handling	Moving
9	Storing heat sink on storage system	Handling	Storing

6.1.1.2. Robot Feasibility Evaluation

The technical feasibility of the execution of the tasks was verified for all tasks in theory and simulation. Due to limitations of the experimental setup, tightening of the screws has not been implemented in practice. Table 25 shows that all criteria, such as spatial reachability, payload, graspability, critical issues, and safety, are met.

6.1.1.3. Human Suitability Evaluation

For the HF/E evaluation, RULA method was used. The assessment was realized through a simulation in a process simulation tool[12] (Figure 31). A different robotic arm was used for the simulation because the system only allows robots with a maximum degree of freedom of six axes. However, this has no effect on the ergonomics evaluation of the human. The simulation shows that one motion has negative effects on the human's ergonomics. When the (virtual) human takes the screw from the dispenser, results show a RULA score of 5 for the left arm and 7 for the right arm. This concerns the task 4. It should be noted that a screwdriver with an automated screw feed could also solve this ergonomic problem. The detailed ergonomics evaluation is documented by Cristea (2020).

[12] Tecnomatix Process Simulate 15.0

Figure 31 Virtual HRI workplace in Tecnomatix Process Simulate 15.0 (own figure).

6.1.1.4.Economic Efficiency Evaluation

The economic efficiency of the process is evaluated based on MTM-UAS for the manual tasks, and recorded execution times for the robot tasks. The human needs 43.78 s to assemble one heat sink manually and the cobot needs 78.51 s. The cobot is slower is due to speed limitations to ensure the safety of the human. The optimal repetition rates f_{opt} (lot size from which automation is more cost-efficient) were calculated for each task. The example calculations exhibit that task 3 should be assigned to the cobot. The calculations also reveal that some tasks have no costs assigned for the cobot, e.g., 2, 4, and 8. The reason for this is that the cobot executes the tasks in a slightly different way than the human. Therefore, some movements are either not necessary for the robot, or they are included in some other tasks. Tasks 2 and 8 are included in other tasks and for task 4, the assumption was made that an automatic screw feeder is available for the robot. Because task 4 has negative effects on the human ergonomics additionally, an automatic screw feed is recommended.

6.1.1.5.Task Analysis Summary

Table 25 shows the results of the task analysis of all tasks of use-case I.

Table 25 Task analysis summary use-case I “assembly of a heat sink.”

Criteria	Sym.	Tasks Use-Case I								
		1	2	3	4	5	6	7	8	9
Robot Feasibility Check *F*										
(Spatial) Reachability	r	0	0	0	0	0	0	0	0	0
Payload	p	0	0	0	0	0	0	0	0	0
Graspability	g	0	0	0	0	0	0	0	0	0
Critical issues	u	0	0	0	0	0	0	0	0	0
Safety	y	0	0	0	0	0	0	0	0	0
Physical Ergonomics *E*										
RULA score		<5	<5	<5	>5	<5	<5	<5	<5	<5
Economic Efficiency Evaluation										
Hourly costs human [€]	c_H	38.04								
Hourly costs robot [€]	c_R	6.00								
Execution time human [s]	t_H	2.52	.72	15.84	15.12	1.98	4	1.26	.72	1.62
Execution time robot [s]	t_R	8.06	0	46.28	0	8	4	6	0	6.17
Setup costs [€]	c_{setup}	6.34	0	6.34	0	3.17	6.34	3.17	0	3.17
Repetition rate	f	100								
Setup costs/ repetition rate [€]	c_{setup}/f	.06	0	.06	0	.03	.06	.03	0	.03
Costs per part human [€]	c_{PH}	.03	.01	.17	.16	.02	.04	.01	.01	.02
Costs per part robot [€]	c_{PR}	.08	0	.14	0	.05	.07	.04	0	.04

6.1.2. Task Assignment

This section describes which tasks are assigned to one agent in advance. The robot feasibility check shows whether the task can be executed by the cobot: if Yes, the result is B (shareable task). In use-case I, all tasks can be executed by both agents. Physical HF/E evaluation shows whether the tasks should be assigned permanently to the cobot. The simulation result shows that task 4 should be done by the cobot or an automatic screw feed should be implemented.

For economic considerations, the fastest and the cheapest process variations are displayed in Table 26. In terms of cost-efficiency, task 3 should be done by the robot, not the human.

Table 26 Task assignment use-case I “assembly of a heat sink.”

Criteria	Sym.	Tasks Use-Case I								
		1	2	3	4	5	6	7	8	9
Robot feasibility check	F	B	B	B	B	B	B	B	B	B
Physical ergonomics	E	B	B	B	R	B	B	B	B	B
Economic Efficiency Evaluation										
Fastest, most time-efficient process	t_{opt}	H	R	H	R	H	H	H	R	H
Cheapest, most cost-efficient process	c_{opt}	H	R	R	R	H	H	H	R	H
Lot size from which robotization is more cost-efficient	f_{opt}	481	0	71	0	418	179	957	0	464

Depending on how the tasks are assigned, the effects on time consumed and costs are calculated. The total costs of the process can vary between € .29 and € .72 (Ø = € .50). The costs spent on the process could be 2.5 times higher than the optimal assignment. The fastest process takes 43.78 s, executed by the human and the slowest process takes 78.51 s (Ø = 61.15 s).

6.1.3. Task Visualization

The process and tasks were modeled using the BPMN-based Camunda engine, which was connected to the robot’s software. The process with its three lanes is shown in Figure 32.

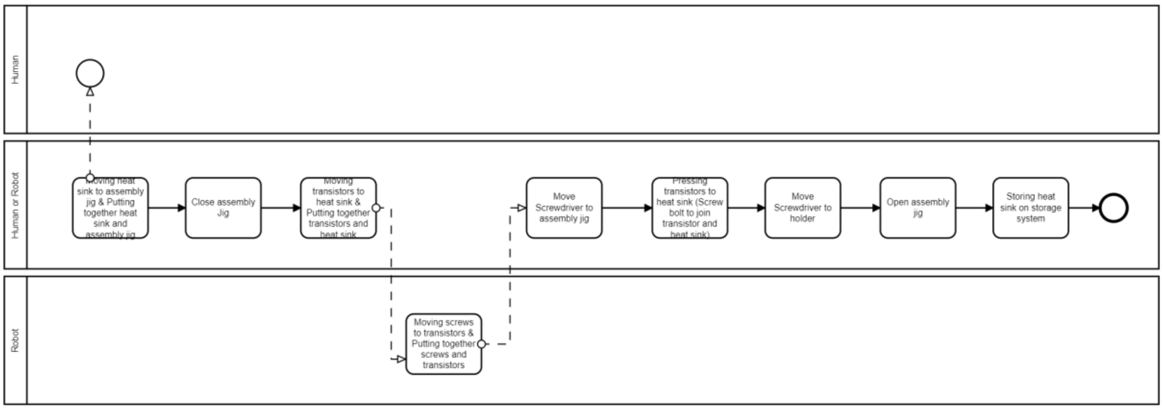

Figure 32 Process chart of use-case I “assembly of a heat sink” (own figure).

6.1.4. Evaluation

The evaluation of use-case I was threefold. First, the setup verified the feasibility of the ATS concept. This was explained in detail in the previous sections. Second, the setup was evaluated comparatively with two other HRI use-cases from the electronics industry regarding the ATS design principles. Third, the task visualization approach was evaluated in terms of human factors and productivity aspects. The last two evaluations are explained in the following section.

6.1.4.1. Comparative Concept Evaluation

In the study by Schmidbauer, Schlund et al. (2020), the use-case was comparatively evaluated with two other HRI use-cases from the electronics manufacturing company (Figure 33). The evaluation criteria were six ATS design principles presented in Section 4.2 and overall development costs. It was shown that the ATS demonstrator scores well in participatory design, scaling on demand, dynamic division of tasks, and participatory robot programing, but needs improvement in terms of loose task coupling. The overall development costs were comparatively low; however, these costs were estimations. The detailed evaluation can be found in the study by Schmidbauer, Schlund et al. (2020).

