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ASSEMBLY

Cognition-enhanced assembly sequence planning for ergonomic and productive human–robot collaboration in self-optimizing assembly cells

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Abstract Self-optimizing robotized assembly systems are able to compensate the restricted operation purpose of traditional robotized automation, in order to adapt dynamically to changed production conditions. As the human operator is directly involved in the assembly process, the interaction between the human and the robot has to be designed carefully to avoid exposing the human to excessive physical and cognitive strain. For controlling a robotized assembly cell, a Cognitive Control Unit (CCU) was developed that uses the cognitive software Soar and human-like assembly strategies to achieve a transparent and understandable assembly process. To minimize the cognitive and ergonomic risks during assembly, the CCU was extended by a graph-based assembly sequence planner (GASP). The GASP is able to find the optimal assembly sequence by using a complete assembly graph of the final product as well as generic production rules for assessing the ergonomic conditions of the individual assembly steps. The presented simulation study validates the functionality of the GASP with respect to the number of workflow switches between the human and the robot, the number of switches between the robotic tools, as well as the number of assembly group switches required to collaboratively assemble a model of a Stromberg carburetor. The results show a significant reduction of all three measures. The number of parts and the type of assessment of the assembly steps have a significant impact here.

Keywords Human–robot collaboration · Ergonomic work conditions · Risk modeling · Assembly planning

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1 Introduction

Increasing customer individualization in the global markets as well as rapid changes in demand, resource availability, quality, or user requirements lead to environmental turbulences and uncertainty in the assembly process of industrial companies [1, 2]. Robotized automation is usually designed for a specific application purpose and the frequent rewriting and retesting of the corresponding robot control (RC) programs, required, for example, to adjust them to a new product [1–3], involve much cost and effort. Such adjustments do not usually make any contributions to the value-adding process, so novel planning and control methods such as self-optimizing production systems [4, 5] are required to adjust autonomously to this turbulent environment.

However, despite self-optimization and novel technologies, many complex assembly tasks still require the human operator to perform manual interventions ranging from the assembly of flexible parts up to high-level problems such as the handling of erroneous situations and the solution of ill-posed problems [2, 6, 7]. Consequently, it is advantageous to combine the operator's extraordinary cognitive and sensorimotor skills with the technical capabilities of the robot [8]. Thereby, the occupational safety of the working person in terms of mental and physical work conditions has to be ensured anytime. While collaborative workplaces can be designed with respect to all technical safety requirements (e.g. [9–12]), hazards coming from the product or the assembly process (e.g. sharp edges, risk of entrapment) may not be totally excluded, especially against the background of dynamic assembly environments with few pre-planning efforts. Cognitive systems try to simulate human cognition and can be used to partially establish an image of the human mental model and its skills within production control. Deficiencies in automation [13–15], human–robot interaction [16], and planning [17] can thus be compensated, enabling a further step towards "intelligent production systems" to be made.

From the human point of view, the operator might still be exposed to physical and mental strain due to his[1] assembly tasks and the non-deterministic system behavior of self-optimizing systems. This should be avoided by adequately designing the autonomous decision-making process during the collaboration with the robot [8, 18–21]. For this purpose, a cognitive production control for controlling a robot-assisted assembly cell [22, 23] was extended by a graph-based assembly sequence planner (GASP).

2 Production control in dynamic environments

Dynamic markets demand new requirements from producing companies. Self-adjusting production control as well as flexible assembly planning processes pioneers an efficient production and forms the basis for effective and ergonomic human–robot collaboration (HRC).

2.1 Cognitive automation for self-optimizing socio-technical production systems

In order to be able to react dynamically to changed production conditions, it is essential to avoid rigid structures and to design the production system flexibly. Such dynamic adaptations can be found in human cognition and its information processing mechanisms [24]. Cognitive software systems such as Soar [25] try to simulate human cognition to propose and evaluate action alternatives and to decide for the most promising action with respect to the target state. Assuming an adequate knowledge base, the transfer of this behavior to production systems and therefore the use of cognitive software systems as control units result in a highly flexible decision-making process [1, 26]. By applying inference techniques, existing knowledge can be used and recombined in order to solve unknown problems that may be due to sensor failures (e.g. wrong detection of parts or semi-finished products) or new product variants to be assembled. These intelligent systems can be viewed as self-optimizing systems characterized by an endogenous adaptation of their objectives due to changing external objectives, operation points, or operating conditions [4, 5, 27]. Parameters, the inner structure, and behavior are adjusted autonomously on the basis of internal decisions. In this process, the knowledge of both human and technical parts of the system is used, as these future systems are mainly characterized by the communication and cooperation between the intelligent system elements [27].

