Multi-robot multi-operator collaborative assembly systems: a performance evaluation model

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Abstract

In the last decade, collaborative assembly systems (CAS) are becoming increasingly common due to their ability to merge the flexibility of a manual assembly system with the performance of traditional robotics. Technical constraints, e.g., dedicated tools or resources, or performance requirements, e.g., throughput, could encourage the use of a CAS built around a multi-robot and multi-operator layout, i.e., with a number of resources greater than 2. Starting from the development of a prototype multi-robot multi-operator collaborative workcell, a simulation environment was developed to evaluate the makespan and the degree of collaboration in multi-robot multi-operator CAS. From the simulation environment, a mathematical model was conceptualized. The presented model allows estimating, with a certain degree of accuracy, the performances of the system. The results have investigated how several process characteristics, i.e. the number and type of resources, the resources layout, the task allocation method, and the number of feeding devices, influence the degree of collaboration between the resources. Lastly, the authors propose a compact analytic formulation, based on an exponential function, and define the methods and the influence factors to determine its parameters.

Keywords Collaborative robots · Assembly systems · Makespan evaluation · CAS

Introduction

The mass customization requested by the current market is pushing companies to offer a wide range of different products. Assembly, due to its position at the end of the production process, is the production technology most affected by this trend (Kim et al. 2020). It is therefore fundamental to use flexible assembly systems that could manage changes in volumes and products (Azzi et al. 2012a, b). For a flexible assembly system to be successful it requires the optimization of Barbazza et al. (2017):

– Unit direct production cost (€/part), i.e. the ratio of the hourly costs of the workcell and the average throughput;
– Mix flexibility, i.e. the ability to handle a wide variety of parts, and manage a wide variety of parts and products;
– Volume flexibility, i.e. the ability to change the productivity of the system without reducing its efficiency.

A possible solution could be the adoption of a traditional Manual Assembly System (MAS), toward which companies are directed due to the requested flexibility and number of product variants (Heilala and Voho 2001). These systems grant the maximum degree of flexibility in comparison to others, but they present several drawbacks. The accuracy of the task and the activity repeatability need improvements; ergonomics problems could also occur (Battini et al. 2011).

To lower the costs of labor, Western countries have adopted automatic systems. Since Boothroyd et al. (1982) described the automatic assembly systems, they are increasing their importance thanks to their high production rates, reduced costs and better quality of the final product. The

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optimization of the assembly process is required for a cost-effective and competitive paradigm shift from mass production to mass customization, while also ensuring the requested product variety (Hu et al. 2011).

Several developments of the flexible assembly systems (FAS) have been proposed in the literature (Rosati et al. 2013, 2015). Among those, Collaborative Assembly Systems (CAS) (Faccio et al. 2019) improve the flexibility and lower the cycle time by using collaborative robots, or *cobots* (Colgate et al. 1996). Indeed, the market request for customized products could be too expensive to be performed with traditional automatic systems, whereas a manual production has the drawbacks mentioned above. Therefore, cobots could lead, under proper conditions, to improved productivity (Gil-Vilda et al. 2017), thanks to reduced setup times and by sharing the tasks between the human operator and the robotic device. Moreover, task-sharing not only reduces the cycle times since the robot operates in parallel with the operator but also because it avoids additional and useless movements of the operator.

A model was previously proposed to allow small- and medium-sized enterprises (SMEs) to evaluate the benefits of CAS, in particular identifying the influence of the product characteristics (Faccio et al. 2020) on the interferences in the shared workspace, and therefore on the cycle time and economic advantage of cobots.

However, the previous simulated model is somewhat restricting towards the possible application of CAS, in particular on the hypothesis of multi-robot and/or multi-operator scenarios. The optimal number of resources in a CAS is not bound to be limited to two, and a multi-resources scenario could improve the throughput. Though, two key factor (Faccio et al. 2020) should be considered to observe a positive change: the spatial interferences between the resources should be kept at a minimum in order to collaborate, and suitable process characteristics, i.e. the resources should have the ability to perform the tasks in a shared workspace. Therefore, multiple resources should be considered for adoption whenever: the needed assembly time of the product is greatly superior to the desired cycle time; in the case of several different tasks that require dedicated tools and resources, e.g. screwing processes; only if the layout size allows for the usage of multiple resources. Several studies were proposed for collaboration of multiple robot systems and the collaboration in CAS systems, however, systems for the analysis and design of multi-robot multi-operator CAS have not been sufficiently studied. For these reasons our works aims to provide a model that allows to estimate the performance of CAS systems in a multi-resource context. Moreover, the model helps to identify a set of variables that should be introduced to take into account the influence of the workplace characteristics.

A fundamental constraint for multi-resource systems is the workspace of the resources. Indeed, not only the size of the workplace needs to be sufficient for the adoption of multiple resources, but it is also a critical key factor that influences the performance of the system. If each workspace overlaps, the resources could interfere with each other; if all the workspaces are completely separated, a CAS does not have any meaning to be used, both from the economic and performance point of view. Thus, to achieve the required performance, the design of the layout, i.e. the resource position in the assembly cell and respective assembly task allocation, and the design of the workspace of each resource are needed. This study is therefore driven by the need to study systems able to carry out complex assembly tasks in multi-resources scenario, guaranteeing a high level of collaboration with proper workspace-sharing.

The main contribution to the field provided by this research is:

– The identification of the characteristics that influences the performance of a multi-resources CAS;
– To provide a model that allows to estimate the cycle time given the product characteristics, the number of feeding devices and resources and the degree of collaboration without the need of a simulation environment.

This study provides to the SMEs a model useful to evaluate with a reasonable error the cycle time obtainable with a multi-resources CAS, therefore allowing to identify if these systems may be a viable solution and evaluating the possible benefits. Starting from the results of a simulation environment used to determine in a preliminary phase the achievable degree of collaboration for a particular application, we propose a mathematical model to estimate the performance of multi-resources systems considering different scenarios. Therefore, we believe that after the preliminary phase the proposed model is of practical interest, since it allows to estimate the performance, and thus the costs and benefits, of collaborative robots even in complex assembly systems without the need of time-consuming simulations.

The mathematical model investigates the influence of the system workplace on its performance. Indeed, previous models take into account only the task distribution or product characteristics. However, other process characteristics such as the resources position have to be taken into account when studying complex assembly systems such as multi-resources CAS, since their influence is relevant. Therefore, our work not only presents a model for the perfomance estimation but also states how to take into account these process characteristics. In this way, we think that we can provide practitioners a model that allows them to estimate if a CAS is suitable for their application and how to optimize the workplace and the task distribution to maximize economic convenience.

The paper is organized as follows: section "Related work" presents the state of the art, which shows the novelty and

the importance of the presented study; section "Performance evaluation model for multi-robot multi-operator CAS" introduces the variables and hypotheses defined and presents the cycle time evaluation model. section "Simulation environment" introduces the assumptions adopted in the simulation environment from which the model has been conceptualized and its experimental validation. Section "Results and discussion" presents the results and, section "Conclusion" concludes the presented work.

Related work

Traditional robotic workcells composed by multiple cooperating robots are nowadays more frequent. Indeed, despite they are a more complex solution to maintain and to recover in case of faults, they present several advantages, i.e. fewer fixtures and reduced cycle time (Ranky 2003). It is therefore understandable that, as soon as robots and human operators could work alongside, multi-robot multi-operator systems were studied. Moreover, since the difference in skill between the human operator and the cobot leads to greater complexity, the use of simulation environments allows to consider the interaction between the resources and the workplace (Bänziger et al. 2020).

Ding et al. (2013) defined a finite state automata to design a human robot application. The algorithm, focused on guaranteeing the worker safety without any production loss, was tested on an CAS workcell composed by two human operators and a ABB Dual-Arm Concept Robot, also referred as FRIDA, cobot. Two intersecting interaction zones were defined, where direct contact between the cobot and the operator might occur; inside these, different thresholds were established, adapting the cobot speed. A similar scenario is studied in Sadik et al. (2017), which is focused on the optimization of the task scheduling through the Johnson's method. As observed by the authors, the two operators might have different assembly speeds, further complicating the task optimization; however it should be noted that the tasks are carried out in a sequential order between the cobot and the human team. In a similar way, Tsarouchi et al. (2017) proposed a method for the allocation of sequential tasks assigned to multiple human and robotic resources that constitute a CAS. The framework was tested in a scenario different from the previous ones, constituted by two industrial robots and a human operator, which interact through a depth sensor and a gesture handler software. A similar scenario is inspected in Tan et al. (2009), who developed a prototype CAS system composed by a human operator assisted by two traditional robots on a mobile platform. The interaction between the human and the robot team is analysed considering the operator safety and mental workload and the performance of the system.

