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Towards the modelling of defect generation in human-robot collaborative assembly

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Abstract

The development of suitable defect generation models is crucial in both academia and industry having the dual purpose of predicting defects occurring in manufacturing processes and planning eligible effective quality controls. In manual assembly processes, much research focused on developing approaches to predict operator-generated defects. Today, collaborative robotics is gaining increasing attention in smart factories by contributing to the reduction of operators' physical and cognitive workload and thus enabling improved productivity. The present study proposes a preliminary investigation on defect generation models in a human-robot collaborative environment aiming to compare quality performances achieved in purely manual assembly.

Keywords: Human-Robot Collaboration; Quality control; Manufacturing

1. Introduction

The key goal of Industry 4.0 is to enable the factory of the future, including new types of intelligent systems and automation as well as more flexible collaborative robots [1]. Historically, automation in industry has been kept separate from human workers for safety reasons, but Industry 4.0 aims to support the development of robots being incorporated into assembly lines near operators [2]. Accordingly, Human-Robot Collaboration (HRC) is one of the enabling technologies in the framework of Industry 4.0 and it has received much attention in recent years due to the growing importance of Industry 4.0 related technologies. The main objective of HRC is to create an environment where humans and robots share the same workspace, the same resources, and the same tasks. This collaboration aims to integrate the strength, endurance, repeatability, and accuracy of the robots with the intuition, flexibility and versatile problem solving of the humans [3].

Collaborative robots are the cornerstone of HRC paradigm. A *cobot* (union of terms "collaborative" and "robot") is a robot that physically interacts with humans in a shared workplace [4]. The distinction between collaborative robots and traditional industrial robots is the direct interaction with human workers [5]. Thus, the main features that distinguish a cobot from a traditional factory robot include improved safety features for working in proximity with the operator and simplified programming enabling simple redeployment within a factory [6]. According to Peshkin et al. [4], cobots are also different from teleoperators, in which a human operator controls a robot and payload remotely.

HRC is a key strategy that may be applied to many manufacturing industries as it supports the effective use of existing resources through the integration of new technologies [7]. However, introducing HRC into assembly lines is complicated. Advanced tools are required to help assembly line designers better understand the requirements of both humans and robots in different situations [2]. Nowadays, collaborative robots are mainly used in product assembly processes. This is due to the cobots' ability to relieve human operators from tedious and repetitive tasks by integrating precision, repetitiveness, and flexibility, reducing

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operators physical and cognitive workload. As a result, using HRC in assembly processes leads to higher overall productivity and better product quality [3].

Despite the above benefits, in human-robot collaborative assembly there is the risk of defects occurring due to the wrong communication between humans and robots. In manual assembly, human operator is responsible for most non-conformities, whereas in automatic assembly most non-conformities may be generated by program errors. HRC risks combining the defects of manual assembly with those of automatic assembly, in addition to specific defects due to communication errors [8]. This introduces the need for developing suitable defects generation models in human-collaborative environment in order to maximize the benefits of HRC. Indeed, it is well known that defects generated in assembly process heavily affect product final quality and cost [9].

This paper presents a preliminary investigation of defects generation in human-robot collaborative assembly. The main objective is to compare the performances achieved in HRC assembly with those obtained in purely manual assembly. In detail, two experimental campaigns were conducted to investigate the effects of the assembly typology on defects generation and assembly times.

2. Background and research gap

Quality is one of the most important factors in the customer's selection process among competing products. Accordingly, implementing and improving quality control are key factors leading to business success [10]. Additionally, quality inspections are performed in almost every production system to prevent nonconforming products from reaching final customers or end-users. In fact, the firm's ability to compete may be compromised if a defective product reaches the customer [11]. In this context, collaborative robots' versatility, as well as their affordability, makes them a suitable choice for quality control in a wide range of applications.

Collaborative robots are significantly lighter than industrial robots and, as a result, it is easier to move them within the factory floor. Moreover, cobots require little space and are suitable for integration into existing resources. This enables in-process control, *i.e.,* quality control performed during production, that prevents defective from reaching the end of the line. Therefore, no space is required at the end of the line for offline inspections. Accordingly, in-process control is an opportunity to make production systems more efficient and bring advantage to today's competitive market [11].

