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Adaptive Human-Robot Collaboration in Industrial Assembly: Augmented Reality-Supported Dynamic Task Allocation with Intuitive Process Planning

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Abstract

As industrial assembly faces increasing demands for cost-efficiency and flexibility, human-robot collaboration (HRC) emerges as a promising solution for small to medium production volumes. To address practical challenges in HRC implementation – such as effective task distribution, trust, and workers' information needs – this paper introduces a system that uses augmented reality (AR) to enhance adaptive HRC. The system intuitively provides essential information to workers and dynamically adjusts task allocation based on individual performance. It consists of five core components: an AR-integrated situation recognition system, situation-aware robot path planning, dynamic task allocation, AR visualization of work information, and a no-code software interface with a digital twin for process creation and monitoring. The paper offers a comprehensive overview of the system architecture, the user interfaces for process creation and AR visualization, and details a novel approach for optimization-based dynamic task allocation. Improvements in efficiency and collaboration are demonstrated through a practical assembly scenario at a laboratory workstation for collaborative assembly.

Keywords: Human-Robot Collaboration; Assembly; Augmented Reality; Task Allocation; Genetic Optimization

1. Introduction

As global manufacturing shifts toward greater flexibility and responsiveness, industries face increasing pressure to adapt to highly variable production demands [1,2]. In particular, small to medium production volumes require solutions that can offer both efficiency and flexibility. Traditional automation, while effective for large production volumes, often lacks the adaptability required in such dynamic environments [3]. In response, human-robot collaboration (HRC) is emerging as a promising approach to meet these challenges. By combining the strengths of human workers – such as cognitive flexibility, problem solving, and dexterity – with the precision and repeatability of robots, HRC can enhance overall productivity and adaptability [4].

Despite its potential, the practical implementation of HRC in industrial assembly poses several challenges. Effective task allocation between humans and robots is critical, but determining the optimal division of labor is a complex problem that many robot manufacturers see as a major challenge [3,5]. The complexity arises on the one hand from the degrees of freedom, as both task assignment and execution sequence must be determined while considering the capabilities and preferences of humans and robots, process-related boundary conditions, and planning targets such as time and physical load. On the other hand, it results from the unpredictable dynamics of human-robot interaction. The static, i.e. pre-assembly, solution of this problem results in a static schedule, which is effective for highly standardized processes, but becomes inefficient for small to medium production volumes due to the

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more frequent schedule deviations and delays that occur in these production environments [6]. Therefore, a dynamic task distribution is required that continuously carries out process planning during the assembly process and can therefore react effectively to deviations.

Additionally, ensuring that workers have sufficient trust in the robot as well as the overall system and that their information needs are met throughout the process is crucial for fostering seamless collaboration [7,8]. Without clear communication and an intuitive interface, the interaction between humans and robots can become inefficient, hindering the benefits of HRC. In this context, augmented reality (AR) can be a suitable enabling technology for more effective HRC. By overlaying critical information directly into the worker's field of view, AR can provide real-time assembly instructions and facilitate better coordination between human workers and robots. In conjunction with a dynamic distribution of tasks, AR has the potential to quickly communicate dynamic changes in the execution sequence to the worker without cognitively overburdening them. However, the combination of AR with both dynamic task allocation and intuitive process planning has not yet been sufficiently addressed in previous research. Therefore, this paper presents a novel approach for adaptive HRC in industrial assembly that aims to enhance both efficiency and trust in HRC systems. To this end, we propose an AR-supported system for dynamic task allocation, which integrates intuitive process planning. As our main contribution, we present an optimization-based method for task allocation that minimizes computational effort and thus enables dynamic application of optimization during process execution.

The remainder of this paper is structured as follows: In Section 2, we review related work on informational worker assistance systems, AR in assembly, and HRC task allocation, and deduce the requirements for AR-supported adaptive HRC. Section 3 presents our proposed concept, detailing the system architecture, user interfaces for worker support and process planning, as well as the dynamic task allocation module. Section 4 demonstrates the system's functionality and its potential for process optimization through an initial application scenario. Finally, Section 5 concludes with a discussion of future research needs.

