Adaptive Task Sharing between Humans and Collaborative Robots in a Manufacturing Environment

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Abstract

Collaborative robots (referred to as cobots) can have a significant potential impact on manufacturing processes by enabling new task allocation possibilities, resulting in improved economic efficiency and human factors/ergonomics. In this chapter, a method for sharing tasks adaptively between humans and cobots is designed, developed, demonstrated, and evaluated. State-of-the-art task allocation approaches and their shortcomings regarding flexibility and human factors/ergonomics are presented. The three parts of the proposed adaptive task sharing method, i.e., task analysis, assignment, and visualization, are specifically described. Also, case studies are demonstrated, and the obtained results are evaluated. A discussion, conclusion, and the research outlook on human–robot interaction in future manufacturing processes conclude this chapter.

Keywords

Collaborative Robots, Flexible Production Systems, Manufacturing, Task Allocation, Task Sharing

1 Introduction

Collaborative robotic arms, referred to as cobots, entered the market more than 20 years ago. Their design differs from that of conventional industrial robots because the objective is to ensure a safe interaction between cobots and human workers [Albu-Schäffer et al. 2007]. Specifically, these robots are equipped with inherent safety measures and intuitive user interfaces. Therefore, after a short period of training, even nonprofessionals can program and control cobots. Cobots have raised high expectations of achieving flexible and resilient manufacturing processes, increasing the productivity, and assisting human workers [Makris 2021; Wang et al. 2019]. However, these expectations have not yet been met, resulting in a productivity gap [Schmidbauer et al. 2020b]. Weiss et al. [2021] provided an overview of the main research areas on human–robot interaction (HRI), work and organizational psychology, and sociology of work in the context of Industry 4.0. These are listed as follows:

- Safety and situation awareness (for example, safety certifications for cobot applications are costly and time-consuming [Rathmair and Brandstötter 2021]).
- Cobot programming and teaching (for example, cobot control and implementation expertise are still limited [Schmidbauer et al. 2020a]).
- Task dynamics, referring (for example) to the ironies of automation, stating that humans can no longer understand automated systems and the associated risks (for example, the fact that humans can no longer intervene when unforeseen errors occur [Bainbridge 1983]).

https://doi.org/10.34727/2022/isbn.978-3-85448-052-5_11

- Trust and acceptance to analyze (for example, factors facilitating or hindering trust and acceptance in HRI [Nordqvist and Lindblom 2018]).
- Skills, training, and workload such as the democratization of cobot technology [Hader et al. 2022].

One fundamental challenge when implementing a cobot on the shop floor is the HRI production planning; among others, the identification of suitable tasks and the determination of the best task allocation [Ranz et al. 2017] are considered. These issues must be overcome to unwrap the potential of HRI in a manufacturing environment. One approach to allocate tasks is the adaptive task sharing (ATS) between humans and cobots in a manufacturing environment [Schmidbauer 2022].

The main difference between ATS and conventional, static task allocation is that not only one best solution for a specific task allocation exists; a variety of options from which a human worker can choose is also available. An example of static task allocation is the optimization of a fitness function with respect to one criterion, usually time (minimum makespan) or (minimum) cost. In ATS, the workers are free to make their decisions. Other criteria, such as learning opportunities, task preferences, and physical and cognitive ergonomics can be considered. Therefore, this approach is not only suitable in terms of process flexibility but also focuses on a worker's well-being in a manufacturing environment.

In this chapter, state-of-the-art task allocation approaches and a main research gap in this area are presented. A new method for sharing tasks adaptively between humans and cobots in a manufacturing environment is proposed as a feasible solution. ATS is presented along with its three main pillars; a task analysis to identify suitable tasks for humans, cobots, and both (referred to as shareable tasks), a task assignment to preassign tasks to the agents or the shareable task set, and a task visualization for human workers to enable them to assign tasks from the shareable task set adaptively during the manufacturing process. The main benefits and the implications of this approach are presented and discussed.

2 Task Allocation Approaches

Task allocation between humans and machines is a massively discussed topic in manufacturing planning research. State-of-the-art scheduling algorithms capable of calculating the sequence and allocation of tasks to different agents, such as human workers, machines, and robots, have been proposed. A comprehensive elaboration of the state-of-the-art human–robot task allocation methods was reported by Schmidbauer [2022]. In this section, different approaches are exemplified.

