Decision support model for implementing assistive technologies in assembly activities: A case study

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Abstract

The use of assistive technologies, such as digital instructions (DIs) and collaborative robots (cobots), can improve the productivity of assembly system. However, their implementation remains arbitrary.

In this study, a decision support system based on tactical-level variables (i.e. throughput, operator and equipment cost, operation time and type) was proposed with the aim of suggesting when the introduction of assistive technologies becomes profitable.

Four different assembly system configurations (i.e. manual assembly, manual assembly with the implementation of DIs, manual assembly with the implementation of cobots and manual assembly with the implementation of both DIs and cobots) were modelled by means of four different cost models and analysed in depth with a parametric analysis carried out by varying the tactical-level variables.

The results suggested that, when the throughput is low, the introduction of cobots should be considered only in cases of high operation times, while the introduction of DIs and/or cobots is the best alternative when the throughput is high. Finally, the validity of the approach is proved by comparing the results suggested by the decision support system with those obtained from a case study.

Keywords: digital instructions; collaborative robots; decision support system; assembly system configurations.

1. Introduction

The globalisation at the beginning of the 1990s modified the world of manufacturing, giving rise to unpredictable market changes, including rapidly varying product demand and the frequent introduction of new products. The customisation of assembled products at low costs, short time to market and high reliability of deliveries began to take hold, leading to the development of the mass customisation concept (Battaïa et al. 2018; Pine 1993; Zennaro et al. 2019).

Flexibility is crucial in assembly systems, and, according to Wolfson and Gordon (1997), a flexible system should be able to handle a wide variety of components, perform frequent model changeovers quickly and easily, be capable of processing multiple components and models simultaneously and swiftly respond to component design changes. Thus, it is clear that traditional assembly lines are no longer suitable for today's industrial environment, and a new generation of assembly systems is needed. Moreover, humans still play a core role in maintaining high the flexibility of the system due to their ability to adapt, learning easily and executing many tasks without any additional cost for the system (Kara, Kayis, and O'Kane 2002; Calzavara et al. 2020; Daria Battini et al. 2018).

From this perspective, the adoption of Industry 4.0 (I40) technologies is revolutionising assembly systems. In particular, assistive technologies, such as digital instructions (DIs), exoskeletons and collaborative robots (cobots), have a direct influence on such systems (S. Wang, Li, and Zhang 2016; Thames and Schaefer 2016; Lee et al. 2018; Gu et al. 2019; Xu, Xu, and Li 2018). Automation, digitalisation, robotics and other advanced technologies can improve operators' abilities thanks to dynamic interactions between humans and machines in the cyber and physical worlds (Romero et al. 2016). In particular, DIs act on cognitive interactions, while exoskeletons and cobots act on physical interactions. DIs, such as computer-aided instructions (i.e. instructions shown on a screen in a fixed or interactive way or projected on the workstation or smart glasses, as in the case of augmented reality (AR)), are technologies where digital information is provided to support the operator during manual operations by generating a digital assistance system. In this way, search and selection activities are sped up, and their related failure rates are reduced. In addition, assembly instructions can be interpreted faster by the operators, and thus, the learning curves improve. In contrast, exoskeletons are mechanical structures that humans can wear during assembling operations to increase their strength and endurance. According to Fox et al. (2019), there are at least eight different types of exoskeletons that, however, can have negative consequences, such as that of reducing human flexibility leading to new sources of musculoskeletal disorders (MSD) and accidents. Due to these drawbacks, exoskeletons are not considered any longer in this work and the authors will focus only on cobots when dealing with technologies acting on physical interactions. Cobots are industrial robots capable of performing a variety of repetitive and non-ergonomic tasks that have been specially designed to work in direct cooperation with human operators without the need for safety barriers. In this way, cobots can perform some activities in parallel, i.e. while the operator performs other tasks, improving the throughput of the system. In addition, by assigning cobots to repetitive and non-ergonomic tasks, the ergonomics of the assembly stations can be highly increased. Other advantages of using cobots in assembly lines together with an analysis of the psychological and sociological implications accompanying their introductions are reviewed by Cohen, Shoval, and Faccio (2019).

At present, the introduction of DI and/or cobots in assembly systems continues to be arbitrary and a quick and easy-to-use tool to understand when to implement DI and/or cobot is highly claimed by managers and practitioners. In fact, as discussed in the next section, no accurate and comprehensive tool has yet been developed to study the conditions under which the implementation of these technologies is economically beneficial. This represent the research question this work aims to answer, i.e.

RQ: which are the conditions (expressed in terms of hourly cost of the human operator, throughput and total operations time) that render the introduction of DI and/or cobots economically profitable?

This work aims to answer this question by introducing a general tool that will help practitioners to determine when the implementation of DIs, cobots or both in assembly systems may be profitable. Particularly, this general tool is a decision support system that, based on a decision tree, will guide managers and practitioners in the understanding of which hourly cost of the human operator (cop), throughput (Q), total operations time (t) and percentage of time engaged in searching and picking activities (α) render the implementation of DI and/or cobots economically beneficial.

The decision whether implementing DI and/or cobots is typically made at a tactical level, where practitioners and managers have to design or redesign the assembly systems, deciding the number of workstations, equipment and technologies to be installed. In this phase, practitioners and managers possess only information about the design of the products (typically of the Virtual Average Model) and about the required throughput, hourly cost of the operator, expected total assembly time and benefits and costs of technology implementation. Considering the traditional product development phases depicted in Figure 1 (Eskilander 2001), the design of the products is the output of the "Detail design" phase, while the tactical level falls into the "Production system design" phase. It is worth mentioning that the use of the Design for Automatic Assembly (DFAA) is strongly suggested in the "Detail design" phase. In fact, according to Maczka (1985), "any product designed for automated assembly will be easier to assemble manually", while the opposite does not hold true. In such a way, irrespective of the assembling systems that will be chosen in the "Production system design" phase, the assembly will be facilitated.

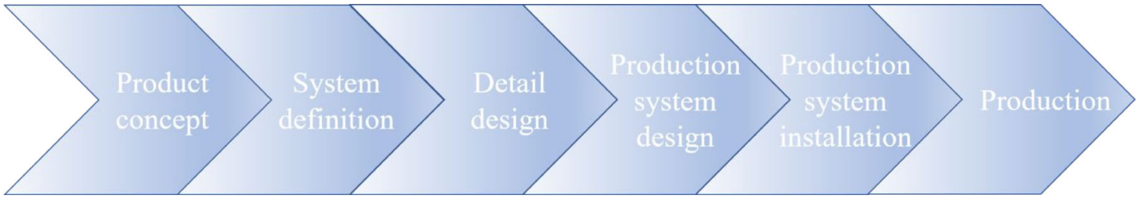

Figure 1. Traditional product development

The main contributions of this paper can be described as follows:

- Development of four cost models, one for each assembly system configuration (i.e. manual assembly, manual assembly with the implementation of DIs, manual assembly with the implementation of cobots and manual assembly with the implementation of both DIs and cobots), allowing estimating the unitary cost per assembled product;
- From an extensive parametric analysis, a decision support system based on a decisional tree has been developed to guide practitioners through the decision of whether to implement assistive technologies. The decision support system proposed here does not provide any detailed information about the cheapest assembly system configuration, but only which assembly system configurations need to be investigated in detail to find the best one. Some hints about the cheapest solution can be obtained considering the cost models at the basis of the decision support system, but their results are limited due to the limitations of these formulations, as described in detail below;
- Application of the proposed decision support system in a case study, where the procedure to apply the decision support system is described, and the assembly system configuration reported as the cheapest from the case study is confronted with the profitable assembly system configurations suggested by the decision support system for the input variables of the case study.

The remainder of the paper proceeds as follows: Section 2 reviews the previous research on DIs and cobots in assembly systems, identifying the gap in the literature and supporting the necessity of the models and their comparison. The cost models are introduced and described in

Section 3, while in Section 4, an economic comparison based on an extensive parametric analysis of the four different assembly system configurations is introduced, and the results of the main parameters' effects are presented. In Section 5, the results of the economic comparisons are reported according to a decision support system based on a decision tree comprising four different variables, which are as follows: hourly cost of the human operator, throughput, total operations time and the percentage of time engaged in searching and picking activities. These variables represent the main input variables available at the tactical level. Section 6 illustrates the application of the approach to a simple case study, and its validity is proved by comparing the solution obtained by the decision support system with that generated from the case study. In addition, the robustness of the decision support system has been further confirmed by extending the case study considering an over- and underestimation of the total time to assemble the Virtual Average Model of 50%.

Finally, insights, discussions and limitations of the study are provided in Section 7, together with future researches.

2. Literature review

From the literature review, it can be seen that there are two different types of interactions between humans and machines in the cyber and physical worlds, namely cognitive and physical interaction (Romero et al. 2016). Among the former, DIs emerge as foremost, while cobots are dominant among the latter.

DIs, such as computer-aided instructions (i.e. instructions shown on a screen in a fixed or interactive way or projected on the workstation or smart glasses, as in the case of augmented reality (AR)), can support the operator during manual operations by becoming a digital assistance system, allowing faster cycle times, increased reliability and a reduced failure rate (Grajewski et al. 2013; Zhang, Ong, and Nee 2011; Z. B. Wang et al. 2013; Ong, Yuan, and

Nee 2008). Hou et al. (2013) reported that replacing paper-based instructions with DI systems can reduce the assembly time of a Lego Mindstorms NXT 2.0 (35 pieces) from 11.91 min to 7.37 min. These results corroborate those obtained in relation to piping assembly (Hou, Wang, and Truijens 2015), whereby the implementation of the DI system was observed to result in a reduction in assembly time of more than 50% compared to the use of paper-based instructions. Moreover, the implementation of DIs was also reported to halve the number of errors. Similarly, in the assembly of a computer motherboard, fewer errors and lower assembly times were observed when a see-through AR system was used, compared with paper-based instructions (Baird and Barfield 1999). However, in assessing the use of DI in the assembly of a three-dimensional puzzle, Syberfeldt et al. (2015) reported that paper-based instructions were associated with better performances. The reason offered by the authors was that the component they used was not complex enough (nine pieces), and the complexity should be sufficiently high to justify DI implementation. However, they provided no description or quantification of what they deemed sufficiently high. A step in this direction can be found in Wiedenmaier et al.'s (2003) study, in which repetitive and intuitive tasks are reported to be better suited to paper-based instructions, while difficult tasks with ambiguous assembly positions are considered well suited to DI. However, to the best of the authors' knowledge, a clear understanding of when the implementation of DI technologies is beneficial has yet to be reached.

Similar conclusions can be drawn for cobots. Cobots can improve the system throughput due to their ability to work in direct cooperation with the operator (Bochmann et al. 2017; Kuhlenkötter et al. 2016; Cencen, Verlinden, and Geraedts 2018). For example, Tsarouchi et al. (2017) reported that the introduction of two cobots to the assembly sequence of a hydraulic pump reduced the time required for a human operator to perform the task by 78%. These results corroborate those obtained by Helmersson and Hesslund (2016) and Krüger, Lien, and Verl

(2009). In the former, a 30% reduction in the cycle time was obtained by substituting traditional robots with cobots, while the latter reported takt times to assemble heavy parts of an automotive rear axle of 220 seconds for the automated solution, 320 s for the human solution and 100 s for the hybrid solution (i.e. combined human/cobot efforts). However, Cherubini et al. (2016) reported that the introduction of the cobot quadrupled the assembly time of a car's homokinetic joint. The possible reason for this suggested by the authors is the limited number of operations that were performed (nine manual operations). In addition, Djuric et al. (2016) suggested that cobots are desirable when repetitive tasks must be performed, while human operators are better at performing tasks characterised by high levels of flexibility. However, as in the case of DIs, no consensus has been reached regarding the range of profitability associated with cobots in production systems.

As stated by Battini et al. (2011), the introduction of new technologies must be accompanied by an analysis of the conditions under which it is worth introducing these new technologies in terms of operator well-being, system performance and economic perspective. Dealing with the former two, Golan et al. (2019) proposed a conceptual framework where the introduction of I40 technologies was optimised to enhance the operator wellbeing and system performance (throughput, error rates and damaged units). Considering the economic perspective, cost models can be considered an effective means of guiding practitioners in their decisions. However, to the best of the authors' knowledge, the cost modelling of DIs and cobots in the assembly line has scarcely been considered by researchers. Antonelli et al. (2016) assessed the total time required to perform a welding operation, depending on the batch size and considering three different solutions—fully manual, fully automated and collaborative cells. They reported that, for a batch size smaller than eight pieces, the fully manual solution was the fastest, while the implementation of the cobot was found to be effective in batch sizes of 8–25 pieces; for bigger batch sizes, the fully automated solution represented the best choice.

However, economic analysis is missing from this study. A step towards addressing this was carried out by Faccio et al. (2019), who investigated the conditions under which a collaborative assembly system performs better than manual or automated assembly systems in terms of throughput and production cost. They studied a simplified configuration in which the durations of the picking and assembling activities were the same for each part. However, a component characterised by parts requiring the same amount of time to be picked and assembled is quite unrealistic. Further, none of the above-mentioned works considered the implementation of DIs.

There is thus a clear need to understand when the introduction of DIs and cobots may be profitable. In this regard, it might be helpful to consider the concept of "Level of Automation" (LoA). The LoA can be defined as the *"allocation of physical and cognitive tasks between humans and technology, described as a continuum ranging from totally manual to totally automatic"* (Frohm 2008), and it aims to determine the right degree of automation for a given case, i.e. whether to introduce a certain technology or not. One of the most common methodology to evaluate the LoA is the so-called Dynamo methodology. In this methodology, the main sub-tasks for each workstation are identified and the LoA of each sub-task is measured according to the taxonomy reported in Frohm (2008). The measured LoA level is then compared to the ideal LoA value for each sub-task: in this way managers are supported in deciding whether implementing new technologies or not. The Dynamo methodology is however limited by some limitations. First, it needs the system to be existent, i.e. it is not applicable in the early phase of new assembly systems design. Second, the determination of ideal LoA values is subjective since it is left to the judgement of operators and/or production technicians. Almannai et al. (2008) overcame the first drawback of the Dynamo methodology, but still the subjectivity remained. They developed in fact a decision tool based on the combination of the quality function deployment (QFD) technique and of the failure mode and effects analysis (FMEA) technique that does not necessitate the system to be existent but that is still left to the subjective interpretation of the managers when dealing with linking the objectives of the automation with the different alternative options. Moreover, the application of this methodology was also reported to be time-consuming since it took two entire working days to apply it in Rolls-Royce (Almannai, Greenough, and Kay 2008).

