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# A Framework for Cyber-Physical Production System Management and Digital Twin Feedback Monitoring for Fast Failure Recovery

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**ABSTRACT**
With the ongoing Industry 4.0 (I4.0) revolution, plant management and supervision play a key role in the development and (re-)design of industrial plants. In the arising scenarios, the need to coordinate human workers and autonomous systems, sharing the same environment, teaming together, becomes a fundamental requirement. Indeed, even though automation in standard assembly lines has reached high efficiency and reliability, for complex and new applications, a certain amount of failure must be considered for future addressing. This paper presents a framework for the flexible coordination of such a complex and heterogeneous cyber-physical system. A Digital Twin mirrors in real-time the plant system, while a dashboard displays plant status, providing the human operators with fundamental tools for supervision and prompt intervention in case of failure. The framework was developed and tested in an industrially relevant environment, specifically for the assembly of the interior of an aircraft fuselage.

**KEYWORDS**
Cyber-physical production system, digital twin, Industry 4.0, human-robot collaboration, Human-in-the-loop production systems

## 1. Introduction

The installation of industrial robots has grown exponentially in the last years, a trend that is not foreseen to change. Day by day, robots have to face new scenarios and cope with increasingly more complex applications, usually handled manually in the nowadays industry. Increasing complexity requires fault-tolerant systems and easy supervision of the whole process, knowledge of robots and process states, and fast failure detection, notification, and intervention. In the factories of the future, a large deployment of autonomous robotic systems will be used for low-level automated tasks, while human capabilities will be demanded for more supervision and exception or failure management. Recent industrial applications, aiming at building complete autonomous robotic assembly lines, had to give up when realized that for many tasks, a reliable, fully autonomous application is not feasible, at least from an industrial point of view

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(Johnsson and Shukovsky 2019). Furthermore, when the applications are successful, the fully autonomous scenario displays the drawback that eventually needs a complete redesign of the plant and/or production flow.

Cyber-Physical Production Systems (CPPS) for the control and monitor of the industrial plants of the future must hence include the presence of human operators, and easy, robust communication between CPPS and humans is fundamental (Franke et al. 2016). Human-cyber-physical systems are presented and studied in (Zamfirescu et al. 2014; Sun et al. 2020; Zhou et al. 2019), with a focus on production systems in (Rossit et al. 2019). The role of the human is fundamental for I4.0 applications to go beyond current automated assembly lines, especially since CPPS with human intervention might be integrated into the standard plant without any disruption of the production process.

Moreover, when humans and robots collaborate, their workspaces are partially overlapped, and safety issues arise. In such cases, it is possible to integrate robotic manipulators into an existing process, via a CPS composed of robots, sensors, and software, as presented in (Nikolakis et al. 2019b). A complete review on safety issues, regulations, and methods can be found in (Robla-Gómez et al. 2017).

In (Chen et al. 2011), a study on human supervision issues of multiple robot teams is presented. This study shows that one of the most critical factors for achieving effective supervisory control of multiple agents is maintaining adequate situation awareness of the overall team as well as individual components. Hence, a user interface design review suggests as guidelines to have highly visible automation behavior and quick and easy information extraction.

As highlighted in (Cruz Salazar et al. 2019), a further step-change for the CPPS consists of the integration of Multi-Agents Robotics Systems (MARS) and Industrial Internet of Things (IIoT) (Alexakos and Kalogeras 2015; Grieco et al. 2014). In such a case, having many different robotic agents and humans sharing the same environment and cooperating requires developing a proper framework for the cooperation, supervision, and process monitoring (Khoshnevis and Bekey 1998; Asama 1994; Román-Ibáñez et al. 2018; Beregi et al. 2019). On the one hand, centralized methods are the most common, and they make a decision through all the information about the systems, being the drawback that fast communication methods and massive data elaboration are needed. On the other hand, decentralization allows each agent to process its information locally but lacks a complete vision of the whole environment (Furno et al. 2015; Son 2011).

Digital Twin-driven manufacturing cyber-physical production (Leng et al. 2019) has been recently studied as a tool to improve various aspects of manufacturing (Ciano et al. 2020; Damjanovic-Behrendt and Behrendt 2019). A Digital Twin (DT) is a virtual model of the system's building blocks, such as workers, products, and assets, which synchronizes according to its physical counterpart to represent relevant factors of its status (Lu et al. 2020). It extends the concept of simulation by connecting and synchronizing the virtual and physical worlds in real-time to focus on what is currently happening in the real system. The DT model comprises two systems, a physical system, and the virtual system which abstracts all the relevant information about this physical system (Fig. 1). Both systems are interconnected, enabling a flow of data and information between them (Grieves and Vickers 2017; Grieves 2015).

A DT can be used to support a system's life-cycle throughout its different phases (design, manufacturing, operations, and disposal), enabling its status monitoring, visualization, and diagnosis, and also to provide analysis and prediction functions to study the long-term behavior of the system (for instance, performance and fault prognosis),