Three different case studies are also presented in Michalos et al. (2015), with one scenario presenting four collaborating resources. The type of resources and the layout to be used in each case are affected by several variables, such as the type of robot, its payload, product characteristics, i.e., geometry and weight, and the process characteristics. However, it should be noted that the work is focused on the safety related aspects that need to be considered during the design of human–robot collaborative applications. The layout design problem is also analysed by Tsarouchi et al. (2017), considering at the same time the task planning problem. The authors propose a model for automatic generation of layout generation and task planning, since the workplace design and task allocation is a critical issue for the throughput increase and the cycle time reduction. When a process changes, the layout is designed with the objective of the cycle time improvement and the time reduction for re-design and reconfiguration (Tsarouchi et al. 2016). Differently, Ore et al. (2016) use a developed simulation software that evaluates the CAS application, minimizing the operation time, both for the robot and for the operator, and the biomechanical load on the operator, observed from the basis of the adopted posture. The method was used to optimize a CAS, considering not only the three-dimensional layout, but also the spatial position of the human–robot handover. Lastly, Fechter et al. (2018) presents a practical approach for workplace design.

The studies presented so far not only highlight the necessity of considering the workplace design when developing a CAS application, but also the increasing presence of multi-resource CAS. However, it is clear examining the literature that the contributions available on multi-resources CAS seem to be focused on proposing technical solutions to increase safety, productivity and reduce costs. On the contrary, to the authors' knowledge, a model which allows to estimate the cycle time obtainable in a particular application, without the need of a simulation environment, is not present. This is probably due to the difficulties encountered when modelling the human–robot interaction, since it is affected by the unpredictability of the human behaviour; this is further complicated when considering multi-resource scenario.

Performance evaluation model for multi-robot multi-operator CAS

The objective of this work is to evaluate the achievable makespan when considering a multi-resource layout. In greater detail, the addressed problem is:

– To obtain a suitable collaboration between the resources;
– To estimate the achievable makespan T_{tot} with the considered task allocation.

Therefore, this work aims to define a function that estimates T_{norm}, i.e. T_{tot} normalized by unit of space and number of parts, for the considered scenario (P, W):

$$T_{norm} = F(P, W) \tag{1}$$

where P are the product characteristics (number of parts and product size) and W represents the workplace characteristics (e.g. number of resources, distance between the resources and task allocation method).

To exemplify the main idea of our approach and also its effectiveness, we will present a numerical example. We consider a collaborative assembly system composed by four resources, 2 collaborative robots and 2 operators, placed in a certain disposition and with 4 feeders; these parameters belongs to the W variables. The considered CAS is tasked to assembly a square product of size equal to 400 mm and composed by 22 parts, which results from previous works to a possible collaboration value of about 45%; these parameters belongs to the P variables. Our model estimates a normalized cycle time T_{norm} equal to: $6.73 \cdot 10^{-4} \left[\frac{h}{mm}\right]$

Nomenclature

Input variables and parameters

N_p Number of parts to be assembled
L Side of the square workspace (mm)
N_r Number of resources
N_f Number of feeding devices
$c_\%$ Total collaboration parameter (%)

For each resource i considered, both human operator(s) and cobot(s), the following parameters were defined:

$t_{a,i}$	Assembly time [h/part]
$t_{pp,i}$	Unit pick time [h/part]
s_i	Hand/end-effector movement speed [mm/h]
w_i	Resource weight on collaboration

Output variables

T_{tot}	Achievable cycle time [h]
T_{norm}	Cycle time normalized by L and N_p [h/mm]

Variables used in the simulation environment

Several other variables are defined in the simulation environment used to test the model:

L_{min}	Minimum arm length of resource i [mm]
L_{max}	Maximum arm length of resource i [mm]
R	Radius i of the 2D sphere-swept line [mm] Ericson (2004)
$c_{\%i,j}$	Collaboration parameter for resources i, j [%]
$T_{tot,a}$	Total assembly time [h]
$T_{coll,i,j}$	Resources i, j collaboration time [h]

Variables used to define the model

T_{task}	Time spent on task completion [h]
T_{motion}	Time spent on motion [h]
$T_{task,c0}$	Time spent on task completion without collaboration [h]
$T_{motion,c0}$	Time spent on motion without collaboration [h]
T_{c0}	Cycle time normalized by L and N_p without collaboration [h/mm]
f	Factor of collaboration

Other variables used in this work

P	Product characteristics
W	Workplace characteristics
$T_{tot,a,i,j}$	Total assembly time for resources i, j [h]
T_k	Time required for task k [h]
T_c	Desired cycle time [h]
r_i	Ratio between the process time of resource i and a reference
t_{ri}	Total time for resource i [h]
r_f	Ratio between N_f and N_r

Hypotheses

The hypotheses that characterize the model are:

– The considered assembly system does not distinguish between different feeding typologies, since this work supposes that all the devices can provide each part when required.
– Between each change in assembly tasks the payload difference is minimal, therefore retooling is not needed and each resource can move every parts.
– The considered assembly process does not take into account any precedence constraint.
– The number of resource N_r is defined as:

$$N_r = \frac{\sum_k^{N_p} T_k}{T_c} \qquad (2)$$

where T_k is the time needed to carry out task k and T_c is the desired cycle time. In this work we will focus only on the scenarios with $N_r > 2$.

Model description

First of all, to describe the model it is important to define the three main tasks considered to represent the assembly process:

– *picking*, i.e. when a resource moves from the feeding point to an assembly point and returns to the feeder or from a point to the following one in the case of a pure assembly process;
– *placing*, i.e. when a resource places the picked part in the proper position;
– *fastening*, i.e. when a resource attaches the part to another or to the product base.

Two main groups were defined from these three tasks, called *picking* and *assembly*, where the latter groups the *placing* and *fastening* tasks. The total process time for each resource will be therefore composed by the total *picking* and *assembly* time for said resource.

Considering the assembly for large pieces, or in the case of large workspaces, it is possible for each resources to work simultaneously. Therefore, when evaluating the total assembly time $T_{tot,a,i,j}$ for two resources i, j as Faccio et al. (2019):

$$\begin{aligned} T_{tot,a,i,j} &= (t_{a,i} - T_{coll,i,j}) + (t_{a,j} - T_{coll,i,j}) + T_{coll,i,j} \\ &= t_{a,i} + t_{a,j} - T_{coll,i,j} \end{aligned} \qquad (3)$$

a certain shared time $T_{coll,i,j}$ between the two resources should be considered. This shared time is dependent by interferences that can happen between cobots and human operators during the assembly process; interferences which are represented by the degree of collaboration $c_\% \in [0,100][\%]$

Faccio et al. (2019). Extending the definition presented in Faccio et al. (2020), the total $c_\%$ is evaluated as the weighted arithmetic mean of the degree of collaboration between two resources i, j $c_{\%,i,j}$, therefore:

$$c_\% = \frac{\sum_{i,j}^{N_r}(w_i + w_j)T_{coll,i,j}}{(N_r - 1)T_{tot,a}\sum_i^{N_r} w_i}[\%] \qquad (4)$$

where w_i and w_j are the weight of the resources i and j respectively and $T_{coll,i,j}$ the collaboration time evaluated for each couple i, j of resources, N_r the total number of resources considered in the layout and $T_{tot,a}$ is the total assembly time of the CAS.