2. Related work

2.1. Informational worker assistance and augmented reality in collaborative assembly

Informational assistance systems have been part of the state of the art in industrial assembly for decades, supporting employees throughout the assembly process with information. The goal of these systems is to reduce training times, minimize assembly errors, and thereby increase productivity [9]. Various technologies and devices are available for the implementation of informational assistance systems. Traditionally, monitors have been used for information provision, and pick-by-light systems for material retrieval in assembly. As a promising new technology, AR offers significant potential for improved human-machine interaction and optimized, process-integrated assistance [4,10]. This potential arises from the ability to overlay real objects with virtual objects, and to provide dynamic and three-dimensional information. The use of head-mounted displays (HMDs) also increases the mobility of employees compared to static monitors. Initial studies indicate that performance can be enhanced and cognitive load reduced compared to traditional instructions [11,12]. The findings are promising, and particularly in combination with HRC, the advantages of AR become evident, though further research is still needed to achieve acceptance and practical applicability. Initial combinatorial systems have been developed in this context [4,13,14]. While these references focus on providing worker instructions for pre-planned HRC processes or on safety aspects, our contribution explores how dynamic task allocation can be effectively combined with real-time adaptive AR displays for worker involvement in flexible HRC workstations, while facilitating intuitive process planning.

2.2. Task allocation in human-robot collaborative assembly

The problem of an efficient task allocation in HRC assembly processes is an important issue for a successful implementation of collaborative robots into assembly stations [5]. Current research identifies two main approaches: static and dynamic task allocation [15]. Static approaches determine task assignments before execution, and create the process schedule manually by user input, by applying heuristics, or by using optimization algorithms (e.g., genetic algorithms) [15]. In contrast, dynamic approaches allow for real-time adjustments of the process schedule in case of changing conditions or delays during process execution. So far, two general approaches have been proposed: reactive approaches that rely on an initially planned process schedule and switch individual task assignments in case of deviations, and ad-hoc approaches that apply heuristics to perform the overall process control during the assembly process [15]. The importance of dynamic task allocation strategies that adapt to real-time conditions (e.g., delays, errors) and worker capabilities (individual performance) becomes evident, as static task plans become suboptimal in these situations [6]. This is exacerbated by the shortage of skilled workers, which leads to the involvement of less experienced workers, whose execution times for assembly activities fluctuate significantly, especially during the training phase [11].

However, while static approaches employ optimization techniques that theoretically yield optimal assembly plans, these optimization methods are impractical to be applied during assembly due to their computational expense [15]: they either require long processing time to find optimal solutions for an entire process, or necessitate costly high-end hardware, making them unsuitable for cost-effective implementation. On the other hand, since current dynamic task allocation approaches primarily rely on relatively simple heuristics, there is significant potential to enhance process outcomes by developing strategies for dynamic task allocation algorithms that apply optimization techniques in real-time during assembly. To this end, respective optimization algorithms need to plan within shorter timeframes.

2.3. Requirements for AR-support in adaptive HRC

In addition to the optimization aspects discussed above, the need for targeted integration of the human worker, along with their acceptance, was identified as critical for effective collaboration, which is fostered by trust and communication between human operators and robotic systems [7]. For example, participants in [8] reported that dynamic changes of human task assignments were sometimes overlooked after multiple executions of the process, primarily because users had to shift their gaze to a monitor for informational updates. The aspect of trust can also be fostered through effective informational integration of the worker by enabling the worker to understand what the robot is doing. AR has the potential to facilitate these two aspects and thus to enhance collaboration between humans and robots in assembly tasks.

Based on these considerations and established requirements for assembly assistance systems [16] and AR systems [17,18], we compiled a list of requirements for AR-support in adaptive dynamic HRC, as shown in Table 1. Requirements R1 to R3 focus on providing accurate, targeted, and self-explanatory information while avoiding redundancy [16]. Ergonomics and hands-free operation demands [17,18] led to R4, while the R6 and R7 address safety considerations in robot-assisted physical tasks [16]. Lastly, R5 pertains to the need for (automatic) quality control throughout the process [16].

Table 1: Requirements for AR-support in adaptive human-robot collaboration

Req.	Description
R1	**3D localized work instructions**: Present accurate instructions at the relevant place to reduce cognitive load and transfer effort.
R2	**Visualization of the next tasks**: Show upcoming tasks for the human and the robot to enhance trust and acceptance by ensuring both know what the other is doing - promoting smooth workflows.
R3	**Information on dynamic changes in task allocation**: Provide real-time updates about any changes in task assignments to keep humans informed and ensure effective collaboration.
R4	**Ergonomics and comfort**: Utilize lightweight AR devices, ensuring high wearing comfort and usability during the entire shift, while keeping hands free for assembly work and providing seamless access to instructions without distracting workers.
R5	**Process supervision and progress confirmation**: Monitor the process progress and (automatically or manually) confirm completed work steps to track the workflow and provide inputs for control algorithms.
R6	**3D visualization of robot trajectories**: Help humans understand robot movements to proactively avoid collisions, thereby increasing safety through active human involvement.
R7	**Detection of human hands and body positions**: Ensure safety by detecting the positions of human hands and bodies, allowing for dynamic collision avoidance by adapting the robot's movements.