2.1. Capability Indicator Evaluation

A compensatory approach to allocating tasks to humans or robots is to use capability or function indicators. The capabilities of the agents and the required capabilities of the tasks are described using quantitative or qualitative methods. This evaluation leads to a matching between the most suitable agent and a specific task.

An example procedure for capability-based task allocation was reported by Ranz et al. [2017]. Initially, the processes are categorized according to the process plan, and the process attributes are matched to the capabilities of the agents and the tasks. Subsequently, the invariable tasks are identified using a knock-out list and allocated to one of the agents. Next, the capability indicators for variable tasks are determined and described for both humans and robots. Then, the agents are comparatively evaluated using a pair-by-pair process. Apart from capability indicators, suitability indicators, such as ergonomic indicators, can be used [Mateus et al. 2019; Gualtieri et al. 2020]. Although this assignment appears to be static, in practice, it is not. The capabilities of humans can change by training, whereas their deskilling and physiological performance may change due to aging [Ranz et al. 2017]. The capabilities of robots can also change due to technological advances, wear and tear, and associated increased inaccuracies.

2.2. Fitness Functions

Based on a capability indicator evaluation or simply on the assumption that all tasks can be executed by both agents, a common task allocation approach is to set up a fitness or optimization function to maximize or minimize a target value. Target values are, for example, the operation time (makespan), cost, and throughput. An example was reported by Tsarouchi et al. [2017], where initially, the resources were evaluated in terms of their suitability and availability. Then, the resources with the lowest operation time that resulted in the minimum time were selected. In some approaches, several goals are also combined in one fitness function. For example, Pearce et al. [2018] focused on improving both the time and ergonomics and formulated them as a mixed-integer linear program.

2.3. Heuristics and Machine Learning

Heuristic approaches are used to provide a task allocation solution more efficiently than other approaches. The decision trees are presented, for example, by AND/OR [Darvish et al. 2018] or by Precedence [Riedelbauch and Henrich 2019] Graphs. If the decision trees are available, genetic algorithms can be used to identify the best task allocation solution. Example deployments of genetic algorithms can be found in Beumelburg [2005]; Howard [2006]; Chen et al. [2014]; Weckenborg et al. [2020]. In those environments where not all decision cases are known, machine learning approaches can be employed. One example is the use of the Markov decision process framework, which is used to model a robot's actions [Roncone et al. 2017].

3 Research Gap

In this section, the task allocation research gap between humans and robots is examined. In operational research, capability indicator evaluations and optimization algorithms are employed to make the task sharing as effective or efficient as possible. In contrast, in the human factors/ergonomics (HF/E) research, a more decision-making authority for a human worker is proposed. Hacker and Sachse [2014] proposed higher decision authority and task diversity for workers to enable job enrichment and enlargement. Both forms of work organization aim at reduced monotony and less negative effects on humans. Additionally, in Ansari et al. [2018], more learning opportunities and less deskilling potential by employing higher task diversity were proposed.

Recent research work indicated that the workers' satisfaction can be increased through "ad hoc" task allocation [Tausch et al. 2020]. An online experiment (n = 151) indicated a higher level of satisfaction with the allocation process, the solution, and the result of the work process in the "ad hoc" scenario, where participants were able to allocate the tasks themselves. Therefore, the inclusion of workers in the task allocation process is crucial in exploiting the acceptance of human–robot interaction and in designing human-centered workplaces [Tausch and Kluge 2020].

Usually, the task allocation is implemented in the work-design-process phase (in industrial engineering) and is completed before the work begins. The reallocation of the so-called *shareable* tasks is enabled by monitoring workers and the work-system environment. Algorithms are being developed to make the robot adaptable to all situations. The active integration of human workers in the decision-making process was recommended by HF/E and engineering researchers [Buxbaum et al. 2020]; however, it was not implemented. The interests of both engineering and HF/E must be considered. These include, on the one hand, the economic efficiency of a process and, on the other hand, the improvement of human workers' ergonomics. For this purpose, the ATS method is developed as a method to share tasks adaptively between a human and a cobot in a manufacturing environment. The objective is to increase the economic efficiency and improve HF/E.