The simulation environment used in Faccio et al. (2020) showed that there is a relation between $c_\%$ and the cycle time. To avoid considering the effects of N_p and L on the cycle time, i.e. the increase in the cycle time due to the increase in N_p and the increase in the motion time due to increase in the product size, it is suggested to evaluate the effects of the collaboration on the normalized cycle time T_{norm}, defined as

$$T_{norm} = \frac{T_{task}}{N_p} + \frac{T_{motion}}{N_p \cdot L}\left[\frac{h}{mm \cdot points}\right] \qquad (5)$$

where T_{task} is the time spent on task completion and T_{motion} the remaining time, thus motion time. Due to its nature, even if T_{task} is not divided by L, it can be considered applied to unit of L. The evaluated time is related to the assembly process speed, since it represents the speed to assembly one part on one millimetre-sized product, thus the lower is T_{norm} the higher the assembly speed and therefore the throughput.

The results obtained from the adopted simulation environment were fitted with different models, e.g. polynomials, power and hyperbolic, and considering the sum of squares due to error (SSE), the model which fitted in the most significant and correct way was the one-term exponential model, with an SSE ranging around a 10^{-7} order of magnitude. Therefore, the relation between $c_\%$ and T_{norm} can be represented by the following one-term exponential model:

$$T_{norm} = T_{c0}e^{-fc_\%} \qquad (6)$$

with T_{c0} and f constants. This model allows therefore to estimate T_{norm} of a particular application with different degree of collaboration; given the product characteristics L and N_p it it then possible to estimate the cycle time.

Definition of T_{c0}

Due to the exponential nature of the model, T_{c0} is equal to the measured T_{norm} in a zero-collaboration scenario, i.e.

$$T_{c0} = \frac{T_{task,c0}}{N_p} + \frac{T_{motion,c0}}{N_p \cdot L}\left[\frac{h}{mm \cdot points}\right] \tag{7}$$

with $T_{task,c0}$ the time required to carry out the tasks without any collaboration and $T_{motion,c0}$ the time required for the resource to move towards the feeding device and towards the placing point with null $c_\%$. In a similar scenario, it is easier to determine this two values: indeed, since the resources are not collaborating, the tasks are carried out in sequence, which could imply that it is the sum of the time required for each process tasks, meant as *picking* and *assembly*. However, the resources presents different *picking* and *assembly* times due to their different nature; therefore, $T_{task,c0}$ is between the sum of the task times of the fastest resource and the sum of the task times of the slowest one, i.e.

$$t_{a,f} + t_{pp,f} \leq T_{task,c0} \leq t_{a,s} + t_{pp,s} \tag{8}$$

with $t_{a,f}$ and $t_{pp,f}$ the *assembly* and *picking* time of the fastest resource respectively and $t_{a,s}$ and $t_{pp,s}$ the *assembly* and *picking* time of the slowest resource respectively. To evaluate $T_{task,c0}$, the distribution of the tasks between the resources should be considered. Without considering any technological limitation, i.e. every resource can perform every task, and without considering any precedence between the tasks, the task allocation for the resource i is based on the weight r_i, i.e. the ratio between the process time between the resources:

$$r_i = \frac{t_{r1}}{t_{ri}} = \frac{t_{a,r1} + t_{pp,r1}}{t_{a,ri} + t_{pp,ri}} \tag{9}$$

with t_{r1} is the total time of the reference resource, i.e. the sum of the *picking* time $t_{pp,r1}$ and the *assembly* time $t_{a,r1}$, and t_{ri} is the total time of the resource i, i.e. the sum of the *picking* time $t_{pp,ri}$ and the *assembly* time $t_{a,ri}$. $T_{task,c0}$ is therefore evaluated as:

$$T_{task, c0} = N_p \frac{\sum_i r_i t_{ri}}{\sum_i r_i} \tag{10}$$

Moreover, the time required for the resource to move towards the feeding device and towards the placing point, hereafter called *motion-time*, should be considered. Considering a uniform distribution of the placing points, the *motion-time* for each resources can be evaluated as the sum of the time needed to move from one placing point and another, and the time needed to move from the feeding device nearest to the resource i and the center of the workspace. These two values

can be obtained by considering a weighted mean speed, with the weight r_i evaluated as before, since the task allocation is based on the time needed to carry out the assembly process. Moreover, the distance between the feeding devices and the center is also the weighted mean distance. The *motion-time* $T_{motion,c0}$ is therefore evaluated as:

$$T_{motion,c0} = \frac{\overline{FC_w} + \overline{P_1 P_2}}{s_w} \tag{11}$$

with $\overline{FC_w}$ the weighted mean distance between the feeding device and the center, $\overline{P_1 P_2}$ the average distance between the placing points and s_w the weighted average speed.

It should be noted that the proposed definition of T_{norm}, and therefore of T_{c0}, reduces the influence of $T_{motion,c0}$ on its value, thus it is possible to evaluate T_{c0} by considering only $T_{task,c0}$ with a fair approximation.

Definition of f

In regards to the exponent constant f, called *factor of collaboration*, our study shows that it represents the level of criticality of the layout, i.e. how much it is important that the resources collaborate on the shared workspace. Indeed, f is higher in scenarios where the probability of interference is higher and thus a higher value of $c_\%$ is needed. As presented in Faccio et al. (2020), the risk of interferences, represented indirectly by $c_\%$, depends on the product characteristics, but also on certain process characteristics, e.g. the layout configuration and/or the assembly process time.

The simulation tests show that f depends on several process characteristics, which can be grouped as related to the resources and the feeding devices.

- **Resources**

- *Resource type and number*, i.e. the distribution of human operators and cobots composing the CAS. Since the resources present greatly different task times (t_a and t_{pp}) between each other, an asymmetrical resource distribution, e.g. n cobots and m operators, results in a more critical layout, increasing f. Moreover, considering n type 1 resources and m type 2 resources, with $m < n$, the considered layout will be more critical if the type 1 resources have higher task times since they will occupy the shared workspace for a longer time, thus increasing the risk of spatial interferences.
- *Resource task time*, i.e. the difference between t_a and t_{pp} of the resources. As shown previously, different times between the resources increase f, since higher differences reduce the possibility of synchronization between the resources, i.e. they cannot enter and leave the shared workspace at the same time. Moreover, in the hypothe-

sis of an assembly process without any precedence, the resources time and distribution influence the task distribution r which in turn further influences f.

– **Feeding devices**

– The ratio r_f between the number of feeding device N_f and N_r. Under the hypothesis that each bulk can provide every part required for the process assembly, each bulk can serve every resource, thus lowering r_f to values inferior to 1 increases the chances of interferences, and as a consequence f. It should be noted that due to the hypothesis set on the feeding devices, values of r_f greater than 1 does not imply a further reduction of f since the resources will reach the nearest unoccupied feeding device.

– *Feeding device position*, since an increase of the minimum distance of each resource from the feeding devices, decreases the possibility of interferences, and therefore f.

Differently from T_{c0}, the great number of variables considerably makes it difficult to provide a significant formula for f; however, as presented in section "Results and discussion", several observations can be inferred from the proposed tests.

Simulation environment

The simulation environment has allowed to evaluate the makespan and $c_\%$ for several layouts in a multi-resources CAS scenario given the product and process characteristics. This section introduces the assumptions adopted in the simulation environment and description of the model.

Model application: assumptions and input values

The simulation environment is based on the following assumptions:

– The pick-and-place time is evaluated as the time needed to move from the completed point to the feeder and then to the placing point, considering also the time required for grasping the object. Regarding the cobot(s), we considered a gripper with a closing/opening time of 0.7 s.

– The human operator(s) is allowed to move his/her *base*, representing the shoulder, around the workspace in order too reach bulks/placing points too far from the *base*. This motion is outside the workspace in order to reduce the risk of interferences, but it is simulated to better compute the expended time.

– Besides the motion time component, the assembly and picking time of each task are equal.

Table 1 Values of the input variables and parameters

Product parameter	Value	Unit
N_p	>16 & <40	–
L	>150 & <600	mm
Manual parameter	**Value**	**Unit**
t_a	$1.04 \cdot 10^{-3}$	h/part
t_{pp}	$3 \cdot 10^{-4}$	h/part
s	$7.2 \cdot 10^5$	mm/h
L_{min}	0	mm
L_{max}	600	mm
R	95	mm
Robot parameter	**Value**	**Unit**
t_a	$2.1 \cdot 10^{-3}$	h/part
t_{pp}	$1.94 \cdot 10^{-4}$	h/part
s	$9 \cdot 10^5$	mm/h
L_{min}	65	mm
L_{max}	1300	mm
R	95	mm

– The space occupied by the cobot(s) and by the human operator(s) is represented by a two-dimensional sphere-swept line (SSL) with corresponding radius.