Hence, it emerges clearly the need for a fast, easy-to-use and objective tool that, during the design phase of new assembly systems, can assist managers and practitioners in understanding the circumstances under which the introduction of DIs and cobots may be profitable. The present study aims to fill this gap, and, to do so, the authors have decided to consider the economic perspective as discriminant in the choice. Four different cost models have thus been developed, one for each assembly system configuration (i.e. manual assembly, manual assembly with the implementation of DIs, manual assembly with the implementation of cobots and manual assembly with the implementation of both DIs and cobots), allowing a fast and objective understanding of the circumstances under which these technologies are worth being introduced. Leveraging on these cost models, a parametric analysis is carried out for mapping and defining the conditions in terms of values of the tactical-level variables (i.e. throughput, operator and equipment cost, operation time and type) for which the introduction of assistive technologies may be beneficial, allowing the author to propose a decision support system that can support managers and practitioners in making common decisions for the design or re-design of an assembly system.

3. Assembly system configurations: description and cost models

Notations

i = configurations of the assembly system: $i = M$ for manual assembly system, $i = DI$ for manual assembly system with DI implementation, $i = C$ for manual assembly system with cobots implementation, $i = DI + C$ for manual assembly system with DI and cobots implementation.

Q = required throughput [pcs/h]

t = time spent to complete the operations for the Virtual Average Model, considering both searching and picking and assembly activities [s]

t^i_{S+P} = time spent for searching and picking activities in the case of configuration i [s]

t^i_{ASS} = time spent for assembly activities in the case of configuration i [s]

$t^i = t^i_{S+P} + t^i_{ASS}$ = time to do all the operations in the case of configuration i [s]

$\alpha = t^i_{S+P}/t^i$ = % of the time spent in searching and picking activities

c_{st} = cost per hour of the assembly station, including also the services [€/h]

c_{op} = cost per hour of the operator [€/h]

c^{DI}_d = cost per hour of DI device [€/h]

c^C_d = cost per hour of one cobot [€/h]

ω = % of the assembly station served by the cobot

β^i = % of improvement provided on searching and picking activities by the implementation of configuration i

γ^i = % of improvement provided on assembly activities by the implementation of configuration i

In this section, different assembly system configurations are described and modelled using cost functions—the manual assembly system, the manual assembly system with the implementation of either the DI or cobot and the combination of these last two options. As explained in the previous sections, the scope of this research is at tactical level, supporting practitioners in making decisions common of the design or re-design of an assembly system. Typical decisions in the design of assembly systems are related to their configurations, such as how many workstations and which equipment and technology to install at the system level. Other decisions regarding balancing, sequencing, feeding policies and so on are made at an operational level, and they relate more to the management of the assembly system. Some of them, like balancing, have some interrelations with previous decisions at a tactical level, such as the minimisation of workstations via optimised balancing solutions. However, to reduce the complexity of the problem and provide a decision support system that is easily usable at a tactical level, balancing is not considered part of the model. Thus, at the tactical level, the required information and input data for the decision makers involve rough estimates, such as the following:

- *The required throughput of system Q:* this can be estimated from the market demand of the products that will be assembled in the systems over the year;
- *The total time to assemble one average product t and its terms, such as the time for searching and picking the components and the time for pure assembly activities, t^i_{S+P} and t^i_{ASS}:* these components can be estimated from the historical data and the production managers' experience. They are also affected by the complexity and size of the products, which influence the dimensions of the workplace where the operators work;
- *The cost of operators c_{op}, cost of assembly station c_{st} and cost of equipment/technology c^{DI}_d and c^C_d:* this information is typically available from the accounting department and from the suppliers of the different equipment and technological components available on the market;
- *The benefits in time reduction using the equipment/technology β^i and γ^i:* the introduction of the various types of equipment/technology usually permits a reduction in task execution time. This reduction is difficult to determine a priori, since at the design phase the equipment/technologies are not yet implemented. However, it is possible to estimate them by implementing the following steps:

- Using pre-tests;
- Using historical data from similar previous projects/implementations;
- Using the experience of the suppliers of this equipment/technology.

In this paper, β^i and γ^i are estimated through the last two points.

Moreover, some general assumptions have been adopted, which are as follows:

- There is one operator for each assembly station;
- Each operator performs both searching and picking and assembly activities;
- The implementation of the DIs and/or cobots can reduce the time required to perform these activities (X. Wang, Ong, and Nee 2016; Pathomaree and Charoenseang 2005; Yuan, Ong, and Nee 2008; Gonzalez and Ruiz Castro 2018; Liu et al. 2019);
- The required throughput is pre-defined;
- The error rate is neglected in this study, along with the effects of DIs and cobots on the error rate;
- The DIs and cobots are considered perfectly available and reliable;
- The interactions between DIs/cobots and the operators are modelled just by the improvement rates β^i and γ^i. Any different effects are not considered;
- The DI is assumed to be available at all stations;
- Operational times are considered deterministic;
- Only one single product is considered to be assembled in the assembly line (generally the Virtual Average Model of the product family);
- The cobot encumbrance is considered negligible.

Following these assumptions, the unitary cost per assembled product has been calculated based on the cost of the operator, the cost of the equipment/devices/cobots and the total number of stations needed to satisfy the required throughput. Then, comparing the unitary cost per assembled product of each configuration, the most suitable one can be easily identified. Using these cost models, an extensive parametric analysis has been carried out to determine the conditions in which the introduction of DIs and/or cobots is beneficial from an economic perspective.

Some limitations arise from the introduction of these assumptions, such as those related to the error rate and deterministic operational times, equipment/technology availability and reliability and interaction with operators. The models introduced here have been limited to generate a first decision support system based on a decision tree, where the main decision variables at the tactical level are considered. Including other variables would have made the decision tree too complex to be applied. In addition, neglecting balancing procedures represents another limitation. The limitations are discussed in detail in the conclusion section, and they will be further addressed in future research.

3.1 Manual assembly: cost-per-product formulations

In the exclusively manual assembly configuration, the time taken to complete all operations, t^M, can be divided into a fraction of the time engaged in searching and picking activities, t^M_{S+P}, and into another of the time spent in assembly activities, t^M_{ASS} (Figure 2).

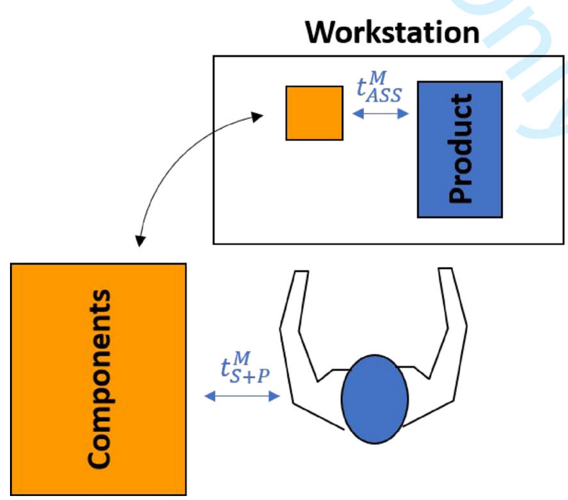

Figure 2. Schematic representation of a station in the manual assembly system

Thus, the number of operators corresponds to the number of stations, measured as

$$n^M = \left\lceil \frac{t^M \cdot Q}{3600} \right\rceil \qquad (1)$$

In this configuration, $t^M = t^M_{S+P} + t^M_{ASS} = t$, since no cognitive or physical interactions are present to help the human operator. The cost of the product considering this configuration is due only to the costs associated with the operator and assembly stations (i.e. costs of workbenches, required tools and equipment, services, etc.):

$$C^M = n^M \cdot \frac{(c_{st} + c_{op})}{Q} \qquad (2)$$

3.2 DI implementation: cost-per-product formulations

DIs acts on the cognitive skills of the operator, reducing the time required to search for parts and facilitating the assembly by making the required positioning of the parts easier to understand. Improvements in the searching activities are accounted for by the factor β^{DI}, while those in the assembly activities are accounted for by the factor γ^{DI} (Figure 3).

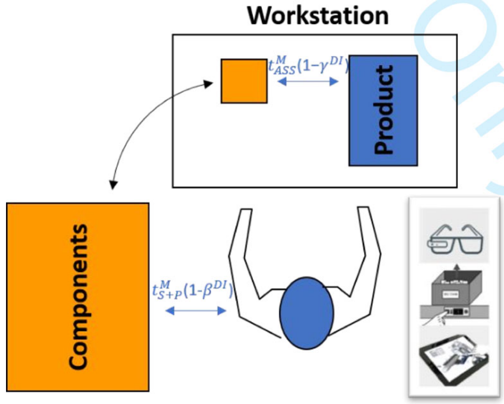

Figure 3. Schematic representation of a station in the assembly system with DI implementation

The time the human operator requires to complete the searching and picking activities, t^{M}_{S+P}, is equal to

$$t^{DI}_{S+P} = t^{M}_{S+P} \cdot \left(1 - \beta^{DI}\right) \tag{3}$$

while the time required by the human operator to perform the assembly tasks corresponds to the following:

$$t^{DI}_{ASS} = t^{M}_{ASS} \cdot \left(1 - \gamma^{DI}\right) \tag{4}$$

The time taken to perform all the operations is

$$t^{DI} = t^{DI}_{S+P} + t^{DI}_{ASS} = \alpha \cdot \left(1 - \beta^{DI}\right) \cdot t + (1 - \alpha) \cdot \left(1 - \gamma^{DI}\right) \cdot \mathrm{t} \tag{5}$$

where α is the percentage of time spent in searching and picking activities. In this case, the number of assembly stations will be

$$n^{DI} = \left\lceil \frac{t^{DI} \cdot Q}{3600} \right\rceil \tag{6}$$

The cost of the product in this solution is close to one we have for the manual assembly system configuration, with the addition of the term related to the implementation of the DI in the system. Due to the low costs of DI devices, it is assumed that every station (i.e. every operator) is equipped with this technology, leading to the following cost per product:

$$C^{DI} = n^{DI} \cdot \frac{\left(c_{st} + c_{op} + c^{DI}_{d}\right)}{Q} \tag{7}$$

3.3 Cobot implementation: cost-per-product formulations

The implementation of the cobot acts instead on the operator's physical skills, since it can replace the operator in performing several searching, picking and assembly activities. In particular, if the activities' scheduling is optimised, the cobot can perform the activities faster than the human operator can; it may be even more effective in reducing the operational time as it can perform these activities while the operator performs other tasks. In this way, the reduction in the process time is higher than that of the DI implementation. In particular, the system is characterised by a reduction of β^C for the searching and picking time and γ^C for the assembling time (Figure 4).

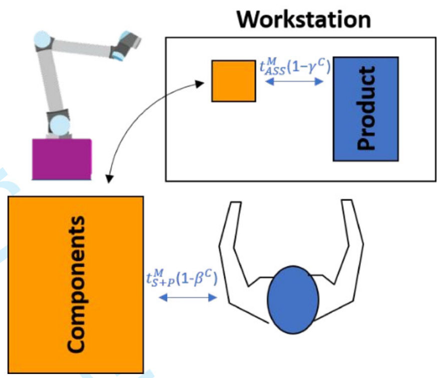

Figure 4. Schematic representation of a station in the assembly system with cobot implementation

In this configuration, the influence of the cobot on searching and picking activities is accounted for by the factor β^C:

$$t^C_{S+P} = t^M_{S+P} \cdot (1 - \beta^C) \tag{8}$$

while the time spent on assembly by the human operator is reduced by the factor γ^C:

$$t^C_{ASS} = t^M_{ASS} \cdot (1 - \gamma^C) \tag{9}$$

This led to a time to perform all the operations equal to

$$t^C = t^C_{S+P} + t^C_{ASS} = \alpha \cdot (1 - \beta^C) \cdot \mathrm{t} + (1 - \alpha) \cdot (1 - \gamma^C) \cdot \mathrm{t} \tag{10}$$

The average values of the indices β and γ differ significantly, depending on whether DIs or cobots are implemented. In fact, while the DI technologies act on the cognitive processes, reducing the time taken to determine where a component is (β^{DI}) or how to assemble it (γ^{DI}), the cobot's effect is much greater since, acting on the operator's physical processes, it can help to perform searching and picking activities (β^{C}) and assembling activities (γ^{C}) faster than the operator can. Furthermore, the possibility provided by the cobots to perform some operations while the operator performs some other tasks can further reduce the operation time. Thus, the indices β^{C} and γ^{C} take into consideration not only the cobot's ability to perform the activities faster than the operator but also the reduction in time due to its potential to perform certain activities in masked time.

The number of stations corresponds to

$$n^{C} = \left\lceil \frac{t^{C} \cdot Q}{3600} \right\rceil \tag{11}$$

Depending on the product under consideration and the scheduling of the activities, the variable ω has been introduced to evaluate the number of stations n_D^C requiring the presence of the cobot:

$$n_D^C = \lceil \omega \cdot n^{C} \rceil \tag{12}$$

Thus, the final cost per product can be calculated as follows:

$$C^{C} = n^{C} \cdot \frac{(c_{st} + c_{op})}{Q} + n_D \cdot \frac{c_d^C}{Q} \tag{13}$$

3.4 DI and cobot implementation: cost-per-product formulations

When the DIs and cobots are implemented together, the operator's cognitive and physical skills are both affected, further increasing the new technologies' potential to reduce the operation time; in particular, the reduction in the time spent on searching and picking activities is quantified as β^{DI+C}, while that spent on assembly is quantified as γ^{DI+C} (Figure 5).