The types of quality inspections based on HRC are manifold. The most widely used is the visual inspection with a camera. Indeed, many simple visual inspections performed previously by human workers can be easily replaced and improved by mounting a camera on the arm of the cobot. For instance, in the study of Muller et al. [12], the main objective is to perform a water leak test on the final assembly of a car manufacturing line. A water leak test is expensive and inefficient as the car has to be watered for a long time and human eyes cannot detect small infiltration. By incorporating a thermographic camera into the robotic arm, water leakages could be detected more accurately, avoiding non-ergonomic tasks for the operator. In such a collaborative environment, the only task of the operator is to guide the cobot through the different areas within the vehicle. Another example is proposed by El Makrini et al. [13]. The paper introduces a collaborative architecture between human and robot on an assembly task. The process consists of assembling and simultaneously inspecting a box. During the assembly, the collaborative robot picks up the appropriate plate, hands it to the human and holds the semi-assembled box. On the other hand, human operator correctly positions the plate and screws it onto the semi-assembled box, while the cobot checks the quality of the assembly through a visual camera. This collaborative assembly involves in-process quality control to prevent that non-conforming parts reach the end of the line.

Another HRC opportunity for quality control is the adoption of machine learning techniques to improve cobot capabilities. An example is proposed by Doltsinis et al. [14], where a complicated snap-fit mechanism is considered. The main problem is that the quality control inspection of a snap-fit assembly is done by the human workers listening to the snapping sound during the insertion process. Consequently, it is difficult for the cobot to learn this procedure since it is not able to hear. The paper proposes a method in which a cobot arm equipped with a force sensor is trained by the operator through several experiments. The goal is to raise the cobot awareness of the force applied in correct and incorrect insertion. Once the collaborative robot is trained, the assembly process can be carried out autonomously by the cobot.

HRC for quality control and inspection processes has increased with the emergence of Industry 4.0. However, compared to the various uses of collaborative robots in manufacturing, quality control still plays a minor role. In addition, some articles covering the topic, lack a real and consolidated industrial application. Indeed, being a topic of recent research interest, the approaches developed have not yet been fully adopted and validated in real industrial applications.

3. Assembly modelling

In recent years, several studies focused on the problem of defect generation in assembly manufacturing processes, since the presence of defects may compromise the final product quality. The development of suitable defect generation models is crucial in manufacturing industries, having the dual purpose of predicting defects and planning effective quality controls [11]. As a result, quality control has become one of the most important issues in modern manufacturing and assembly defect generation models are required to prevent the occurrence of defects during the process [15]. Nowadays, defect generation models are widely used in manual assembly, and it is well known that there is a close connection between assembly complexity and operator-generated defects [16].

The present paper aims to investigate defect generation models in a human-robot collaborative environment to compare quality performances achieved in purely manual assembly. In order to study the defects generation both in manual and collaborative assembly, the assembly of organic molecular structures is considered. These structures are typically considered in the literature to effectively emulate real assembly products, as they can be assembled from elementary components as for industrial products [17]. Molecular structures emulate the corresponding products by using atoms to represent product constituent parts and bonds to represent the connections. In the reference literature, molecular assembly is adopted to minimize confounding effects typical of real productions and to replicate real assembly in a controlled way [17]. These molecular models were used to model the complexity of the corresponding physical products and relate it to the performance of the manufacturing process. For the purposes of this paper, the number of parts (including both atoms and bonds) is used as a reasonable indicator of product complexity. Indeed, the greater the number of parts, the greater the complexity of the molecules [17].

Using the molecules as products to be assembled, experimental tests performed only by human operators and in collaboration with cobots were carried out, allowing a comparison between the two types of assembly to be drawn.

4. Experimental setup and procedure

The effects of assembly type on defects generation and assembly time have been investigated through the implementation of two different experimental campaigns. The first campaign is the manual assembly where human operators had to assemble manually the different structures. During the assembly, human operators did not follow a specific assembly sequence and they were free to implement their own assembly strategy. In these experiments, the ability of individual operators was emphasized. The second campaign involves the human-robot collaborative assembly in which human operators were supported by collaborative robot to assemble the structures. The same molecular structures of manual experiments were considered. In HRC assembly, the cobot passed the parts one by one to the operator following a predefined strategy. The operators were tasked to assemble the structures by joining the parts at the rate defined by the cobot. Therefore, operators were tied to the cobot's sequence and could not define their own strategy.