4 Adaptive Task Sharing

In this section, the ATS method is presented. The method was developed using an iterative design science research process based on Nunamaker Jr. et al. [1990]. The results of the five-stage research process contributed to the body of knowledge and vice versa [Schmidbauer 2022]. The proposed method consists of three parts with eight steps in total. In Figure 1, an overview of the ATS procedure is illustrated to show its different parts and steps. In the following subsections, the three parts of the proposed method are elaborated in more detail.

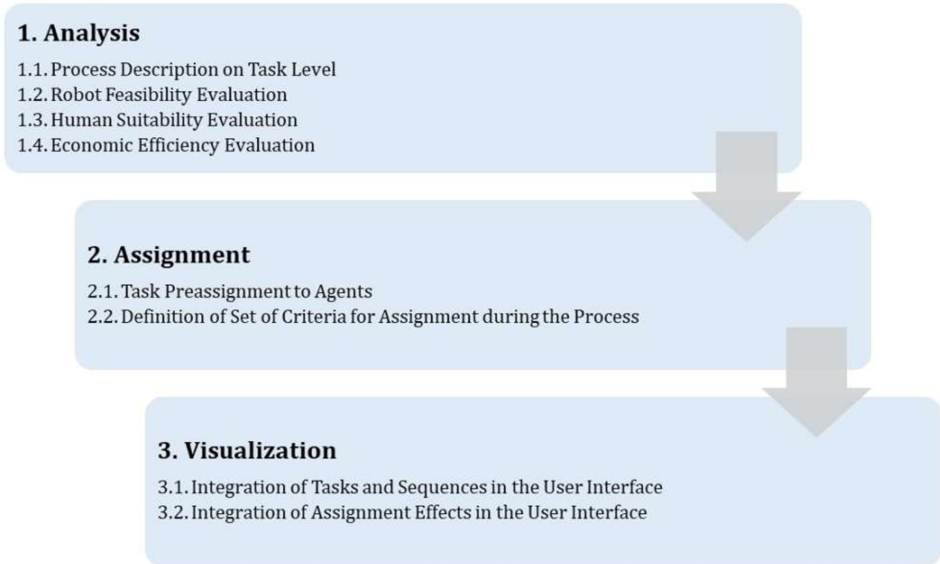

Figure 1 Adaptive Task-Sharing Method Procedure [Schmidbauer 2022].

4.1. Task Analysis

The task analysis of the proposed ATS method includes four steps. Initially, a task level process description is conducted. Therefore, a method based on several standards, such as DIN 8580, DIN 8593, and VDI 2860 is employed [Lotter 2012]. Then, the described tasks are evaluated regarding the automation feasibility using a cobot. The proposed method is based on a previous work [Gualtieri et al. 2020] and is further being developed. Five decision criteria are defined to identify if a task is feasible to be performed by a cobot. These criteria are spatial reachability, payload, graspability, critical issues, and safety. It is assumed that a human worker can also execute all tasks. Therefore, no feasibility evaluation is required for a human worker. However, the tasks are evaluated for their suitability to a human worker. An ergonomics assessment using rapid upper-limb assessment (RULA) was reported in [McAtamney and Corlett 1993]. Finally, an economic efficiency evaluation of the proposed method is presented. Execution times and costs are assigned to each task and agent. The execution times are calculated by employing time stopping and the methods-time measurement (MTM). Then, the optimal time- and cost-efficient task allocations along with the optimal repetition rates are calculated.

4.2. Task Assignment

The key idea of ATS is to assign as many tasks to the shareable task set as possible. Therefore, only tasks that cannot be executed by the robot are permanently assigned to a human worker, and only tasks that are harmful (in terms of ergonomics) to the human worker are permanently assigned to the robot. This allows a high level of flexibility during the process. In the context of HF/E, three criteria for assignment, which are considered in ATS, are defined.