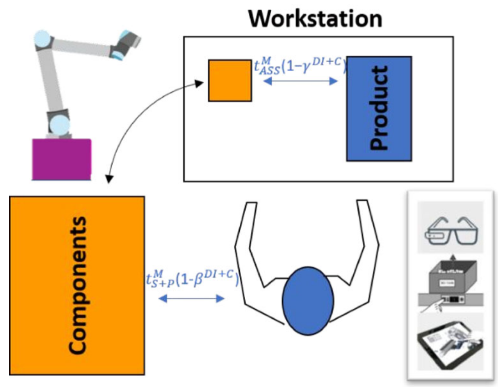

Figure 5. Schematic representation of a station in the assembly system with DI and cobot implementation

This configuration essentially combines the ones described in the previous sections, with the time spent on searching and picking by a human operator without any interaction reduced by the factor β^{DI+C}:

$$t^{DI+C}_{S+P} = t^{M}_{S+P} \cdot \left(1 - \beta^{DI+C}\right) \qquad (14)$$

and that spent on assembly activities reduced by the factor γ^{DI+C}:

$$t^{DI+C}_{ASS} = t^{M}_{ASS} \cdot \left(1 - \gamma^{DI+C}\right) \qquad (15)$$

This leads to a total time taken to complete the tasks equal to

$$t^{DI+C} = t^{DI+C}_{S+P} + t^{DI+C}_{ASS} = \alpha \cdot \left(1 - \beta^{DI+C}\right) \cdot \mathrm{t} + (1 - \alpha) \cdot \left(1 - \gamma^{DI+C}\right) \cdot \mathrm{t} \qquad (16)$$

The main concern that can arise concerns the indices β^{DI+C} and γ^{DI+C}. Their values are intrinsically related to the product configuration and the scheduling adopted, but it usually holds that

$$\begin{cases} \beta^{DI+C} \leq \beta^{DI} + \beta^{C} \\ \gamma^{DI+C} \leq \gamma^{DI} + \gamma^{C} \end{cases} \tag{17}$$

Like in the previous section, the index ω accounts for the evaluation of the number of stations equipped with a cobot (again, the DI is assumed to be available at all stations):

$$n_D^{DI+C} = \lceil \omega \cdot n^{DI+C} \rceil \tag{18}$$

where

$$n^{DI+C} = \left\lceil \frac{t^{DI+C} \cdot Q}{3600} \right\rceil \tag{19}$$

Both the DI and cobot contribute to the final cost of the product:

$$C^{DI+C} = n^{DI+C} \cdot \frac{(c_{st} + c_{op} + c_d^{DI})}{Q} + n_D^{DI+C} \cdot \frac{c_d^C}{Q} \tag{20}$$

4. System comparison and parametric analyses

As mentioned above, the aim of this study was to determine the conditions in which the introduction of cognitive (DI) interaction, physical (cobot) interaction or both is beneficial from an economic perspective. To this end, the four different solutions are compared by means of the ratios $\frac{C^M}{C^{DI}}$, $\frac{C^M}{C^C}$ and $\frac{C^M}{C^{DI+C}}$. Clearly, when all ratios are lower than the unit, a system without any interaction is preferable.

Before proceeding with the comparison of the different configurations, the impact of each variable (t, Q, α, c_{st}, c_{op}, β^{DI}, γ^{DI}, β^{C}, γ^{C}, β^{DI+C}, γ^{DI+C}, ω, c_d^{DI} and c_d^{C}) on the ratios must be assessed. To this end, an analysis of 110 592 different scenarios was carried out. The values of each parameter, chosen based on the authors' experiences and on the typical values available in technical and economic datasheets, have been varied in a discrete way (Table 1), as usually done in literature (Manzini et al. 2007; Battini et al. 2009; Fragapane et al. 2020).

Parameter	Unit of measure	Values
t	s	600; 1,500; 3,600
Q	pcs/h	5; 25; 50; 100
α	-	20%; 50%; 80%
β^{DI}	-	5%; 15%
γ^{DI}	-	5%; 15%
β^{C}	-	25%; 75%
γ^{C}	-	25%; 75%
β^{DI+C}	-	25%; 90%
γ^{DI+C}	-	25%; 90%
ω	-	25%; 50%; 75%
c_{st}	euro/h	1.1; 1.6
c_{op}	euro/h	20; 40
c_d^{DI}	euro/h	0.6; 1.2
c_d^{C}	euro/h	3.4; 6.8

Table 1. Parameters and their values used for the ANOVA test

It is worth mentioning that, in the main effects plot analyses below (Figure 6), the authors decided to consider the total cost of the cobot implementation as a variable, combining the percentage of the assembly station served by the cobot (ω) and c_d^C in a single parameter defined as the product of the two $(\omega \cdot c_d^C)$.

a) b) c)

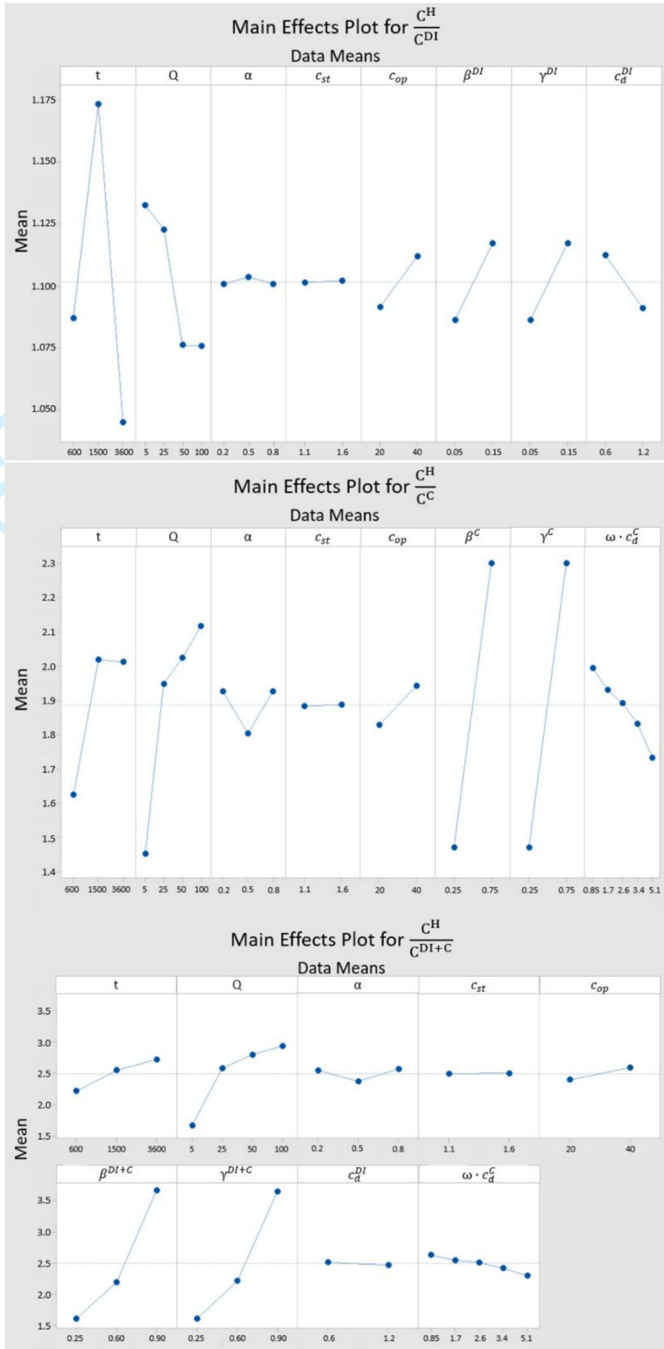

Figure 6. Main effect plot analysis of $\frac{C^M}{C^{DI}}$ (a), $\frac{C^M}{C^C}$ (b) and $\frac{C^M}{C^{DI+C}}$ (c)

From the main effects plot analysis, it can be concluded that the cost of the assembly station has a negligible effect on the results; thus, it is kept fixed and equal to 1.35 euro/h in the analyses.

5. The decision support system and economic assessment

As highlighted in the introduction, a decision support system that can provide indications regarding the conditions under which the implementation of DIs and/or cobots is economically beneficial is urgently needed. In particular, this decision support system should include input variables that are known a priori by managers and practitioners, and as output, it should provide the optimal system characteristics.

Considering the equations introduced in Section 2, the numerous variables can be divided into two main groups:

- *System-related variables:* Variables related to managerial decisions (c_{op}), market demands (Q) and product characteristics (t and α) are included in this group;
- *Equipment-related variables:* The characteristics of the cognitive and physical interaction systems (β^{DI}, γ^{DI}, β^{C}, γ^{C}, β^{DI+C}, γ^{DI+C}, ω, c_d^{DI} and c_d^{C}) form this group.

The first group is the group of variables known a priori by managers and practitioners; thus, a decision support system based on this group can be deployed (Figure 7).

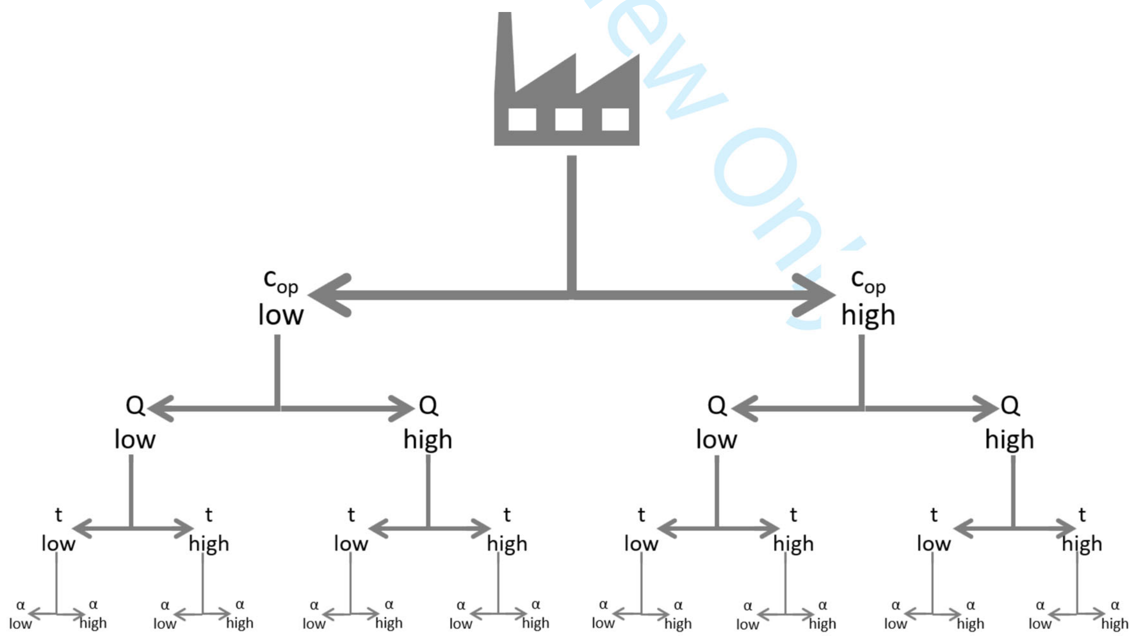

Figure 7. Decision support system

Based on this decision support system, it would be possible to gain deeper insight into the conditions (low or high c_{op}, Q, t and α) under which the introduction of cognitive and/or physical interaction would be profitable. The choice to consider only two levels (low and high) is related to the authors' will to provide the practitioners with an easily usable tool.

In particular, in each scenario, the profitability of introducing these new technologies is highly dependent on their efficiencies (β and γ) and their costs. Thus, the threshold curves for each ratio ($\frac{C^M}{C^{DI}}$, $\frac{C^M}{C^C}$ and $\frac{C^M}{C^{DI+C}}$) have been plotted as a function of these efficiencies (β on the x-axis and γ on the y-axis), and they are reported in Figures 7, 8 and 9, considering the low and high values as shown in Table 2.

It is worth mentioning that the left side of the threshold curve defines the area in which manual assembly is suitable, while on the right side, the introduction of the cognitive interaction (Figure 8), physical interaction (Figure 9) or both (Figure 10) is profitable. Red and blue lines are obtained with low and high values of α, respectively, while solid and dashed lines stand for the high and low costs of the implemented assistive technologies, respectively. In some circumstances, the dashed lines are not visible because they overlap with solid lines.

	low	**high**
$\mathbf{c_{op}}$	20 (euro/h)	40 (euro/h)
Q	5 (pc/h)	100 (pc/h)
t	600 (s)	3600 (s)
α	20%	80%
$\mathbf{C_d^{DI}}$	0.6 (euro/h)	1.2 (euro/h)
$\mathbf{C_d^{C}}$	3.4 (euro/h)	6.8 (euro/h)
ω	25%	75%

Table 2. Low and high values used to build the contour plots according to the decision support system