During the experimental tests of both campaigns, assembly time and defects were collected, as will be discussed in detail in Section 5.

4.1 Assembled structures

The main characteristics of organic molecular structures assembled during the experiments are summarized in Table 1. In Table 1, for each structure, the ID and the molecular formula are specified, as well as the number of atoms and bonds, and the detailed quantities, subdivided per typology, of atoms (carbon, hydrogen, oxygen, nitrogen and sulphur) and bonds (single or double). The number of parts reported in Table 1 refers to the sum of the number of bonds and atoms that compose the structures.

Participants of both manual and human-robot collaborative assembly were tasked with assembling the six molecular organic structures in Table 1 using a molecular modelling kit (Orbit™ by 3B Scientific®). This kit is composed of different atoms (*i.e.,* balls) and bonds (*i.e.,* sticks). Concerning the bonds, two different typologies were considered during the experiment: single covalent bonds (rigid connectors) and double covalent bonds (flexible connectors). On the other hand, five different typologies of atoms were considered: carbon (grey), hydrogen (white), oxygen (red), nitrogen (blue) and sulphur (yellow).

4.2 Manual assembly

In the manual experimental campaign, operators were tasked to assemble the six molecular structures manually. Before the tests, an equipped assembly workstation was prepared, and some preliminary information were provided to the operators. In the workstation, each type of atom and bond was placed in a specific box, where operators picked up the parts according to the given assembly instruction. During the experiment, operators used 2D and 3D molecular work instructions as an assembly guide (see Fig. 1). The 3D instruction could be rotated in the space, allowing molecules to be seen from different perspectives. Each operator could define its own strategy for assembling and completing the represented structures, thus minimizing the effect of sequence complexity.

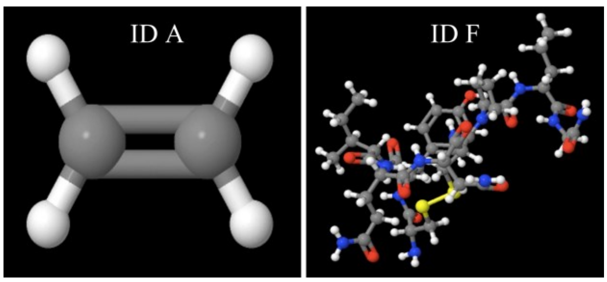

Fig. 1. 3D representation of molecular structures ID A and ID F.

Table 1. Six organic molecular structures assembled during both manual and HRC experimental campaigns and their characteristics.

ID	Molecular formula	Number of parts (N_p)	Number of atoms	Number of bonds	Carbon (C)	Hydrogen (H)	Oxygen (O)	Nitrogen (N)	Sulphur (S)	Single bonds	Double bonds
A	C_2H_4	11	6	5	2	4	-	-	-	4	1
B	$C_2H_{17}NO_6$	93	44	49	20	17	6	1	-	42	7
C	$C_{33}H_{46}O_5$	169	84	85	33	46	5	-	-	76	9
D	$C_{46}H_{70}O$	234	117	117	46	70	1	-	-	106	11
E	$C_{50}H_{64}N_2O_{12}$	261	128	133	50	64	12	2	-	119	14
F	$C_{43}H_{66}N_{12}O_{12}S_2$	272	135	137	43	66	12	12	2	123	14

A total of 52 assembly operators were involved, selected from the students of the course "Quality Engineering" of the Master of Science in Management Engineering at Politecnico di Torino. All the participants had no previous industrial assembly experience. The experimental campaign was organized over 8 days in the period between October and December 2021. The assembly of each ball-and-stick model was repeated one time by each operator, and all the six structures were assembled by following a random order. As abovementioned, the operators were free to assemble by deciding their own strategy. There was no optimal reference strategy, thus the experiment showcased the individual skills of the operators. During assembly, a quality controller was responsible for recording assembly time and defects of each structure. Assembly time is the time needed to complete the structure. Concerning defects, both process and product defects were considered. Process defects are those occurring during assembly, involving disassembling one or more parts, and repeating the operations to correctly complete the structure. Product defects were identified by the controller on the finished structure by comparing the number of parts of the assembled structure with the reference values shown in Table 1. Each extra or missing part was counted as a defect.