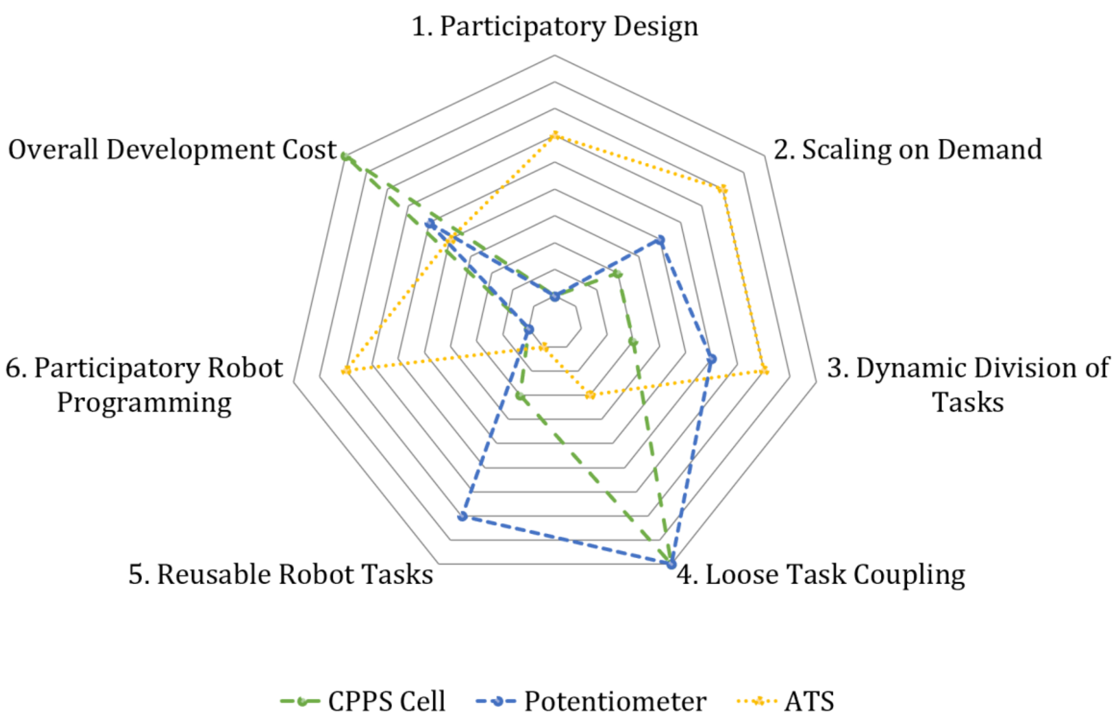

Figure 33 Comparative evaluation of the applications in respect to the six ATS design principles and overall development costs (Schmidbauer, Schlund et al., 2020, p. 549).

6.1.4.2. Task Visualization Evaluation

To evaluate the task visualization approach, an online study ($n = 51$) was undertaken. The focus lied on the evaluation of the previously presented requirements and design parameters for task visualization.

Participants had to model a short process (four robot and two human tasks) with the worker assistance system. There was no interaction with the real robot, but videos of the task execution were played on the screen. Productivity impacts were evaluated through time tracking during process modeling and a quality check of the solution. Ease of use and system comprehension were evaluated through the System Usability Scale (SUS) by Brooke (1996) and a task load assessment using the NASA-raw-TLX (Schmidbauer et al., 2021). The results of the evaluation revealed an excellent system usability (SUS: Ø = 86, SD = 12). The task load evaluation[13] showed very good results below the maximum of 1.6 for mental and physical demand, stress, effort, and frustration. The perceived success was on average 4.4. The average duration of accomplishing the modeling of the process was 7:44 min, time that comes additionally to programming the robot and setting up the whole workplace. 15.7% of the participants were not able to finish the modeling without any mistakes.

The results showed that the participants who were experienced with process modeling, in particular BPMN, found the BPMN-based assistance system to be more user-friendly but participants without experience were also able to succeed in executing the task without significant disadvantages. The conclusion of the online study was that the task visualization and worker assistance system were proven to be easy to understand and use; however, it takes additional time to design the process in BPMN. Details about the online study and results can be found in the study by Schmidbauer, Hader, Schlund (2021).

6.1.5. Discussion and Conclusion of Use-Case I

Use-case I was deployed to verify the feasibility of the ATS concept and to investigate the effects on productivity and human factors. With the setup of use-case I, the feasibility of the ATS concept was demonstrated. A hybrid workplace including a shared work area of a human and a cobot was implemented. It must be considered that this workplace has not been subjected to safety certification. For the setup, a low-cost approach was followed, for example, the fixtures were manufactured using fused deposition modeling (additive manufacturing).

[13] NASA-raw-TLX using a 5-point Likert scale (1: very low, 2: low, 3: medium, 4: high, 5: very high).

The demonstrator developed shows that an improvement in terms of costs is possible with the presented task analysis. In addition, through the presented ergonomics evaluation, an improvement of human factors can be achieved. By calculating and showing the key figures, better decisions can be made by the workers who assign the tasks.

The task visualization method was evaluated using use-case I as an example for process modeling. The use-case, or rather the description of it, was slightly simplified for the user study. It was proven that the method of representing the tasks to the workers without expert knowledge is suitable.

Use-case I served as the first demonstrator, but the tasks were not particularly diverse. Therefore, another use-case was sought to investigate a greater variety of different tasks of a workplace. One challenge with use-case I was that some of the described tasks could not be taken over directly by the robot because the robot summarized some tasks in its movements. This made it difficult to compare individual tasks. More focus must be placed on this problem in a further investigation of processes in order to enable transparent comparability here.

6.2. Use-Case II: Assembly of a Timing Relay

The assembly of a timing relay was deployed as a second use-case. The example HRI setup was based on the actual manual setup of the workplace at the electronics manufacturer TELE Haase Steuergeräte Ges.m.b.H in Vienna, Austria. The workplace was replicated at the Pilot Factory for Industry 4.0 at TU Wien, using a Franka Emika Panda cobot. Figure 34 shows the setup of the demonstrator. Machines such as the labeling machine were partly replaced by demonstrators so as not to disrupt ongoing production operations during the setup and evaluation. With the help of the setup, the developed method including the worker assistance system of the demonstrator was validated by actual workers of the electronics manufacturer. The aim was to find out whether the workers prefer the ATS method compared to a predefined task allocation. In addition, the effects of ATS on humans were researched.

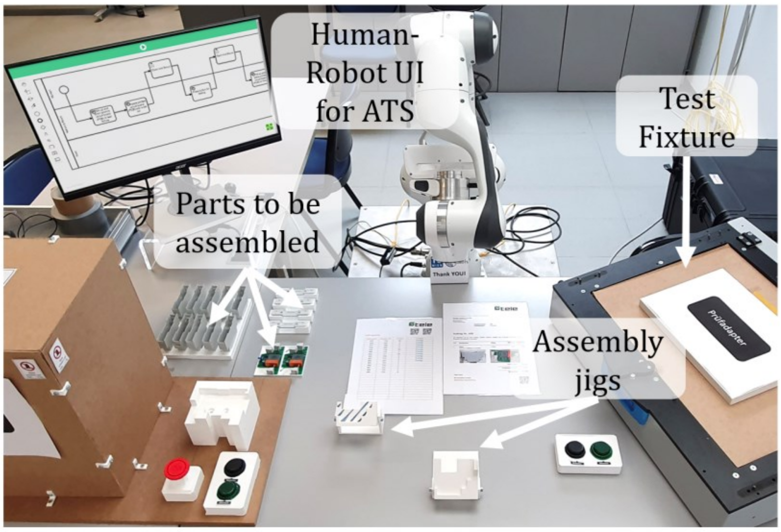

Figure 34 Use-case II "assembly of a timing relay" demonstrator at TELE Haase Steuergeräte Ges.m.b.H in Vienna, Austria (own figure).

6.2.1. Task Analysis

The task analysis performed for use-case II is explained below.

6.2.1.1. Process Description on Task Level

The objectives of the process include testing, assembling, and labeling the timing relay. The components of the relay are shown in Figure 35. The assembly process of the timing relay comprises 18 tasks, which are summarized in Table 27.