Based on multiple approaches to model self-optimizing systems [4, 28–30] a hierarchical, self-similar architecture for cognitively automated, self-optimizing production systems was developed [5, 31]. Each level of the architecture has its own cognitive controller with its own decision cycle that is responsible for goal-oriented knowledge processing and decision making. The human operator is considered as an integral part of the production system, so that he is involved on each level and interacts directly with the cognitive controller. For cognitively controlling a robotic assembly cell [32], a Cognitive Control Unit (CCU) based on Soar was developed to control pick and place processes for individual parts and components in line with the human mental model [22, 23]. Thereby, the human operator does not only perform supervisory tasks, but takes active part in the assembly process in a collaborative manner with the robot. To ensure effective and ergonomic collaboration, a model for assessing assembly processes was developed based on a graph-based representation of the product for assembly sequence planning.

2.2 Approaches to assembly planning

General approaches to assembly planning can be found in the field of artificial intelligence, where finding solutions for structured problems is one of the central research areas. Forward planners, for instance, search a specified state-space in order to find a deterministic plan to achieve a goal from a given starting state [33]. The fast-forward planner [34] is suitable to derive actions sequences for given problems in deterministic domains. Further approaches such as heuristic forward search [35] or SAT-based planning [36] are additionally able to cope with incomplete information and uncertainty. However, as these planners rely on symbolic representations based on logic, the representation of geometric relations between objects become very complex even for small tasks, which impacts the performance of the planners dramatically.

Specialized planners designed especially for assembly planning mainly work directly on geometric data and transform them into a graph-based representation to derive action sequences. By means of the "assembly by disassembly" strategy compact structural representations of the product can be obtained (e.g. [37–39]). Most approaches proposed in the literature are not able to adapt online to environmental changes (e.g. [37, 38, 40, 41]), whereas the support system proposed by Zaeh and Wiesbeck [42] and the robot plan execution system by Shah [43] observe and identify the human's actions and adopt their own planning correspondingly. Regarding the operation purpose of the planning system most approaches are designed for

[1] For ease of reading, the masculine form has been used in the text to refer to both genders.

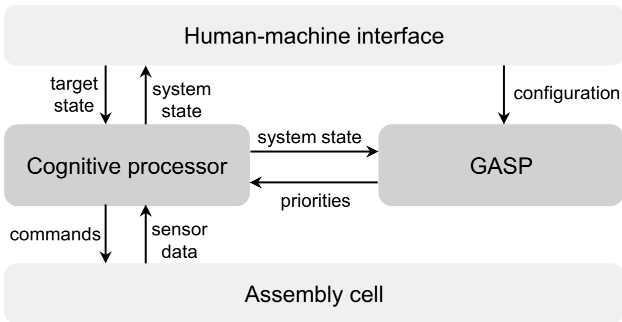

Fig. 1 Integration of the graph-based assembly sequence planner (GASP) into the cognitive control of the assembly cell

autonomous assembly [37–39, 44]. Only few consider HRC [41, 43], manual assembly [42], or are generally applicable [40]. Consequently, none of them is able to allocate assembly tasks to different assembly units such as the human and a robot, except the IkeaBot [44] that assigns the assembly tasks to multiple cooperative robots. In addition, the ergonomic conditions of assembly steps are considered at best in terms of mental load of the human (e.g. [42, 43]). Physical ergonomics is addressed nowhere. Hence, there is a need to develop a method for planning and assessing assembly processes with regard to HRC and the consequent ergonomic work conditions for the human. Against the background of dynamic production environments, this method has to cope with incomplete information and uncertainty.

3 Model-based assembly sequence planning for human–robot collaboration

In order to take ergonomics and safety aspects of the collaborative assembly process into account, the CCU was extended by a novel GASP that incorporates a model for assessing the risk of individual work steps for the human operator [23, 31] (see Fig. 1). The GASP works using a reusable assembly graph that contains all feasible assembly sequences of the product and is searched for the optimal assembly sequence within each planning cycle. For this purpose, it obtains the current system state by the cognitive processor and returns a list of priority-ordered possibilities to the cognitive processor to continue the planning process.