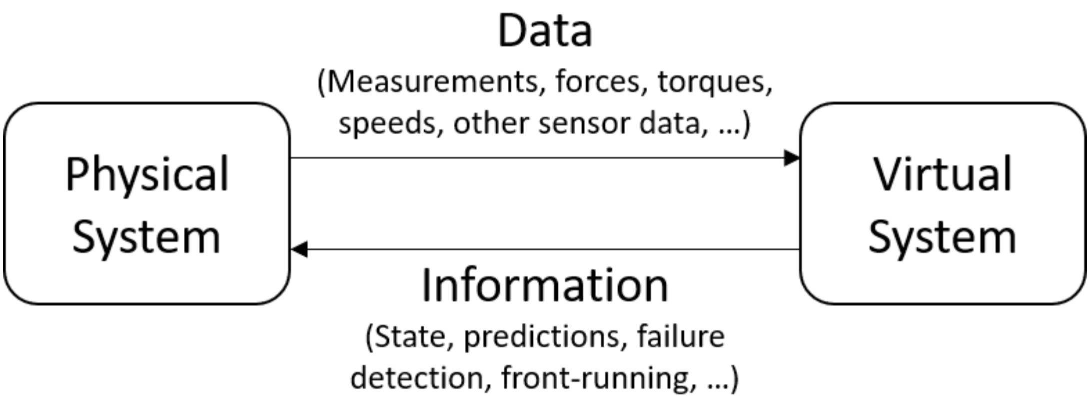


**Figure 1.** The DT model (Based on (Grieves 2015)).

improve its maintenance, and optimize its processes, among others. These features are important to support decision-making (Lu et al. 2020; Negri et al. 2017). Multiple DT tools have been developed to support different activities throughout the product life-cycle, such as product design, studying model reliability, analyze material deformation, decision-making, forecasting maintenance, predict performances (Negri et al. 2017; Schleich et al. 2017), and to enable the optimisation of the planning and commissioning of human-based production processes using simulation-based approaches (Nikolakis et al. 2019a). In particular, for the manufacturing phase, a CPPS can benefit from a DT, as it can reflect the physical system's state by getting information in real-time, monitor the manufacturing tasks, and detect failures. In (Ding et al. 2019) the concept of Digital Twin Cyber-Physical Production System (DT-CPPS) is formalized, but the human presence is not considered on the shop floor. In (Wang et al. 2020) a dashboard is proposed for real-time monitoring a cutting process, displaying information useful for decision making, allowing remote monitoring of the process. The study is limited to a single machine and does not propose a solution for process interruption or failure management. Finally in (Malik and Bilberg 2018) a framework to support the design, build, and control of human-machine cooperation workstation is presented, involving the simulation of a human operator for task allocation, workstation layout, and ergonomic analysis, but does not focus on the real-time connectivity to the physical system.

A promising field of integration of DT and CPPS is the human-robot collaborative assembly. Indeed, many assembly operations cannot be solved by fully autonomous systems due to tolerance chains as well as sensing variability. A recent work (Wang et al. 2019) classifies the human-robot relationship in different classes: coexistence, interaction, cooperation, and collaboration, and it highlights how the transition between different levels of interaction is fundamental to have an efficient and robust production system. Therefore, the DT is a promising technology to make the human operator aware of the system state and to speed up the transition between the different human-robot levels of interaction during production, according to the operation needs and task properties.

Within this broad field of research and application, the architecture's flexibility becomes fundamental to deploy complex applications. In (Ottogalli et al. 2019), the authors present a flexible framework that focuses on modeling Industry 4.0 processes for virtual simulators, and the methodology described proposes a solid groundwork upon which to allow faster development of new simulators, adaptation to different simulation scenarios, and, hence, the ability to cope with fast-changing industrial processes and satisfy the need for cost-effective solutions for testing a process before its actual implementation. On the one hand, such a methodology can speed up integrating the human in the control loop of any multi-agent setup. On the other hand, this work does not deal with the actual connection between the Virtual Reality (VR)/Augmented Reality (AR) framework and the agents acting in a real environment.

Starting from this flexible framework, this work aims at extending the methodology to the real supervision and coordination of setup involving many agents, both robotic systems and human operators teaming together for efficient and comfortable production, focusing on a framework where the system allows a fast and reliable reconfiguration according to the best level of relationship between human and robots. Such a system is fundamental for rapid human intervention in case of robot failure. Indeed, increasing the complexity of the tasks, a failure must be foreseen and considered. What matters is the fast response and resolution of the failure to avoid prolonged production interruption. The main contribution is to present a framework for plant process management involving heterogeneous agents (robots and humans). This framework considers the execution of complex tasks and the efficient management of failures and exceptions. In this context, the autonomous robotized processes are flanked by the human capabilities and potentialities, through continuous feedback of the plant and process states. The core of the work, hence, is to present a method, with the necessary components, for the integration and supervision of a semi-automated industrial process. A use case that implements this framework on the aeronautics domain is presented. In this scenario, the framework's implementation allows a single human operator to completely assemble the interiors (sidewall panels, hat-racks, and cargo panels) of an aircraft with the aid of real-time monitoring of the ongoing processes through the DT. A comparison of the production times and human labor times between the manual production system and the proposed CPPS approach is presented.

## 2. Framework Description

The framework that integrates and coordinates agents in the environment and their interaction, as well as the DT, is presented in this section. The whole architecture, as shown in Fig.2, is composed of three main parts: (A) the physical system components, which are all the agents present in the real industrial plant, (B) the virtual plant, which comprises a DT and a dashboard to display the status of the plant, and (C) the mainframe, which is a central node in charge of tasks and data flow management.

### 2.1. *Physical System*

The physical system comprises the real components of the production system, in particular, the agents. An agent, in this work, can be an autonomous system (such as a robotic arm, AGV, UAV) or a human operator, which operates in the real environment.

#### *2.1.1. Autonomous Systems*

Within the framework's hierarchical architecture, an autonomous system is defined as a singular entity, endowed with the necessary tools and sensors (e.g., robot, cameras) to perform specific functions. Agents receive high-level commands, hereafter defined as tasks, from the mainframe. To ensure modularity in the whole framework and improve the overall reliability, each agent manages its own devices and the tasks are locally divided into sub-tasks to provide simple commands to the agents' devices. Each agent produces constant rate feedback for the mainframe with the information needed only such as the task state (e.g., waiting, ongoing, end), system state (robot joints values, position, among others), and possible errors.