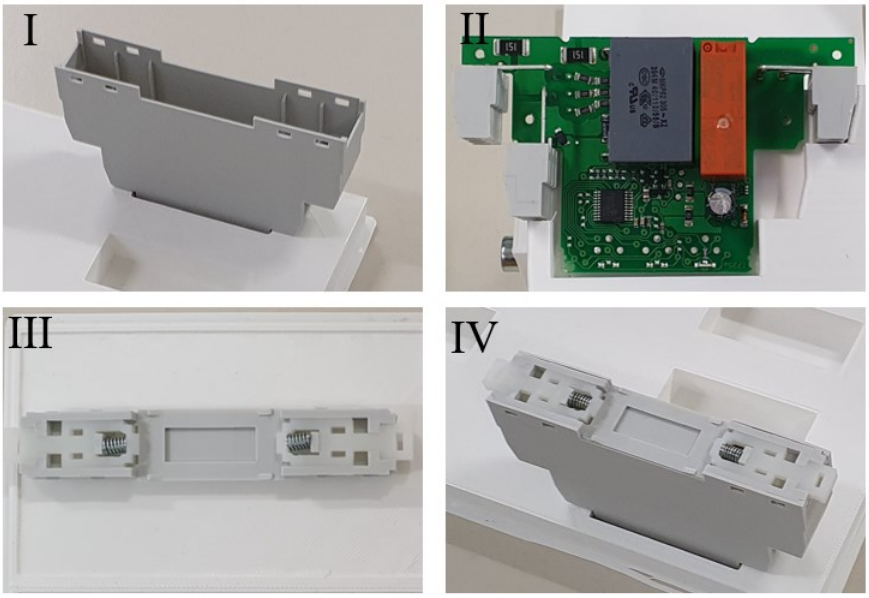

Figure 35 Components of timing relay: I: case, II: printed circuit board (PCB), III: cover, IV: assembled product (own figure).

Table 27 Assembly functions applied to use-case II “assembly of a timing relay”.

No.	Task	Assembly Function	Function specified
1	Pick up and place PCB in test fixture	Handling	Moving
2	Compare PCB with order list	Checking	Comparing
3	Close test fixture	Handling	Moving
4	Press button for testing	Checking	Confirming
5	Open test fixture	Handling	Moving
6	Pick up and place PCB on fixture	Handling	Moving
7	Compare individual order with order list	Checking	Comparing
8	Pick up and place case/housing on fixture	Handling	Moving
9	Visual inspection of case/housing	Checking	Comparing
10	Pick up and place PCB in case/housing	Joining	Putting together
11	Pick up and place cover on case/housing	Handling	Moving
12	Tighten/fix the cover	Joining	Putting together
13	Visual inspection of the component	Checking	Inspecting
14	Pick up and place component for labeling	Handling	Moving
15	Press button for labeling	Checking	Confirming
16	Visual inspection of the component	Checking	Inspecting
17	Updating the order list	Special	Marking
18	Placing the product for transport	Handling	Saving

6.2.1.2. Robot Feasibility Evaluation

The technical feasibility of the task execution was verified in practice. Although it is partly an imitation of the real setup, the same movements could be used in real assembly processes. Some tasks are not feasible by the robot. For instance, the cover of the test fixture is too heavy for the robot, and the final deposit of the finished timing relays is outside of the robot’s spatial reachability. One critical issue occurred on the task “tighten/fix the cover” of the timing relay. Force must be applied to fix the lid in place. It was impossible to perform this task repeatedly in decent quality with the cobot. Too high accuracies in combination with the application of force led to errors. For this reason, this task should be performed by humans. All results are shown in Table 28 and Table 29.

6.2.1.3. Human Suitability Evaluation

For the HF/E evaluation, RULA method was used. The assessment was realized by evaluating the setup using pen and paper. Task 8 “pick up and place case/housing on fixture” revealed unacceptable results, as the deposit of the covers is too far away, and the human has to stretch too much or stand up and lean over to reach the covers. This task should be assigned to the cobot. All results are shown in Table 28 and Table 29.

6.2.1.4. Economic Efficiency Evaluation

The economic efficiency of the process is evaluated based on MTM-UAS for the manual tasks, and recorded execution times for the robot tasks. The human needs 26.64 s to assemble one relay manually (without task 8, the robot needs 16 s). If the cobot would execute all executable tasks and the human only does the leftover tasks, the process would take about 166.2 s. From an economic point of view, assuming a lot size of 100, all tasks should be executed by human. The optimal repetition rate f_{opt} shows from which lot size the tasks are more cost-efficient to be executed by the cobot.

6.2.1.5. Task Analysis Summary

Table 28 and Table 29 show the analysis results of all tasks of use-case II.

Table 28 Analysis of tasks 1-9 of use-case II "assembly of a timing relay".

Criteria	Sym.	Tasks Use-Case II								
		1	2	3	4	5	6	7	8	9
Robot Feasibility Check *F*										
(Spatial) Reachability	r	0	0	0	0	0	0	0	0	0
Payload	p	0	0	1	0	1	0	0	0	0
Graspability	g	0	0	0	0	0	0	0	0	0
Critical issues	u	0	0	0	0	0	0	0	0	0
Safety	y	0	0	0	0	0	0	0	0	0
Physical Ergonomics *E*										
RULA score		3	4	3	3	3	3	4	6	4
Economic Efficiency Evaluation										
Hourly costs human [€]	c_H	38.04								
Hourly costs robot [€]	c_R	6.00								
Execution time human [s]	t_H	2.52	.54	2.34	.9	2.34	2.52	.54	NA	.54
Execution time robot [s]	t_R	22	11	NA	7	NA	18	6	16	7
Setup costs [€]	c_{setup}	9.17	9.17	NA	9.17	NA	9.17	9.17	9.17	9.17
Repetition rate	f	100	100	NA	100	NA	100	100	100	100
Setup costs/ repetition rate [€]	c_{setup}/f	.09	.09	NA	.09	NA	.09	.09	.09	.09
Costs per part human [€]	c_{PH}	.04	.01	.04	.01	.04	.04	.01	NA	.01
Costs per part robot [€]	c_{PR}	.13	.11	NA	.01	NA	.12	.10	.12	.10

Table 29 Analysis of tasks 10-18 of use-case II “assembly of a timing relay”.

Criteria	Sym.	Tasks Use-Case II								
		10	11	12	13	14	15	16	17	18
Robot Feasibility Check *F*										
(Spatial) Reachability	r	0	0	0	0	0	0	0	0	1
Payload	p	0	0	0	0	0	0	0	0	0
Graspability	g	0	0	0	0	0	0	0	0	0
Critical issues	u	0	0	1	0	0	0	0	0	0
Safety	y	0	0	0	0	0	0	0	0	0
Physical Ergonomics *E*										
RULA score		3	3	2	2	3	3	2	3	3
Economic Efficiency Evaluation										
Hourly costs human [€]	c_H	38.04								
Hourly costs robot [€]	c_R	6.00								
Execution time human [s]	t_H	2.52	2.5	.72	.54	2.52	.9	.54	2.34	1.8
Execution time robot [s]	t_R	11	14	NA	7	18	7	7	8	NA
Setup costs [€]	c_{setup}	9.17	9.17	NA	9.17	9.17	9.17	9.17	9.17	NA
Repetition rate	f	100	100	NA	100	100	100	100	100	NA
Setup costs/ repetition rate [€]	c_{setup}/f	.09	.09	NA	.09	0	.09	.09	.09	NA
Costs per part human [€]	c_{PH}	.04	.04	.01	.01	.04	.01	.01	.04	.03
Costs per part robot [€]	c_{PR}	.11	.12	NA	.10	.12	.10	.10	.11	NA

6.2.2. Task Assignment

This section describes which tasks are assigned to one agent in advance. The robot feasibility check shows if the robot can execute the task: if Yes, the result is B (shareable task). Some tasks are preassigned to human because robot feasibility is not given in this setup. The physical HF/E evaluation shows if the tasks should be assigned permanently to the robot. The RULA evaluation result shows that task 8 should be done by the robot or the layout needs to be changed. For economic considerations, the fastest and the cheapest process variations are displayed in Table 30 and Table 31.