3.1 Generation of the model for assessing assembly steps

Following the approach of Ewert et al. [45], the planning process is divided into an offline and an online phase. In preparation of the production process, a directed state graph is initially generated according to the

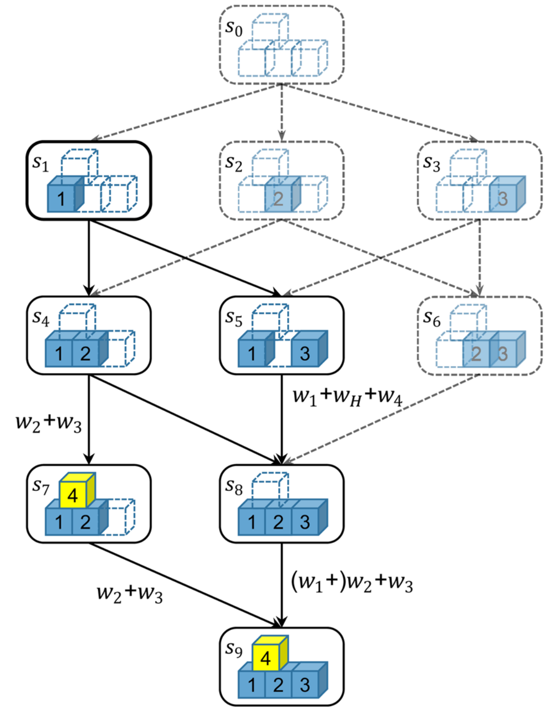

Fig. 2 Exemplary assembly graph for a product consisting of four cubic components and two assembly groups (w_H: manual assembly, w_1: human–robot switch, w_2: robotic tool switch, w_3: assembly group switch, w_4: poor ergonomics due to high pressure needed)

assembly-by-disassembly strategy [38]. For this purpose, the CAD data of the final product are searched for the geometric data and the pose of the parts in order to derive the neighborhood relationships. By recursively decomposing the product, all feasible assembly sequences can be identified and transformed into the assembly graph. Consequently, each node s_i of the graph represents a valid subassembly of the product and all outgoing edges (s_i, s_{i+1}) possible assembly steps, with each step consisting of the assembly of exactly one single component. The assembly graph of an exemplary product consisting of four cubic components is depicted in Fig. 2.

Each edge of the assembly graph is attached with weights induced by the corresponding assembly step. As the assessment of an assembly step needs to be determined dynamically during the assembly phase, rules representing planning criteria are specified in the knowledge base that can be combined according to the current optimization criteria. The resulting edge weights consider, on the one hand, the assignment of the assembly task to the human operator or the robot. On the other hand, edge weights are calculated with respect to the currently activated planning criteria in the knowledge base. In particular, these rules represent human-like assembly strategies and include planning aspects of both physical and cognitive ergonomics, in order to make the assembly sequence as safe and transparent as possible for the human operator. Using standardized methods for assessing the ergonomic work conditions of single work steps such as DIN EN 1005-2 [46], Ovako Working Posture Analysing Systems (OWAS) [47, 48], or RULA [49] as well as direct measurement techniques (e.g. [50]) allow for assigning numeric values as weights to the edges. Thereby, occupational hazards justified by the characteristics of the assembly step (e.g. high forces) or the course of the previous assembly steps (e.g. risk of entrapment) can be avoided at an early stage in planning.

Regarding cognitive ergonomics, such assembly strategies could be identified and validated successfully in two independent experimental trials [21, 51] and include among others: (1) buildup with respect to the vicinity of neighboring parts, (2) buildup in layers. As many products can be decomposed into several assembly groups, a further rule concerning the buildup in logical groups of parts is added. This also reflects the natural assembly strategy of the human. Due to the increased transparency and predictability of the assembly sequences, wrong perceptions and therefore misunderstandings in the interaction between the human and the robot are avoided. Besides these ergonomic rules, the assembly planning also copes with technical criteria, as the robotic tools generally have limitations with respect to, for instance, the required space at the joint position or the kind of object that can be handled. In the exemplary assembly graph of Fig. 2, part 4 denotes a second assembly group that has to be handled with another tool. In addition, the robot might not be able to position part 2 autonomously if the parts 1 and 3 have already been assembled (see state s_5). Hence, the last rule requires two freely accessible parallel sides, in order to be able to use a parallel gripper. In case this condition is not satisfied, the assembly step has to be delayed or taken over by the human.