As reported in our previous work (Faccio et al. 2020), the input variables are set to be compatible with the industrial practice, to include a wider range of possible cases; however considering different values from the ones in Table 1 provides for similar results to the ones presented in this work.

Differently from Faccio et al. (2020), the range of N_p is between 16 and 40 points considering only even numbers, while the side length L is defined between 150 mm and 600 mm with increments of 25 mm for L values up to 300 mm and increments of 100 mm after that. This separation for L was required to better evaluate the increase in $c_\%$ which, as shown in Faccio et al. (2020), presents a plateau after a certain value of L depending on the considered process characteristics. The increment in the number of points is due to the increased N_r, since scenarios where one of the resources was idle were considered not significant. Lastly, the diameter of the 2D sphere-swept line representing the cobot arm is considered equal to the footprint of a Universal Robots UR10 cobot (https://www.universla-robots.com).

The simulation environment was applied on two different allocation method presented in Faccio et al. (2020):

– *shared tasks* allows each agent to perform *picking* and *assembly* tasks, i.e. every resource fasten each part they picked.

Table 2 Comparison between the estimated and mean values: example for a 2-cobots-2-operators layout

Std. deviation σ	Estimated T_{c0}	Mean T_{c0}	Unit
0.1μ	$1.7 \cdot 10^{-3}$	$1.62 \cdot 10^{-3}$	h/mm
0.3μ	$1.7 \cdot 10^{-3}$	$1.61 \cdot 10^{-3}$	h/mm
Std. deviation σ	Estimated f	Mean f	Unit
0.1μ	1.95	1.97	–
0.3μ	1.95	2.00	–

– *human p/p* separates the *placing* from the *assembly* tasks, thus the human operators pick and place every part so that the robots can fasten it; this choice was driven by the assembly considered, which showed a manual picking faster than the robotic one.

with different N_r, resource position, and number of bulks.

Validation test

We analysed the robustness of the model to uncertainties, which could lead to performance deterioration (Boudjelida 2019). The operator(s) task times are considered as the main sources of uncertainty, which is reasonable since the robot(s) task times are more repeatable. We assumed that the operator(s) task times are normally distributed, which is realistic in most cases of manual work (Moodie 1965; Buzacott 1990): for each scenario we set the mean μ equal to the value in Table 1 and the standard deviation σ equal to 10% and 30% of μ, respectively. For each scenario the mean values of T_{c0} and f have been evaluated using 100 samples of the operator(s) task times, as seen in Table 2. The results show that the estimation of T_{c0} and f is compatible with the mean value.

An experimental test was also carried out to confirm the reliability of the results in a real scenario since some effects could not be considered in the simulation algorithm. Indeed, the used simulation environment has been developed following the extension to a multi-resource system, i.e. $N_r > 2$, and therefore a new validation test is required. For this purpose, a prototype collaborative workcell has been developed in the Robotics and Automation Laboratory at the Department of Management and Engineering of the University of Padova starting from the experimental setup presented in Faccio et al. (2020). Similarly to Faccio et al. (2020), the test compares the measured makespan with the simulated one for several layouts, resource number and distribution and r_f; one of these scenarios is presented in Fig. 1, where two human operators collaborates with the robotic device, a KUKA LBR iiwa 14 R820, a cobot widely used by industries (https://www.kuka.com).
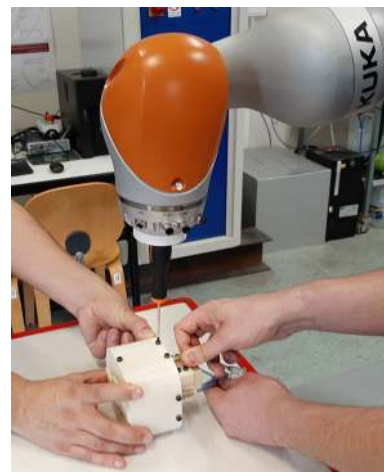
Fig. 1 One of the layouts developed for the validation test, composed by 2 human operators and 1 robotic device.

To better compare the measured makespan with the simulated one, the task allocation proposed by the simulation was provided to the human operator(s) and the cobot: the measured idle times are therefore due to real physical interferences between the resources. Similarly to Faccio et al. (2020), we defined a minimum force limit (± 30 N) to avoid that an accidental impact would disable the cobot. However, the model does not consider the force setting as one of its variables since it focuses on presenting an optimistic evaluation of the performance achievable with collaborative systems.

Figure 2 presents a comparison between the measured makespan (light blue) and the simulated one (red) for one of the configurations considered. The mean percentage error observed between the measured and the simulated data is equal to -2.35% with a standard deviation of 4.06%. The results presented are similar to the ones obtained for the other scenarios considered, which are not presented for shortness.

Results and discussion

The next section will present the results obtained from the simulation environment for several configurations and how the different process characteristics influence f and T_{c0}, as briefly presented in section "Model description".

Process characteristics

The different process characteristics, e.g. the layout, have a great influence on the exponent f and thus on the exponential behavior. To better grasp this influence, several tests were carried out by changing only one of the possible variables. Table 3 presents the values used for the results presented in this work.
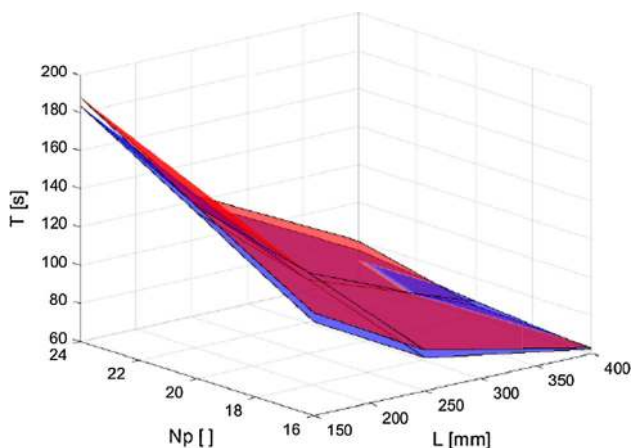
Fig. 2 Comparison between the simulated (red) and measured (light blue) makespan for one of the configurations. The mean percentage error is −2.35% with a standard deviation of 4.06% (Color figure online)

Table 3 Tested process characteristics influencing f

Process characteristic	Scenarios
N_r	3,4
Resource distribution	2 cobots 1 operator
	1 cobot 3 operators
	2 cobots 2 operators
	3 cobots 1 operator
r_f	1/2
	2/2
	3/4
	4/4
	2/3
	3/3
Layouts for $N_r = 3$	a,b,c
Task allocation method	*Shared tasks*
	Human p/p

Firstly, a *number of resources N_r* greater than 2 was considered to show how an increased number of resources can lead to greater f. Since the given resources are classified by only two different types in the model, i.e. human operator or cobot, scenarios composed by an uneven or equal number of cobots and human operators are possible. The effects of an asymmetrical *resource distribution* on f in comparison to symmetrical one is therefore studied for both the N_r considered.

Moreover, the resources position has also a great effect on f and different *layouts* were examined: e.g. Fig. 3 presents the layouts used for a scenario composed of 2 cobots, 1 human operator, 3 feeding devices and product size of 150 mm, i.e. the minimum L. The circles represents the base point and the hand/end-effector, where the cobots are represented by the green and black cirlces and the human operator by the red ones. Three feeding points are represented as three small cyan circles, and the black square represents the product. Layouts studied for different resource distribution and N_r, while presenting similar results, are omitted for shortness.