Table 30 Task assignment of tasks 1-9 of use-case II “assembly of a timing relay.”

Criteria	Sym.	Tasks Use-Case II 1	2	3	4	5	6	7	8	9
Robot feasibility check	F	B	B	H	B	H	B	B	B	B
Physical ergonomics	E	B	B	H	B	H	B	B	R	B
Economic Efficiency Evaluation										
Fastest, most time-efficient process	t_{min}	H	H	H	H	H	H	H	R	H
Cheapest, most cost-efficient process	c_{min}	H	H	H	H	H	H	H	R	H
Lot size from which robotization is more cost-efficient	f_{opt}	5000	∞	NA	4400	NA	1079	∞	1	∞

Table 31 Task assignment of tasks 10-18 of use-case II “assembly of a timing relay.”

Criteria	Sym.	Tasks Use-Case II 10	11	12	13	14	15	16	17	18
Robot feasibility check	F	B	B	H	B	B	B	B	B	H
Physical ergonomics	E	B	B	H	B	B	B	B	B	H
Economic Efficiency Evaluation										
Fastest, most time-efficient process	t_{min}	H	H	H	H	H	H	H	H	H
Cheapest, most cost-efficient process	c_{min}	H	H	H	H	H	H	H	H	H
Lot size from which robotization is more cost-efficient	f_{opt}	455	605	NA	∞	1079	4400	∞	409	NA

Depending on how the tasks are assigned, the effects on time consumed and costs are calculated. The total costs of the process can vary between € .62 and € 2.94 (Ø = € 1.78). The costs spent on the process could be almost five times higher than the optimal assignment. The fastest process takes 42.64 s (executed mostly by the human), and the slowest process takes 166.2 s (executed mostly by the cobot) (Ø = 104.42 s).

6.2.3. Task Visualization

The process and tasks were modeled using the BPMN-based Camunda engine, connected to the robot's software. The process with its three lanes is shown in Figure 36. A detailed glance at the interface is shown in Figure 37.

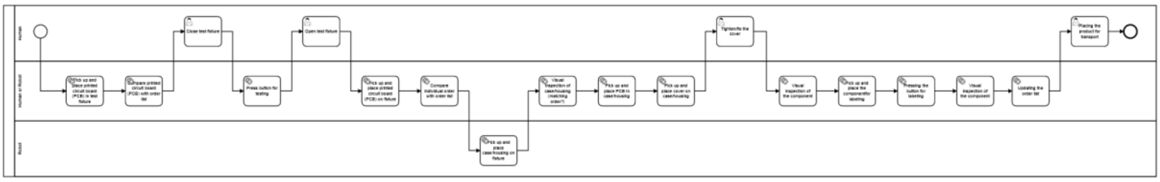

Figure 36 Process chart of use-case II "assembly of a timing relay" (own figure).

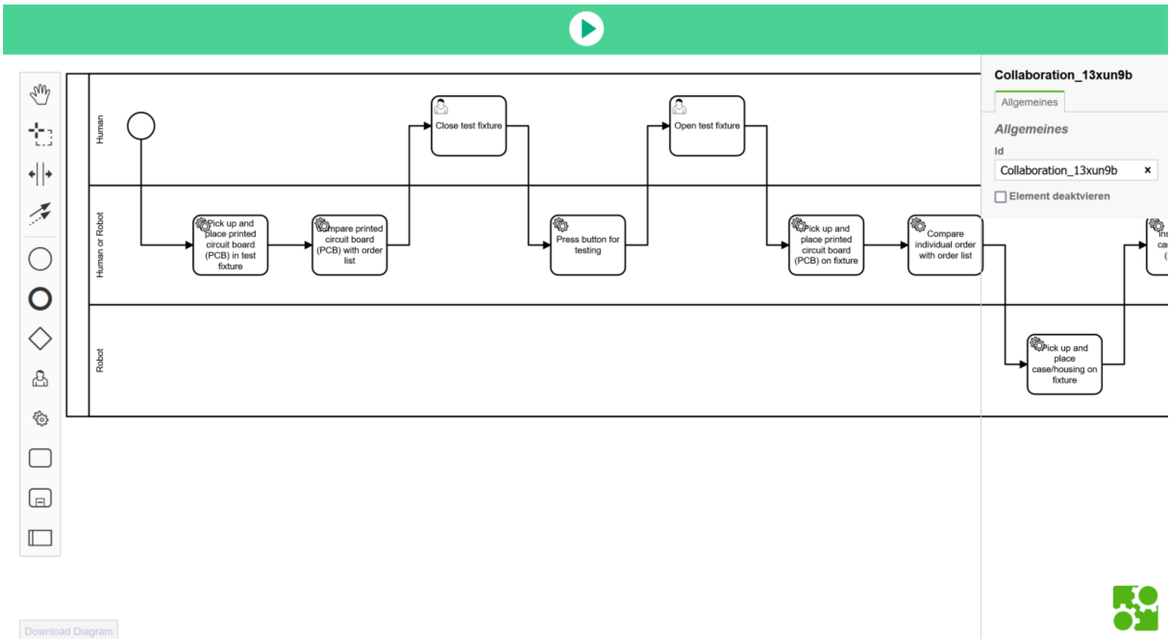

Figure 37 Process chart of use-case II "assembly of a timing relay" implemented in the digital worker assistance system (own figure).

6.2.4. Empirical Study on Workers' Preferences in ATS

Use-case II was deployed to validate the ATS concept and explore workers' preferences regarding task allocation and effects on HF/E within an empirical study. The previous results did not consider whether industrial workers would like to make their own decisions about task assignment. This question should be answered with a user study with 25 experienced workers from the shop floor (12 females, 12 males, and 1 unreported). To enable this, the hybrid use-case was set up at the company where workers are usually executing the tasks of the use-case without the help of a robot.

6.2.4.1.Procedure

As part of the experiment, participants got an overall introduction to the study and watched a safety video. Participants consented to participate in the study and filled in a preliminary questionnaire. One important part of the questionnaire was ranking the 18 tasks from least to most favorite to execute (1: most preferably assign to human and 18 least preferably assign to human).

Then, participants had to undergo two scenarios: One scenario where they had to assign all shareable tasks by themselves and another scenario where they executed the leftover tasks (all tasks the cobot could not do). The order of the scenarios was random. After assigning the tasks, the participant had to test, assemble, and label the timing relay together with the cobot.

After each scenario, participants filled in a short questionnaire about how they perceived control, competence, workload, and humanness perceptions of the robot. In the end, they answered some demographic questions within a questionnaire and open questions about their experience and preference of scenarios as well as the criteria for task assignment in a short interview.

6.2.4.2.Results

The participants and cobot system caused some failures and mistakes during the experiment. Some of them were corrected by the participant, experimenter, cobot, or nobody because no intervention was necessary. In total, nine failures and mistakes happened in each of the scenarios.

The results were analyzed using analysis of variance (ANOVA) for differences between groups of normally distributed populations and Wilcoxon signed-rank test for differences between populations with nonparametric distribution.

The results showed that participants preferred the self-determining ATS concept to a predetermined task allocation (18/25). Asking the participants “If you were going to add a robotic assistant to your manufacturing team, to whom would you give the job of task allocation?”, most participants chose the person involved in production ($\chi^2(2) = 8$, $p < .05$).

Participants reported increased satisfaction with the allocation ($Z = -2.15$, $p < .05$), but not with the execution ($Z = -.25$, $p = .80$) or result ($Z = -.74$, $p = .46$). The collaboration with the robot was reported to be better in the leftover condition than ATS ($Z = -2.05$, $p < .05$). Participants reported increased perceived control ($F(1, 24) = 27.76$, $p < .001$) and competence ($Z = -2.20$, $p < .05$) in the ATS scenario.

Participants anthropomorphized the cobot more in ATS than in the leftover condition (F(1,24) = 5.19 , p < .05). There was no significant difference for perception of intelligence in the cobot between the two scenarios (Z = -.22, p = .82).