The aforementioned rules can be applied to each edge (i.e. to each assembly step) of the assembly graph. Their preconditions are checked at each intermediate state of the assembly, yielding a numerical assessment. As a result, each edge of the assembly graph has a vector $w = \left(w_H, w_1, \ldots, w_m\right)^T$ attached to it, containing all weights, with w_H indicating the weighting for manual assembly steps and w_i the weighting for rule i. The resulting graph is a generic description of the assembly process that can be reused for different optimizations depending on the current system objectives. Rules can be activated and deactivated, but only the weights of the activated rules are considered in the following planning procedure.

3.2 Assessment of the assembly process

During the assembly process, the GASP has to decide about the next options for continuing the assembly sequence. To do so, the current node of the assembly graph is identified by means of the current system state. Starting from this node the weights of all outgoing assembly sequences have to be determined in order to be able to compare them. Let $\mathcal{P} = (s_0, \ldots, s_i, \ldots, s_{i+j}, s_{i+j+1}, \ldots, s_n)$ describe an arbitrary assembly sequence, where s_0 denotes the initial (i.e. empty) state, in which no part has been assembled yet, s_i the current state, and s_n the final state, in which the product has been assembled completely. Next, the total weight of one possible continuing assembly sequence $\mathcal{P}' = (s_{i+1}, \ldots, s_{i+j}, s_{i+j+1}, \ldots, s_n)$ is determined by summing up the weights along the path, which consist of the basic weight w_b for each assembly step and the additional weight $w_a = w \cdot r^T$. Here, $r \in \{0, 1\}^{m+1}$ denotes the activation vector for the planning rules, while $r_i = 0$ deactivates and $r_i = 1$ activates rule i. Having the particular rules for assessing assembly steps in mind the aforementioned procedure results in a description of the technical and ergonomic conditions of the remaining assembly sequence $\mathcal{P}'$. Against the background of HRC these sequences can be compared and balanced, for instance, with respect to the contained (poor) ergonomic conditions, which result in higher assessments.

In the exemplary assembly graph of Fig. 2, it is assumed that s_1 is the current system state. Furthermore, component 2 needs to be assembled manually with high pressure [see assembly step (s_5, s_8)], if component 1 and 3 are already assembled, and component 4 belongs to a second kind of components that needs to be assembled with a different tool [steps (s_4, s_7) and (s_8, s_9)]. Then, all assembly steps can be assessed using the following rules: w_H for manual assembly, w_1 for human–robot switches, w_2 for tool switches, w_3 for assembly group switches, and w_4 for poor ergonomics due to high pressure needed. The decision whether the workflow switches from the human to the robot [w_1 in step (s_8, s_9)] depends on the history of the assembly sequence. Furthermore, the high pressure needed for component 2 is negligible if the robot assembles the component [step (s_1, s_4)], but it does matter in case of manual assembly [w_4 in step (s_5, s_8)]. Depending on the numerical evaluation of the planning criteria, one possible continuation of the assembly sequence might therefore be (s_4, s_7, s_9). Hereby, the additional tool switch is preferred to the intervention of the human, which might expose him to high physical stress.

Assuming that the component supply does not provide all necessary parts at once but only j parts, the total weight can be calculated reliably only for the next j assembly steps, i.e. up to state s_{i+j}. For the remaining assembly sequence it is uncertain which parts will be available assuming a random component supply. Hence, these weights have to be estimated by assuming that in each state of the considered sequence the necessary part is available, in order to not underestimate the total weight of the assembly sequence.

The estimated weights therefore base on the assembly of the component (w_b), which is assumed to be available, and the relevant additional weights of the planning criteria (w_i). Otherwise, these assembly steps would have to be marked as infeasible preventing a complete planning process for the assembly sequence.

With the aforementioned assessment of individual assembly sequences in mind, the alternative assembly steps of the current state are compared by means of the total weights of the corresponding sequences. The remaining assembly sequences are found by applying a modified version of the algorithm A*Prune [23, 52]. As result, the best k continuing assembly sequences having the lowest total weight are returned. Paths with equal beginnings of the assembly sequence are reduced to one single path by choosing the one with the lowest weight in order to maximize the diversity of the possible next assembly steps.