4.3 Human-robot collaborative assembly

The experimental campaign involving the collaboration between operator and cobot was performed using a single-arm collaborative robot UR3 (Universal Robots ™) equipped with OnRobot RG6 flexible two fingers robot gripper (OnRobot™). In Table 2, the cobot and gripper parameters used in the experiment are reported. For fields not specified, the symbol "-" is used. MoveJ and MoveL are two different types of movement that the collaborative robot can adopt. MoveJ involves a movement in which each joint of the cobot reaches the desired end location at the same time. This movement type results in a curved path for the tool. The two parameters that apply to this movement type are the maximum joint speed and joint acceleration, expressed in °/s and °/s^2, respectively. On the other hand, MoveL makes the tool move linearly between waypoints. The two parameters that have to be set for this type of movement are the desired tool speed and tool acceleration, expressed in mm/s and mm/s^2, respectively. Concerning the gripper, the shared parameters are the distance between the two fingers when the gripper is open and the clamping force used to close the gripper, expressed in mm and N, respectively [18].

Table 2. Cobot and gripper parameters used in the experimental campaign.

Tool	MoveJ speed [°/s]	MoveJ acc. [°/s^2]	MoveL speed [mm/s]	MoveL acc. [mm/s^2]	Distance [mm]	Force [N]
Cobot	200	200	200	200	-	-
Gripper	-	-	-	-	25	80

Since the cobot was unable to recognize parts, being not equipped with visual recognition systems, the workstation was organized by dividing the parts into several columns, as shown in Fig. 2. Fig. 2 also compares the workstations used in the HRC assembly and manual assembly. During the experiments, the collaborative robot took the parts from the columns and passed them to the operator following *a priori* defined order. Human operators connected the different parts together in the order defined by the cobot. The cobot was in control of the assembly process and dictated assembly time, but the operator could stop the process at any time. The MoveL movement was used for vertical moves (*e.g.,* to pick up the parts from the columns or to deposit the parts in the storage area, where the operator picked up the parts for assembly), being a linear and controlled movement, while the curved and faster MoveJ movement was used for all other moves (*e.g*., to move the parts, after picking them up from the columns, over the storage area).

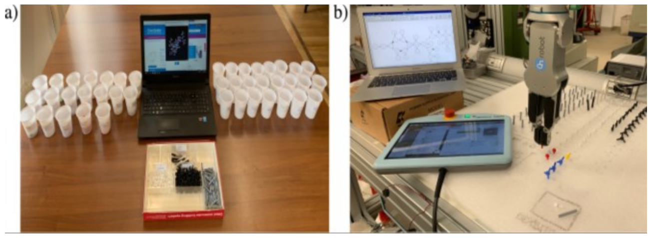

Fig. 2. Workstation of (a) manual assembly and (b) HRC assembly.

A total of 10 participants with no previous industrial assembly experience were involved in the experiment. The experiment was organized over 10 days in the period between February and March 2022. Each molecular structure was assembled one time by each operator in random order. All participants were provided with some introductory information about the cobot and its role in the experiment. In addition, a precedence diagram was given to the operators to follow the assembly order (see Fig. 3). It represents the order in which the collaborative robot passes the parts to the operators. On each arrow, there is a number that indicates the order in which the assembly should be completed, while in the circles the name of atoms followed by an identifier number is reported. Human operator had to follow this sequence until the structure was completed.

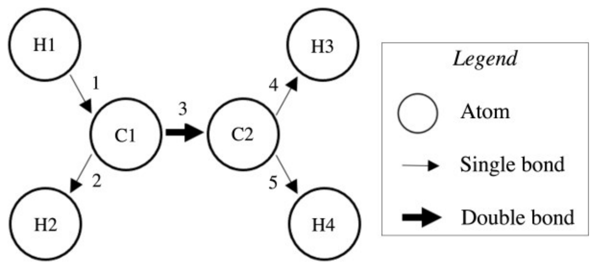

Fig. 3. Example of the precedence diagram of molecular structure ID A.

