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Plug & Produce robot assistants as shared resources: A simulation approach

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ABSTRACT

Plug and produce robot assistants have been developed to support flexible automation in smart factories as a shared resource on the shop floor. However, although the technology is reaching commercial maturity, there is still a scarcity of methods to support analysing their implementation feasibility, making it difficult to evaluate their use in real-world operations. In this study, we propose an approach that combines physical experiments and hybrid simulation to support analysing the feasibility and viability of operating plug and produce robot assistants before making considerable investments and without disturbing the running production. The applicability and usefulness of this new approach have been demonstrated through an in-depth case study conducted in a large manufacturing company. The results show that the approach supports verifying, analysing and improving the operation of plug and produce robot assistants as shared resources in dynamic production environments.

1. Introduction

Manufacturing automation seeks to reduce operation time or save human labor time, supporting the business capital by increasing the efficacy and effectiveness of processes [1,2]. Although companies are making massive investments in advanced technologies and robotics, a survey from PWC [3] found that the majority of companies expect to see a return on investment (ROI) for their manufacturing automation and Industry 4.0 projects within two years or less. Meanwhile, the increasing need for more frequent product innovation results in a significantly increased need for change on the production shop floor. This makes many automation solutions unfeasible from an economic point of view due to the high cost of equipment compared to its low utilization rate if implemented purely as a static, dedicated resource [4]. In this way, the smart factories of the future, especially those dealing with high-mix low-volume production systems (HMLV) [5], will depend on flexible and reconfigurable manufacturing equipment to cope with the increasing consumer need for product customization [6]. In parallel, approaches to increase the utilization rate enables higher return on investment and shorter payback periods for automation. Many studies have been carried out to understand how shared resources and flexible automation provide greater utilization of resources available on the shop floor [7], while strategies for easing flexible automation have evolved [8].

Such strategies have been wildly applied to ease the integration of collaborative robots (cobots), a category of robots that perform tasks in collaboration with workers in industrial settings [9]. Although cobots support automation to replace repetitive and trivial manual work while improving the workflow, inefficient utilization is one of the main challenges for companies to adopt cobots [10,11]. The high cost of cobot acquisition makes the adoption financially unrealistic for applications whose utilization rate is low. Thus, finding new ways to enable the use of the same cobot in different stations, and thereby decreasing their idle time, can potentially make various automation projects more viable. In such context, plug and produce collaborative robot assistants (from here on referred to as *robot assistants*) have been developed to support flexible automation in smart factories focusing on being a shared resource able to complete a multitude of heterogeneous tasks [6].

The technical feasibility of robot assistants and their integration with manufacturing systems have been extensively addressed in prior research [6,10], and the technology is reaching commercial maturity [12]. Consequently, research should start to address the operational implications of deploying robot assistants [13]. However, evaluating their deployment in real-world operations is not straightforward. In complex environments like shop floors, the vast number of possible scenarios makes it difficult for practitioners to analyse at the same time

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(i) the implementation feasibility of a shared resource, (ii) in which cases automation based on a shared resource becomes a more viable option than a dedicated automation or a manual process, (iii) and make the necessary tests without disturbing the running production.

Consequently, the use of virtual environments to run tests and validate hypotheses can be highly supportive, and simulation has been used to plan and optimize decision-making, from design to operations of complex and smart production systems [14]. While physical experiments support collecting realistic cycle and changeover times, simulation can be used to extend the physical tests by evaluating multiple scenarios in a risk-free environment, that besides compressing the time for observations, also decrease the entailed costs of physical tests [15]. Although the simulation research field is well developed, it most often tackles problems with standalone solutions. Literature still lacks studies addressing the use of hybrid simulations to evaluate the feasibility and viability of using shared resources in smart factories.

Therefore, in this study, we propose a 3-step approach that combines physical experiments and hybrid simulation to analyse the feasibility and viability of operating robot assistants as a shared resource in factories. The applicability and usefulness of this new approach have been demonstrated through an in-depth case study conducted in a Danish manufacturing company. The aims of the proposed approach are twofold: first, support manufacturing companies to increase the viability of automation using cobots by reducing idle time through shared resource usage; and second, identify and verify potentially viable use cases for robot assistants faster, more accurately, prior to purchase, and without disturbing the running operations.

The remaining of the article is organized as follows: Section 2 presents a background review on hybrid simulation and the main characteristics of the plug and produce paradigm and its implication for implementing robots as shared resources in production. Next, Section 3 describes the research design followed in the empirical study, while Section 4 shows the results from the in-depth case study developed in a large company. Finally, implications, contributions, and final remarks are discussed in Section 5.

2. Theoretical background

This section explores related work on robot assistants and the implications of using the plug and produce approach to allow deploying robot assistants into production as shared resources easily and quickly, with minimal or no setup needed. Finally, the background of hybrid simulation is discussed, as well as its role in evaluating robotics deployment feasibility.