First, learning and training are important for a human worker. When workers are introduced to a new process, it is recommended that they take over the task, until they reach the tasks-pecific acceptance level of the learning curve [Jeske et al. 2014]. Second, task diversity affects a worker's satisfaction by reducing monotony [Hacker and Sachse 2014]. The perception of task diversity is not mathematically described because it is different for each individual. Therefore, ATS only incorporates the question "Does the task variety of the current task assignment correspond to my desired way of working?" in the user interface (UI). This question is a reminder to the workers that they can change the task assignment if they want. Third, the worker's preferences are considered to achieve job satisfaction. Research results on workers' preferences regarding tasks and allocations showed that workers tend to assign manual tasks to the robot and take over cognitive tasks such as checking tasks themselves [Schmidbauer 2022]. However, this is an individual study, and more data is needed to integrate workers' preferences into the ATS method. For this reason, preferences should not be suggested or calculated. However, if desired, they could be obtained from personal experience data. Considering the privacy of the workers, assignments could be collected, and later profiles of these workers could be created to suggest preferred task assignments they would probably like. At the moment, however, this is left solely to the worker to decide spontaneously and without applying any bias.

4.3. Task Visualization

To apply ATS, the visualization of tasks in a digital worker assistance system is necessary. An important requirement for visualization is that it can be easily understood by workers. To ensure high usability, a business process model and notation (BPMN)-based UI was selected. For each agent, i.e., human, robot, and *shareables* (human or robot), tasks can be modeled in lanes. The *shareables* tasks must be assigned to one of the execution agents, before the process starts. The interface features a start/stop button. Additionally, user instructions can be displayed on the interface. During the process, the current task is highlighted, so the user knows which task the cobot is executing and which tasks the user should execute. When the user finishes a task, they must confirm this by clicking on the task on the UI. The developed UI is depicted in Figure. 2.

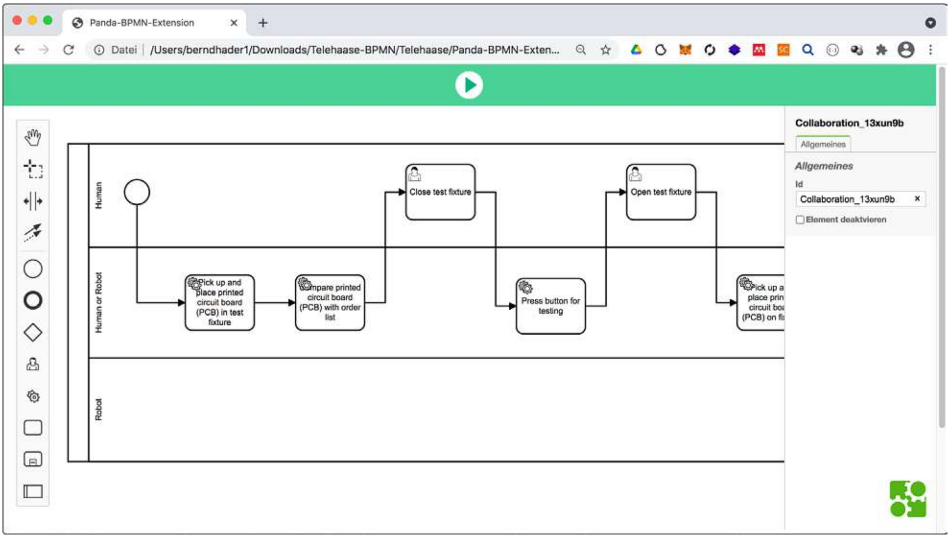

Figure 2 User interface visualizing the human, robot, and shareable (human or robot) tasks [Schmidbauer 2022].

The task visualization was realized using the BPMN-based Camunda[1] engine. The engine was connected with a *Franka Emika Panda* cobot to ensure efficient collaboration. The system architecture was introduced by Hader [2021] and Schmidbauer et al. [2021] and is available to the public on Github[2].

1 https://camunda.com/

2 https://github.com/berndhader/BPMN-Extension-Franka-Emika-Desk

5 Demonstration and Evaluation

In the following subsections, the demonstration and evaluation of the proposed ATS method are described.

5.1. Demonstration

The ATS method is demonstrated using two different case studies from the electronics industry (Figure 3). The first case study refers to the assembly of a heat sink, and the second study refers to the assembly of a timing relay. Both case studies are manual processes performed by electronics manufacturers in Vienna, but they differ in their number of tasks (case study I: 9 tasks; case study II: 18 tasks) and their task variety. In case study I, handling and joining assembly functions are mainly performed, whereas in case study II, some checking and special tasks (i.e.,., pressing a button or marking the order list) are performed. Both case studies were set up as hybrid workstations in the *Pilot Factory for Industry 4.0*[3] at TU Wien. A *Franka Emika Panda* cobot with a standard two-jaw gripper was used to execute the robot tasks.