Reducing the *number of feeding devices*, and therefore testing values of r_f less than 1, increases the probability of interferences, as the resources could interfere both near the common feeding device, but also in the shared workspace. Indeed, under the hypothesis of an assembly process without any precedence, the tasks carried out by each resource will be the nearest to the resource bases, but also to the common feeding device, therefore increasing the risk of interferences. This effect could be considered even in the case that the feeding devices provide only specific parts, by placing a sufficient number of feeding devices to satisfy each resource simultaneously; however, a compromise with the cost of this solution should be considered. As stated above, values of r_f greater than 1 are not considered relevant due to the hypotheses. Furthermore, for the *Human p/p task allocation method* the feeding devices concern only the human operators, therefore r_f is evaluated as 2/2 or 1/2 even if N_r is greater than 2. Again, several ratios were examined but this work presents only a limited number for shortness.

The following paragraph will present some of the obtained results for each task allocation method considered and focusing on the effect of one parameter at a time.

Shared tasks method

Resources distribution

Considering N_r equal to 4, three scenarios for different distributions of resources are possible:

– 1 cobot and 3 human operators;
– 2 cobots and 2 human operators;
– 3 cobots and 1 human operator.

whereas scenarios composed of only cobots or human operators are not considered significant for the purpose of the research. For r_f equal to 1 and the same resources position, we can observe the behaviour represented in Fig. 4, where the equation of the one-term exponential model represented is obtained through least square fitting.

Considering one of the scenarios for reference, e.g. the first scenario with 3 human operators and 1 cobot, the coefficient T_{c0} can be roughly estimated considering only Eq. (10) as

$$T_{c0} = \frac{3 \cdot (t_{pp} + t_a)_{op} + r_c \cdot (t_{pp} + t_a)_{rc}}{3 + r_c}$$
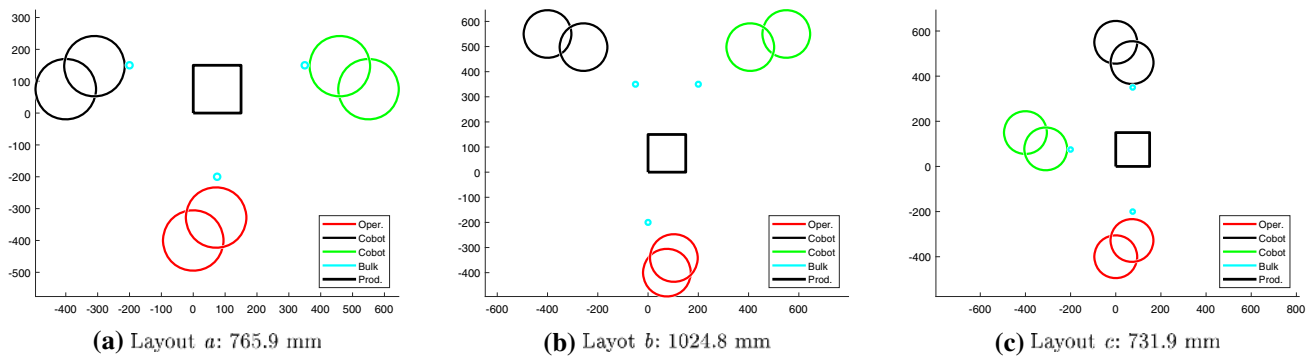$$= 1.5 \cdot 10^{-3} \text{ [h/part]}$$
(12)

(a) Layout a: 765.9 mm   **(b)** Layot b: 1024.8 mm   **(c)** Layout c: 731.9 mm

Fig. 3 Resource and bulk position tested. For each one of them, the mean distance between the resources is presented

(a) 1 cobot 3 operators
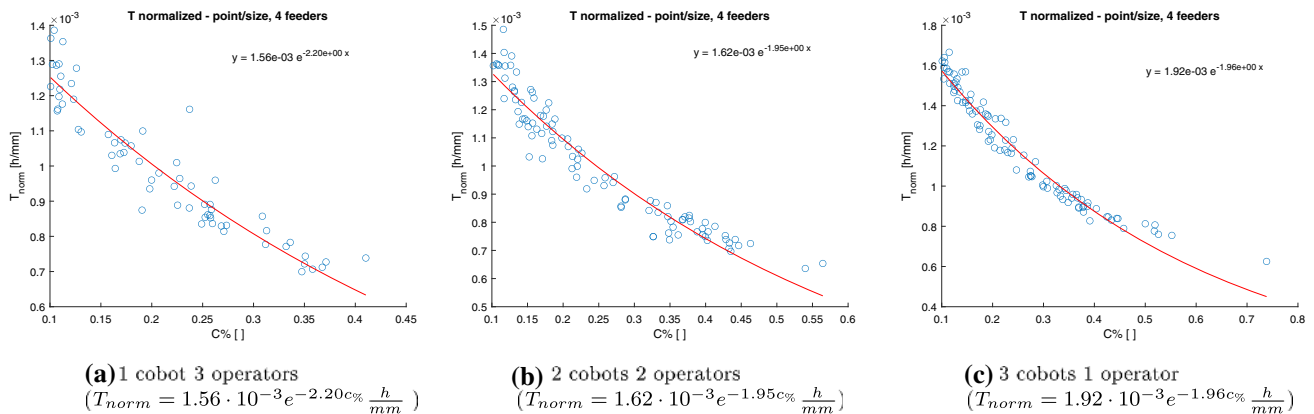$(T_{norm} = 1.56 \cdot 10^{-3} e^{-2.20 c_\%} \frac{h}{mm})$

(b) 2 cobots 2 operators
$(T_{norm} = 1.62 \cdot 10^{-3} e^{-1.95 c_\%} \frac{h}{mm})$

(c) 3 cobots 1 operator
$(T_{norm} = 1.92 \cdot 10^{-3} e^{-1.96 c_\%} \frac{h}{mm})$

Fig. 4 Effect of the resources type and distribution on the exponential model considering four resources with r_f equal to 1 and the same resources position

with the weight r_c evaluated as presented in (9), considering the human operator as the reference resource r_1 and equal to 0.5841. The resulting percentage error between the estimated value and the one resulting from the simulation environment ($1.56 \cdot 10^{-3}[h/part]$) is therefore -4.13%, which can be considered acceptable in a rough design phase. Analogously, the value of T_{c0} for the other two scenarios, i.e. 2-cobots-2-operators and 3-cobots-1-operator, can be estimated equal to $1.7 \cdot 10^{-3}[h/part]$ and $1.9 \cdot 10^{-3}[h/part]$ respectively, thus the estimation differs from the simulated values by a percentage error of 4.93% and -1.04%, which can be considered acceptable. Regarding the exponent f, despite it cannot be estimated similarly to T_{c0}, two important consideration can be made, especially observing the layout composed by 3 operators and 1 cobot. The higher value of f (-2.20) for this scenario is due to two different effects: first of all, the odd resource distribution, differently from the scenario with two resources per type (-1.95). As previously stated, the different task time between the two type of resources increases the probability of spatial interferences, which is related to f.

However, the other layout with odd resource distribution (3 cobots-1 operator) has a lower f (-1.96), which is due to the characteristics of the single resource: in the layout

composed by 3 cobots, the human operator is faster than the cobots in terms of task time, therefore they will occupy the shared workspace for a lower amount of time, and therefore it presents a decrease in the probability of spatial interference, given a certain task distribution. On the contrary, the scenario presenting only 1 cobots has a higher f since the single resource is slower than the others in terms of task time. Moreover, despite the higher speed of the cobot, the motion time is much lower than the task time due to the size of the workspace, thus, with the data considered, the human operators occupy the shared workspace for less time than the cobots.