There was no significant increase in perceived workload, except for physical demand (Z = - .21, p = .84). This was expected because the participants had only four tasks to do in the leftover scenario.

The ranking and assignment during the ATS scenario were analyzed regarding any dependencies. The most favorite task identified through the ranking was "compare PCB with order list" (mean ranking = 5) and the least favorite tasks were "pick up and place cover on case" and "pick up and place component for labeling" (mean ranking = 12). Participants more likely assigned manual tasks to the cobot (78%) in contrast to cognitive tasks (63%), which indicates that they do not entrust all types of tasks, in particular cognitive tasks, to robots. However, since significance in the assignment could only be determined for some tasks (three handling, one joining, one checking, and one special tasks), no generalization about assigning manual and cognitive tasks to the cobot or the human can be derived. The comparison between the ranking and assignment of tasks to the cobot is shown in Figure 38. Some participants (16%) allocated all shareable tasks to the robot.

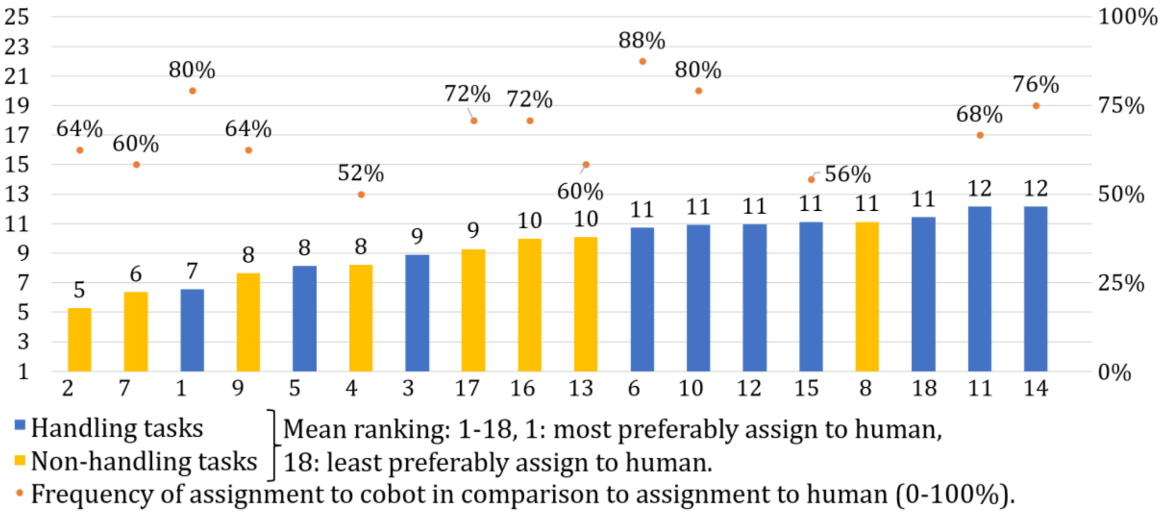

Figure 38 Comparison between ranking and assignment of tasks to the cobot. Tasks 3, 5, 8, 12, and 18 were preassigned (own figure).

6.2.4.3.Discussion and Conclusion of Use-Case II

First, it must be considered that the setup of use-case II has not been subjected to safety certification. Use-case II was deployed to analyze and consider different tasks. This was shown because use-case II includes tasks that cannot or should not be performed by both agents. In addition, the economic consideration of use-case II has to be evaluated differently than use-case I. In use-case II, with an order size of 100 pieces, no savings are possible using a cobot. This will only be the case for higher quantities.

A user study was carried out in the company where the use-case is usually processed without the help of a cobot. The workers preferred the ATS method in comparison to a static leftover task allocation and reported higher satisfaction with the task allocation when they had the decision-making authority. These results partly support previous theoretical considerations and concepts on this topic, such as those provided by Tausch et al. (2020). Moreover, participants perceived higher competence and control in the ATS scenario than in the reference scenario. The results of the empirical study showed that participants preferred the ATS rather than the leftover condition. This outcome contradicts the studies indicating that people prefer ceding complete decision-making authority to the robot (Gombolay et al., 2015).

The result indicated that having the decision-making authority over task assignment positively affects the worker's satisfaction with the task allocation, but not with task execution or results. Contrary assumptions were made by Tausch et al. (2020). The differences could be caused by the relatively low speed of the robot (due to safety reasons), resulting in low productivity. Moreover, there were more errors/failures of the participant in the ATS than in the leftover scenario.

A common aspect of the results of this study and the study by Wiese et al. (2021) was that participants tend to give tasks to the robot if they have the impression that it can perform the task. Even if participants are told and shown that the robot can also perform the other tasks, it seems that it is up to the individual perception and conviction of the participants which tasks they entrust the robot to perform. This possible correlation should be part of future research.

Another finding of the study is similar to previous studies: participants tend to assign more tasks to the robot than to themselves (Gombolay et al., 2015; Tausch and Kluge, 2020; Wiese et al., 2021).

Participants perceived themselves to be more competent and in control in the ATS scenario, which has important implications regarding their intrinsic motivation and effectiveness at work (Deci and Ryan, 2000).

The perception of anthropomorphism and intelligence of the cobot indicate that an increased automation level by assigning the decision-making authority for task allocation to the robot, may not lead to an increased perception of the robot's intelligence, but anthropomorphism.

The results of the NASA-raw-TLX showed that cognitive workload was not perceived higher due to the decision-making authority of task allocation. This shows that ATS is a suitable method for HRI in assembly processes: the workers' perceived satisfaction, competence, and control are increased without placing additional workload on them.

6.3. Discussion and Limitations

In this section, generalizations and limitations of this work are discussed. This work focuses on ATS in assembly workplaces, as these offer a high potential for (partly) automation using cobots and the related increase in economic efficiency and improvement of HF/E (Wang, L. et al., 2019). The method was developed to enable adaptive task sharing between humans and cobots, including the worker as a decision-maker assigning shareable tasks.

6.3.1. Differentiation to Similar Approaches

ATS is one method to share tasks between humans and cobots on the assembly shop floor. The difference to static task allocation is that the worker on the shop floor has the final decision-making authority on task assignment. The worker is supported by a worker assistance system visualizing tasks and sequences.

Conventional scheduling prescribes a specific task allocation and sequence of tasks. Section 3.4 gives an overview to the state-of-the-art in task allocation methods. The presented work describes a new method that allows adaptive task sharing between humans and cobots in assembly processes, where the worker has the decision-making authority over task assignment during the process. However, the concept of self-organized production is not innovative but can be found, e.g., in integrated scheduling and holonic manufacturing systems (distributive controlled systems) (van Brussel, 2014; Zhao et al., 2010). Integrated process planning and scheduling aim at realizing flexible manufacturing systems that allow a choice in task allocation and sequencing. Zhao et al. (2010) listed various approaches to integrated scheduling problems such as deploying genetic algorithms or real-time negotiation mechanisms to solve task allocation and planning problems. In the latest publications, the term matrix production described a reconfigurable production system using flexibly linked process modules instead of rigidly coupled assembly lines (Trierweiler et al., 2020).

The main difference between flexible or holonic manufacturing systems and adaptive task sharing is that human workers are machine/workstation operators (ElMaraghy and Caggiano A., 2014) and execute (value adding) assembly tasks. In matrix production, humans are seen as executing agents (Trierweiler et al., 2020); however, not task allocation decision-makers.

6.3.2. Applicability in Practice

One limitation of the existing ATS method is that the system only considers one robot and one human. Multiple robots or humans in the system would require an extension of the BPMN visualization as well as organizational measures.

The exemplary demonstration use-cases were selected from the electronics industry, where production is characterized by job shop or batch production. There, workers assemble products at assembly workstations and take over several tasks. Cobots can assist the worker within the hybrid workplace in taking over some of these tasks. The goal is not the substitution of the human worker. Instead, the aim is the adaptive division of tasks within hybrid assemblies (Section 2.3). In a setting where the batch sizes are small, using a cobot may not make sense; purely manual production does. In a setting where large batch sizes (mass production) are required, cooperation between humans and robots makes limited sense. In mass production, task allocation is rather static because the focus is not on flexibility but effectiveness. Of course, the cobot can also take over some tasks such as applying adhesives or pick and place, but the use of other machines could also be considered and even more effective.