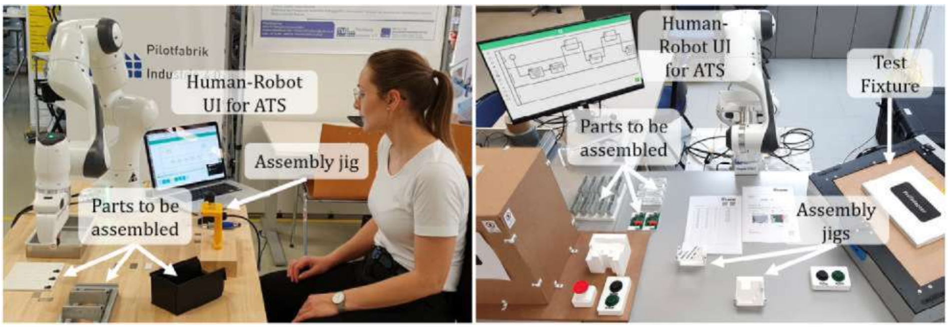

Figure 3 Case study I: “Assembly of a heat sink” demonstration experiment in *Pilot Factory for Industry 4.0* at TU Wien (adapted from Schmidbauer et al. [2020b]) and case study II: “Assembly of a timing relay” demonstration experiment at *TELE Haase Steuergeräte Ges.m.b.H* in Vienna, Austria (adapted from Schmidbauer [2022]).

Initially, the processes were defined at the task level, and a cobot feasibility evaluation was conducted to identify tasks that could not be assigned to a cobot because of issues related to spatial reachability, payload, graspability, safety, and other critical issues. Specifically, all tasks were evaluated according to these criteria and implemented on the cobot when possible. A human suitability evaluation was also conducted using RULA, where a simulation tool (Process Simulate

3 https://www.pilotfabrik.at/

Tecnomatix 15.0) was used to evaluate case study I. In case study II, RULA was applied using pen and paper.

Additionally, an economic efficiency evaluation was conducted using MTM-UAS for the manual tasks and by recording the execution times of the robot tasks. The optimal repetition rate and time- and cost-efficient task assignment variations were calculated. Detailed results of the task analysis have been presented in Schmidbauer [2022].

During task assignment, it was decided which tasks should be preassigned to an agent because not all tasks could be executed by both agents; for example, the RULA evaluation indicated that some tasks should be assigned to the cobot. An example task in case study I is “moving screws to transistors and putting together screws and transistors.” This task leads to a hand position, which is not ergonomic, and, therefore, it should always be taken over by the robot or an automated screwdriving machine. Both these processes were then modeled using BPMN.

5.2. Evaluation

5.2.1. Verification and Validation of the ATS Concept

The case studies were presented both for demonstrating the feasibility of the ATS method and for conducting different evaluations. Using the first demonstration experiment, economic efficiency calculations were performed, and the feasibility of the method was verified. Case study I was compared to other HRI cases related to manufacturing (i.e., the *cyber-physical production system (CPPS) Cell* and the *Potentiometer*) regarding different design aspects such as participatory design, scaling on demand, dynamic division of tasks, loose task coupling, reusable robot tasks, participatory robot programming, and overall development costs [Schmidbauer et al. 2020b]. The comparison showed that the ATS demonstration experiment scored well in participatory design, scaling on demand, dynamic division of tasks, and participatory robot programming. The overall development costs were relatively low. However, a specific laboratory setup was not ready to be directly integrated into the industry; the reason was that the loose task coupling and the reusable tasks had not been elaborated on time, since no UI for task reuse was implemented at the time. A comparison of different applications is presented in Figure 4.