#### *2.1.2. Human Operator*

A particular class of autonomous agents is represented by the human operators. The human operator is able, through different devices, to monitor in real-time the whole plant and process states. The DT gives feedback of the plant state, *i.e.* where are the agents and what are they doing, while through a dashboard it is possible to monitor the process state. When an error is detected, the operator is notified by the DT and the Dashboard about the reason and location of the issue, and can promptly intervene.

### 2.2. *Virtual Plant*

The virtual plant is comprised of two modules: (1) A DT, which is a 3D virtual environment linked to the real system, that allows visualizing the industrial plant and its agents in real-time, and (2) A dashboard application to have a clear and rapid overview of the plant state, as ongoing processes and automated devices states.

#### *2.2.1. Digital Twin*

This module comprises the virtual system of the DT model (Grieves and Vickers 2017) and features a virtual environment with high-fidelity 3D models of the physical system, comprising all the plant components, automated devices, and human operators. It is connected to the physical system through the mainframe and receives data related to the agents' status and positions, and data related to the ongoing tasks. Furthermore, it acts as a server to send the data to the dashboard.

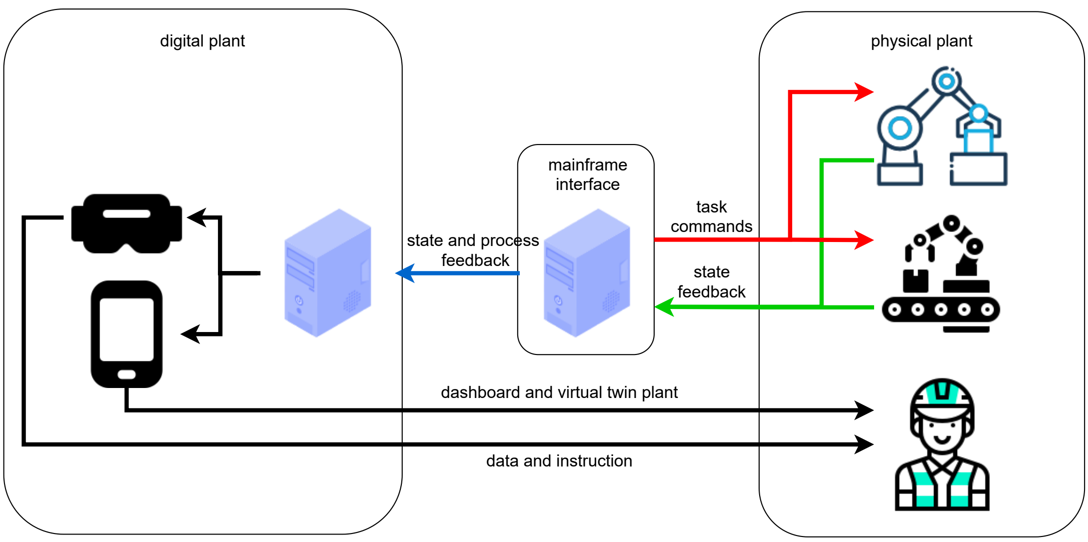


**Figure 2.** Physical systems interconnection

#### 2.2.2. *Dashboard*

It is a client application that shows the plant status. It shows a brief description of the ongoing tasks and their status in real-time and how many components of each type have been assembled. It also shows the status of the autonomous agents (i.e., idle, running, error). As a client application, it can be executed in different devices connected to the network, such as PCs, smartphones, or AR devices.

### 2.3. *Mainframe*

The mainframe is the central control unit of the framework, connected to every agent and the system's virtual counterpart. It is the interface between the physical and the virtual plant, collects data, and manages both the real and virtual components information. It is composed of two modules, for tasks and data management, respectively.

In the *Task Manager* all the tasks are defined in configuration files with all the necessary information: name of the task, agents required, resources needed, constraints, nominal execution times. It creates offline an optimal schedule of the tasks, taking into account the information defined in the configuration files, and performs online re-scheduling according to feedback data and exceptions. For the optimization and rescheduling was used the Google tool provided by OR-Tool (Perron and Furnon) It also communicates to the DT when an error is detected to request human intervention.

The *Data manager* collects feedback from the plant and communicates relevant information to the interested modules. It is the link with the DT to share data regarding the positions and joint states of the autonomous agents, keeps track of the current state of the process for the dashboard update and can collect other kinds of data (e.g lidar, force/torque, images, etc.), useful for further elaboration, as predictive maintenance.