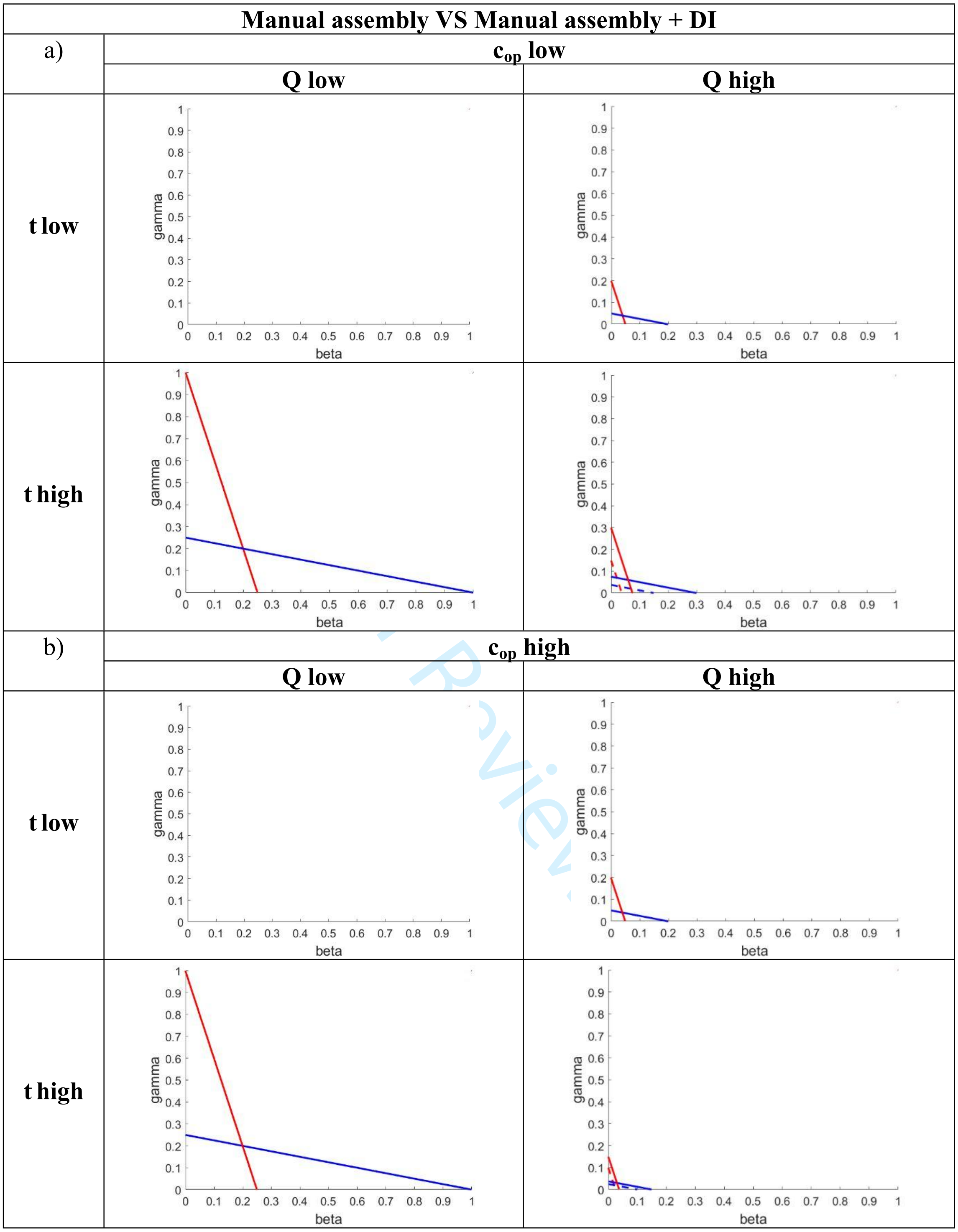

Figure 8. Threshold lines of the ratio $\frac{C^M}{C^{DI}}$ for c_{op} low (a) and c_{op} high (b). Red and blue lines are obtained with the low and high values of α, respectively, while full and dashed lines stand for the high and low costs of the DI system, respectively.

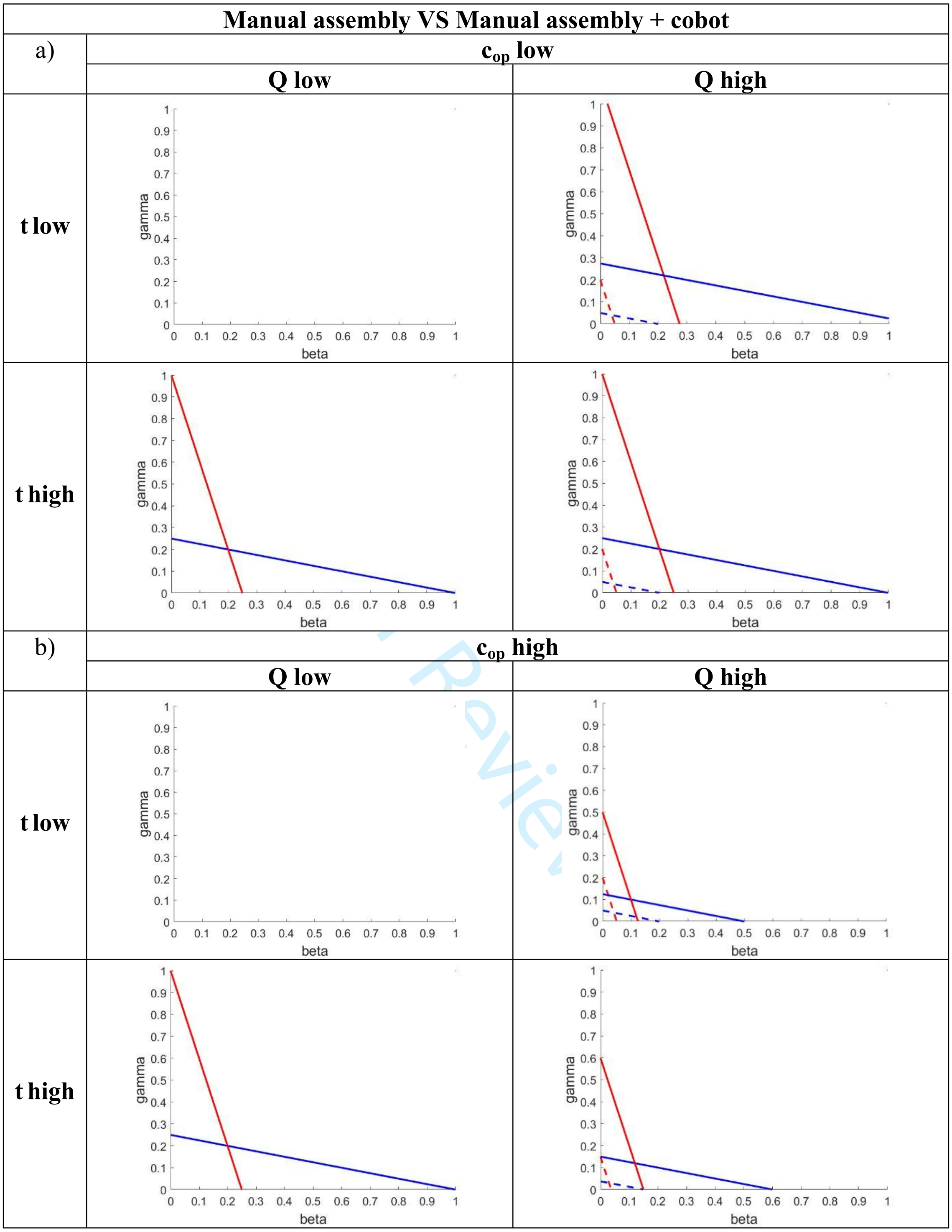

Figure 9. Threshold lines of the ratio $\frac{C^M}{C^C}$ for c_{op} low (a) and c_{op} high (b). Red and blue lines are obtained with the low and high values of α, respectively, while full and dashed lines stand for the high and low costs of the cobot system, respectively.

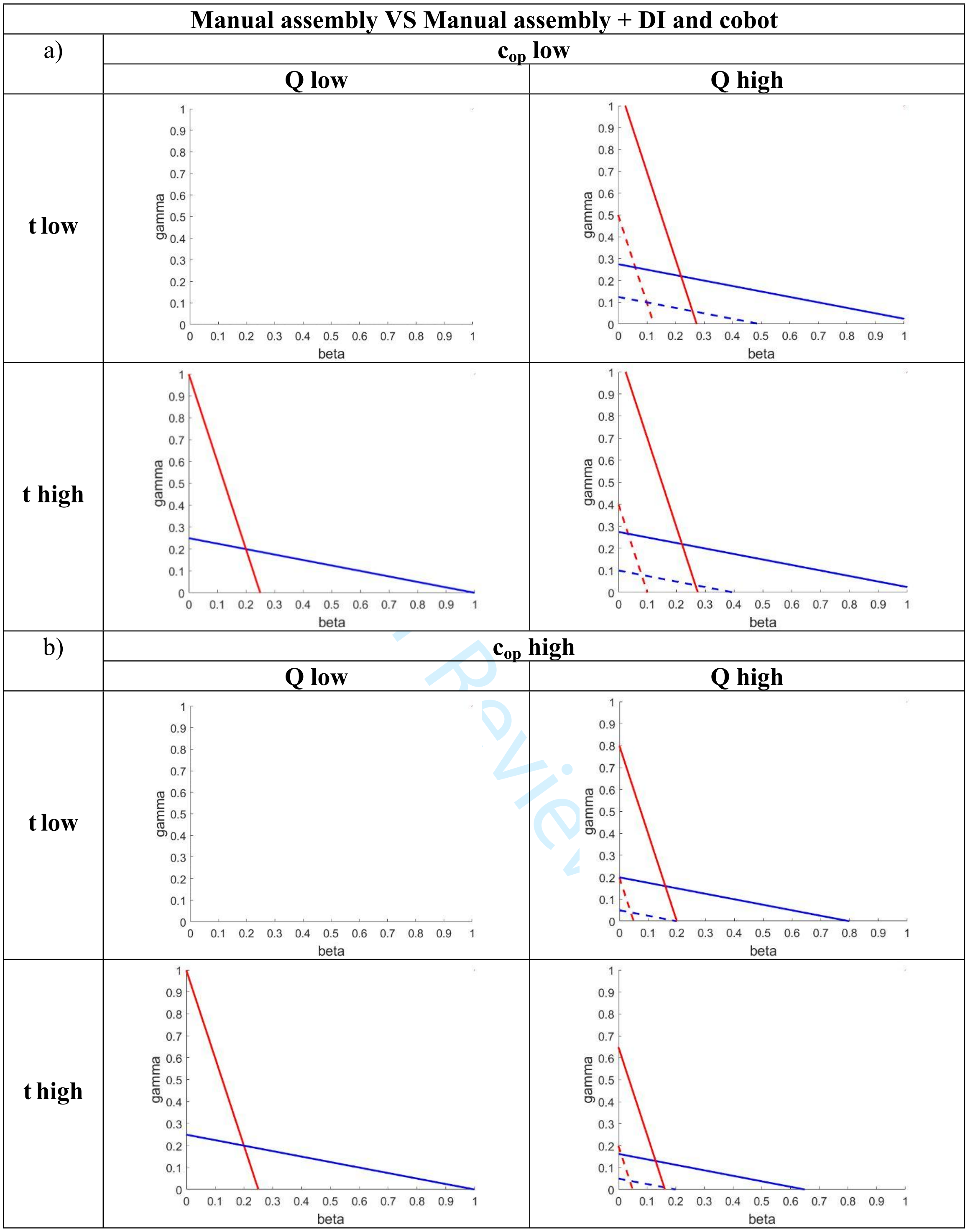

Figure 10. Threshold lines of the ratio $\frac{C^M}{C^{DI+C}}$ for c_{op} low (a) and c_{op} high (b). Red and blue lines are obtained with the low and high values of α, respectively, while full and dashed lines stand for the high and low cost of the cobots system, respectively.

From Figure 5, it can be seen that the cost of the DI device had a lower effect than that of the cobot in the case where both the cognitive and physical interaction were implemented, and thus, the cost has been fixed at 0.9 euro/h.

Analyses of the results gathered in Figures 7, 8 and 9 indicate that, for a low throughput Q and low time to complete the operations t, the system without interactions is always convenient from a cost perspective (blank maps). In fact, from Equations 2, 7, 13 and 20, the manual assembly configuration is always cheapest when its number of stations is equal to 1. For example, comparing the manual assembly configuration (Equation 2) to the system equipped with DI technology (Equation 7), when the number of stations is 1, that is, $Q \cdot t^M \leq 3600$, the cost per product will always be lower due to the additional term related to the DI, c_d^{DI}. This also holds for the other two configurations.

For low throughput and high time required to complete the operation, regardless of the operator's hourly cost, the introduction of DI technologies is quite unlikely due to the high values of β^{DI} and γ^{DI} required to economically justify their incorporation. For the sake of simplicity, considering a case wherein the time required to perform all tasks is equally distributed across searching and picking and assembling activities (i.e. α = 50%), the introduction of DI technologies must lead to an improvement such that $\beta^{DI} + \gamma^{DI} \geq 40\%$ (Figure 11).

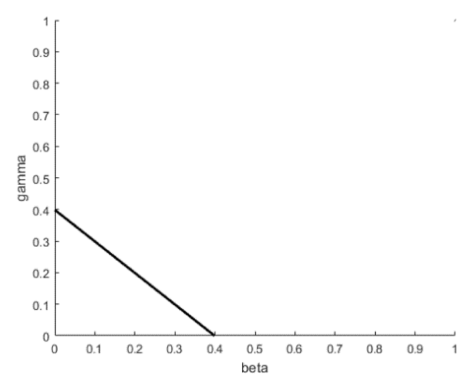

Figure 11. Threshold line of the ratio $\frac{C^M}{C^{DI}}$ in the case of Q low and t_{op} low.

The same values are more easily achievable with the implementation of cobots, so their implementation is preferable in this scenario.

Finally, when Q is high, the values of β^{DI} and γ^{DI} required to economically justify the introduction of the DI technologies are shown to be more feasible, particularly when c_{op} and t are high. Concerning the introduction of cobots, whether exclusively or in combination with DI technologies, the β and γ values required are considerably reduced if a system with a low cobot cost is implemented, and its implementation will be even more eased when the operator's cost is high. To summarise these conclusions, the decision support system from Figure 6 is modified in Figure 12, where the final branches report the possible, economically convenient solutions for each case.