The final set of possible next assembly steps is presented to the cognitive processor of the CCU by assigning preferences that correspond to the total weights. In particular, assembly steps with high weights are rated with a low probability within Soar and vice versa. During the decision phase the CCU can apply an additional threshold in order to neglect solutions that deviate too much from the optimal solution. Actions that are proposed by the CCU but not by the GASP are also neglected, because the GASP has more information available for the planning process than the CCU. Using the external preferences, the cognitive processor can proceed with its decision-making process and selects the action considered to be the best based on the internal and external knowledge. The CCU thus retains its cognitive features and is able to consider complex planning criteria and changes in its environment dynamically.

4 Validation

The decision-making process of the developed CCU as well as the assembly sequence planning by the GASP were validated by means of a simulation study. This study focused both on the correctness of the planning procedure and the support of the collaborative assembly procedure between the human and the robot. The following hypotheses were made:

- Reduction of human–robot switches and switches between robotic tools: Switches in the workflow between the human and the robot may induce physical or mental stress and strain [18–20]. The number of switches should thus be reduced to a minimum. At the same time, the temporal variance of manual work tasks is decreased enabling a continuous workflow. The reduction of the number of switches between the robotic tools makes the assembly process more efficient and releases the operator from supervisory tasks.
- Reduction of switches between assembly groups: The temporal course of the assembly process should contain as few switches between assembly groups as possible. This increases the transparency of the assembly process and facilitates the potential intervention of the operator for manual assembly.

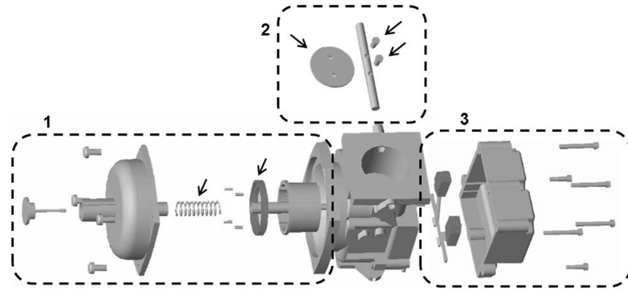

Fig. 3 Model of a Stromberg carburetor. The parts marked with an *arrow* have to be assembled manually by the human operator [53]

4.1 Method

During the assembly process, a model of a Stromberg carburetor (see Fig. 3) was assembled collaboratively between the human and the robot. The carburetor consists of three independent assembly groups and 26 parts in total. The parts marked with an arrow in Fig. 3, such as the sealing ring or the retaining spring, were classified for manual assembly by the human as they require extensive sensorimotor skills during joining. The other parts are assumed to be assembled autonomously by the robot using a gripper and an electric screw driver.

The independent variables of the simulation study were the number of supplied parts, the usage of the GASP, and the weights for the graph edges with respect to assembly group switches. The number of parts supplied simultaneously was varied systematically between 1 and 24. The simulation was run for each condition with activated and deactivated GASP. In case the GASP was activated, the simulation was run with a deactivated planning rule and an activated planning rule for the buildup in assembly groups. In order to examine the dependency of the results on the chosen edge weights, the weights were varied exploratory between 10, 20, and 50. The number of workflow switches between the human and the robotic tools and the number of assembly group switches were chosen as dependent variables. In order to avoid unnecessary switches of the work piece between the human and the robot as well as between the robotic tools, the

Table 1 Reduction of the number of switches between the human operator, the robot using gripper, and the robot using screwdriver, when activating the GASP, and the results of the corresponding Wilcoxon rank sum tests

	Gripper	Human operator	Screwdriver
Gripper	–	−19.36%***	−19.42%***
Z-value		12.81	24.63
Effect size r		0.203	0.390
Human operator	−11.80%***	–	−2.60%
Z-value	4.53		1.53
Effect size r	0.072		0.024
Screwdriver	−33.10%***	+11.12%***	–
Z-value	30.24	−5.03	
Effect size r	0.478	−0.080	

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

additional weights for human–robot switches and switching the robotic tools were chosen at a rate of 1:2 with the weights 10 and 20, respectively.

As the data are not normally distributed, they were analyzed using the Wilcoxon rank sum test and Kruskal–Wallis test, respectively, at a level of significance of $\alpha = 0.05$. Regarding trend analyses, the Jonckheere–Terpstra test was applied, an extension of the Kruskal–Wallis test that takes an existing a priori ordering of the populations into account in order to achieve a higher statistical power [54, 55]. The statistical analyses were conducted with MATLAB R2016a and IBM SPSS Statistics 21.