## 3. Case Study: ACCLAIM Project

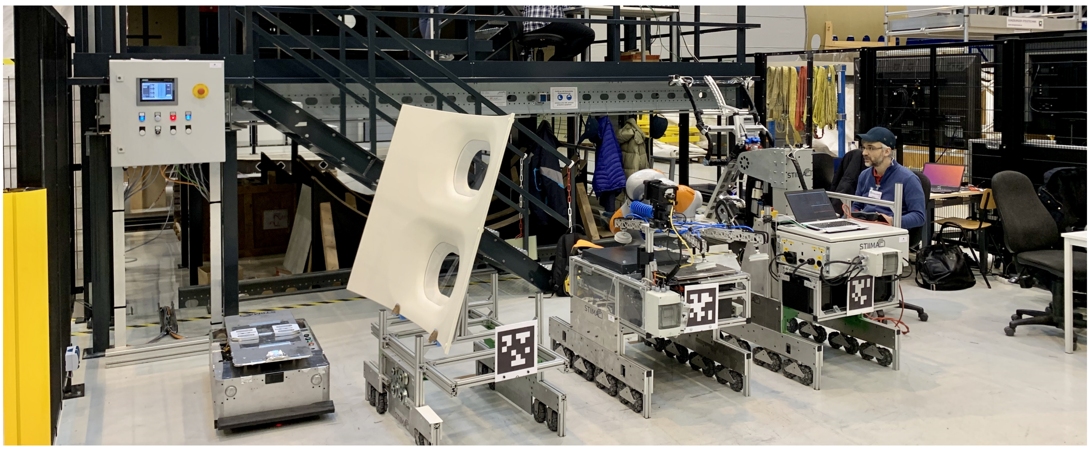

**Figure 3.** The agents in the logistic area. From left to right Heavy AGV, Sidewall panel carrier, Lightweight cobot module, High payload cobot

The framework presented above has been tested and used in EURECA (EURECA 2017) and SIMFAL (SIMFAL 2017) projects, part of the ACCLAIM (ACCLAIM 2017) H2020 Clean Sky 2 project, for the assembly of aircraft interiors.

### 3.1. ***Physical System***

The software architecture design takes advantage of the ROS framework (Quigley et al. 2009) for its capabilities, modularity, reconfigurability, and compelling libraries for the system purpose.

A multi-master approach (Tiderko et al. 2016) is adopted to enable each autonomous agent to manage its own devices locally while communicates and synchronizes only the needed information with the mainframe. Furthermore, this way, assures modularity in the whole framework and improves the overall reliability. Each agent is a ROS action server for the mainframe, this allows reliable communication and ongoing monitoring of the requests.

Four autonomous agents plus a human operator have been deployed and are shown in the real scenario in fig 3.

#### *3.1.1. Lightweight robot module*

A KUKA iiwa 14 is mounted on a passive wheeled cart equipped with a vacuum system for grasping, an RGBD camera for objects pose identification and assembly checks, computers for data elaboration and communication, batteries for the power supply. Since it is designed to perform two different assembly tasks (sidewall and cargo panels assembly), it can handle two different task requests and subsequently manage the devices required.

#### *3.1.2. Empowering robot module*

A high payload, 4 degrees of freedom, collaborative robot specifically designed for hat-rack installation is mounted on a passive cart. The robot arm, shown in fig. 4, has been internally designed to handle heavy (40 kg) objects, to be compliant with the limiting requirements. The system is also endowed with an RGB camera, mounted on the shoulder, for the hat-rack position identification during the grasping, and with a force-torque sensor on the gripper, for the autonomous assembly.

#### *3.1.3. Heavy AGV*

An omnidirectional AGV is used to move the robotic and objects carrier carts to the respective locations, equipped with a docking system to attach and release the carts. The AGV is also provided with two laser scanners for mapping, localization, and safe navigation, an RGB camera for carts tag recognition, and an onboard computation device. The tasks that the AGV has to perform include moving the robotized carts to the respective assembly positions, moving the objects carriers carts to the corresponding positions, or the loading positions. During the tasks, the robot can plan a collision-free path in a dynamic environment, and time-wise optimize the path using the ROS navigation framework (Eitan Marder-Eppstein 2020).

#### *3.1.4. Lightweight AGV*

For carrying the cargo panels a lightweight AGV was built on purpose from scratch. The need to have a second AGV comes from the fact that in the cargo area there is no room for maneuver, hence it is impossible for the heavy AGV to carry more than one agent. Despite many lightweight AGVs exists on the market, the choice of making one from scratch was made because, due to the huge dimensions of the panels and the

**Figure 4.** The heavy payload collaborative robot module while assembling an hat-rack

strict requirements imposed by the environment, was easier and cheaper create a new platform than adapting an existing one.

#### *3.1.5. Human operator*

The human operator monitors and checks the overall phases from the dashboard and the digital twin. In case of unhandled exceptions or errors, the operator can trigger recovery procedures directly at the dashboard. Furthermore, the operator can physically go into the assembly zone and operate the robot manually while reading all the needed information, using devices such as the Hololens or a tablet.

### 3.2. *Virtual plant*

The virtual plant's design and development were done according to the framework module described in Section 2.2. In this case, the virtual plant was comprised of a PC where the DT application was running. To this application, which is also a server for the client dashboards, three devices were connected via C# WebSockets (WS): (1) a local client, (2) a smartphone, and (3) a Microsoft Hololens device. The Fig. 5 shows a scheme of the proposed virtual plant.

#### *3.2.1. Digital Twin*

A DT allows to model a system at the different lifecycle phases, with enough granularity to answer the design questions Boschert and Rosen (2016). In this case study, only the autonomous systems (lightweight robot module, empowering robot module, heavy AGV, lightweight AGV), the fuselage, and the assembly parts were modeled. This definition comprises the 3D models of all these elements and the motion data obtained from the physical system. Although the case study involved a human operator, it was not required to model it for the study, however, it is easy to model the human