In each test, defects occurring during the assembly process were recorded. Any wrongly positioned or repositioned part was considered a product defect. In addition, if the operator was unable to maintain the assembly rate, the cobot could be stopped and each part remaining in the storage area (because not yet assembled) was considered an assembly defect. Moreover, defects attributable to the cobot due to non-execution, or incorrect execution, of the task were also accounted for. At the end of the assembly, the assembly time was also recorded.

5. Experimental data analysis and discussion

In order to compare the results obtained in the two experimental campaigns, manual and with HRC, the boxplots of assembly time and total defects are reported in Fig. 4. In the boxplots, the single values collected during the experiments for each molecular structure, identified by the number of total parts (N_p), are represented. It has to be noted that for both assembly time and total defects there is a large difference in the dispersion of data between manual and HRC scenarios. The difference is more pronounced for structures composed of many parts, whereas for few parts structures this difference is less evident. Moreover, in manual assembly, the variability of times and defects increases more than proportionally as N_p increases. In contrast, in the collaborative scenario, the variability appears to be unrelated to the assembled structure. Such a high difference in data variability between the two scenarios may be attributed to the difference in cognitive effort that the two experiments required. Indeed, in the manual assembly, time and defects variability increase more than proportionally with increasing parts due to the high cognitive effort of complex structures. On the contrary, the presence of the cobot in the HRC scenario reduces the cognitive effort of operators, as they do not have to find assembly strategies and choose the correct parts to assemble, resulting in a significant reduction in data variability. Accordingly, the introduction of cobot, leading to a reduction in variability, may bring an advantage also to the manufacturing context. Indeed, it is known that greater variability leads to lower product quality [10].

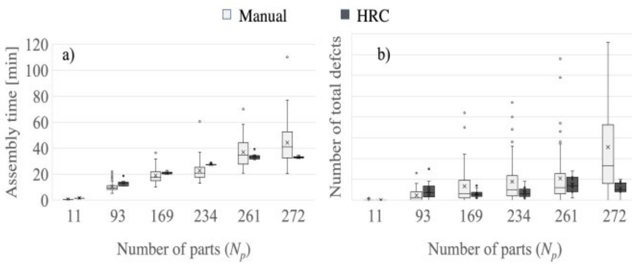

Fig. 4. Boxplots of (a) assembly time and (b) number of total defects.

To identify significant differences between manual and HRC results, hypothesis tests at 95% confidence level were implemented. Firstly, a t-test on the difference between the means of assembly time and total defects of manual and HRC assembly is performed [10]. The test is performed assuming different variances between manual and HRC populations. This test aims to determine whether the differences between the means of the experiments of the two experimental campaigns is statistically significant. Secondly, a comparison of the variability of data obtained in manual and collaborative assembly is performed through a Levene's test [10]. The Levene's method is used when the samples have less than 20 observations and populations cannot be considered normally distributed [10]. In Table 3, the p-values obtained in each hypothesis test is provided, separately for assembly time and total defects. In Table 3, when p-values cannot be calculated since data are identical, the symbol "-" is used. Considering a significance level of 5%, the difference between manual and collaborative assembly results is statistically significant if the p-value is less than 0.05. In Table 3, the differences between the means and the variances statistically significant are written in bold.

Table 3. p-value of t-test and Levene's test hypothesis tests on assembly time and total defects of manual and HRC experimental results.

ID	Assembly time		Total defects	
	t-test p-value	Levene's test p-value	t-test p-value	Levene's test p-value
A	**<0.0005**	0.362	-	-
B	**0.003**	0.349	0.132	0.139
C	**0.019**	**0.008**	**0.009**	0.122
D	**<0.0005**	**0.021**	**0.003**	0.071
E	**0.046**	**0.005**	0.180	0.272
F	**<0.0005**	**0.002**	**<0.0005**	**0.007**

Regarding assembly time, the differences of means are statistically significant for all the structures. On the other hand, the difference of variances is significant starting from the structure ID C. Such pronounced differences are also due to assembly time constraints. In manual assembly, the lower limit is driven by physical constraints of operators to pick up the parts. For HRC assembly, the lower limit is the cycle time of the cobot to pick up and pass all parts. In both cases, however, the maximum assembly time is not limited and depends on the errors that occur in the assembly process. Consequently, since the number of defects in HRC assembly is generally lower, the maximum assembly time in HRC is smaller. Regarding defects, significant differences are observed for structures with high number of parts due to the drastically reduction of operator cognitive effort. It would be necessary to investigate this aspect further by considering more complex structures and verifying whether the cobot brings higher benefits when the complexity increases.