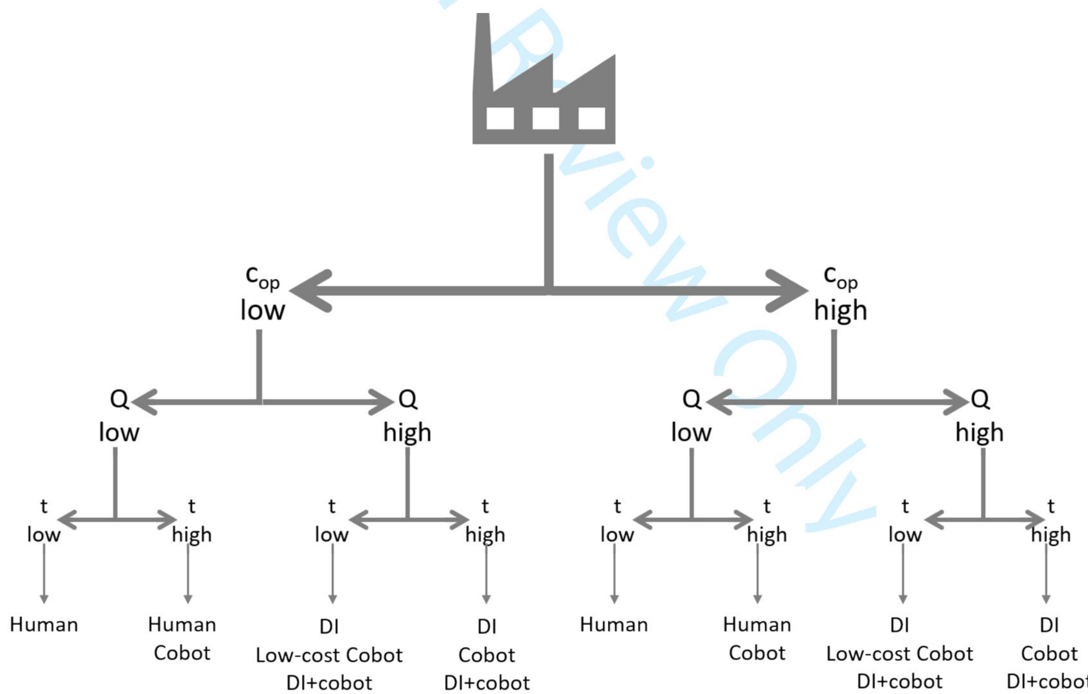

Figure 12. Decision support system with suggestions for the practitioners

By using this simple decision support system, managers and practitioners, based on the conditions characterizing their systems (i.e., low or high cop, Q, t and α), can understand whether the introduction of cognitive and/or physical interaction would be beneficial or not. It is worth mentioning that this decision support system does not aim to provide any detailed information about the cheapest assembly system configuration, but instead, aims to suggest which assembly system configurations need to be investigated in detail to find the best one.

6. Case study

In this section, the decision tree is applied to a simple but representative case study, and the assembly system configuration reported as the cheapest from the case study is confronted with the profitable assembly system configurations suggested by the decision support system for the input variables of the case study. The product considered is a self-priming jet pump, that represents also the Virtual Average Model of a product family.

Based on the data available from an on-going collaboration with the pump manufacturer, the throughput Q has been considered equal to 96 pcs/h, that corresponds to a takt time of 37.5 s per product. The assembly of the pump is characterized by 19 different activities distributed on seven workstations, and the precedence diagram is reported in Figure 13.

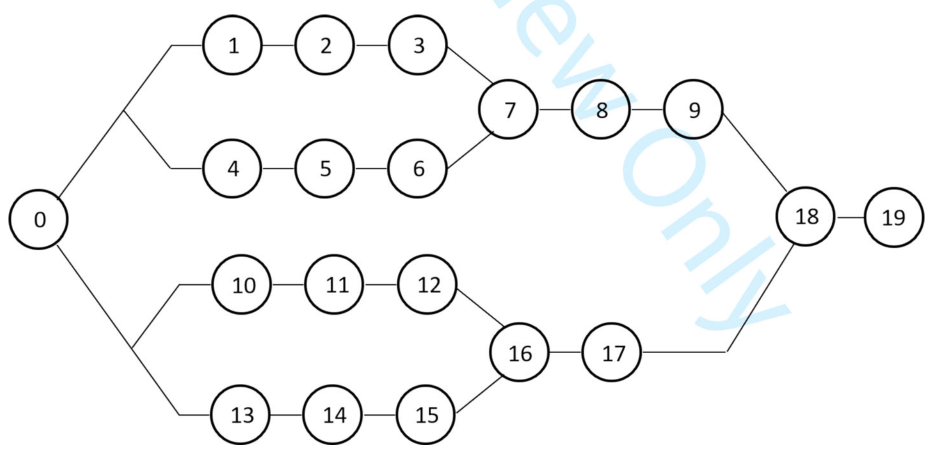

Figure 13. Precedence diagram

A prototype of the production line was produced at the Logistic 4.0 Laboratory at NTNU, and the task times (Table 3) were obtained by a Ph.D. student of the Department of Mechanical and Industrial Engineering at NTNU, with an age of 28 years. Although the student had no previous experience in pump assembling, he was trained. The total time to assemble the Virtual Average Model $t = t^M$ was found to be equal to 230.0 s, with the percentage of time dedicated to searching and picking activities α equal to 15% (Table 3). In addition, to extend the soundness of the case study validation by overcoming the limitation of the absence of repeatability in the task times, the total time to assemble the Virtual Average Model has been varied by ±50%.

Activity number	**Total time (s)**	**Searching&Picking (s)**	**Assembling (s)**	**Workstation**
1	18.2	3.0	15.2	1
2	17.7	1.8	15.9	1
3	8.6	1.3	7.3	2
4	7.5	0.9	6.6	2
5	6.2	1.1	5.1	2
6	9.7	2.3	7.4	2
7	15.7	2.2	13.5	3
8	13.0	1.5	11.5	3
9	9.0	1.9	7.1	3
10	9.2	2.1	7.1	4
11	9.6	1.1	8.5	4
12	14.3	3.0	11.3	4
13	14.7	2.1	12.6	5
14	15.1	1.5	13.6	5
15	7.1	1.1	6.0	5
16	12.9	2.4	10.5	6
17	16.3	1.4	14.9	6
18	13.3	1.9	11.4	7
19	11.9	3.0	8.9	7
Total	**230.0**	**35.6**	**194.4**	

Table 3. Activities list with the corresponding times (total time, time for searching & picking and time for assembly)

Considering a high cost of the operator ($c_{op} = 50€/h$, which is typical in Northern European countries), we can apply the decision tree introduced in the previous section using as input c_{op} = HIGH, Q = HIGH and t = LOW. The decision support system suggests implementing DI in any case and using the cobot if its cost is low. By considering the cost models at the basis of the decision support system, we can see that these suggested configurations are robust. To do so, the input variables β^i, γ^i , ω, c_d^{DI} and c_d^C are needed. To determine β^i and γ^i , the different activities are analysed and the benefits in time reduction due to the possible implementation of DI and cobot are estimated a priori based on the characteristics of the tasks and using the experience of the authors in similar industrial projects, supported by discussions with suppliers of this equipment/technology.

When DIs are implemented, the reduction in searching and picking time has been estimated as β^{DI} = 10%, and the benefit in assembly time has been assessed as γ^{DI} = 10%. In this case, the use of tablets to support the operators has been selected as a type of DI technology, and thus, c_d^{DI} can be considered low and equal to 0.12 euro/h. The use of cobots has also been considered. In this case, cobots can assist the operators in doing some activities in parallel, such as placing the components or fastening/screwing some parts, while the operators complete other tasks. The benefits of using this equipment are estimated in β^C = 25% and γ^C = 25%. Due to the limited set of activities they can perform, it was decided that the cobot would be installed in few workstations, so the percentage of the assembly stations served by the cobot ω is 25%. Moreover, these activities do not require complex cobots, and thus, cobots with a low c_d^C can be used (3.97 euro/h).

If the two assistive technologies are both implemented, it is assumed that there is not a pure additive benefit, so the reductions when using both technologies have been estimated as β^{DI+C} = 30% and γ^{DI+C} = 30%, with ω equalling 25%. As introduced above, the configurations suggested by the decision support system are robust; this is depicted in the graphs in Figure 14, where the estimated β^i and γ^i (black points) are all on the right part of the threshold limits (indicating that the implementation of the technologies is profitable) and far from them.

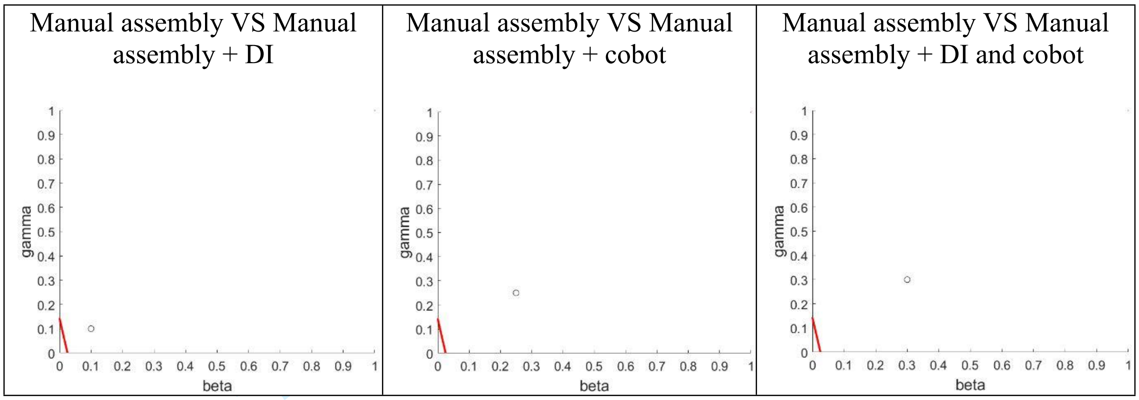

Figure 14. Threshold lines in case study configurations

Therefore, even if the estimations of the benefit parameters β^i and γ^i are not accurate, the decision of investing on assistive technologies is well supported by the considerable saving for the case study as confirmed by the scenario analysis reported in Table 4. In the scenario analysis, the costs per product of each configuration based on the cost models developed in the paper are assessed by varying the benefits from the assistive technologies (considering also situations where Eq. 17 does not hold true) to show that their implementations remain the best solutions. In particular, the cost models suggest the solution with the implementation of the cobot to be often the cheapest. However, these cost models have been developed as the basis of a simple and easily applicable decision support system that does not aim to provide any detailed information about the cheapest assembly system configuration, but instead, aims to suggest which assembly system configurations need to be investigated in detail to find the best one. As the cost of the manual assembly system with the implementation of cobots alone is almost equal to that of the solution characterised by the implementation of DI and cobots, the cheapest solution is expected to be one of these.

Scenario	β^{DI}	γ^{DI}	β^{C}	γ^{C}	β^{DI+C}	γ^{DI+C}	ω	c_d^{DI} [€/h]	c_d^{C} [€/h]	C^{M} [€/pc]	C^{DI} [€/pc]	C^{C} [€/pc]	C^{DI+C} [€/pc]
Basic	10%	10%	25%	25%	30%	30%	25%	0.12	3.97	3.74	3.22	**<u>2.75</u>**	2.76
A	**5%**	**5%**	25%	25%	**27.5%**	**27.5%**	25%	0.12	3.97	3.74	3.22	**<u>2.75</u>**	2.76
B	10%	10%	**12.5%**	**12.5%**	**20%**	**20%**	25%	0.12	3.97	3.74	3.22	3.29	**<u>2.76</u>**
C	**5%**	**5%**	**12.5%**	**12.5%**	**15%**	**15%**	25%	0.12	3.97	3.74	**<u>3.22</u>**	3.29	3.30
D	**5%**	10%	**12.5%**	25%	**15%**	30%	25%	0.12	3.97	3.74	3.22	**<u>2.75</u>**	2.76
E	10%	**5%**	**20%**	**15%**	**35%**	**30%**	25%	0.12	3.97	3.74	3.22	3.29	**<u>2.76</u>**
F	**7.5%**	10%	25%	**20%**	30%	**35%**	25%	0.12	3.97	3.74	3.22	**<u>2.75</u>**	2.76
G	10%	10%	**15%**	**15%**	**35%**	**35%**	25%	0.12	3.97	3.74	3.22	3.29	**<u>2.19</u>**

For Q = 96 pcs/h, t = 230 s, α = 15%, $c_{op} = 50€/h$.

Table 4. Scenarios analysis - bold values are referred to the changed input values, while underlined values are the optimal cost-per-product

To evaluate the accuracy of the decision support model presented, assistive technologies have been introduced in assembling the pump. The prototype of the production line produced at the Logistic 4.0 Laboratory at NTNU was thus modified by including tablets (Microsoft Surface Pro X, 8 GB, cost = 0.12 euro/h) as DI and Universal UR5e (Universal Robots A/S, Denmark, cost = 3.97 euro/h) as cobot. All the workstations were equipped with a tablet due to its limited cost (as also assumed in the decision support system), while only the workstations where repetitive and non-ergonomic tasks were predominant were served by a cobot, for a total of two. The times to perform the different tasks with the implementation of DI, cobots and both DI and cobots are reported in Tables 5, 7 and 9, respectively. The experimental β^i and γ^i values are also reported. In addition, Tables 6, 8 and 10 report the effects of implementing DI, cobots and both DI and cobots from a workstation perspective, showing the tasks allocation and the workstation times. It can be seen from these tables that the workstation times are unbalanced. This could be improved by considering balancing operations, but this is beyond the scope of this model since it is supposed to be used at a tactical level, where the main goal is that to decide the equipment and technologies that need to be installed in the workstations.

To obtain the task time values, three participants (one participant per each assembly system configuration) were selected for the study. As before, the participants were randomly selected from the Ph.D. students of the Department of Mechanical and Industrial Engineering at NTNU, with an age ranging from 26 to 30 years. Although none of them had any previous experience in pump assembling and in the use of DI and/or cobot for assembling operations, they were trained for one hour. The training was conducted on a different pump, and each participant were trained based on the assembly system configuration he/she would have used, i.e. the participant that would have operated in the human assembly configuration with the implementation of DI and cobot was trained in that system configuration. After the base training was completed, the trainees relaxed for 15 min before starting the experiment.