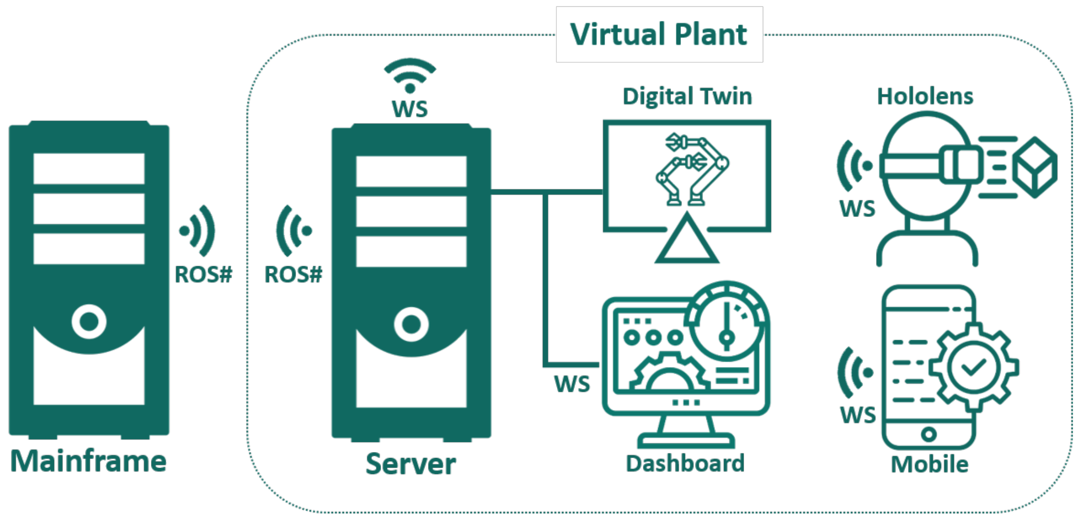


**Figure 5.** Virtual plant scheme for the ACCLAIM project.

operator motion by using a motion capture system and sending this data to the DT.

The 3D environment of the DT was developed as a Unity3D application, comprised by:

a. *Fuselage section:* a section of an A320 aircraft fuselage, with the elevator for the mobile vehicles and a pair of stairs for the human workers (Fig. 6).
b. *Assembly Parts:* the available assembly parts were 1 hat-rack, 1 sidewall panel, and 2 linings (Fig 7).
c. *Carts:* 1 lightweight cart, 1 empowering cart, 1 hat-rack cart, 1 sidewall panel cart, and 1 linings cart.
d. *Automated Devices:* the devices in the simulation were 1 KUKA Iiwa 14 robot arm for the sidewall panel and linings assembly, 1 empowering arm for the hat-rack assembly, 1 AGV for transporting the carts with the robots and the sidewall panel, and 1 lightweight AGV (fixed to the linings cart) for moving the linings (Fig 7).

To connect to the physical system, the ROS# API for Unity3D was used. The mainframe communicates via the ROS rosbridge package ( Jonathan Mace 2020) with the DT via JSON API to be compliant to (Ottogalli et al. 2019). The architecture used for the communication with the Mainframe was publisher/subscriber, in which the DT application subscribed to the topics related to the odometry of the mobile vehicles, joint states of the robots, and standard messages to capture the current state of the process, i.e., the ongoing tasks, the parts already assembled, and the state of the automated devices (idle, running, or error). To develop the server module to allow connections from the Dashboard clients, the WebSocket C# library was used. The server sends the status data of the assembly process to the connected clients every second in JSON format.

### *3.2.2. Dashboard*

For this use case, two different clients were developed: (1) A web client for PCs, tablets, and smartphones, and (2) A hololens client. Fig. 8 shows the two versions of the client dashboard.

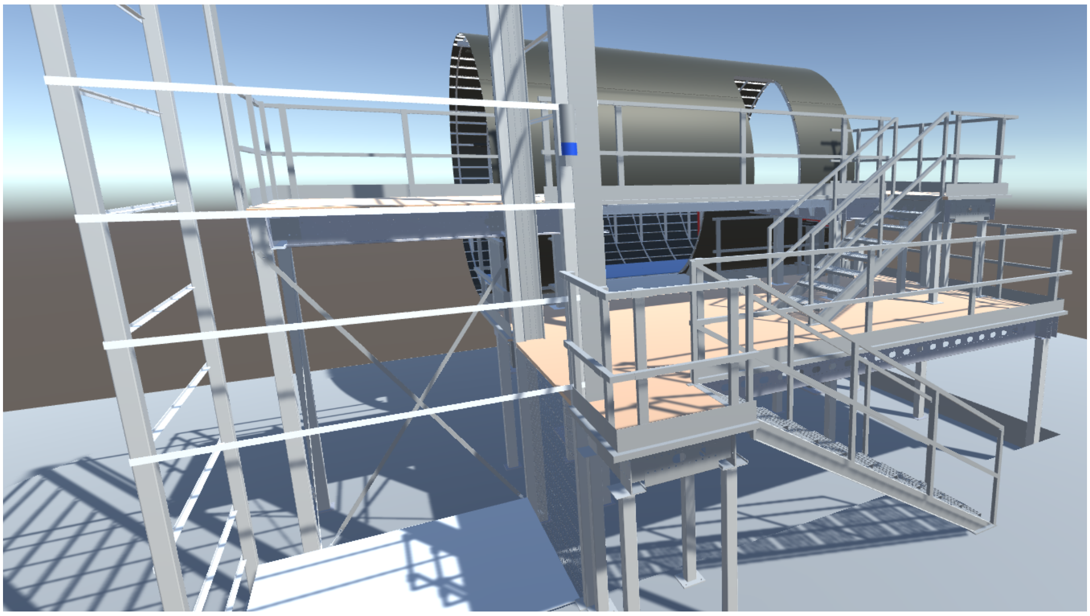

**Figure 6.** Fuselage model for the DT environment.

The web client dashboard was developed using React (Facebook 2020), a JavaScript framework for building user interfaces. On the left, it shows the data corresponding to the elapsed time since the process started, the ongoing task, and the timeline with all the tasks that have been completed. On the right, the count of the different parts that have been assembled and the devices' status is displayed. The Hololens client is an AR application, developed using Unity3D with the Mixed Reality Toolkit (Microsoft 2020). The purpose of this client was to guide the worker during the hat-rack assembly. As shown in Fig. 8, the AR application has two displays. The left display shows visual guides and videos to the worker, showing each step of the hat-rack assembly. The right display shows the assembly process status, similar to the web client.