4.2 Results

The conducted simulation study shows a reduction of both human–robot switches and switches between the robotic tools during the collaborative assembly when using the GASP for planning the assembly sequence. As shown in Table 1, there is a significant reduction for nearly all combinations according to the Wilcoxon rank sum test [53]. The increased number of switches between the human operator and the robot using a screwdriver may be due to the structure of the carburetor, whose assembly groups are mainly assembled sequentially. As one of the main design goals of the GASP is to support the human in situations of HRC and to minimize the ergonomic risks, the interaction between the human and the robot is of particular interest. The effect sizes r state a small to moderate effect for all cases in which the human operator is involved, and a moderate to large effect for the switches between the robotic tools. The total number of switches between the human and the robot could be reduced significantly by 5.09% (deactivated GASP: $M = 6.06$, $SD = 1.77$; activated GASP: $M = 5.75$, $SD = 1.69$; $Z = 5.32$, $p < 0.001$, $r = 0.084$).

The number of workflow switches is additionally influenced by the number of parts that are supplied simultaneously, as these are the only parts the GASP can use to plan the assembly sequence reliably. For running the CCU with 1–24 parts, the mean number of workflow switches between the human and the robot is 6.06 ($M \in [5.76;6.26]$, $SD \in [1.64;1.92]$), whereas the mean number of switches between the robotic tools is 5.43 ($M \in [5.25;5.64]$, $SD \in [1.11;1.39]$). According to the Jonckheere–Terpstra test, both measures show a significant trend with respect to the number of parts: as more parts were supplied, the number of switches increased (human–robot switches: $J = 936746.0$, $z = 4.382$, $r = 0.098$; tool switches: $J = 906136.0$, $z = 2.173$, $r = 0.049$). The numbers of observed workflow switches are the baselines for comparing the results of the following simulation runs, in which the GASP was activated.

Figure 4 depicts the mean relative deviation of the number of switches between the human and the robot as well as between the robotic tools with respect to the number of supplied parts. According to the Wilcoxon rank sum test, no significant effect is found for the number of human–robot switches for up to four parts. However, there is a significant decrease within the range of 8–24 parts (each $p < 0.05$, each $r \in [0.089;0.197]$). This corresponds to an average decrease of 7.98% (deactivated GASP: $M = 6.21$, $SD = 1.80$; activated GASP: $M = 5.72$, $SD = 1.72$; $Z = 7.03$, $p < 0.001$, $r = 0.141$).

A very similar effect (albeit even stronger) can be observed with respect to the number of tool switches within the assembly sequence. They can be reduced on average by 25.97% (deactivated GASP: $M = 5.43$, $SD = 1.27$; activated GASP: $M = 4.02$, $SD = 1.33$). Independently of the number of supplied parts, statistical analysis shows a strong effect by using the GASP (each $p < 0.001$, each $r \in [0.409;0.574]$).

Regarding the second research hypothesis, the number of switches between the assembly groups within one assembly sequence is of particular interest. Running the CCU without GASP yields an average number of 9.52 switches ($SD = 0.18$). Regarding the number of supplied parts, there exists a significant positive trend ($J = 1045519.5$,$z = 11.593$,$r = 0.259$). Figure 5 depicts the relative deviation of the mean number of assembly group switches with respect to the simulation runs with deactivated GASP. Here, not using the planning rule is equivalent with using the rule with a weight of 0. For edge weights up to 20 no positive effect is caused by the GASP. Rather, an increase can be observed that has a significant trend for the weights 0 ($J = 788547.5$, $z = -5.847$, $r = -0.131$) and 10 ($J = 917239.5$, $z = 2.857$, $r = 0.064$) according to the Jonckheere–Terpstra test.