Activity number	**Total time (s)**	**Total time with DI (s)**	**S & P with DI (s)**	**Assembling with DI (s)**	**Workstation**	$\boldsymbol{\beta^{DI}}$ **(%)**	$\boldsymbol{\gamma^{DI}}$ **(%)**
1	18.2	17.3	2.7	14.6	1	10.0	3.9
2	17.7	16.6	1.5	15.1	1	16.7	5.0
3	8.6	8.2	1.1	7.1	2	15.4	2.7
4	7.5	7.3	0.9	6.4	2	4.3	3.0
5	6.2	5.9	0.9	5.0	2	18.2	2.0
6	9.7	9.3	2.2	7.1	2	4.3	4.1
7	15.7	15.3	2.1	13.2	3	4.1	2.2
8	13.0	12.7	1.4	11.3	3	4.8	1.7
9	9.0	8.6	1.8	6.8	3	5.3	4.2
10	9.2	7.8	1.7	6.1	4	17.9	14.1
11	9.6	8.0	0.8	7.2	4	29.8	15.3
12	14.3	10.9	2.4	8.5	4	20.0	24.8
13	14.7	10.7	1.6	9.1	4	23.8	27.8
14	15.1	14.4	1.3	13.1	5	13.3	3.7
15	7.1	6.7	0.9	5.8	5	18.2	3.3
16	12.9	11.6	2.3	9.3	5	4.2	11.4
17	16.3	12.2	1.3	10.9	6	7.1	26.8
18	13.3	11.0	1.8	9.2	6	5.3	19.3
19	11.9	10.3	2.9	7.4	6	3.3	16.9
Total	**230.0**	**204.8**	**31.6**	**173.2**		**11.3**	**10.9**

Table 5. Activities list with the corresponding times (total time, time for searching & picking and time for assembly) in the case of DI implementation. (S & P stands for searching and picking activities)

As-is						DI					
Workstation	**Type**	**Tasks**	**Workstation time (s)**	**S & P (s)**	**Assembling (s)**	**Workstation**	**Type**	**Tasks**	**Workstation time (s)**	**S & P (s)**	**Assembling (s)**
1	Manual	1, 2	35.9	4.8	31.1	1	DI	1, 2	33.9	4.2	29.7
2	Manual	3, 4, 5, 6	32.0	5.6	26.4	2	DI	3, 4, 5, 6	30.7	5.1	25.6
3	Manual	7, 8, 9	37.7	5.6	32.1	3	DI	7, 8, 9	36.6	5.3	31.3
4	Manual	10, 11, 12	33.1	6.2	26.9	4	DI	10, 11, 12, 13	37.4	6.5	30.9
5	Manual	13, 14, 15	36.9	4.7	32.2	5	DI	14, 15, 16	32.7	4.5	28.2
6	Manual	16, 17	29.2	3.8	25.4	6	DI	17, 18, 19	33.5	6.0	27.5
7	Manual	18, 19	25.2	4.9	20.3						

Table 6. Tasks allocations and workstations times in the as-is condition and in the case of DI implementation. (S & P stands for searching and picking activities)

Activity number	Total time (s)	Total time with C (s)	S & P with C (s)	Assembling with C (s)	Workstation	β^C (%)	γ^C (%)
1	18.2	11.2	1.9	9.3	1*	36.7	38.8
2	17.7	11.4	1.2	10.2	1*	33.3	35.8
3	8.6	5.9	1.0	4.9	1*	23.1	32.9
4	7.5	4.9	0.7	4.2	1*	25.5	36.4
5	6.2	4.0	0.9	3.1	1*	18.2	39.2
6	9.7	6.3	1.7	4.6	2*	26.1	37.8
7	15.7	8.3	1.6	6.7	2*	26.9	50.4
8	13.0	6.7	0.9	5.8	2*	38.8	49.6
9	9.0	5.2	1.2	4.0	2*	36.8	43.7
10	9.2	4.9	1.3	3.6	2*	37.2	49.3
11	9.6	5.7	0.8	4.9	2*	29.8	42.4
12	14.3	14.3	3.0	11.3	3	0.0	0.0
13	14.7	14.7	2.1	12.6	3	0.0	0.0
14	15.1	15.1	1.5	13.6	4	0.0	0.0
15	7.1	7.1	1.1	6.0	4	0.0	0.0
16	12.9	12.9	2.4	10.5	4	0.0	0.0
17	16.3	16.3	1.4	14.9	5	0.0	0.0
18	13.3	13.3	1.9	11.4	5	0.0	0.0
19	11.9	11.9	3.0	8.9	6	0.0	0.0
Total	**230.0**	**183.6**	**29.1**	**154.5**		**18.4**	**20.5**

Table 7. Activities list with the corresponding times (total time, time for searching & picking and time for assembly) in the case of cobots implementation. *=workstations where the cobot is implemented. (S & P stands for searching and picking activities)

As is						Cobot					
Workstation	Type	Tasks	Workstation time (s)	S & P (s)	Assembling (s)	Workstation	Type	Tasks	Workstation time (s)	S & P (s)	Assembling (s)
1	Manual	1, 2	35.9	4.8	31.1	1	Cobot	1, 2, 3, 4, 5	37.4	5.7	31.7
2	Manual	3, 4, 5, 6	32.0	5.6	26.4	2	Cobot	6, 7, 8, 9, 10, 11	37.1	7.5	29.6
3	Manual	7, 8, 9	37.7	5.6	32.1	3	Manual	12, 13	29.0	5.1	23.9
4	Manual	10, 11, 12	33.1	6.2	26.9	4	Manual	14, 15, 16	35.1	5.0	30.1
5	Manual	13, 14, 15	36.9	4.7	32.2	5	Manual	17, 18	29.6	3.3	26.3
6	Manual	16, 17	29.2	3.8	25.4	6	Manual	19	11.9	3.0	8.9
7	Manual	18, 19	25.2	4.9	20.3						

Table 8. Tasks allocations and workstations times in the as-is condition and in the case of cobot implementation. (S & P stands for searching and picking activities)

Activity number	Total time (s)	Total time with DI + C (s)	S & P with DI + C (s)	Assembling with DI + C (s)	Workstation	β^{DI+C} (%)	γ^{DI+C} (%)
1	18.2	10.5	1.7	8.8	1*	43.3	42.1
2	17.7	10.7	1.0	9.7	1*	44.4	39.0
3	8.6	5.7	0.9	4.8	1*	30.8	34.2
4	7.5	4.8	0.7	4.1	1*	25.5	37.9
5	6.2	3.9	0.9	3.0	1*	18.2	41.2
6	9.7	6.0	1.6	4.4	2*	30.4	40.5
7	15.7	8.0	1.5	6.5	2*	31.5	51.9
8	13.0	6.6	0.9	5.7	2*	38.8	50.4
9	9.0	4.9	1.1	3.8	2*	42.1	46.5
10	9.2	3.9	1.0	2.9	2*	51.7	59.2
11	9.6	4.5	0.7	3.8	2*	38.6	55.3
12	14.3	10.9	2.4	8.5	3	20.0	24.8
13	14.7	10.7	1.6	9.1	3	23.8	27.8
14	15.1	14.4	1.3	13.1	3	13.3	3.7
15	7.1	6.7	0.9	5.8	4	18.2	3.3
16	12.9	11.6	2.3	9.3	4	4.2	11.4
17	16.3	12.2	1.3	10.9	4	7.1	26.8
18	13.3	11.0	1.8	9.2	5	5.3	19.3
19	11.9	10.3	2.9	7.4	5	3.3	16.9
Total	**230.0**	**157.3**	**26.5**	**130.8**		**25.6**	**32.7**

Table 9. Activities list with the corresponding times (total time, time for searching & picking and time for assembly) in the case of DI and cobots implementation. *=workstations where the cobot is implemented. (S & P stands for searching and picking activities)

As is						DI + Cobot					
Workstation	**Type**	**Tasks**	**Workstation time (s)**	**S & P (s)**	**Assembling (s)**	**Workstation**	**Type**	**Tasks**	**Workstation time (s)**	**S & P (s)**	**Assembling (s)**
1	Manual	1, 2	35.9	4.8	31.1	1	DI + cobot	1, 2, 3, 4, 5	35.6	5.2	30.4
2	Manual	3, 4, 5, 6	32.0	5.6	26.4	2	DI + cobot	6, 7, 8, 9, 10, 11	33.9	6.8	27.1
3	Manual	7, 8, 9	37.7	5.6	32.1	3	DI	12, 13, 14	36.0	5.3	30.7
4	Manual	10, 11, 12	33.1	6.2	26.9	4	DI	15, 16, 17	30.5	4.5	26.0
5	Manual	13, 14, 15	36.9	4.7	32.2	5	DI	18, 19	21.3	4.7	16.6
6	Manual	16, 17	29.2	3.8	25.4						
7	Manual	18, 19	25.2	4.9	20.3						

Table 10. Tasks allocations and workstations times in the as-is condition and in the case of DI and cobot implementation. (S & P stands for searching and picking activities)

The experimental β^i and γ^i values do not differ much from those estimated a priori. The costs per product for manual assembly, manual assembly with the implementation of DIs, manual assembly with the implementation of cobots and manual assembly with the implementation of both DIs and cobots were 3.74 euro, 3.22 euro, 3.46 euro and 2.89 euro, respectively. The solution with the implementation of both DIs and cobots was the best from an economic perspective, differing from that suggested by the cost models (i.e. the solution with the implementation of cobots alone). As mentioned above, this mismatch between the experimental and theoretical solutions was due to the balancing of the workstations, which was neglected in the decision support system. This represents a limitation of the decision support system, and it is also the reason for the observed difference between the costs-per-product values suggested by the decision support system and those found in the case study. However, as mentioned above, the decision support model does not aim to provide either an estimation of the unit cost of the product or the exact technology to implement, but rather, it is only intended to provide suggestions for managers and practitioners about which assembly system configurations need to be investigated in detail to find the best one. For the input conditions of the case study (c_{op} = HIGH, Q = HIGH, t = LOW), the decision support system suggested implementing DIs and/or cobots if the cost is low; in particular, from the analysis of the cost models, the cheapest solution was reported to be most likely either the assembly system with the cobot or the assembly system with the cobot and DI, matching the results of the case study, where the solution with the cobot and DI was found to be the most convenient.

As mentioned at the beginning of the section, to further prove the robustness of the decision support system presented, two more scenarios were considered. In these two scenarios we considered to underestimate and overestimate the total time to assemble the Virtual Average Model with the manual assembly configuration by 50%. Dealing with the underestimation, the total time to assemble the Virtual Average Model $t = t^M$ is now equal to 115.0 s. We are still in the case with c_{op} = HIGH, Q = HIGH and t = LOW, for which the decision support system suggests to implement DI in any case and use the cobot if its cost is low. In particular, considering the same values of the coefficients β and γ that were assumed before (i.e. β^{DI} and γ^{DI} equal to 10%, β^{C} and γ^{C} equal to 25% with ω equalling 25%, β^{DI+C} and γ^{DI+C} equal to 30% with ω equalling 25%), the cost models at the basis of the decision support system report a cost per product of 2.14 euro, 1.61 euro, 1.64 euro and 1.65 euro for manual assembly, manual assembly with the implementation of DIs, manual assembly with the implementation of cobots and manual assembly with the implementation of both DIs and cobots, respectively. Again, these cost models (and hence the decision support system) do not aim to provide the exact technology to be implemented and its cost, but only some suggestions about the assembly system configurations that need to be further investigated. In this case, these are manual assembly system with the implementation of DIs, manual assembly system with the implementation of cobots and manual assembly system with the implementation of both DIs and cobots. Considering the experimental values of β and γ reported in Tables 5, 7 and 9 and the activities times of the Virtual Average Model reported in Table 3 reduced by 50% to consider an underestimation of the total time to assemble the Virtual Average Model with the manual assembly (Table 11), we derived a first modified case study to validate our decision support system, to which, in the following, we will refer as "modified case study A". For each activity, we assumed the same relative values of time spent on searching and picking and of spent on assembly as resulted in the initial case study (see absolute values of these times in Table 3).

Activity number	Total time (s)	Searching&Picking (s)	Assembling (s)	Workstation
1	9.1	1.5	7.6	1
2	8.9	0.9	8.0	1
3	4.3	0.7	3.7	1
4	3.8	0.5	3.3	1
5	3.1	0.6	2.6	1
6	4.9	1.2	3.7	1
7	7.9	1.1	6.8	2
8	6.5	0.8	5.8	2
9	4.5	1.0	3.6	2
10	4.6	1.1	3.6	2
11	4.8	0.6	4.3	2
12	7.2	1.5	5.7	2
13	7.4	1.1	6.3	3
14	7.6	0.8	6.8	3
15	3.6	0.6	3.0	3
16	6.5	1.2	5.3	3
17	8.2	0.7	7.5	3
18	6.7	1.0	5.7	3
19	6.0	1.5	4.5	4
Total	**115**	**17.8**	**97.2**	

Table 11. Activities list with the corresponding times (total time, time for searching & picking and time for assembly) in case of an underestimation of 50% of the total time to assemble the Virtual Average Model

As before, due to the limited cost, a tablet was thought to be implemented in all the workstations, while the cobot was considered to be introduced only in the workstations where repetitive and non-ergonomic tasks were predominant (for a total of one). Tables 12, 13 and 14 report the estimated time to perform the different tasks with the implementation of DI, cobots and both DI and cobots based on experimental values of β^i and γ^i the previously obtained.