## 4. Performance Analysis

To compare the manual production with the proposed approach, total assembly times and labor assembly time are considered. This decision relies on the fact that both the Overall Equipment Effectiveness and the costs, and the Return of Investment are confidential and sensitive data from the use case provider.

The analysis focuses on two main comparisons: (i) the comparison of the execution times; (ii) the comparison of the human labor time. It has to be noted that the assembly of every component may require a different number of operators working concurrently for a different time on the task.

For each type of component $c$, denote $s_c$ as the success rate achieved during the experiments for the assembly of $n_c$ different items of the same type, that can be evaluated as

$$s_c = \frac{n_c^s}{n_c} \tag{1}$$

**Figure 7.** Assembly parts and automated systems. Top row: Hatrack, sidewall panel and lining. Bottom row: robot arm, AGV, and empowering arm.

where $n_c^s$ is the number of successfully (i.e. without any human intervention) assembled components of the same type and $n_c$ the total number of components per type, while for the AGV tasks, the $n_c^s$ is the number of successfully agents driven to goal positions with respect to the total $n_c$ requests.

In case of errors, human intervention may take a different amount of time according to the error and the type of component. Considering the component $c$, the total intervention time to solve all the errors for the set of all the items of type $c$ can be denote as $T_{h,c}$, that can be computed as

$$T_{h,c} = \sum_{i}^{n_c^f} t_{h,c}^i \tag{2}$$

where $t_{h,c}^i$ is the time needed by the human for the $i$-th intervention, and $n_c^f = n_c - n_c^s$ is the number of failures. Similarly, denote $T_{a,c}$ as the autonomous execution time:

$$T_{a,c} = \sum_{i}^{n_c} t_{a,c}^i = n_c\, t_{a,c} \tag{3}$$

where $t_{a,c}^i$ is the time needed for each component autonomous assembly, that is almost constant over all the different tasks repetitions.

In order to evaluate the time increment due to the human intervention, denote $\Delta\, t_{h,c}^{\%}$ as the mean percentage time lost for the human intervention, that can be computed as

$$\Delta\, t_{h,c}^{\%} = \frac{1}{n_c^f} \sum_{i}^{n_c^f} \frac{t_{h,c}^i}{t_{a,c}^i}. \tag{4}$$