Number of resources

The number of resources can indeed influence f since it is strictly related to the number of interferences in the shared workspace. Figure 5 represent the scenario of 2 cobots and 1 human operator, r_f equal to 1, with the resources and feeding devices defined to keep the same distance between the resources as the previous scenarios, thus removing the effect of the layout.
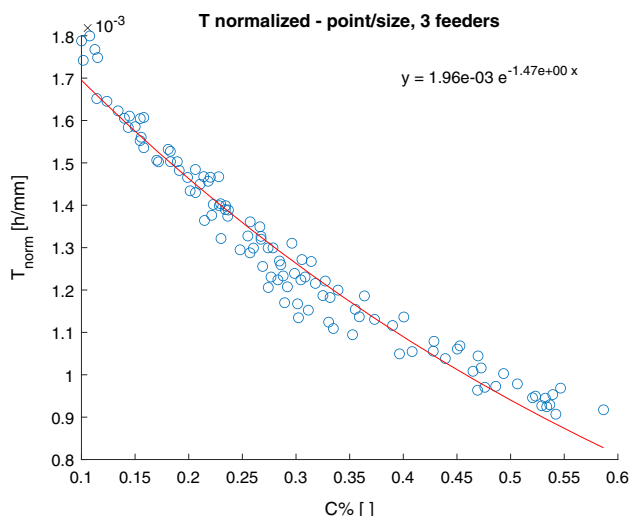
Fig. 5 Effect of the number of resources on the exponential model considering 2 cobots and 1 operator with r_f equal to 1 and the same resources position. ($T_{norm} = 1.96 \cdot 10^{-3} e^{-1.47 c_\% \frac{h}{mm}}$)

The value of f is lower for 3 resources (2 cobots and 1 human operator, -1.47) than for four (3 cobots and 1 human operator, -1.95): indeed, the influence of N_r should be considered, since fewer resources are used in the CAS, and therefore that occupy in the shared workspace, lowering the possibility of spatial interferences.

Furthermore, the value of T_{c0} is different from the ones of the previous layouts due to the different resource distribution. The value of T_{c0} can be estimated considering (10) as

$$T_{c0} = \frac{(t_{pp} + t_a)_{op} + 2 \cdot r_c \cdot (t_{pp} + t_a)_{rc}}{1 + 2 \cdot r_c} \qquad (13)$$
$$= 1.86 \cdot 10^{-3} \text{ [h/part]}$$

with the weight r_c again evaluated as 0.5841. The resulting percentage error between the estimated value and the one resulting from the simulation environment ($1.96 \cdot 10^{-3}[h/part]$) is therefore -5.37%, which can be considered acceptable in a rough design phase. Lastly, the influence of the resource distribution is also noticeable for different number of resources, with results similar to the ones presented above.

Layout

The influence of the resources and feeding devices position on f is studied by considering three scenarios composed by 2 cobots and 1 human operator, with r_f equal to 1, placed at different distances between each other, i.e. Layout a,b, c in Fig. 3.

While the Layout a corresponds to the one presented in Fig. 5, and therefore is omitted here for shortness, the simulation results for the other two layouts are presented in Fig. 6.

As shown, Layout b, characterized by the furthest resources, with a mean distance between their base position equal to 1024.8 mm, presents the minimum absolute value of f, equal to -1.34. Indeed, considering that without any precedence the current task for each resource will be the nearest one, as the distance between the resources increase, the risk of spatial interferences decreases. This effect could be considered even in the case of precedence between the tasks, by keeping the maximum possible distance between the simultaneous tasks of the resources.

As the mean distance decreases (Layout a, 765.9 mm) the value of f increases, and the maximum value of f for the three scenarios is measured in Layout c, which presents the minimum mean distance, equal to 731.9 mm, and an exponent f equal to -1.48. Interestingly, the difference between these two values of f is smaller than with the one of Layout b, since the difference between the mean distance is also smaller.

Number of feeding devices

The last variable that was observed influencing f is the number of feeding devices, as seen in Fig. 7, where we considered two layouts composed by 2 cobots and 2 human operators, placed at the same distance in the two scenario.

For the considered task allocation method, this effect is the one that most influences f, with an increase of over 70% by only reducing r_f from 1 to 0.75. Further reduction of the number of feeding devices greatly increases the factor of collaboration, since the possibility of interferences greatly increases also near the common feeding device. Similar results are obtained for different r_f, N_r, resource distribution and position.

Human p/p method

Resource distribution

The results of the tests for the resource distribution considering the *Human p/p* task allocation method are presented in Fig. 8. Differently from the previous one, this method requires less feeding devices, as only the human operators are carrying out the *picking* tasks. However, this method also leads to greater makespan and lower $c_\%$, as shown in Faccio et al. (2020). Moreover, this scenario differs in the evaluation of T_{c0}: indeed, r_c will be equal to 1 since every *placing* tasks carried out by the operators correspond to an equal number of fastening tasks by the cobots. Therefore the value of T_{c0} for a layout composed of 2 operators and 2 cobots can be evaluated as:
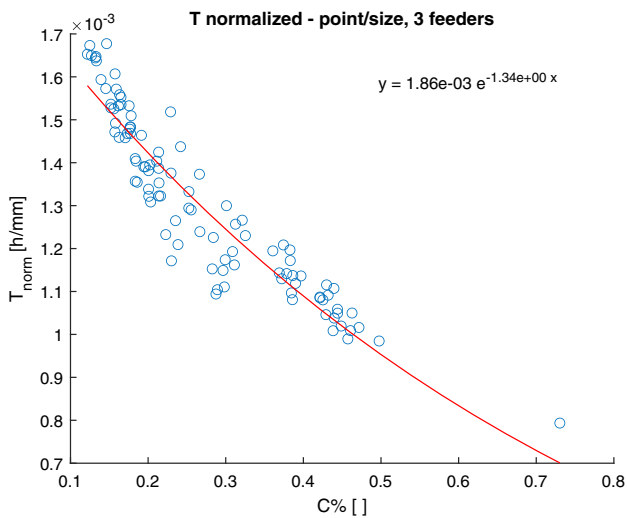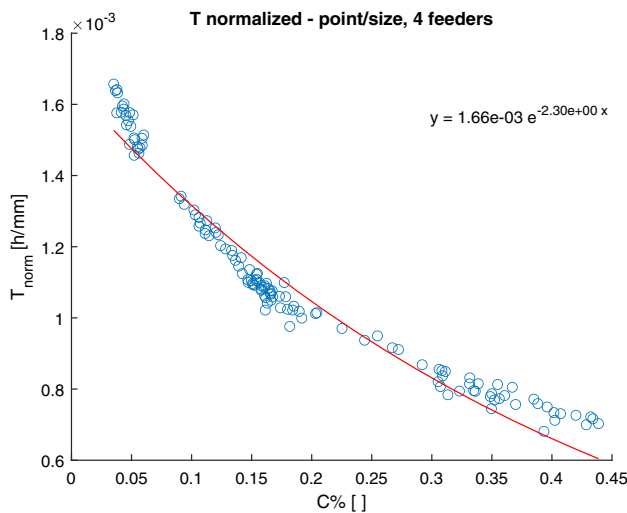
(a) Results for Layout b (1024.8 mm): ($T_{norm} = 1.86 \cdot 10^{-3} e^{-1.34 c_\%} \frac{h}{mm}$)
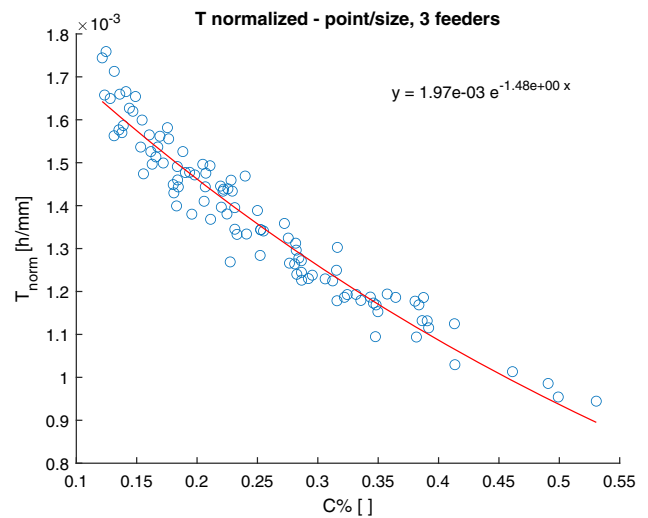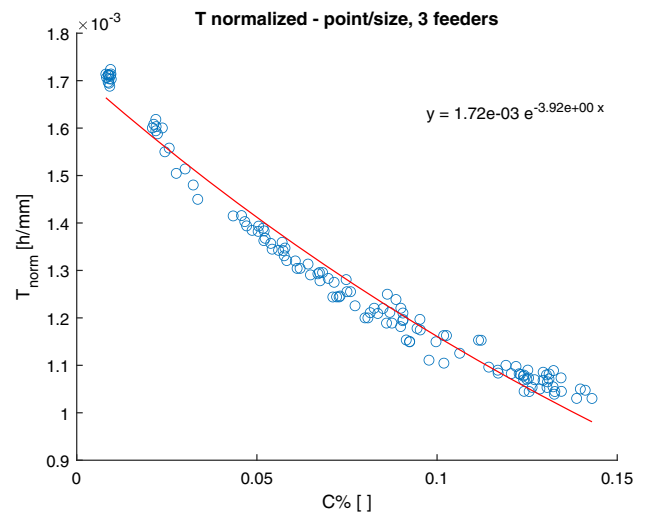
(b) Results for Layout c (731.9 mm): ($T_{norm} = 1.97 \cdot 10^{-3} e^{-1.48 c_\%} \frac{h}{mm}$)