Activity number	Total time (s)	Total time with DI (s)	S & P with DI (s)	Assembling with DI (s)	Workstation	β^{DI} (%)	γ^{DI} (%)
1	9.1	8.7	1.4	7.3	1	10.0	3.9
2	8.9	8.3	0.7	7.6	1	16.7	5.0
3	4.3	4.1	0.5	3.6	1	15.4	2.7
4	3.8	3.6	0.4	3.2	1	4.3	3.0
5	3.1	2.9	0.4	2.5	1	18.2	2.0
6	4.9	4.6	1.1	3.5	1	4.3	4.1
7	7.9	7.7	1.1	6.6	2	4.1	2.2
8	6.5	6.4	0.7	5.7	2	4.8	1.7
9	4.5	4.3	0.9	3.4	2	5.3	4.2
10	4.6	3.9	0.9	3.0	2	17.9	14.1
11	4.8	4.0	0.4	3.6	2	29.8	15.3
12	7.2	5.4	1.2	4.2	2	20.0	24.8
13	7.4	5.3	0.8	4.5	2	23.8	27.8
14	7.6	7.2	0.7	6.5	3	13.3	3.7
15	3.6	3.4	0.4	2.9	3	18.2	3.3
16	6.5	5.8	1.1	4.7	3	4.2	11.4
17	8.2	6.1	0.7	5.5	3	7.1	26.8
18	6.7	5.5	0.9	4.6	3	5.3	19.3
19	6.0	5.1	1.5	3.7	3	3.3	16.9
Total	**115.0**	**102.4**	**15.8**	**86.6**		**11.3**	**10.9**

Table 12. Activities list with the estimated corresponding times (total time, time for searching & picking and time for assembly) in the case of DI implementation when the total time to assemble the Virtual Average Model is underestimated by 50%. (S & P stands for searching and picking activities)

Activity number	Total time (s)	Total time with C (s)	S & P with C (s)	Assembling with C (s)	Workstation	β^C (%)	γ^C (%)
1	9.1	5.6	0.9	4.7	1*	36.7	38.8
2	8.9	5.7	0.6	5.1	1*	33.3	35.8
3	4.3	2.9	0.5	2.4	1*	23.1	32.9
4	3.8	2.4	0.3	2.1	1*	25.5	36.4
5	3.1	2.0	0.4	1.6	1*	18.2	39.2
6	4.9	3.2	0.8	2.3	1*	26.1	37.8
7	7.9	4.2	0.8	3.3	1*	26.9	50.4
8	6.5	3.4	0.5	2.9	1*	38.8	49.6
9	4.5	2.6	0.6	2.0	1*	36.8	43.7
10	4.6	2.5	0.7	1.8	1*	37.2	49.3
11	4.8	2.8	0.4	2.4	1*	29.8	42.4
12	7.2	7.2	1.5	5.7	2	0.0	0.0
13	7.4	7.4	1.1	6.3	2	0.0	0.0
14	7.6	7.6	0.8	6.8	2	0.0	0.0
15	3.6	3.6	0.6	3.0	2	0.0	0.0
16	6.5	6.5	1.2	5.3	2	0.0	0.0
17	8.2	8.2	0.7	7.5	3	0.0	0.0
18	6.7	6.7	1.0	5.7	3	0.0	0.0
19	6.0	6.0	1.5	4.5	3	0.0	0.0
Total	**115.0**	**90.0**	**14.8**	**75.2**		**18.4**	**20.5**

Table 13. Activities list with the estimated corresponding times (total time, time for searching & picking and time for assembly) in the case of cobot implementation when the total time to assemble the Virtual Average Model is underestimated by 50%. *=workstations where the cobot is implemented. (S & P stands for searching and picking activities)

Activity number	Total time (s)	Total time with DI + C (s)	S & P with DI + C (s)	Assembling with DI + C (s)	Workstation	β^{DI+C} (%)	γ^{DI+C} (%)
1	9.1	5.3	0.9	4.4	1*	43.3	42.1
2	8.9	5.3	0.5	4.8	1*	44.4	39.0
3	4.3	2.9	0.4	2.4	1*	30.8	34.2
4	3.8	2.4	0.3	2.0	1*	25.5	37.9
5	3.1	1.9	0.4	1.5	1*	18.2	41.2
6	4.9	3.0	0.8	2.2	1*	30.4	40.5
7	7.9	4.0	0.8	3.2	1*	31.5	51.9
8	6.5	3.3	0.5	2.9	1*	38.8	50.4
9	4.5	2.4	0.6	1.9	1*	42.1	46.5
10	4.6	2.0	0.5	1.4	1*	51.7	59.2
11	4.8	2.2	0.3	1.9	1*	38.6	55.3
12	7.2	5.4	1.2	4.2	2	20.0	24.8
13	7.4	5.3	0.8	4.5	2	23.8	27.8
14	7.6	7.2	0.7	6.5	2	13.3	3.7
15	3.6	3.4	0.4	2.9	2	18.2	3.3
16	6.5	5.8	1.1	4.7	2	4.2	11.4
17	8.2	6.1	0.7	5.5	2	7.1	26.8
18	6.7	5.5	0.9	4.6	3	5.3	19.3
19	6.0	5.1	1.5	3.7	3	3.3	16.9
Total	**115.0**	**78.6**	**13.2**	**65.4**		**25.6**	**32.7**

Table 14. Activities list with the estimated corresponding times (total time, time for searching & picking and time for assembly) in the case of both DI and cobot implementation when the total time to assemble the Virtual Average Model is underestimated by 50%. *=workstations where the cobot is implemented. (S & P stands for searching and picking activities)

The costs per product in the case of an underestimation of the total time to assemble the Virtual Average Model of 50% were 2.14 euro, 1.61 euro, 1.64 euro and 1.65 euro for manual assembly, manual assembly with the implementation of DIs, manual assembly with the implementation of cobots and manual assembly with the implementation of both DIs and cobots, respectively. This time the "experimental" costs obtained from the modified case study A match those found with the cost models since there is no effect of balancing.

However, this is not always the case, as if we consider an overestimation of 50% of the total time to assemble the Virtual Average Model. In the following we will refer to this case as to “modified case study B”. In this case, in fact, the costs provided by the cost models differ from those obtained from the modified case study B, where we considered again the experimental values of β and γ reported in Tables 5, 7 and 9 and the activities times of the Virtual Average Model reported in Table 3 increased by 50% (Table 15). The costs models for the manual assembly system, manual assembly system with the implementation of DIs, manual assembly system with the implementation of cobots and manual assembly system with the implementation of both DIs and cobots report a cost per product of 5.35 euro, 4.82 euro, 4.36 euro and 3.84 euro respectively, while the cost from the modified case study B are respectively 7.49 euro, 5.36 euro, 6.01 euro and 4.41 euro. As mentioned earlier, the discrepancies are due to the fact that balancing is not considered in the cost models: the cost models in fact consider a total number of workstations equal to 10, 9, 8 and 7 for the manual assembly system, manual assembly system with the implementation of DIs, manual assembly system with the implementation of cobots and manual assembly system with the implementation of both DIs and cobots, respectively, while from the modified case study B the number of workstations increased to 14, 10, 11, 8, respectively (Tables 15, 16, 17, 18). Nevertheless, the decision support system confirmed also in this case its reliability since it suggested to implement DI in any case and use the cobot if its cost is low (the total time to assemble the Virtual Average Model $t = t^M$ is now equal to 345.0 s, so we are still in the case with c_{op} = HIGH, Q = HIGH and t = LOW), and the implementation of both DI and cobot was found to be the cheapest solution from the analysis of the modified case study B.

Activity number	Total time (s)	Searching&Picking (s)	Assembling (s)	Workstation
1	27.3	4.5	22.8	1
2	26.6	2.7	23.9	2
3	12.9	2.0	11.0	3
4	11.3	1.4	9.9	3
5	9.3	1.7	7.7	3
6	14.6	3.5	11.1	4
7	23.6	3.3	20.3	5
8	19.5	2.3	17.3	6
9	13.5	2.9	10.7	6
10	13.8	3.2	10.7	7
11	14.4	1.7	12.8	7
12	21.5	4.5	17.0	8
13	22.1	3.2	18.9	9
14	22.7	2.3	20.4	10
15	10.7	1.7	9.0	10
16	19.4	3.6	15.8	11
17	24.5	2.1	22.4	12
18	20.0	2.9	17.1	13
19	17.9	4.5	13.4	14
Total	**345.0**	**53.4**	**291.6**	

Table 15. Activities list with the corresponding times (total time, time for searching & picking and time for assembly) in case of an overestimation of 50% of the total time to assemble the Virtual Average Model

Activity number	Total time (s)	Total time with DI (s)	S & P with DI (s)	Assembling with DI (s)	Workstation	β^{DI} (%)	γ^{DI} (%)
1	27.3	26.0	4.1	21.9	1	10.0	3.9
2	26.6	24.9	2.2	22.7	2	16.7	5.0
3	12.9	12.3	1.6	10.7	2	15.4	2.7
4	11.3	10.9	1.3	9.6	3	4.3	3.0
5	9.3	8.8	1.3	7.5	3	18.2	2.0
6	14.6	13.9	3.3	10.6	3	4.3	4.1
7	23.6	23.0	3.2	19.8	4	4.1	2.2
8	19.5	19.1	2.1	17.0	5	4.8	1.7
9	13.5	12.9	2.7	10.2	5	5.3	4.2
10	13.8	11.7	2.6	9.1	6	17.9	14.1
11	14.4	12.0	1.2	10.8	6	29.8	15.3
12	21.5	16.3	3.6	12.7	7	20.0	24.8
13	22.1	16.0	2.4	13.6	7	23.8	27.8
14	22.7	21.6	2.0	19.6	8	13.3	3.7
15	10.7	10.1	1.3	8.7	8	18.2	3.3
16	19.4	17.4	3.4	14.0	9	4.2	11.4
17	24.5	18.3	2.0	16.4	9	7.1	26.8
18	20.0	16.5	2.7	13.8	10	5.3	19.3
19	17.9	15.4	4.4	11.1	10	3.3	16.9
Total	**345.0**	**307.2**	**47.4**	**259.8**		**11.3**	**10.9**

Table 16. Activities list with the estimated corresponding times (total time, time for searching & picking and time for assembly) in the case of DI implementation when the total time to assemble the Virtual Average Model is overestimated by 50%. (S & P stands for searching and picking activities)

Activity number	Total time (s)	Total time with C (s)	S & P with C (s)	Assembling with C (s)	Workstation	β^C (%)	γ^C (%)
1	27.3	16.8	2.8	14.0	1*	36.7	38.8
2	26.6	17.1	1.8	15.3	1*	33.3	35.8
3	12.9	8.8	1.5	7.3	2*	23.1	32.9
4	11.3	7.3	1.0	6.3	2*	25.5	36.4
5	9.3	6.0	1.3	4.7	2*	18.2	39.2
6	14.6	9.5	2.5	6.9	2*	26.1	37.8
7	23.6	12.5	2.4	10.0	3*	26.9	50.4
8	19.5	10.1	1.4	8.7	3*	38.8	49.6
9	13.5	7.8	1.8	6.0	3*	36.8	43.7
10	13.8	13.8	3.2	10.7	4	0.0	0.0
11	14.4	14.4	1.7	12.8	4	0.0	0.0
12	21.5	21.5	4.5	17.0	5	0.0	0.0
13	22.1	22.1	3.2	18.9	6	0.0	0.0
14	22.7	22.7	2.3	20.4	7	0.0	0.0
15	10.7	10.7	1.7	9.0	7	0.0	0.0
16	19.4	19.4	3.6	15.8	8	0.0	0.0
17	24.5	24.5	2.1	22.4	9	0.0	0.0
18	20.0	20.0	2.9	17.1	10	0.0	0.0
19	17.9	17.9	4.5	13.4	11	0.0	0.0
Total	**345.0**	**282.4**	**46.0**	**236.4**		**18.4**	**20.5**

Table 17. Activities list with the estimated corresponding times (total time, time for searching & picking and time for assembly) in the case of cobot implementation when the total time to assemble the Virtual Average Model is overestimated by 50%. *=workstations where the cobot is implemented. (S & P stands for searching and picking activities)

Activity number	Total time (s)	Total time with DI + C (s)	S & P with DI + C (s)	Assembling with DI + C (s)	Workstation	β^{DI+C} (%)	γ^{DI+C} (%)
1	27.3	15.8	2.6	13.2	1*	43.3	42.1
2	26.6	16.0	1.5	14.5	1*	44.4	39.0
3	12.9	8.6	1.3	7.2	2*	30.8	34.2
4	11.3	7.2	1.0	6.1	2*	25.5	37.9
5	9.3	5.8	1.3	4.5	2*	18.2	41.2
6	14.6	9.0	2.4	6.6	2*	30.4	40.5
7	23.6	12.0	2.3	9.7	3*	31.5	51.9
8	19.5	9.9	1.4	8.6	3*	38.8	50.4
9	13.5	7.3	1.7	5.7	3*	42.1	46.5
10	13.8	5.9	1.5	4.3	3*	51.7	59.2
11	14.4	12.0	1.2	10.8	4	29.8	15.3
12	21.5	16.3	3.6	12.7	4	20.0	24.8
13	22.1	16.0	2.4	13.6	5	23.8	27.8
14	22.7	21.6	2.0	19.6	6	13.3	3.7
15	10.7	10.1	1.3	8.7	6	18.2	3.3
16	19.4	17.4	3.4	14.0	7	4.2	11.4
17	24.5	18.3	2.0	16.4	7	7.1	26.8
18	20.0	16.5	2.7	13.8	8	5.3	19.3
19	17.9	15.4	4.4	11.1	8	3.3	16.9
Total	**345.0**	**241.2**	**39.9**	**201.3**			

Table 18. Activities list with the estimated corresponding times (total time, time for searching & picking and time for assembly) in the case of both DI and cobot implementation when the total time to assemble the Virtual Average Model is overestimated by 50%. *=workstations where the cobot is implemented. (S & P stands for searching and picking activities)

In conclusion, the decision support system presented here appears to be a reliable tool to understand whether the introduction of assistive technologies may be beneficial from a cost perspective, even in the case of a mistake of ±50% in the estimation of the total assembly time. However, further analyses need to be carried out to evaluate the validity of the proposed decision support system.

7. Discussions and managerial implications

In this paper, a decision support system aiming to assist managers and practitioners in the decision whether implementing DIs and/or cobots in assembly stations has been developed. To do so, a parametric analysis based on four different cost models (one per each assembly configurations, i.e. manual assembly, manual assembly with the implementation of DIs, manual assembly with the implementation of cobots and manual assembly with the implementation of both DIs and cobots) have been carried out. It is worth mentioning that these costs models have been written for the introduction of DIs and/or cobot, but any other technology could have been considered and therefore it is possible to easily extend the analysis to the use of other technologies not herein considered. To do so, the only input parameters needed are the costs and improvements in assembly and searching & picking operations associated with the introduction of new technology. The decision support system so developed is of immediate use. In fact, once managers and practitioners have the required input (i.e., hourly cost of the human operator, throughput, total operations time and percentage of time engaged in searching and picking activities, which are all generally known in the design phase), the use of the developed decision support system is easy and fast since they have just to choose the leaf of the decision support system corresponding to their case. It is again worth mentioning that decision tree herein proposed does not aim to provide any detailed information about the cheapest assembly system configuration, but only which assembly system configuration need to be investigated in detail to find the best one. This is due to one of the main limitations of the cost models, namely the neglect of the balancing and other information related to the operational level (sequencing, feeding policies and so on). This was evident from the case study: the cheapest solution suggested by the cost models was the assembly system with the implementation of the cobot, which differs from that found experimentally in the case study (i.e. assembly system with the implementation of the cobot and DI). Although the cost models reported the solution with the implementation of both the cobot and DI to be slightly different from that suggested as optimal, this drawback needs to be overcome to develop a complete tool able to provide detailed information about the best solution. Therefore, developing a decision support system able to consider the balancing, sequencing and other information related to the operational level is highly important, and it represents a research topic that the authors are currently investigating. One possible solution to achieve this goal is that of integrating the cost models with simulation tools.