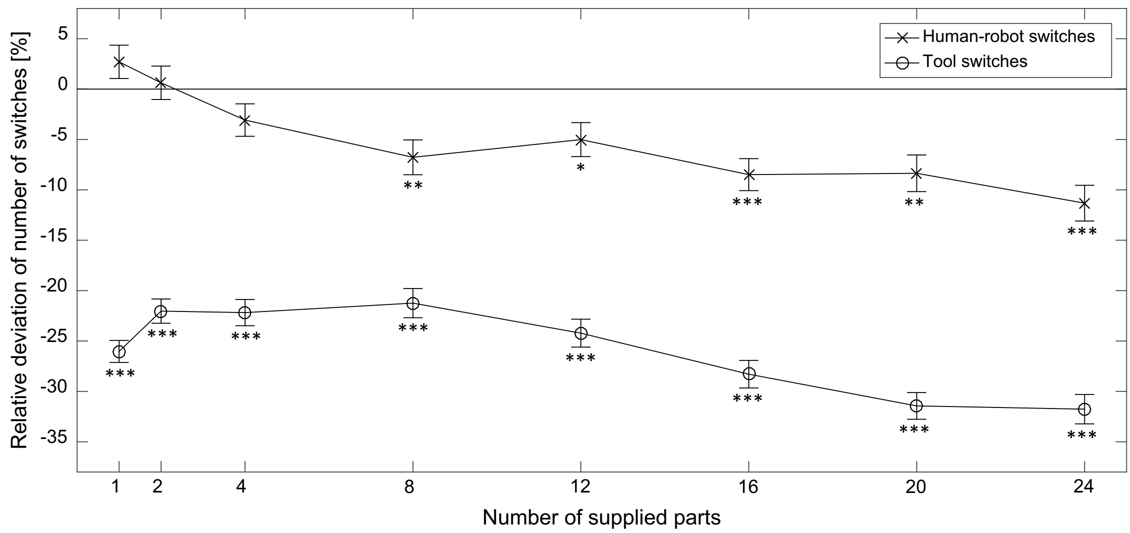

Fig. 4 Relative deviation of the mean number of human–robot and tool switches with respect to the CCU and the corresponding standard deviations (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$)

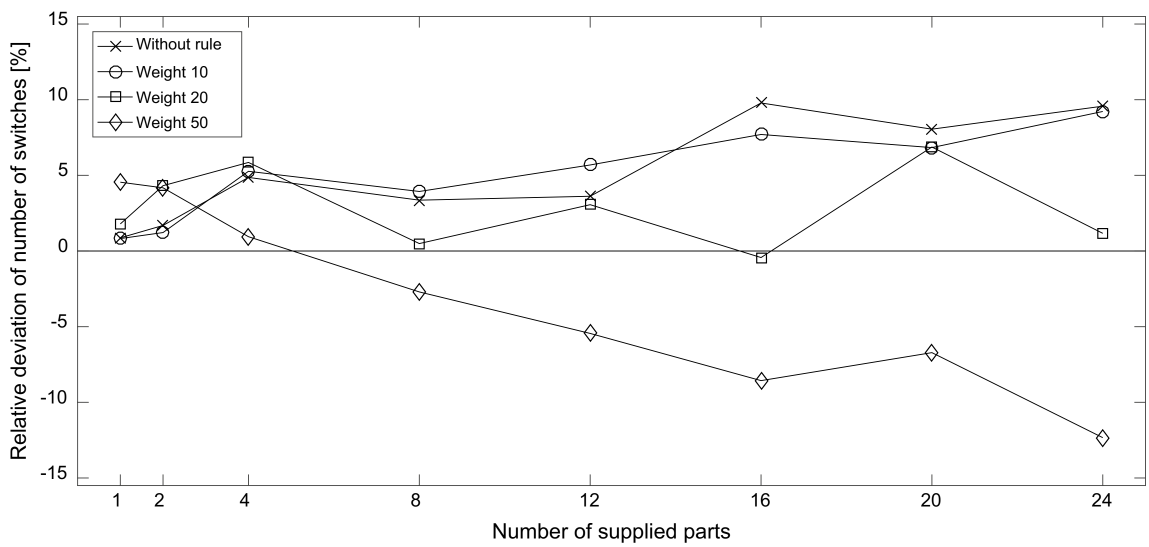

Fig. 5 Relative deviation of the mean number of assembly group switches with respect to the CCU

This increase is closely related to the Pareto principle (e.g. [56, 57]) of the GASP. As the planning rules are additive, the GASP has to balance different optimization criteria against each other. The weight for switching the assembly groups competes with the aforementioned weights for switching the workflow between the human and the robot, which are in this case higher than those for the assembly groups. However, increasing the edge weight for switching the assembly group to 50 yields a reduction (see Table 2). According to the Wilcoxon rank sum test this effect is significant for more than 12 parts supplied simultaneously. Regarding the number of supplied parts the data again contains a significant trend ($J = 788547.5$, $z = -5.847$, $r = -0.131$).