Fig. 6 Effect of resource position on the factor of collaboration f for Layout b and c

(a) 4 resources and 4 feeding devices: ($T_{norm} = 1.66 \cdot 10^{-3} e^{-2.3 c_\%} \frac{h}{mm}$)

(b) 4 resources and 3 feeding devices: ($T_{norm} = 1.72 \cdot 10^{-3} e^{-3.92 c_\%} \frac{h}{mm}$)

Fig. 7 Effect of the number of feeding devices on the factor f in a layout composed of 4 resources, 2 cobots and 2 human operators

$$T_{c0} = \frac{(t_{pp} + t_a)_{op} + r_c \cdot (t_a)_{rc}}{1} \qquad (14)$$
$$= 2.7 \cdot 10^{-3} \text{ [h/part]}$$

This equation can be better explained by considering that each tasks time is composed by the *picking* (t_{pp}) and *placing* (t_a) time of the human operators and the *fastening* (t_a) time of the cobots.

Two different scenarios were considered, with N_r equal to 4, r_f equal to 1 and same resources position:

– 2 cobots and 2 human operators;
– 3 cobots and 1 human operator.
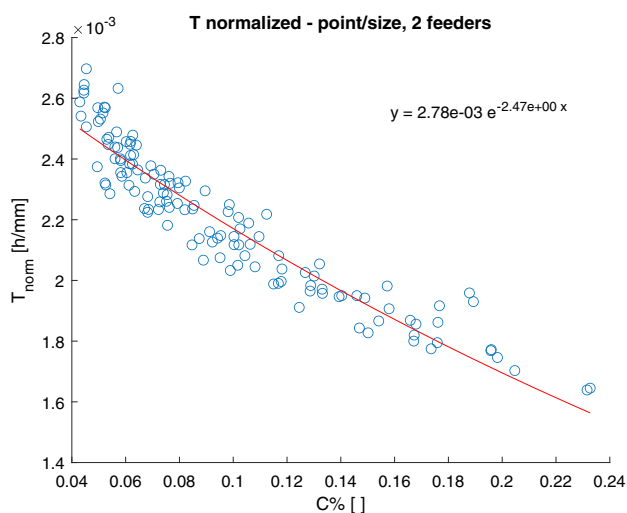
(a) 2 cobots 2 operators:
$(T_{norm} = 2.78 \cdot 10^{-3} e^{-2.47 c_\%} \frac{h}{mm})$
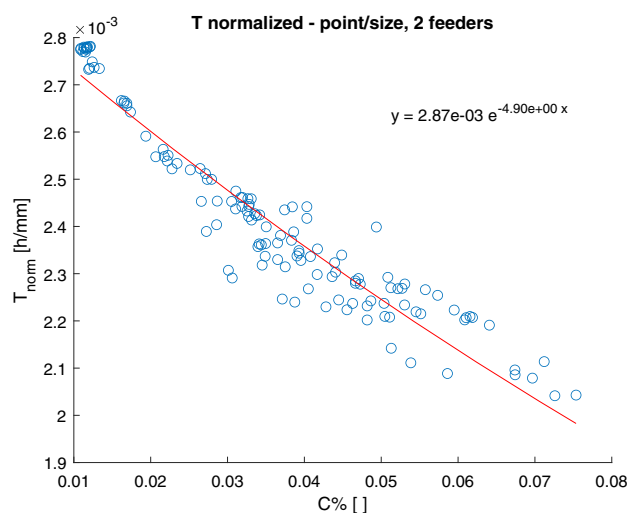
(b) 3 cobots 1 operator:
$(T_{norm} = 2.87 \cdot 10^{-3} e^{-4.90 c_\%} \frac{h}{mm})$

Fig. 8 Effect of the resources distribution on the exponential model considering four resources with r_f equal to 1 and the same resources position, applying the *Human p/p* task allocation method

A layout composed of 3 human operators and 1 cobot were not considered due to the resulting low value of $c_\%$, lower than 0.1%, which makes it difficult to distinguish the trend of $c_\%$ from its variability. This is due to the low collaboration of the cobot, which greatly interferes with the three operators. This leads to a behavior similar to the ones presented in Faccio et al. (2020), therefore it is not considered significant for the proposed study.

Regarding the other two layouts, as previously shown, an uneven distribution of the resources leads to an increase in f; moreover, this increment is greater than before, with an increase of over the 98% in comparison to the 12.8% reached with the *shared tasks* method. This increase is due to the task allocation method, which designate the single human operator to carry out all the *picking* tasks, thus increasing the criticality of the layout. Lastly, the values of T_{c0} obtained by the simulation environment for the 2 cobots and the 3 cobots layouts are equal to $2.78 \cdot 10^{-3}$ [h/part] and $2.87 \cdot 10^{-3}$ [h/part] respectively, which differ from the estimated one by -2.8% and -5.9% respectively.

Number of resources

As shown in Fig. 9, N_r greatly effects f, since considering three resources, placed as the Layout a presented in Fig. 3, f decreases by the 33% in comparison of a layout composed by 2 cobots and 2 human operators with r_f equal to 1.

Indeed, the *Human p/p* task allocation method is more susceptible to the number of resources, especially to the number of cobots: while the human operator is carrying out the *picking* tasks, the cobots are able to carry out only a limited
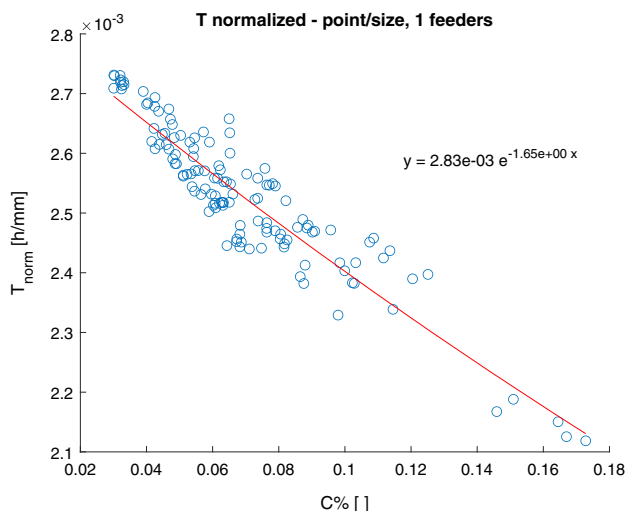

Fig. 9 Effects of the number of resources on f with the *Human p/p* task allocation method, considering a layout composed by 2 cobots and 1 human operator. $(T_{norm} = 2.83 \cdot 10^{-3} e^{-1.65 c_\%} \frac{h}{mm})$

number of *assembly* tasks, i.e. the tasks where the operator already carried out the picking, therefore an increase in the number of cobots leads to a more severe increase in the probability of interferences. Similarly to the previous task allocation method, the effects of the resource distribution are also observable for different number of resources.