3. Concept for adaptive HRC and software framework

Based on the research needs and system requirements, this section presents the conceptual framework for the adaptive HRC system, including the system architecture (section 3.1), the AR interface (section 3.2), the optimization-based dynamic task allocation approach (section 3.3), and its integration into a no-code software framework (section 3.4).

3.1. System architecture

Figure 1 illustrates the conceptual architecture of the system. To ensure modularity and enable distributed edge computing, the system is composed of three interconnected computing units: a central assembly station computer, responsible for coordinating the process flow; a robot system computer, which manages trajectory planning and acts as the middle-layer controller for both the collaborative robot and the end-effector; and a computing unit dedicated to the AR device.

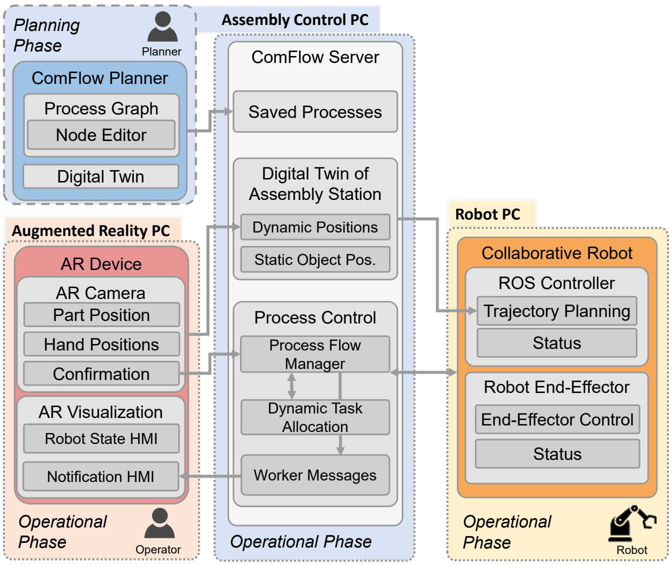

Fig. 1. Schematic architecture of the software framework for adaptive and AR-supported human-robot collaborative assembly.

The assembly processes are created by a planner using the ComFlow software framework ([19]; see section 3.4), which facilitates block-based no-code programming and the saving of developed processes. During the operational phase, the process execution is controlled by the ComFlow Process Flow Manager, which communicates with a dynamic task allocation module to determine and assign the next tasks to be executed (cf. architecture presented in [8]).

Depending on the assigned tasks, individual assembly steps are sent either as worker messages in the form of assembly instructions to the AR device or as actions to be executed by the robot. When a robot task is assigned, the robot calculates the trajectory for movement execution, incorporating both static (assembly station) and dynamic object positions (part positions, positions of workers' hands and bodies) from the digital twin of the assembly station. The collaborative robot is controlled via ROS, while the communication to the robot end-effector occurs through its communication protocol, for example, via a Modbus/TCP interface.

3.2. User interface for AR visualization during assembly

For the AR HMD, based on the requirements from Table 1, we opted for a lightweight solution with an integrated camera (XReal Air 2 Pro) to combine efficient provision of spatial information visualization and situation recognition. This integrated approach fulfills the visualization requirements (R1, R2, R3, R6), ensures ergonomic wearability for long-duration use (R4), and is suitable for implementing camera-based recognition functionalities (R5, R7) without the need for external cameras. Hence, it also enables the implementation of both automatic and manual confirmation of completed tasks. While the HMD weighs only 75 g, it lacks integrated computing power. Therefore, it is connected via USB-C to a portable mini-computing unit that processes the camera data.

Figure 2 shows the created mockup for the user interface of the AR HMD, which visualizes the following aspects:

a) **Human assembly instructions**: Displays a detailed description of the current human task for each assembly step, including an illustration or picture.
b) **Location-based spatial information:** Provides information directly at the assembly object, such as circles indicating assembly positions or labels on bins for part retrieval, including the quantity of required parts.
c) **Task assignment**: Simplified representation of the current tasks for both the robot and the human.
d) **Robot state**: Color-coded visualization of the robot's status (e.g., moving, waiting, planning, or error).
e) **Robot trajectory**: Shows the planned robot trajectory, allowing the worker to be aware of the robot's movements.
f) **Safety zones**: Color-coded visualization of areas that the worker should avoid for safety reasons.