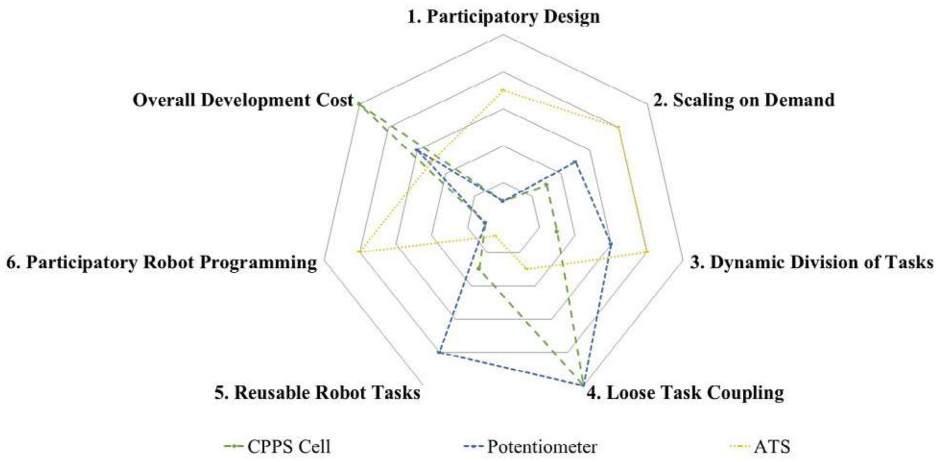

Figure 4 Comparison of different applications regarding the design aspects and overall development costs [Schmidbauer et al. 2020b].

5.2.2. Verification and Validation of the ATS User Interface

The first UI prototype was a mockup, which was used for a video vignette study [Zafari and Koeszegi 2020]. The mockup was used to design and develop the UI, which was evaluated within an online user study (n=51). During this study, the participants were introduced to the UI, and they modeled a human–robot process themselves. The usability, task load, task duration, and quality of the modeled tasks of the UI were evaluated. The usability was rated as excellent (System Usability Scale SUS: Ø = 86, SD = 12). A task load evaluation using the NASA raw-task load index also showed a very positive picture. The average results regarding the six task load variables were all below 1.6 on a 5-point Likert scale, where 1 indicates a very low and 5 indicates a very high demand, stress, effort, or frustration. The average perceived success was rated as 4.4. The average time spent by the participants accomplishing the BPMN modeling was 7:44 minutes (SD = 6:11). However, almost 16% of participants were not able to model the task without mistakes. This result indicates that at least a short period of training is necessary. The results showed that the BPMN processes could be understood by the participants, who were also able to model the tasks themselves. The UI can therefore be used by nonprofessionals with only a small period of training. The evaluation methodology and all results have been presented in Schmidbauer et al. [2021].

5.2.3. Final Validation of Concept and Verification of Requirements

The final evaluation of the method was performed for a user study (n=25) for case study II. This study was conducted in a factory, where, usually shop floor participants execute case study II. The main objective of this study was to validate the ATS concept in comparison to a static leftover task allocation and to explore a worker's preferences regarding task allocation and its effect on human factors. First, the participants attended a briefing and filled in an initial questionnaire. They were also introduced to 18 tasks and had to rank them according to their preference, i.e., whether a robot should take over the task or the participants wanted to execute the task themselves. Next, the participants went through two scenarios. In the ATS scenario, they were able to assign all *shareable* tasks to either the robot or them, whereas, in the other scenario, the tasks were already assigned to the robot, following a maximum automation approach. In each scenario, the participants also worked directly with the robot in the corresponding case study. After each scenario was completed, they filled in another questionnaire.

Most of the participants answered that they preferred the ATS scenario in comparison to the static task allocation (18/25, 72%). Additionally, the task allocation satisfaction was higher in the ATS scenario, and the participants reported that, in the production process, the task allocation should be assigned by humans and not by the robot or the "system". The participants' satisfaction with the task execution and the result was not significantly higher in the ATS scenario than in the static task allocation. The perceived competence and control were higher in the ATS scenario. The perceived (mental) task load was not higher in the ATS scenario, although the participants had additional decision tasks to do. These results show the positive impact of ATS on HF/E.

The ranking and assignment were analyzed regarding any pattern. The ranking exhibited no significance. The assignment showed that the participants assigned manual tasks more often to the robot than checking tasks. Significance in the assignment was found in four of the five handling tasks and in two of the eight other tasks (only 13 of the 18 tasks could be assigned by the participants). More results and information about the empirical user study have been presented in Schmidbauer [2022].