The ATS method was developed and evaluated within this job shop or batch production application context. In contrast, further considerations must be made to apply the method to other production processes, such as flow or line production. Balancing and sequencing are of high importance to ensure an efficient flow within a flow production process. The varying assembly times depending on the task assignment in ATS would cause inconsistency, which would require additional organizational and planning effort. This was not considered in this work. For this reason, the applicability of the ATS method is limited to a job shop and batch production, where workers assemble products at assembly workstations.

6.3.3. Safety Implications

The use of ATS in practice is limited by safety-relevant implications of the cobot's capabilities and the hybrid workplace. On the one hand, this concerns the speed of the robot and, on the other hand, the application possibilities. For example, from a safety point of view, it will not be possible to let the robot handle dangerous tools (such as a cutting tool) if a human interacts with the robot.

A risk assessment of the entire workplace is done to ensure safe interaction between workers and cobots. This means assessing the cobot, the use-case with its work pieces and fixtures, the robot program and the tools needed. To date, standards and risk assessments consider workplaces designed and implemented once and then not changed. Regarding ATS, this means that all variants of task sharing would have to be subjected to a separate risk assessment.

Researchers are working on this issue by developing simulations (Vicentini, Askarpour et al., 2020), where all possibilities could be evaluated upfront in the digital twin of a workplace (Bilberg and Malik, 2019). However, these possibilities are not yet mature enough for series production and thus still represent a limitation in implementing ATS.

6.3.4. Engineering Effort Upfront

Shareable tasks must be designed and implemented (executable by both the robot and the human) to enable ATS. This causes additional effort in the design and implementation of workplaces and processes. If, for example, the task "screwing" is to be performed by both the cobot and the human, a manual screwdriver for the human and a screwing device for the cobot must be available. Moreover, the BPMN modeling effort needs to be considered. The UI of the worker assistance system was rated excellent, but participants in the user study needed some minutes to model a short process with six tasks (Schmidbauer et al., 2021). A short training time reduces the modeling time; however, it is still additional engineering time. The benefits must be focused and evaluated over longer trials: whether the benefits compensate for the additional effort in the long term.

6.3.5. Further Applications

A first step in integrating ATS in reconfigurable production systems was undertaken. Based on a skill-based production scheduling system, multiple possible production execution graphs optimized according to different KPIs, such as time, costs, workers' preferences, and HF/E, are calculated. To enable (re-)scheduling on the shop floor, a service function *NextOps* (short for "get possible next operations"), calculating all next possible tasks leading to a finished product considering the factory's resource utilization, was introduced (Dhungana et al., 2022). With this support, human workers can decide on the next tasks. The system concept is illustrated in Figure 39.

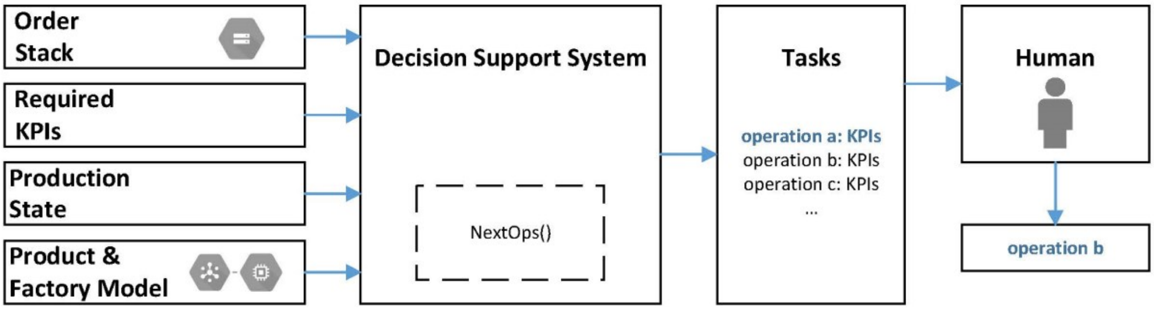

Figure 39 Decision support system for human workers (Dhungana et al., 2022, p. 202).

This concept shows that ATS can be integrated into existing systems. It also shows that although ATS has been demonstrated so far on assembly workstations in the electronics industry, it is not limited to them.

7. CONCLUSION AND OUTLOOK

In this section, the presented work is summarized, conclusions are drawn, and the requirement fulfillment is consolidated. The following subsection discusses how the research questions are answered. In the end, an outlook on possible future research is given.

7.1. Conclusion

This work presents a method to share tasks adaptively between humans and cobots, their applications, and evaluation in assembly processes. The main difference between the proposed ATS method and state-of-the-art task allocation is that the decision of task allocation is postponed to the shop floor. The decision is no longer made in the industrial engineering departments but by the worker on the shop floor, enabling worker's job enrichment.

The method is structured by three main steps: task analysis, assignment, and visualization. Task analysis employs a four-step approach, including process description on a task level, robot feasibility, human suitability, and economic efficiency evaluation. Task assignment is structured into two steps starting with task preassignment to agents followed by a definition of set of criteria for assignment during process. Task visualization describes the integration of tasks and sequences followed by the effects of assignment in the UI.

Two industrial use-cases from the electronics manufacturing industry demonstrated and evaluated the method. The method primarily increased the flexibility of task assignment by breaking up with static compensatory work assignments. This is especially relevant for medium and fluctuating order sizes to fulfill market demands such as mass customization.

Through the method, the worker is empowered and has the decision-making authority over task assignment. This was proven to be preferred by workers, and more satisfying for workers by not imposing them additional cognitive workload. Demonstration and evaluation results show that the method provides both potentials to save time and costs and reduce physical stress of human workers in hybrid manufacturing assemblies. Moreover, perceived control and competence were higher when workers had the task allocation decision-making authority.

Decision cases when a task in the process can be handed over to another agent are shown in Table 32. The list does not claim to be complete but is intended to provide an insight into the possibilities of flexibility opened by ATS.

Table 32 Decision cases affecting task assignment during the process.

Decision cases to assign the task to human	Decision cases to assign the task to cobot
Learning and training: human worker needs training on this task or there is a risk of deskilling of the human	Repetitive tasks: human perceives task as monotonous
Foreseen technical cobot or required work system issues: maintenance (service or cleaning), software updates, integration of new programs	Foreseen human recreation phases: recovery breaks, time for learning and alternate tasks
Unforeseen technical cobot or required work system issues: software or hardware breakdown	Foreseen absenteeism of human: vacation, sickness, short-time work
Product deviations that cause process deviations: trade fair, prototype, test, individual part etc.	Unforeseen absenteeism of human: sickness, pandemic, troubleshooting other tasks in the process

The fulfillment of the presented requirements for the method is presented in Table 33.

Table 33 Requirements, design parameters, and their fulfillment of the adaptive task sharing method.

No.	Requirements	Design Parameters	Fulfillment
1	Apply the method in the planning of assembly systems.	Descriptive power and comprehensiveness of definition, simplicity of analysis, reuse of definitions and evaluations. Preassignment of tasks only for those that are not suitable for sharing.	The task analysis provides a structured method that can be used in the planning of applications. Tasks can be reused and interfaces can be kept flexible. The requirement is considered to be sufficiently fulfilled.
2	Apply the method during human–robot interaction.	Calculation of effects of task sharing, visualization of the human, robot, and shareable tasks, visualization of the sequence of tasks, and online connection to robot software.	The worker assistance system with its simple process-based task visualization enables adaptive collaboration between the human and robot. The requirement is considered to be sufficiently fulfilled.
3	Enable the identification of tasks clearly assigned to humans or robots.	Holistic evaluation of a task in terms of matching skills.	Task analysis identifies tasks that are not feasible for the robot or not suitable for humans due to HF/E implications. All other tasks are referred to as shareables. The requirements are considered to be sufficiently fulfilled.
4	Enable the identification of task that could be performed by humans or robots.		

Table 33 Requirements, design parameters, and their fulfillment of the adaptive task sharing method (continued).