2.1. Robot assistants

In the last decade, the development and application of assistive robotic solutions in industrial environments, e.g. production, have increased significantly. This rise in assistive robotic solutions can be traced back to the development of collaborative-enabled manipulators like the KUKA LWR 4 [16], ABB Yumi [17], and Universal Robots UR-Series [18].

In combination with various advanced technologies, they reduce the required safety distance between manipulators and humans within industrial settings leading to closer, more complex, and immersive interaction between humans and robots. These improvements in human-robot collaboration and interaction have roots in various technological advancements. One of them is the development of advanced control strategies presented by Lachner et al. [19], Osorio et al. [20,21], Mohammed et al. [22], Landi et al. [23], which enable the manipulator to safely handle or avoid physical interactions with autonomous entities within their work environments. Additionally to the technical progress in mechanical design and control strategies, the utilization of artificial intelligence (AI) has enabled humans to express their intentions to such robotics systems, as presented by Li et al. in [24] and Neto et al. [25], as well as to transfer human knowledge and skills to a manipulator [24].

These advancements have enabled research institutions as well as companies to create mobile robot assistants like the Enabled Robotics [26] and the Little Helper platform [27–29] (see Fig. 1), among others. Their design enables them to support the human operator by overtaking various routine tasks (e.g., replenishing components from storage racks and repetitive assemblies), which would otherwise take the focus and time from the human worker.

Such collaborative robot assistants have already been demonstrated in several industrial applications, e.g. the collaborative assembly of products [31] and disassembly of products [32]. The flexible nature of robot assistants makes them well suited for handling multiple, low-volume and ad-hoc tasks during the working day. However, to remain economically feasible, the transition of the robot from one task to another must be fast and easy; i.e., it must follow the vision of plug and produce.

2.2. Plug and produce for robotics

Derived from the term plug and play from the IT domain, plug and produce entails quick and seamless connection of production equipment with minimal or no setup required. Although the idea sounds simple, designing plug and produce capable systems has proven to hold numerous technical challenges that must be overcome. Consequently, since the introduction by Arai et al. [33] in 2000, research on the concept of plug and produce has almost solely addressed technical and integration challenges. A comprehensive overview of many of these challenges along with technical requirements in implementing plug and produce is presented by Schleipen et al. [13]. They highlight four main requirements:

- *Component description*: Representation of equipment information must be formalized
- *Component selection*: Matching equipment capabilities with task requirements must be partly automated.
- *Component access*: Interfaces and communication protocols towards the equipment must be standardized.
- *Component control*: Control architectures must allow equipment to be used across a wide range of tasks.

Focusing on plug and produce for robotics, Schou and Madsen [34] propose a roadmap to enable shop floor operators to reconfigure industrial collaborative robots easily and quickly. The roadmap highlights the need for modularity in both hardware and control systems and the need for intuitive tools supporting the configuration task for the operator. Thus, it aligns well with the four key requirements identified by Schleipen et al. [13].

2.2.1. Component description

On the challenge of component description, Schleipen et al. [13]. propose the use of AutomationML as a formal language for encoding equipment information, such as capabilities, spatial, communication, and logic parameters. Several have adopted ontologies for storing equipment information and combined this with semantic information [35–37].

Ye et al. [38] use the Asset Administration Shell (AAS) [39] to store component information. AAS is a symbolic model constituting the virtual representations of components in the IT domain. It is closely tied to the Reference Architectural Model for Industry 4.0 (RAMI), and AAS is under development to become an international standard.

Importing and exporting scenarios is AAS requires a serialization of the AAS model which can be done in a number of formats. Lüder et al. [40] present a serialization using the AutomationML format. Being a free, open and already widely used format, serialization using AutomationML would enable easier sharing of component descriptions between AAS models. AutomationML can in fact be used as a component

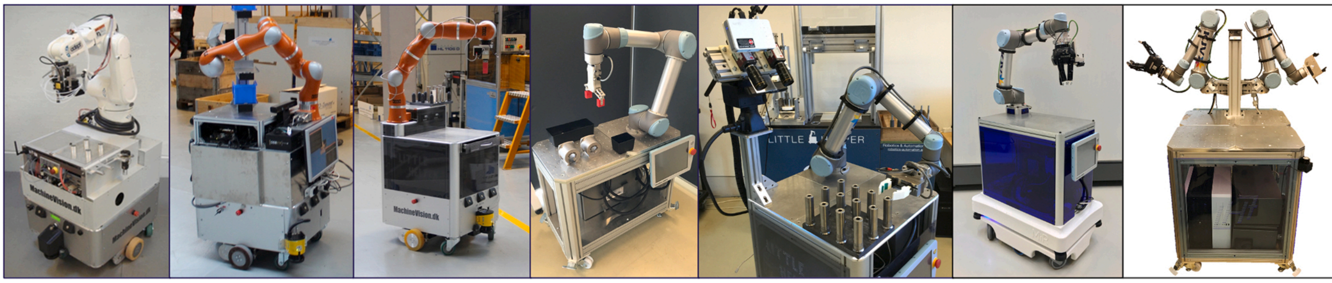

Fig. 1. Iterations of the Little Helper platform [30].

description model on its own, as done by Heymann et al. [41] as part of the Smart Factory Web IIC Testbed [42]. In which four smart factories are interconnected, and the sharing and reuse of component descriptions is a central enabler to achieving plug and produce capabilities.