6 Discussion and Limitations

The results of the final evaluation of the method and the worker assistance system showed that participants prefer having the decision-making authority over task allocation. This result is in contrast to previous study results reported by Gombolay et al. [2015]. The outcome of the perceived satisfaction with the task allocation conforms with the assumptions made by Tausch et al. [2020]. However, the results have not shown significant positive effects on the perceived satisfaction regarding task execution and results. The reasons for the difference in the results between the two studies can be attributed to the selection of participants or the performance of the robot during the experiment. The ATS evaluation results also showed that participants tend to assign tasks to the robot if they think that the robot is capable of performing these tasks. Wiese et al. [2021] obtained similar results. A common finding in all studies is that participants tend to assign more tasks to the robot than to them [Gombolay et al. 2015; Wiese et al. 2021; Tausch and Kluge 2020]. Another aspect is the increased perceived competence and control, which has implications for the intrinsic motivation and effectiveness of humans at work [Deci and Ryan 2000].

The practical implementation of ATS also exhibits some limitations. First, the additional engineering effort upfront must be mentioned. To implement ATS, the *shareable* tasks must be designed and implemented to be executable by both the robot and the human. This requires additional efforts 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 worker, a manual screwdriver for the human and a screwdriving device for the cobot must be available [Schmidbauer et al. 2022].

Second, a safe interaction between the human worker and the cobot must be ensured. Cobots are considered as partly completed machinery, according to machinery directives (Directive 2006/42/EC of the European Parliament and of the Council of May 17, 2006 on machinery; amending Directive 95/16/EC (recast)). Therefore, standards regarding safety, such as the technical specification ISO/TS 15066:2016 on robots and robotic devices (specifically, collaborative robots) should be followed, and a risk assessment must be conducted. During a risk assessment, the entire workplace (including the cobot, the specific case study with its workpieces and fixtures, the robot program, and the required tools) must be considered. To date, these standards and risk assessments have considered workplaces that are set up once, and then, remain unchanged. Considering ATS, this means that all task sharing variants should be subjected to a separate risk assessment. Some approaches that could be integrated into a simulation have been reported [Vicentini et al. 2020]. Thus, the possibilities can already be evaluated in the digital twin [Bilberg and Malik 2019]. However, these possibilities are still immature for series production. Thus, they are considered as limitations in the ATS implementation.

7 Conclusion and Research Outlook

7.1. Conclusion

In this chapter, the design, development, demonstration, and evaluation of the proposed ATS method were described. ATS was proved to be an efficient method for adaptively sharing tasks between a human and a collaborative robot in a manufacturing environment. This method is capable of increasing the economic efficiency and improving human factors/ergonomics. The main differences between ATS and the static task allocation method are the postponement of the task allocation decision from the design phase to the shop floor and the ability of ATS to enable workers to have decision-making authority over task assignments. This is achieved via a digital worker assistance system, which visualizes the human–robot processes and serves as a UI to control the robot. The main benefits of this method are the following:

- Higher flexibility on the shop floor, which increases the economic efficiency, due to its higher potential to cope with mass customization requirements than the potential of other methods
- Cost savings via hybrid assembly, thus, increasing the economic efficiency
- Potential to reduce workers' physical stress through a task analysis, which improves human factors/ergonomics
- Increasing workers' satisfaction with "ad hoc" task allocation, which improves human factors/ergonomics.

7.2. Research Outlook

Adaptive task sharing between humans and collaborative robots enables dynamic and even individualizeable work organization in hybrid human–machine production systems. The implementation of ATS provides complementary task allocation to industrial practice and extends the possibilities for a flexible use of cobots in a manufacturing environment. ATS may be regarded as a further step toward democratization in terms of non-discriminating access for end users to the design, development, and use of cobot technology. To achieve this objective, complementary concepts, such as multimodal human–machine interfaces [Ionescu and Schlund 2021], intuitive teaching and programming concepts [El Zaatari et al. 2019], and dynamic simulations of adaptive work organization of human–robot teams [Pellegrinelli and Pedrocchi 2018] are needed. Furthermore, advances in (semi-)automated safety certification of reconfigurable human–cobot work systems as well as integrated safety and security concepts are required [Hollerer et al. 2021]. Finally, the importance of workplace-based learning [Komenda et al. 2021] is crucial to maintain end users' competences and especially problem-solving skills within a more automated work environment, even in times when cobots will be widely-used as flexible and multipurpose manufacturing tools.

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