Regression analyses were performed to evaluate trends in times and total defects for both manual and HRC assembly, considering average values. In Fig. 5, the most suitable regression curves in terms of residual analysis and goodness-of-fit test are represented, with the relevant 95% confidence and prediction intervals. It has to be noted that 95% confidence and prediction intervals are limited to zero since time and defects cannot assume negative values.

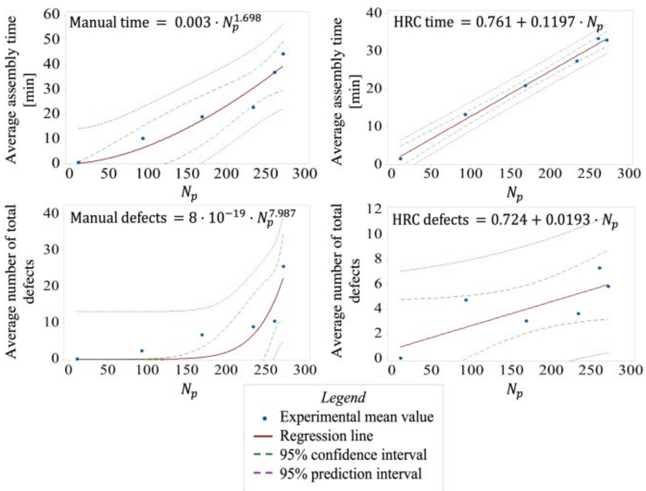

Fig. 5. Regression curves of average assembly time and average number of total defects for manual and HRC assembly.

As shown in Fig. 5, HRC average assembly time and defects follow a linear trend, while manual ones follow a power-law trend, in line with previous studies in the field [15-17]. Indeed, in manual assembly, time and defects increase more than linearly compared to the number of parts, whereas in HRC assembly the growth is linear. These trends confirm that in the collaborative assembly the cognitive effort required to the operator is maintained almost constant in all the structures, and this does not involve a power growth of times and defects.

6. Conclusion and future work

In recent years, the interest in collaborative robots has grown exponentially thanks to their light weight, flexibility, and precision, enabling industries to be more productive and efficiently respond to market needs. However, compared to the various application of collaborative robotics in manufacturing (*e.g.,* material handling, pick and place and positioning), quality control still plays a marginal role. Indeed, literature on quality control in HRC is scarce and lacks real application cases. Thus, there is an stringent need to further investigate the field of quality control in the HRC framework and define suitable defect generation models.

This paper investigates the effects of the assembly type on defects and assembly time. In detail, purely manual assembly was compared with human-robot collaborative assembly. Two experimental campaigns were conducted, using six different ball-and-stick molecular models. The experimental results showed that manual assembly data are generally affected by greater variability than collaborative assembly data. Furthermore, using collaborative robots in assembly processes lead, on average, to a reduction of time and defects, especially for complex structures. On the other hand, cobots seem to be less beneficial when dealing with simple products. Moreover, it was shown that collaborative assembly time and defects increase linearly with the number of parts, while in HRC assembly they grow superlinearly. Thus, the cobot, by supporting the operator, prevents time and defects from increasing sharply with the complexity of the structures. A limitation of the present study is that in manual assembly, the choice of the most appropriate strategy was left to the operator, whereas, with the use of the cobot, a single optimal strategy was adopted for each structure. In future work, cobot capabilities will be enhanced through machine learning, allowing it to recognize the parts and autonomously choose the optimal strategy from among several available. In addition, real assembly processes and a wider range of products will be considered in order to verify the trends identified in this preliminary study.

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