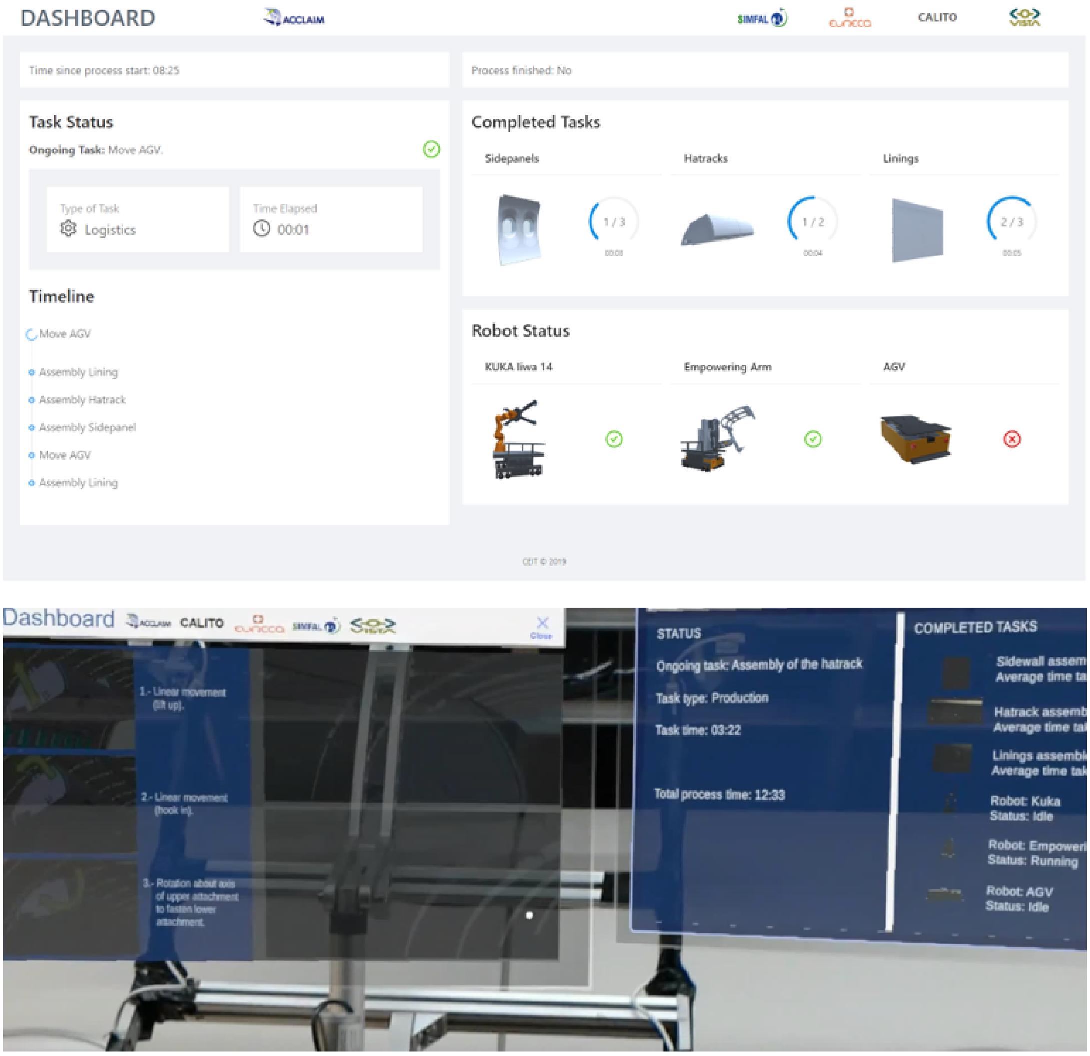


**Figure 8.** Dashboard. Top: Web client. Bottom: Hololens AR client.

and considering the assembly of all the components, the percentage of the human intervention over the assemble time of all the components of type $c$ can be easily computed as:

$$T^{\%}_{h,c} \quad = \quad = (1 - s_c)\, \Delta\, t^{\%}_{h,c} = T_{h,c}/T_{a,c} \tag{5}$$

As a remark, despite the $\Delta\, t^{\%}_{h,c}$ for a single component may be high, the total time asked over a complete assembly of all the components may results low if the success rate is high. Finally, the total assembly time for one component of type $c$ results

$$T_c = T_{a,c} + T_{h,c} = \left(1 + (1 - s_c)\, \Delta^{\%}_{h,c}\right)\, T_{a,c} \tag{6}$$

and the total assembly time results

$$T_{assembly} = \sum_c T_c \tag{7}$$

**Figure 9.** The robot moving a large panel (1x0.85 [m]) in the narrow space of the cargo area (1.2 [m] in height)

Once given the total times, the mean times for each component can be estimated. Therefore, let denote $\tau_{h,c}$, $\tau_{a,c}$, and $\tau_c$ as the the total human labour time, the execution clock-time of the agent and the total execution time per component respectively. Specifically, for standard manual tasks, $\tau_{h,c}$ corresponds to the sum of the time taken by each operator in the assembly of the components $c$, while in the proposed approach, following (4), $\tau_{h,c}$ can be computed as

$$\tau_{h,c} = (1 - s_c)\Delta^{\%}_{a,c}\,\tau_{a,c}, \tag{8}$$

and, using (3), it results

$$\tau_{a,c} = T_c/n_c, \tag{9}$$

and, finally,

$$\tau_c = \tau_{a,c} + \tau_{h,c} \tag{10}$$

## 5. Results

Four application scenarios were used to evaluate automation reliability and human intervention influence to complete the tasks efficiently: the assembly of a sidewall panel, a hat-rack, two complementary cargo panels, and the docking and carrying of the carts by the AGV. The assembly of aircraft components has very strict tolerances; hence, the whole system must be precise and reliable.

As an illustrative example, the sidewall panel assembly task is explained. The task manager commands the AGV to carry the lightweight cart and the panel carrier to

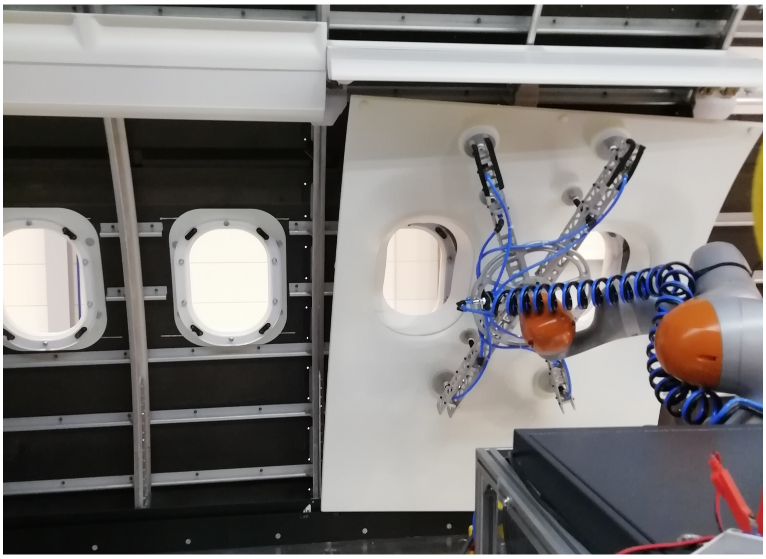

**Figure 10.** The typical misalignment due to a failed panel insertion

the assembly positions, introducing two small positioning errors due to the AGV dock mechanism and localization-related inaccuracies.

Afterward, the task manager sends the assemble sidewall panel request, then monitors the process. Errors introduced by the AGV may be partially corrected by the vision system that identifies the panel and assembly positions in accordance with its own resolution and employed algorithm. However, depending on the chosen technology, this procedure suffers from environmental conditions changes and object characteristics. The grasping of the object itself may introduce errors due to misalignment and structure compliance if bulky objects are considered, as in this case, a small punctual error is propagated and augmented at the edges. Algorithms were deployed to detect failures, particularly for the final assembly check, which is the most critical phase. In the event of a failure, the mainframe is notified and then communicates the error to the virtual plant server, updating DT and the dashboard. In this way, the human operator is notified of the error, which kind of error, and where is located in the plant.

Figure 10 represents a typical failure in the assembly phase of a sidewall panel. In this case, it is easy for the vision system to detect the failure by checking the parallelism of the panel borders and the external environment, but it is extremely complicated for the robotic system to recover. However, just a few seconds of human intervention is sufficient to recover from this situation and continue with the assembly process.