Differently from the other task allocation method, the value of T_{c0} is not influenced by N_r, as shown by comparing the value for 3 resources in Fig. 9 ($2.83 \cdot 10^{-3} \frac{h}{mm}$) with the values for 4 in Fig. 8 ($2.78 \cdot 10^{-3} \frac{h}{mm}$ and $2.87 \cdot 10^{-3} \frac{h}{mm}$).
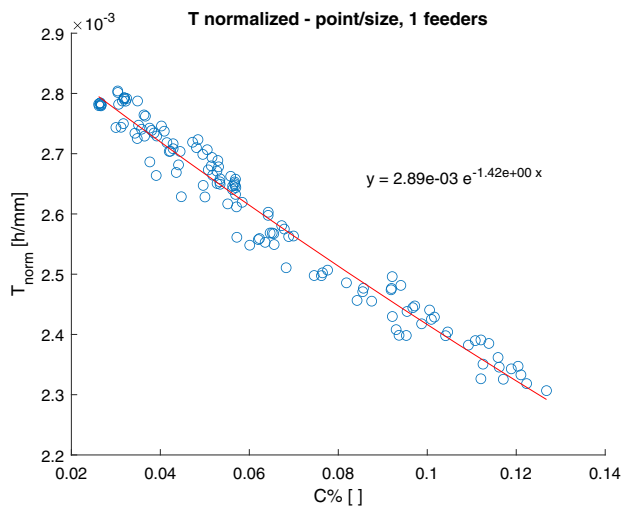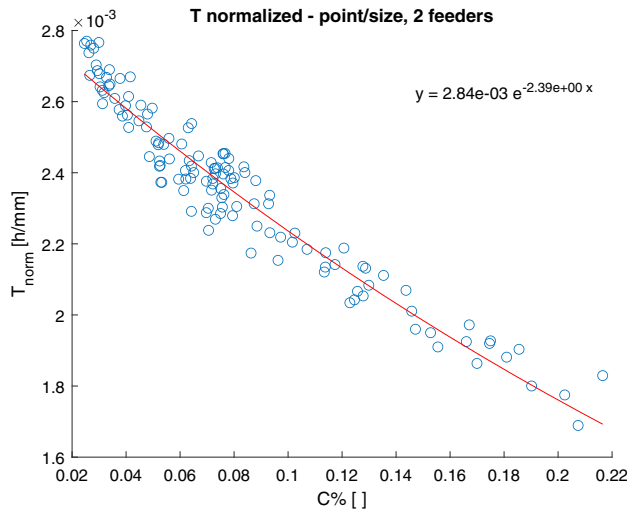
(a) Results for Layout b:
$(T_{norm} = 2.89 \cdot 10^{-3} e^{-1.42c_\% \frac{h}{mm}})$
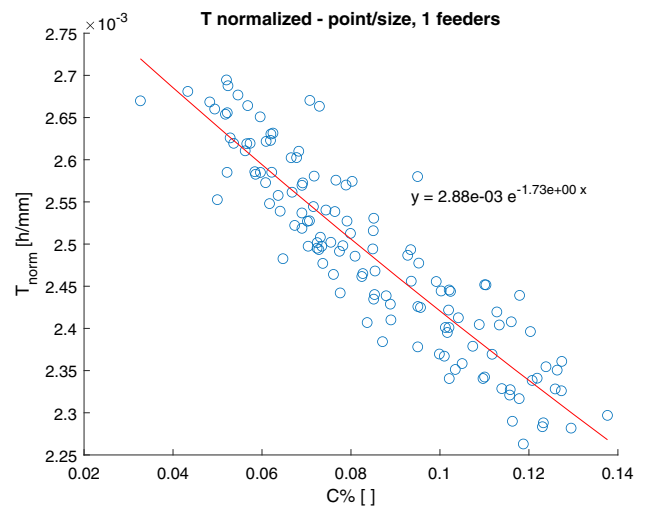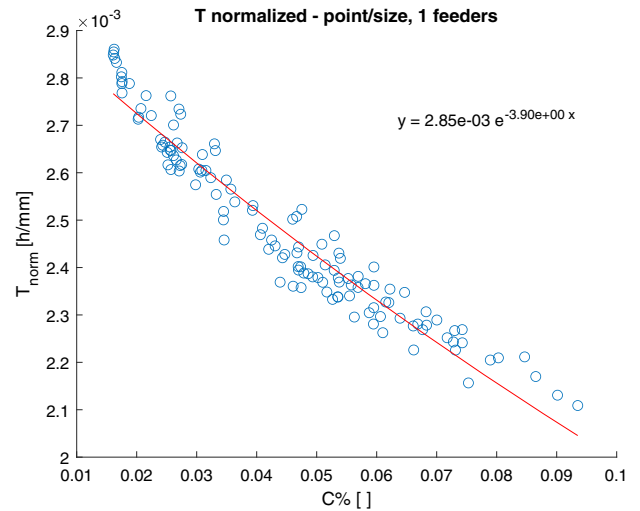
(b) Results for Layout c:
$(T_{norm} = 2.88 \cdot 10^{-3} e^{-1.73c_\% \frac{h}{mm}})$

Fig. 10 Effect of resource position on the factor of collaboration f for Layout b and c applying *Human p/p* task allocation method

(a) 2 cobots, 2 operators and 2 feeding devices:
$(T_{norm} = 2.84 \cdot 10^{-3} e^{-2.39c_\% \frac{h}{mm}})$

(b) 2 cobots, 2 operators and 1 feeding device:
$(T_{norm} = 2.85 \cdot 10^{-3} e^{-3.90c_\% \frac{h}{mm}})$

Fig. 11 Effect of the number of feeding devices on the factor f in a layout composed by 4 resources, 2 cobots and 2 human operators

Since the cobots should complete all the tasks started by the operator, r_c is equal to 1 and T_{c0} is evaluated as the sum of the picking and placing time of the operator and the assembly time of the cobots.

Layout

Considering the same layouts presented in Fig. 3, the effect of the resources and feeding devices position on f were studied for the *Human p/p* task allocation method for 2 cobots and 1 operator, with r_f equal to 1. The simulation results for

Layout b and c are presented in Fig. 10, whereas Fig. 9 has presented the results for Layout a.

Similarly to the previous task allocation method, an increase in the mean distance between the resources, decreases f, since it reduces the probability of spatial interferences. Moreover, the influence of the layouts is greater, with an increase of f of about 21.8% in comparison to the 10.4% reached with the *shared tasks* method. This is due to the same reasons that led to a greater effect of N_r, since an increased distance limits the interferences caused when the cobot assembly the limited number of tasks.

Number of feeding devices

Lastly, the influence of r_f on f was observed using the *Human p/p* method in Fig. 11. Differently from the previous task allocation method, r_f is related only to the number of human operators, since the *picking tasks* are not carried out by the cobots. Therefore, considering a layout composed by 2 human operators and 2 cobots, the possible value of r_f will be 1, i.e. 2 feeding devices, and 0.5, i.e. 1 feeding device; for the same reasons presented above, values of r_f greater than 1 were not considered in this study.

Figure 11 presents the results for two scenarios:

– 2 cobots and 2 operators, r_f equal to 1;
– 2 cobots and 2 operators, r_f equal to 0.5;

with the same resource position. The results show, similarly to the previous method, that the reduction of r_f leads to an increase of f above the 60%, therefore the great impact of the number of feeding devices on the criticality of the layout is confirmed also with the *Human p/p* method. It should be noted that, due to the nature of the proposed method, the resource distribution has a greater influence on f, leading to even lower collaboration values.

Conclusion

This paper presents a model developed starting from a prototype workcell which aims to estimate the cycle time of a CAS given the product characteristics, the number of feeding devices and resources, and the degree of collaboration. The exponential model shows how different process characteristics, such as the number and type of resources, the layout and the number of feeding devices, affect the exponent f. These effects were presented and discussed for two different task allocation using a tested simulation environment. The results demonstrate that:

– An exponential model for determining the T_{norm} of a CAS is provided;
– A method for evaluating T_{c0}, the coefficient of the exponential model, is provided; moreover the difference between the estimation and the simulated result is up to 5%.
– The influence of different process characteristics, e.g. the layout, on the exponent f is presented along with their effect.

The proposed model will be useful for practitioners that aims to evaluate the feasibility of a multi-resource CAS, and also the most appropriate design, in a rough design phase.

Future research will examine the effects of the introduction of task precedence on the exponential model, which limits the collaboration between the resources; moreover, we will analyze if other characteristics, such as technological constraints, will be considered. The effect of the uncertainties on the model will be studied in more detail, considering other probability density functions, such as the gamma model. Lastly, studying several case studies will allow defining a guide for the evaluation of the exponent.

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