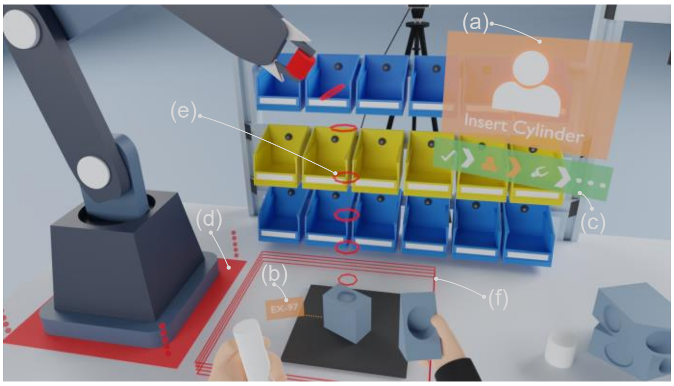

Fig. 2. Mockup of the AR assistance user interface during process execution.

3.3. Optimization method for dynamic task allocation module

For the dynamic task allocation module, we developed a novel algorithm that enables optimization-based ad-hoc task allocation during assembly execution instead of relying on a greedy approach (cf. [8]). Figure 3 visualizes the proposed algorithm's functionality, which employs a divide-and-conquer approach to break down the optimization problem of the overall process into smaller sub-problems. These sub-problems can be solved online in a short time due to their lower complexity.

The proposed algorithm consists of the following five steps:

1. **Progress Update**: The current progress of the process graph is continuously monitored (Process Flow Manager, cf. Figure 4). Once the number of process steps completed reaches the parameterized update rate n, a new planning cycle is initiated by executing the steps 2 to 5 of this algorithm.

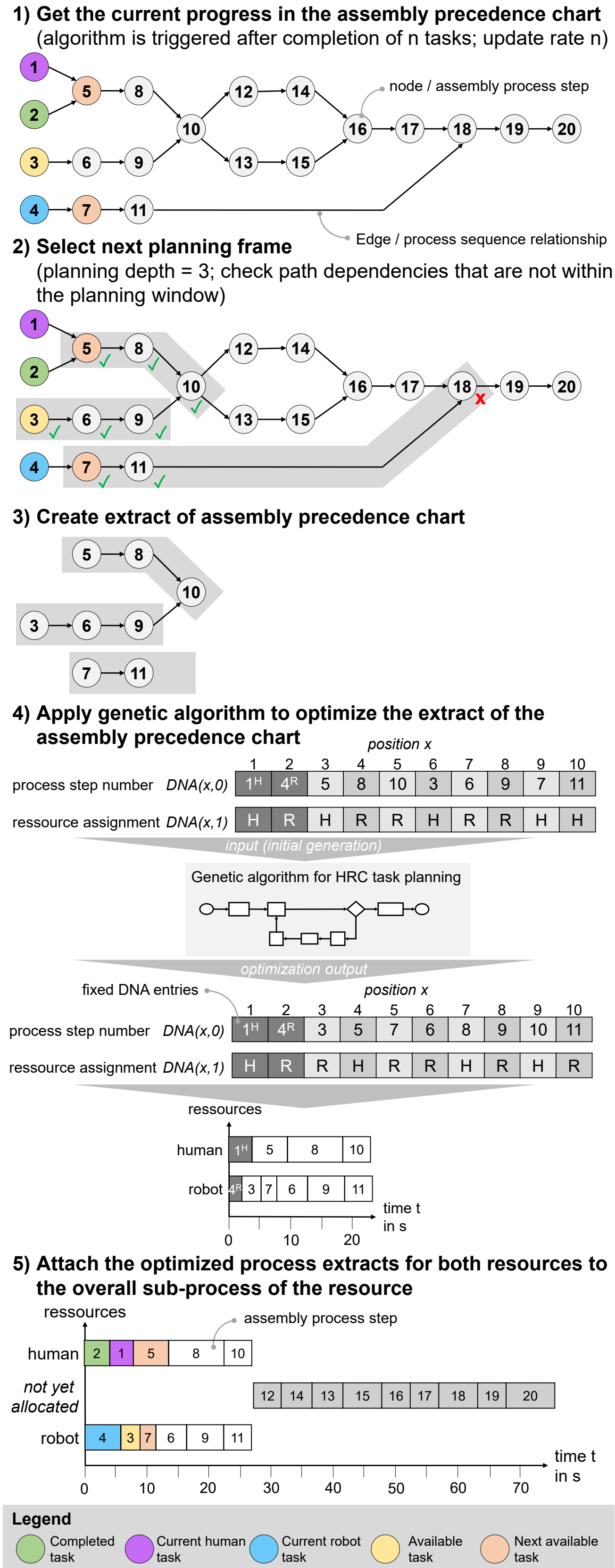

Fig. 3. Illustration of the procedure and functionality of the proposed algorithm for optimization-based dynamic task allocation.