No.	Requirements	Design Parameters	Fulfillment
5	Increase economic efficiency of the process.	Consideration of economic aspects and easy and fast implementation.	The efficiency is increased by the method because it calculates and visualizes the effects of assignment. The requirement is considered to be sufficiently fulfilled.
6	Allow flexibility of the assembly system in terms of fluctuating order sizes.	Calculation of effects of task sharing.	Due to ATS, fluctuating order sizes can be considered. The order size, from which an assignment to the robot is cost-efficient, is calculated. The requirement is considered to be sufficiently fulfilled.
7	Allow flexibility of the assembly system in terms of product variations.		If one product differs from another by minor detail, the deviations can be carried out by the human. Tasks resulting from the deviations do not have to be implemented on the robot due to the small order size. The requirement is considered to be sufficiently fulfilled.
8	Improve human factors/ ergonomics.	Consideration of ergonomic aspects, preassignment of tasks only for those that are not suitable for sharing, easy to understand, and high usability for non-professionals.	By considering physical HF/E during task analysis, strenuous tasks are handed over to the robot, even if this is not the best solution economically. Mental HF/E is not significantly increased by the effort of task assignment and worker satisfaction is increased by retaining decision-making authority. The requirement is considered to be sufficiently fulfilled.

In the following section, the findings and results identified through the development of the method are explained in terms of their contribution to the main research question and subresearch questions of this work.

The main research question of this thesis is

What is an appropriate method to adaptively share tasks in assembly processes between a human and collaborative robot to increase economic efficiency and improve human factors/ergonomics?

The development of the method to share tasks adaptively between a human and a collaborative robot requires several factors that had to be considered. The literature review showed that various methods for task allocation had been developed but few consider the human agent in the work system as a decision-maker. Although from an HF/E point of view, increased decision-making authority predicts positive effects on the work system, such as increased worker satisfaction, this has rarely been considered in practice. The method presented considers the human agent as a decision-maker and supports them in decision-making.

The method's demonstration and evaluation showed that cost efficiency can be increased in hybrid processes. However, the need for increased flexibility entailing a reduction in time or cost efficiency can also happen. Therefore, understanding that the benefits from increased flexibility offset potential reductions in time and cost is a prerequisite. The method allows a flexible response to individual customer requirements or to (un-)foreseen events in assembly processes. Additional costs in the development of a hybrid workstation must be considered. Besides economic efficiency, the method improves physical and mental HF/E, such as worker's task allocation satisfaction. Physical non-ergonomic tasks are assigned directly to the cobot (if possible). Mental HF/E is increased due to the increased decision-making authority of workers and a potential reduction of monotonous tasks. In addition, the method considers whether a worker has been trained or is in the process of being trained.

I. *How to analyze tasks for human–robot teamwork in assembly processes?*

The presented procedure for task analysis was developed regarding simple and fast execution. Detailed methods are also conceivable and can be found in the literature. However, task analysis should be carried out as efficiently as possible. A user or implementer of the method can add individual criteria relevant to the specific assembly process.

II. *How to assign tasks to the human, robot, or "shared tasks" for human–robot teamwork in assembly processes?*

Preassignment and definition of criteria for the assignment of tasks aim to support the human decision-maker. A large number of allocation variants could otherwise overwhelm the human. In addition, the calculations show which effects which assignment has. This enables transparency and better decision-making quality. Criteria can be replaced or supplemented depending on which topics and objectives are relevant for the assembly process. The basic model considers the learning opportunities as well as the monotony of tasks.

III. *How to visualize the human–robot tasks for both the human and robot?*

The developed worker assistance system aims to visualize the task sharing and makes it transparent to the human worker. A process-based representation using BPMN was chosen for the implementation. This enables simple interaction with the cobot and a connection to it to control it.

7.2. Outlook

This last section provides insight into possible future work. The next points, shortly described in the following paragraph, could be part of further development of the ATS method, the ATS worker assistance system, and their evaluation:

1. *Integration of parallelization of tasks*

One point which could lead to an increase in efficiency is the introduction of a "parallelization" criterion. Here, tasks could be related to each other to describe whether they can run parallelly or purely sequentially. The technical implementation of parallel tasks in the worker assistance system is feasible. However, the organizational aspects, such as the planning and calculating times and costs, are part of future elaborations.

2. *Integration of the learning curve*

Planned enhancements to the software include integrating the workers' learning curve. Learning opportunities should be calculated by an algorithm and it should be shown in the UI when a worker should take over a task in order not to unlearn tasks or to learn new tasks.

3. *Adding multiple agents*

As shown in the study by Dhungana et al. (2022), the ATS method can also be integrated in existing production planning systems where multiple agents are considered. However, the presented visualization tool, enabling ATS on the shop floor, is, at the moment, realized for two agents: one human and one cobot. This could be expanded in the future, not neglecting that these would also need reconsiderations in the organization of the human–cobot interaction.

4. *Facilitating human–cobot task shifts*

Collaboration will become more intuitive. There are already many approaches and viable solutions (Gualtieri et al., 2020, p. 373), but these must be commercialized in the next few years actually to influence the interaction between humans and robots in manufacturing. Intuitive and fast task shifts (rescheduling) between the agents will be made possible without needing an external UI or active human involvement (Boschetti et al., 2021).

5. *Long-term evaluation study*

The positive effects on the production process shown by the demonstration and evaluation of this work were shown using industrial human–cobot demonstrators. The implementation of the method shown in a production process and an accompanying ongoing evaluation study would provide information about the long-term effects on the flexibility of the assembly and on the HF/E effects of the workers. Not only physical and mental ergonomics and job/task satisfaction but also the influence of the method on other topics, such as situation awareness

(Endsley, 2019), could be investigated. In addition, the topic of workers' preferences could be explored in more detail.

6. *Incorporating workers' preferences*

Research has been undertaken to incorporate preferences using a Markov model that learns from simulation (Grigore et al., 2018). Based on previous work on workers' preferences and a long-term evaluation study on this topic, machine learning algorithms improve the decision-making support system. To this end, the motives for assignment and their interrelationships should be explored. The question as to why workers are more likely to hand over manual tasks to robots than cognitive ones could be investigated in this context. Similarly, the spatial arrangement of workplaces could be examined: if workers tend to assign tasks that are spatially closer to them to themselves and tasks spatially closer to the robot to the robot.

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List of Abbreviations

Abbreviation	Description
ANOVA	Analysis of Variance
BPMN	Business Process Model and Notation
CAD	Computer Aided Design
CLAM	Cognitive Load Assessment for Manufacturing
Cobot	Collaborative Robot
EAWS	European Assembly Worksheet/Ergonomic Assessment Worksheet
EPC	Event Driven Process Chains
HF/E	Human Factors/Ergonomics
HRC	Human–Robot Collaboration
HRI	Human–Robot Interaction
HTA	Hierarchical Task Analysis
js	JavaScript
KIM	Key Indicator Method
KPIs	Key Performance Indicators
MDP	Markov Decision Process
MOST	Maynard Operations Sequence Technique
MTM	Methods Time Measurement
MTM-UAS	Methods Time Measurement – Universal Analyzing-System
NASA-TLX	National Aeronautics and Space Administration Task Load Index
NIOSH	National Institute for Occupational Safety and Health
OCRA	Occupational Repetitive Actions
OWAS	Ovako Working Posture Analyzing System
PTMS	Predetermined Time Method Systems
REBA	Rapid Entire Body Assessment
REST API	Representational State Transfer Application Programming Interface
RULA	Rapid Upper Limb Assessment
SLR	Systematic Literature Review
SMEs	Small and Medium-sized Enterprises
UI	User Interface
UML	Unified Modeling Language
WDQ	Work Design Questionnaire
WF	Work Factor

List of Supervised Student Research Projects

I have supervised the following student research projects that were finished and published in the years from 2019 to 2021 or will be finished and published in 2022. Some of the results obtained are included in this work. I would like to thank all the students for their support during this scientific work and wish them all the best in their professional careers.