5 Conclusion and outlook

Self-optimizing production systems can be used to satisfy novel challenges of the global markets. As the human operator directly collaborates with this system, the interaction interface requires an adequate design. For this purpose, a CCU was developed that transparently controls a robotized assembly cell in line with the operator's expectations.

Table 2 Results of the Wilcoxon rank sum test for the number of assembly group switches, when running the GASP with the edge weight 50

Supplied parts	*Mdn*	Reduction to CCU [%]	W_s	Z	p	r
1	9	4.55	59,580	−1.9001	0.057	−0.042
2	9	4.18	59,871	−1.7150	0.086	−0.038
4	9	0.95	61,779	−0.5269	0.598	−0.012
8	9	−2.70	64,564	1.2068	0.228	0.027
12	10	−5.45	65,809	1.9838	0.047*	0.044
16	9	−8.57	68,031	3.3652	0.001**	0.075
20	9	−6.72	66,742	2.5622	0.010*	0.057
24	9	−12.33	69,978	4.5736	<0.001***	0.102

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Furthermore, the CCU was extended by a GASP in order to further reduce the cognitive and physical risk of the collaborative assembly process. By assigning preferences to the individual assembly steps, an assembly sequence is chosen that best provides a complete and optimal assembly process.

The presented GASP was validated by means of a simulation study in which a model of a Stromberg carburetor was assembled collaboratively by the human and the robot. The study focused on creating an ergonomic work process that reduces the cognitive and physical workload for the operator. The results show a significant reduction of both the number of workflow switches between the human and the robotic tools and between the robotic tools themselves. This ensures not only a transparent and understandable workflow, but also avoids unnecessary instances of possibly erroneous and dangerous interaction between the human and the robot. Consequently, the working person is able to work more efficiently and therefore might be more satisfied. The reduction of potential hazards helps to improve the preventive health care. However, minimizing mental workload may also be related with an increasing number of monotonous work steps that have to be performed by the human. Hence, both excess and insufficient mental workloads have to be avoided by defining appropriate selection criteria for the assembly steps.

However, the study also reveals a significant increase of the switches between the screw driver and the human. This may be due to the product model and should be validated by means of another product in order to exclude any systematic effect. In the same way, the effect of small numbers of supplied parts should be revalidated using a different product, which should also consist of different assembly groups but provide more flexibility in choosing the assembly sequence. A possible minimum number of parts that are needed by the GASP to optimize the assembly process effectively may thus be confirmed or rejected. The increasing complexity of products (up to real production environments) can be encountered by automating the generation of the edge weights. Some weights can already be derived autonomously (e.g. switches between assembly groups or resources), while others have to be obtained manually (e.g. ergonomic risk). By processing additional product information such as the component information or the geometric data or by recording directly objective measures of the working person (e.g. [50, 58, 59]) these ergonomic assessments could be achieved.

Regarding the number of assembly group switches, a sensitivity analysis showed that the effect of this planning rule crucially depends on the value of the edge weight that is assigned to the corresponding assembly step. Using a weight of 50 yields partially a significant reduction, but the effect sizes state only small effects. Further studies should thus examine if higher values lead to stronger effects.

However, as mentioned above, the GASP performs a Pareto optimization. Consequently, the effect of one planning rule may be influenced by another. In particular, when adjusting the weights for the assembly group switches, the weights for human–robot switches and switches between the robotic tools also have to be considered, as both criteria influence each other adversely. Against this background, it also seems reasonable to adjust the weights, which are assigned by the planning rules, and their mutual relationship to the real conditions of a company. This can be achieved, for instance, by conducting expert interviews in order to balance the different optimization criteria.

Finally, the presented approach of optimizing the assembly sequence and the resulting ergonomic work conditions have to be validated in a real assembly scenario. A robot-assisted workplace that ensures safe and efficient HRC has been designed for this purpose and is currently under construction. Besides conventional ergonomics a light-weight robot arm will assist the human operator with the assembly while multiple sensors monitor the assembly process and the safety of the human. The behavior of the robot will adjust dynamically not only to environmental conditions but also to the operator's position and behavioral patterns.

This workplace will be the basis of future experimental trials.

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