2. **Next Planning Frame**: The next planning window is selected. For this, the next d steps from each parallel branch are chosen according to the parameterized planning depth. This includes both currently available steps

(highlighted in yellow in Figure 3) and steps that will become available after the current tasks are completed (orange). Process steps that cannot meet all prerequisites due to path dependencies within the planning window are excluded from the planning.

3. **Precedence Chart Extraction**: The selected process steps are extracted from the overall precedence graph, forming the extract for the subsequent sub-process optimization.
4. **Genetic Optimization**: The selected process steps are encoded as a HRC-Process-DNA (a representation of the process and resource assignments analogous to biological DNA; cf. Figure 3). This DNA consists of two components: a Process Step DNA(x,0) and a Resource Assignment DNA(x,1), with x entries corresponding to the number of process steps in the extract. The first generation of HRC-Process-DNAs is randomly initialized (both the order and the resource assignment), while the steps currently being executed (in the example, steps 1 and 4) are locked into the first two positions of the DNA and are not altered during optimization (highlighted in dark grey in Figure 3). In total, p DNAs are initialized according to the parameterized population size. A genetic optimization algorithm, based on [20], is then applied, evolving the population through the genetic operators of mutation and crossover. The selection of the best m DNAs is based on minimizing the total cycle time of the process extract. After j generations, the best HRC-Process-DNA is selected.
5. **Process Plan Update**: Based on the result of the genetic optimization, the process steps are appended to the respective resource execution sequences in the order determined by the Resource Assignment DNA. Previous plans are deleted beforehand.

3.4. Integration into software framework for process creation

The ComFlow software framework is used to coordinate the entire system by allowing the process flow to be created easily through drag-and-drop of functional blocks based on the assembly precedence graph. The already implemented user interface for creation and monitoring of processes is visualized in [8]. However, previously, specific HRC sub-process blocks had to be stored for each HRC process step. These blocks were then combined at a higher level into the process and had to be specified with process details (classification, execution times for both human and robot for the combined skill) in each case.

In this paper, we propose a simplification where only the execution times of the elementary functions need to be specified. A system selector then automatically determines both the execution time of the combined skill (the sum of execution times in subsequent function block groups) and the classification (i.e., whether task branches for human and/or robot are linked). The dynamic optimization algorithm described in section 3.3 leverages these system selectors and performs the optimization accordingly. With this approach, we expect to achieve a more intuitive and faster creation of dynamic HRC process flows.

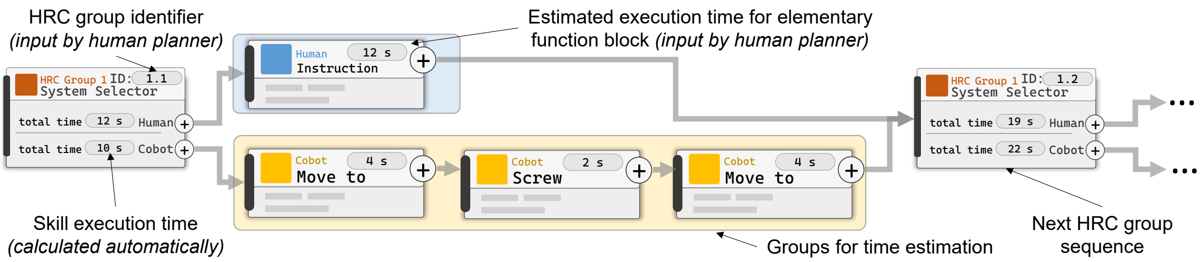

Fig. 4. User interface for intuitive no-code HRC process design, implemented in ComFlow.

4. Demonstration by application in laboratory scenario

The proposed algorithm is demonstrated in a laboratory setting at a collaborative assembly workstation, utilizing the assembly component from [8] (cf. Figure 5). Unlike our previous study [8], the robot (Universal Robot UR10e) is now equipped with a screwdriver (OnRobot Screwdriver with automatic screw feeder), enabling it to execute all screwing operations (steps 10 to 14), i.e., placing and fastening screws. Thus, pick-and-place (steps 1 to 9, and step 15) and quality-checking tasks (step 16) remain exclusively with the human.