- *Master and Diploma Theses*

1. Marcus Alexander Ophoven (2019) Konzeption und Konstruktion einer Schrauberhalterung für eine Mensch-Roboter-Kollaboration in der Montage und Validierung mittels Prototyping.
2. Marcel Umele (2020) Akzeptanz der Mensch-Maschine-Interaktion mit einem sozialen Roboter am Beispiel eines Empfangsszenarios.
3. George Viorel Cristea (2020) Simulation supported ergonomics evaluation of human-robot workplaces.
4. Bernd Hader (2021) Intuitive programming of collaborative human-robot processes.
5. Alexander Luger (2022, forthcoming) Integration von Methoden zur Bewertung von Arbeitsprozessen mit Systemunterstützung inklusive praktischer Beispiele.
6. Thomas Wendelin (2022, forthcoming) Enhancing adaptive task sharing between a human and robot considering work-placed learning.

- *Bachelor Theses*

1. Michael Wollendorfer (2019) Darstellung und Analyse derzeitiger Anwendungen von Mensch-Roboter-Kollaboration in der Montage von Produktionsbetrieben.
2. Betül Sik (2019) Roadmap für die sichere Gestaltung einer Cobot Applikation – Sicherheitsrelevante Maßnahmen bei der Implementierung von Cobot-Applikationen in der Industrie.
3. Johann Li (2020) Konzeption und Erprobung von digitalen Lehreinheiten zum Thema Robotik.
4. Vanessa Großkopf (2020) Maßnahmen für montagegerechtes Produktdesign im Vergleich: Roboter- vs. Automaten- vs. Mensch-montagegerechtes Produktdesign.
5. Johannes Berger (2020) Human-robot collaboration (HRC) in production and manufacturing – a systematic literature review.
6. Florian Hudetz (2020) Recherche und Ausarbeitung eines Konzepts zur Zuführung von Bauteilen zu einem Mensch-Roboter-Montagearbeitsplatz.

7. Merve Türüdi (2020) Systematische Literaturrecherche über das Thema Assistenzsysteme und Arbeitsteilung in der teil- und hochautomatisierten Landwirtschaft.
8. Florian Krammer (2021) Systematic literature research of software-based planning of human-robot-cooperation in logistics and assembly.
9. Nemanja Miljevic (2022, forthcoming) 3D Druck- und Gewichtsoptimierung einer Werkzeughalterung zur lösbaren Verbindung mit einem Zwei-Backen-Greifer an einem Roboterarm.
10. Stefanie Bauer (2022, forthcoming) Marktanalyse einer Werkzeughalterung zur lösbaren Verbindung mit einem Roboterarm.

- *Seminar papers*

1. Dominik Strommer (2020) Klassifizierung von Aufgaben von kollaborativen Robotern.
2. Mariam Marshall (2020) Datenschutz im Bereich der Mensch–Maschine Kollaboration.
3. Christian Blasbichler (2020) Learning target dimensions/domains (LTDs) regarding teaching robotics.
4. Johann Li (2021) Task analysis and evaluation for adaptive task sharing in human-robot interaction in manufacturing.
5. Lukas Mahlfleisch (2021) Algorithmen zur Aufgabenverteilung zwischen Mensch und Roboter.
6. Lukas Mahlfleisch (2021) Learning nugget for teaching collaborative robots “Introduction to Universal Robots”.
7. Christian Weißegger (2021) Learning nugget for teaching collaborative robots “Control Universal Robots”.
8. Johannes Hagenauer (2021) Simulation einer Schrauberhalterung.

Resume

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Work Experience (Excerpt)

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09/2021–present:	Lecturer in *Human Factors/Ergonomics* at FH Technikum, Wien
09/2020–present:	Lecturer in *Collaborative Robots* at University of Applied Arts Vienna, FHWien der WKW and FH St.Pölten
10/2015–12/2017:	Product Data, Order, and Project Management, Mercedes Benz G GmbH, Graz

Education (Excerpt)

2018–present:	Doctoral Studies in *Mechanical Engineering - Economics* & Doctoral College *Trust Robots*, TU Wien
2013–2015:	Master Studies (MSc) in *High Tech Manufacturing*, FH Campus Wien
2010–2013:	Bachelor Studies (BSc) in *Production und Management*, FH OÖ, Campus Steyr
2006–2010:	A-levels, BG/BRG Ramsauerstraße Linz

Certificates

- Professional Scrum Master™ I (12/2020)
- Process Analyst, Gesellschaft für Prozessmanagement (12/2020)

List of Publications

1. Dhungana Deepak, Haselböck Alois, Schmidbauer Christina, Taupe Richard, Wallner Stefan (2022) Enabling Resilient Production Through Adaptive Human-Machine Task Sharing. In: Andersen AL. et al. (eds) Towards Sustainable Customization: Bridging Smart Products and Manufacturing Systems. CARV 2021, MCPC 2021. Lecture Notes in Mechanical Engineering. Springer, Cham., pp. 198-206. https://doi.org/10.1007/978-3-030-90700-6_22
2. Christina Schmidbauer, Bernd Hader, Sebastian Schlund (2021) Evaluation of a Digital Worker Assistance System to enable Adaptive Task Sharing between Humans and Cobots in Manufacturing. Procedia CIRP, vol. 104, pp. 38-43. https://doi.org/10.1016/j.procir.2021.11.007
3. Helena Frijns, Christina Schmidbauer (2021) Design Guidelines for Collaborative Robot User Interfaces. In: Ardito C. et al. (eds) Human-Computer Interaction – INTERACT 2021. INTERACT 2021. Lecture Notes in Computer Science, vol 12934. Springer, Cham., pp. 407-427. https://doi.org/10.1007/978-3-030-85613-7_28
4. Walter Mayrhofer, Steffen Nixdorf, Clara Fischer, Tanja Zigart, Christina Schmidbauer, Sebastian Schlund: Learning Nuggets for Cobot Education (2021) A Conceptual Framework, Implementation, and Evaluation of Adaptive Learning Content for Robotics and Physical Assistance Systems. Proceedings of the Conference on Learning Factories (CLF), pp. 1-6. http://dx.doi.org/10.2139/ssrn.3868713
5. Titanilla Komenda, Christina Schmidbauer, David Kames, Sebastian Schlund (2021) Learning to Share - Teaching the Impact of Flexible Task Allocation in Human–Cobot Teams, Proceedings of the Conference on Learning Factories (CLF), pp. 1-6. http://dx.doi.org/10.2139/ssrn.3869551
6. Christina Schmidbauer, Sebastian Schlund, Tudor B. Ionescu, Bernd Hader (2020) Adaptive Task Sharing in Human-Robot Interaction in Assembly. 2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), pp. 546-550. https://doi.org/10.1109/IEEM45057.2020.9309971
7. Christina Schmidbauer, Marcel Umele, Tanja Zigart, Astrid Weiss, Sebastian Schlund (2020) On the Intention to Use the Pepper Robots as Communication Channel in a Business Context: Results of a User Acceptance Survey. In Proceedings of the 8th International Conference on Human-Agent Interaction (HAI), pp. 204-211. https://doi.org/10.1145/3406499.3415062

8. Christina Schmidbauer, Titanilla Komenda, Sebastian Schlund (2020) Teaching Cobots in Learning Factories - User and Usability-Driven Implications. Procedia Manufacturing, Vol. 45, pp. 398-404. https://doi.org/10.1016/j.promfg.2020.04.043

9. Setareh Zafari, Isabel Schwaninger, Matthias Hirschmanner, Christina Schmidbauer, Astrid Weiss, Sabine T. Köszegi (2019) "You Are Doing so Great!" – The Effect of a Robot's Interaction Style on Self-Efficacy in HRI. 28th IEEE International Conference on Robot and Human Interactive Communication (ROMAN), pp. 1-7. https://doi.org/10.1109/RO-MAN46459.2019.8956437

10. Tudor B. Ionescu, Sebastian Schlund, Christina Schmidbauer (2019) Epistemic Debt: A Concept and Measure of Technical Ignorance in Smart Manufacturing. In: Nunes I. (eds) Advances in Human Factors and Systems Interaction. AHFE 2019. Advances in Intelligent Systems and Computing, vol 959. Springer, Cham., pp. 81-93. https://doi.org/10.1007/978-3-030-20040-4_8