Furthermore, the decision support system has also been proved to be robust towards an error in the estimation of the total time to assemble a product. Usually, during the design phase, it might happen that the total time to assemble the product is overestimated or underestimated. In this work, the authors have tested the decision support system in the case of an overestimation and underestimation of the total time to assemble the product of 50%. The decision support system revealed to be robust against the variation of the total time to assemble the product since the results of the case studies were in line with what reported by the decision support system. This confirms the reliability of the decision support system herein proposed in understanding whether the introduction of assistive technologies may be beneficial from a cost perspective. Further analyses are however needed.

Another limitation of this work is that the decision support system herein presented has been developed considering only one single product (typically the Virtual Average Model), while instead assembly lines are usually designed for multi-products (product families). In this perspective, the benefits provided by DI and/or cobot might change, and this also represents a research topic that the authors are investigating, together with the considerations of stochastic operational times and errors in the cost models. In fact, in situations where the effects of searching and picking errors and/or assembly errors are significant, the introduction of these assistive technologies can significantly improve the quality of the process, leading to error-free systems. This implies a major reduction of costs, seen as potential benefits/additional profits due to the system's higher quality and higher throughput. This must be compared with the extra costs associated with these technologies via a return on investment analysis to determine whether their implementation will be profitable.

8. Conclusions

The implementation of assistive technologies in assembly systems has been investigated in a limited way. The literature review made clear that it is necessary to introduce a decision support system that can support practitioners in the assembly system design at the tactical level, where the introduction of assistive technologies like DIs and cobots can be evaluated from a cost perspective. In fact, several contributions have been developed concerning the technological aspects of the implementation of these technologies, while their effects on the design of assembly system configurations have not yet been investigated. This paper contributes to cover this research gap thanks to the development of a decision tree based on cost models of four different assembly system configurations (i.e. manual assembly, manual assembly with the implementation of DIs, manual assembly with the implementation of cobots and manual assembly with the implementation of both DIs and cobots).

The decision tree, obtained from a parametric analysis based on the mentioned cost models, can guide practitioners in their decisions regarding the circumstances (c_{op}, Q, t and α) under which the human operator can be conveniently assisted. The decision tree herein proposed does not aim to provide any detailed information about the cheapest assembly system configuration, but only which assembly system configuration need to be investigated in detail to find the best one. For the case considered (c_{op} = HIGH, Q = HIGH, t = LOW), the decision support system suggested implementing DIs and/or cobots if the cost of cobot is low, that matches the results find from the case study, where the solution implementing both DI and cobot was found to be the cheapest. Furthermore, the decision support system was also found to be robust against an overestimation and underestimation of the total time to assemble the product of 50%, confirming again its trustworthiness. The development of this decision support system is thus beneficial in a perspective of continuous technological improvements as that we are currently experiencing since it allows a fast and easy understanding of whether the introduction of a new technology is worthy to be investigated in details or not. In fact, the cost models at the base of the decision support system can be used to develop decision support systems also for other technologies, not only for DIs and cobot. In light of this, it is thus clear that this work can serve as a breakthrough in the support to managers and practitioners for the understanding of whether a new technology should be considered for implementation or not.

References

Almannai, B., R. Greenough, and J. Kay. 2008. “A Decision Support Tool Based on QFD and FMEA for the Selection of Manufacturing Automation Technologies.” *Robotics and Computer-Integrated Manufacturing* 24 (4): 501–7. https://doi.org/10.1016/j.rcim.2007.07.002.

Antonelli, Dario, Sergey Astanin, and Giulia Bruno. 2016. “Applicability of Human-Robot Collaboration to Small Batch Production.” In , 24–32. Springer, Cham. https://doi.org/10.1007/978-3-319-45390-3_3.

Baird, K. M., and W. Barfield. 1999. “Evaluating the Effectiveness of Augmented

Reality Displays for a Manual Assembly Task." *Virtual Reality* 4 (4): 250–59. https://doi.org/10.1007/BF01421808.

Battaïa, Olga, Alena Otto, Fabio Sgarbossa, and Erwin Pesch. 2018. "Future Trends in Management and Operation of Assembly Systems: From Customized Assembly Systems to Cyber-Physical Systems." *Omega* 78 (July): 1–4. https://doi.org/10.1016/j.omega.2018.01.010.

Battini, D., M. Faccio, A. Persona, and F. Sgarbossa. 2011. "New Methodological Framework to Improve Productivity and Ergonomics in Assembly System Design." *International Journal of Industrial Ergonomics* 41 (1): 30–42. https://doi.org/10.1016/J.ERGON.2010.12.001.

Battini, Daria, Martina Calzavara, Alessandro Persona, Fabio Sgarbossa, Valentina Visentin, and Ilenia Zennaro. 2018. "Integrating Mocap System and Immersive Reality for Efficient Human-Centred Workstation Design." *IFAC-PapersOnLine* 51 (11): 188–93. https://doi.org/10.1016/J.IFACOL.2018.08.256.

Battini, Daria, Maurizio Faccio, Alessandro Persona, and Fabio Sgarbossa. 2009. "Design of the Optimal Feeding Policy in an Assembly System." *International Journal of Production Economics* 121 (1): 233–54. https://doi.org/10.1016/j.ijpe.2009.05.016.

Bochmann, Lennart, Timo Bänziger, Andreas Kunz, and Konrad Wegener. 2017. "Human-Robot Collaboration in Decentralized Manufacturing Systems: An Approach for Simulation-Based Evaluation of Future Intelligent Production." *Procedia CIRP* 62 (January): 624–29. https://doi.org/10.1016/J.PROCIR.2016.06.021.

Calzavara, Martina, Daria Battini, David Bogataj, Fabio Sgarbossa, and Ilenia Zennaro. 2020. "Ageing Workforce Management in Manufacturing Systems: State of the Art and Future Research Agenda." *International Journal of Production Research* 58 (3): 729–47. https://doi.org/10.1080/00207543.2019.1600759.

Cencen, Argun, Jouke C. Verlinden, and J. M. P. Geraedts. 2018. "Design Methodology to Improve Human-Robot Coproduction in Small- and Medium-Sized Enterprises." *IEEE/ASME Transactions on Mechatronics* 23 (3): 1092–1102. https://doi.org/10.1109/TMECH.2018.2839357.

Cherubini, Andrea, Robin Passama, André Crosnier, Antoine Lasnier, and Philippe Fraisse. 2016. "Collaborative Manufacturing with Physical Human–Robot Interaction." *Robotics and Computer-Integrated Manufacturing* 40 (August): 1–13. https://doi.org/10.1016/J.RCIM.2015.12.007.

Cohen, Yuval, Shraga Shoval, and Maurizio Faccio. 2019. "Strategic View on Cobot Deployment in Assembly 4.0 Systems." *IFAC-PapersOnLine* 52 (13): 1519–24. https://doi.org/10.1016/j.ifacol.2019.11.415.

Djuric, Ana M., R.J. Urbanic, and J.L. Rickli. 2016. "A Framework for Collaborative Robot (CoBot) Integration in Advanced Manufacturing Systems." *SAE International Journal of Materials and Manufacturing* 9 (2): 2016-01–0337. https://doi.org/10.4271/2016-01-0337.

Eskilander, Stephan. 2001. "Design For Automatic Assembly-A Method For Product Design: DFA2." Stockholm: Royal Institute of Technology.

Faccio, Maurizio, Matteo Bottin, and Giulio Rosati. 2019. "Collaborative and Traditional Robotic Assembly: A Comparison Model." *The International Journal of Advanced Manufacturing Technology* 102 (5–8): 1355–72. https://doi.org/10.1007/s00170-018-03247-z.

Fox, Stephen, Olli Aranko, Juhani Heilala, and Päivi Vahala. 2019. "Exoskeletons: Comprehensive, Comparative and Critical Analyses of Their Potential to Improve

Manufacturing Performance." *Journal of Manufacturing Technology Management*. https://doi.org/10.1108/JMTM-01-2019-0023.

Fragapane, Giuseppe, Dmitry Ivanov, Mirco Peron, Fabio Sgarbossa, and Jan Ola Strandhagen. 2020. "Increasing Flexibility and Productivity in Industry 4.0 Production Networks with Autonomous Mobile Robots and Smart Intralogistics." *Annals of Operations Research*, February, 1–19. https://doi.org/10.1007/s10479-020-03526-7.

Frohm, Jörgen. 2008. "Levels of Automation in Production Systems." Gothenburg: Chalmers University of technology. https://research.chalmers.se/en/publication/65769.

Golan, Maya, Yuval Cohen, and Gonen Singer. 2019. "A Framework for Operator – Workstation Interaction in Industry 4.0." *International Journal of Production Research*, July, 1–12. https://doi.org/10.1080/00207543.2019.1639842.

Gonzalez, Victoria, and Pamela Ruiz Castro. 2018. "Evaluation of a Human-Robot Collaboration in an Industrial Workstation." http://hh.diva-portal.org/smash/record.jsf?pid=diva2%3A1220295&dswid=4594.

Grajewski, Damian, Filip Górski, Przemysław Zawadzki, and Adam Hamrol. 2013. "Application of Virtual Reality Techniques in Design of Ergonomic Manufacturing Workplaces." *Procedia Computer Science* 25 (January): 289–301. https://doi.org/10.1016/J.PROCS.2013.11.035.

Gu, Fu, Jianfeng Guo, Philip Hall, and Xinjian Gu. 2019. "An Integrated Architecture for Implementing Extended Producer Responsibility in the Context of Industry 4.0." *International Journal of Production Research* 57 (5): 1458–77. https://doi.org/10.1080/00207543.2018.1489161.

Helmersson, Pontus, and Johanna Hesslund. 2016. "Design and Development of a

Worksta-Tion for Cutting and Kitting Pipes." http://publications.lib.chalmers.se/records/fulltext/255124/255124.pdf.

Hou, Lei, Xiangyu Wang, Leonhard Bernold, and Peter E. D. Love. 2013. "Using Animated Augmented Reality to Cognitively Guide Assembly." *Journal of Computing in Civil Engineering* 27 (5): 439–51. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000184.

Hou, Lei, Xiangyu Wang, and Martijn Truijens. 2015. "Using Augmented Reality to Facilitate Piping Assembly: An Experiment-Based Evaluation." *Journal of Computing in Civil Engineering* 29 (1): 05014007. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000344.

Kara, Sami, Berman Kayis, and Shaun O'Kane. 2002. "The Role of Human Factors in Flexibility Management: A Survey." *Human Factors and Ergonomics in Manufacturing* 12 (1): 75–119. https://doi.org/10.1002/hfm.10004.

Krüger, J., T.K. Lien, and A. Verl. 2009. "Cooperation of Human and Machines in Assembly Lines." *CIRP Annals* 58 (2): 628–46. https://doi.org/10.1016/J.CIRP.2009.09.009.

Kuhlenkötter, Bernd, C Thomas, B Matthias, and B Kuhlenkötter. 2016. "Human-Robot Collaboration-New Applications in Industrial Robotics." https://www.researchgate.net/publication/303809721.

Lee, C.K.M., Yaqiong Lv, K.K.H. Ng, William Ho, and K.L. Choy. 2018. "Design and Application of Internet of Things-Based Warehouse Management System for Smart Logistics." *International Journal of Production Research* 56 (8): 2753–68. https://doi.org/10.1080/00207543.2017.1394592.

Liu, Quan, Zhihao Liu, Wenjun Xu, Quan Tang, Zude Zhou, and Duc Truong Pham. 2019. "Human-Robot Collaboration in Disassembly for Sustainable

Manufacturing." *International Journal of Production Research* 57 (12): 4027–44. https://doi.org/10.1080/00207543.2019.1578906.

Maczka, W. J. 1985. "Planning for Automated Assembly: The Common Denominators." *Assembly Engineering* 28 (2): 16–18. https://jglobal.jst.go.jp/en/detail?JGLOBAL_ID=200902030996130736.

Manzini, Riccardo, Mauro Gamberi, Alessandro Persona, and Alberto Regattieri. 2007. "Design of a Class Based Storage Picker to Product Order Picking System." *International Journal of Advanced Manufacturing Technology* 32 (7–8): 811–21. https://doi.org/10.1007/s00170-005-0377-2.

Ong, S. K., M. L. Yuan, and A. Y. C. Nee. 2008. "Augmented Reality Applications in Manufacturing: A Survey." *International Journal of Production Research* 46 (10): 2707–42. https://doi.org/10.1080/00207540601064773.

Park, Sung Hyuk, Bong Sun You, Raja K. Mishra, and Anil K. Sachdev. 2014. "Effects of Extrusion Parameters on the Microstructure and Mechanical Properties of Mg–Zn–(Mn)–Ce/Gd Alloys." *Materials Science and Engineering: A* 598 (March): 396–406. https://doi.org/10.1016/J.MSEA.2014.01.051.

Pathomaree, N., and S. Charoenseang. 2005. "Augmented Reality for Skill Transfer in Assembly Task." In *ROMAN 2005. IEEE International Workshop on Robot and Human Interactive Communication, 2005.*, 500–504. IEEE. https://doi.org/10.1109/ROMAN.2005.1513829.

Pine, B. Joseph. 1993. *Mass Customization : The New Frontier in Business Competition*. Harvard Business School Press. https://books.google.no/books/about/Mass_Customization.html?id=Seli55Gt-sEC&redir_esc=y.

Romero, David, Peter Bernus, Ovidiu Noran, Johan Stahre, and Åsa Fast-Berglund.