Figure 6 presents different Gantt charts of the resulting assembly process, showing: *i)* static process planning (in the case of no delays), *ii)* the impact of a 3-second delay in steps 1-5 (e.g., due to less experienced workers) under static planning, and *iii)* and *iv)* the process outcomes after compensating for the delay using the proposed algorithm.

The comparison between *iii)* and *iv)* illustrates that higher update rates improve responsiveness to delays or plan deviations (potentially reducing resource waiting times), but necessitate more frequent planning (which must be executed quickly enough to avoid computation-induced delays).

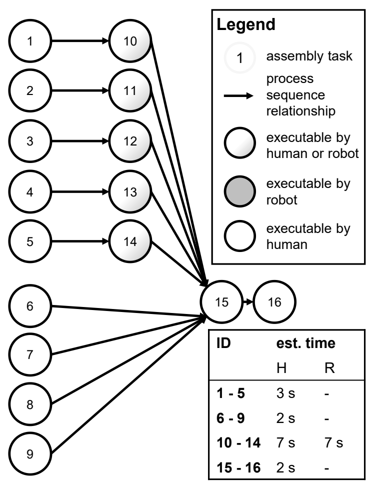

Fig. 5. Precedence graph for the assembly component, including time estimates and task classifications.

Moreover, greater planning depth yields better planning results but requires more computation time. Therefore, a trade-off between update rate, planning depth, and the number of generations in the genetic optimization is necessary.

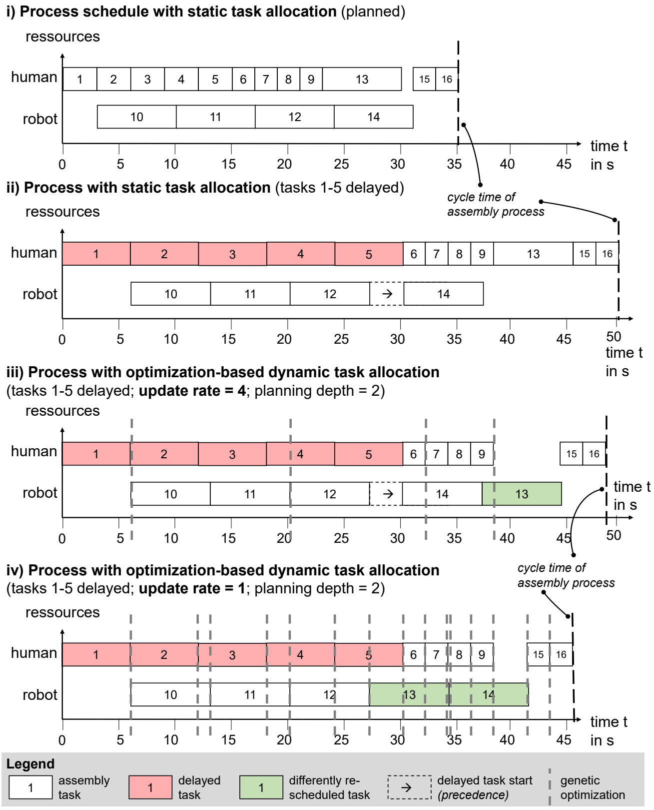

Fig. 6. Comparison of static and dynamic process execution under delay conditions, highlighting different parameter configurations of the algorithm.

5. Conclusion and Outlook

In this paper, we introduced a comprehensive system for adaptive HRC assembly, combining an optimization-based dynamic task allocation algorithm with AR-support for workers. The system addresses key challenges such as effective task distribution, trust-building and real-time information provision, while improving flexibility and efficiency by handling delays in dynamic process planning more effectively.

Our ongoing research focuses on fully implementing the system. Once the AR user interface is complete, we will assess its impact on worker acceptance and trust in adaptive HRC compared to screen-based information. Furthermore, we will analyze process-dependent parameter configurations (e.g., planning depth, update rate) by developing a tool to automate the generation of various process scenarios and simulate execution under uncertainty. Finally, we plan to compare the performance of our optimization-based method with heuristic ad-hoc dynamic task allocation in future user studies. While the dynamic ad-hoc approach has already reduced cycle times by approx. 11% compared to static planning [8], we expect further efficiency gains from the approach presented in this paper.

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