Because (1) the tasks are very complex (large assembly parts, narrow spaces, bulky onboard devices [Fig 9]), (2) the tolerances are very strict ($5 \div 10$ mm over components wider than 1 m), and (3) the system's characteristics (e.g., brightness, roughness, multiple contact points between complex shapes) are challenging to model, it is fundamental to consider certain situations in which the process fails. In almost all these situations, a single human operator with minimum effort and very low response time represent the best solution to manage the process stops rapidly. The problem addressed in (2), 5:10 mm tolerances for assembly, is not challenging in general and with the available technologies can be managed, typically. Despite this, in this application the components to be handled are very huge: a small error when picking an object can become huge at its extremity. As an example, consider an error of 1 degree rotation in picking an object, this becomes 17mm at 1 meter distance from the picking position.

This is out of the tolerances and the assembly is not feasible in such a situation

### 5.1. *Analysis Outcome*

Table 1 reports the success percentage for each type of component, according to (1). It can be noted that the success rate is quite high. Indeed the human intervention is needed in about 1 out of 10 tasks. Table 2 reports the human intervention times per each component-time, expressed as percentage of the execution time of the agent $T_{a,c}$, as in (4) and (5). It can be noted that the overall human intervention time is minimal, despite when he/she is requested to assist the robots, the needed time can be considerably high. Table 3 reports the times for each component. However, the numbers are normalized over the assembly time of a single sidewall. Indeed, the actual time cannot be communicated due to the non-disclosure agreement.

To have a realistic understanding of these data, consider the scenario where 40 sidewall panels, 20 hat-racks, and 50 cargo panels have to be assembled. The time analysis leads to:

- The assembly time $T_{assembly}$ is completed in 172 units by the human operators, while the human-robot collaboration approach takes 351 unit time, in the case all the operations are done in sequence.
- The total man labor time is about 272 units for the manual assembly, while the human-robot collaboration approach takes 26 units.

The total time indicates the time required to completely assemble the interiors of an aircraft. Since the occupancy of the human is quite limited (26 units over 351), it can be assumed that the agents can work in parallel. Indeed, parallelizing tasks will increase the necessary human intervention, due to an increase of failure events, increasing then the human occupancy. Despite this, the human occupancy is limited, allowing the human to supervise more autonomous systems working in parallel. Due to the mobility issue, only one agent at a time can work in the cargo area, while two agents may work in parallel in the cabin area. This would lower the time needed by the human-robot collaboration approach time to 157 units (that is the time needed by one agent in the cargo area), which is comparable with the actual production time.

Finally, in the analysis, the logistics times are not considered since data were not available. Despite this, one consideration can be done: the logistics take a long time in current industrial plants since the components are large and more operators are needed to handle them and carry them inside the fuselage. With the proposed approach, instead, the parallel execution of logistics tasks is allowed without increasing the total time.

## 6. Discussion and future developments

In this paper, a framework for a production system based on multi-agent management and coordination and monitored by a digital twin is presented. Such a framework represents an implementation for flexible and modular semi-autonomous industrial assembly process management. Different agents are connected and supervised, both industrial products (KUKA Iiwa, H-STAR AGV) and designed on purpose (heavy collaborative robot, lightweight AGV), each one to accomplish specific tasks. The communication is transparent with respect to the agents' nature and purpose, making the integration of other components easy. Results show the power of including a DT in the frame-

**Table 1.** Success rates $s$ of the various autonomous tasks

| | sidewall | hat-rack | cargo | navigation |
|---|---|---|---|---|
| $s_c$, computed as in (1) | 90% | 85% | 75% | 95% |

**Table 2.** Percentage time increment of the assembly time due, to the human intervention, when an error occurs, averaged among the various error types

| | sidewall | hat-rack | cargo | navigation |
|---|---|---|---|---|
| $\Delta t^{\%}_{h,c}$ as in (4) | 25% | 45% | 50% | 25% |
| $T^{\%}_{h,c}$ as in (5) | 2.5% | 6.75% | 12.5% | 1.25% |

**Table 3.** Assembly times. The manual assembly time of a sidewall panel is used as unitary value. The execution time $\tau_c$ and the The man labour time $\tau_{h,c}$ are given for the manual task, while the result from (10) and from (4)

.

| | sidewall | | hat-rack | | cargo | |
|---|---|---|---|---|---|---|
| | Exec. Time $t_c$ [u] | Man Labour Time $t_{h,c}$ [u] | Exec. Time $t_c$ [u] | Man Labour Time $t_{h,c}$ [u] | Exec. Time $t$ [u] | Man Labour Time $t_{h,c}$ [u] |
| Manual | 1 | 1 | 3.1 | 8.091 | 1.4 | 1.4 |
| Aut. | 2.305 | 0.0057 | 4.163 | 0.263 | 3.139 | 0.03875 |

work as feedback for fast plant supervision. In this way, a single human operator, supervising many different robots, can assemble an entire aircraft interiors, rapidly recovering the process from known failures. Despite an increase in time production, it is shown that the man-hours required dramatically decrease. The presented approach core contribution is that an industrial plant can be (re-)designed and improved, with high benefits in terms of human labor time, hence the overall quality of the working environment can be improved. The human operator, in this way, is promoted to a supervisor of the system, instead of a task executor. Future developments involve bidirectional communication between the DT and the real plant to improve the human capability further to rapidly and possibly remotely manage process interruption. The possibility to tele-operate the systems through the DT will be investigated, to shorten intervention time. A video showing the entire use case can be found on the following link https://www.youtube.com/watch?v=YccGhCyobs4.

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## Declaration of interests

The authors declare no conflict of interest.

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