2.2.2. Component selection

Pairing the equipment information with semantic information becomes an enabler for partly or fully automating the selection of appropriate equipment for a given task. Schou et al. [37] demonstrate this by creating a selection wizard which is partly manual and partly automatic. The system derives all valid configurations, and the user afterwards selects the desired specific configuration. During this process, inter-equipment dependencies are continuously evaluated, and the list of valid components is updated.

Engel et al. [43] apply a two-stage selection approach. Firstly, logic-based matching filters are used to match task requirements with equipment capabilities, deriving a weighted ranking amongst the equipment. Secondly, semantic behavior models are used to determine and match continuous behaviors of the processes, e.g., throughput or energy consumption.

2.2.3. Component access

Enabling equipment to access and communicate with each other is the foundation for most automation solutions. However, as the industrial landscape includes a large variety of different protocols and interfaces, integration has traditionally been an engineering task. In a plug and produce environment, the establishment of communication between equipment should be automatic, with little to no configuration. Several researchers approach this challenge by implementing architectures and frameworks adopting one or more protocols as a common, well-defined interface implemented on all equipment. Schleipen et al. [13], Profanter [36], and Heymann et al. [41] all use OPC/UA as the communication protocol between equipment, and Profanter [36] furthermore shows how automatic device discovery integrated into the OPC/UA protocol can be utilized to avoid pre-registering devices and can be tied with the semantic information in their ontology. Heymann et al. [41] show how the AutomationML component description models can be mapped to an OPC/UA data structure, and thus structuring the component interface accordingly. A detailed description of the possibilities in combining of AutomationML and OPC/UA is presented by Schleipen [44].

Schou and Madsen [45] build a framework for plug and produce of robot components on top of Robot Operating System (ROS) and thus use the ROS-communication layer as an access protocol. ROS already facilitates communication across a network of computers and provides node management, which is utilized in the access and management of connected devices.

2.2.4. Component control

Both Antzoulatos et al. [46] and Michalos et al. [35] propose the use of an agent-based architecture for configuring and controlling plug and produce assembly systems. Schou and Madsen [45] propose an architecture and control framework that allows commercial robotic components to be adapted into plug and produce components for building industrial robot setups. The architecture introduces a generic function layer called primitives, abstracting away from specific vendor syntax and implementations, and thus resembling a service-oriented architecture. Similarly, Profanter et al. [36] also propose an architecture for commercial, industrial robot components. Closely related to that of Schou and Madsen [45], the commercial components are physically augmented with a device adapter to make them all adhere to a common, standardized interface both physically and interface-wise. In terms of control, generic functions are implemented as software blocks termed *skills*.

2.2.5. Feasibility tests

Wojtynek et al. [47] present a scheme promoting robot autonomy for the robot to self-adapt to a given task context in a modular production system. Hence, the task of the human operator only includes plugging the robot in and omits any complicated setup and installation. Maeda et al. [48] developed and conducted a feasibility test on a multi-robot setup. Three fixed manipulators were amended with a plug and produce, movable robot for assembly tasks. Maeda et al. [48] emphasized the need for semi-automatic or fully automatic calibration as a central element of plug and produce robotics, meanwhile using a semi-automatic, vision-based calibration method. Zimmer et al. [49] see plug and produce enabled resources as a key to decreasing the ramp-up time of assembly systems.

2.2.6. Operations

Looking at the operation of plug and produce resources, Colledani and Angius [50] propose a method for combined planning of both operation and reconfiguration tasks for modular plug and produce systems. The method optimizes batch completion time and sequence for maximizing the system utilization.

While reporting on recent standardization efforts towards equipment modules for plug and produce, Bernshausen et al. [12] view this as the final maturity level before rendering plug and produce concepts commercially ready. In a final reflection on commercialization, Schleipen et al. [13] highlight the need for research on how production plants can benefit from plug and produce solutions.

Despite a significant body of research within the paradigm of plug and produce, we have not been able to find research explicitly on how to evaluate the operational benefits of using plug and produce robot assistants in a dynamic production setting. Given this gap in research, the authors of this paper have in a prior study [6] proposed an approach combining physical experiments for deriving actual operation timing with discrete event simulation for evaluating production scenarios. The approach was in [6] tested on an industrial-like laboratory setup. In this paper, we extend our prior approach with a hybrid simulation step, reducing the need for physical experiments in the actual production environment. Furthermore, this time we assess our approach in a real industrial case from a large Danish company.

2.3. Hybrid simulation modeling

Simulation has been a method to design and analyse manufacturing systems since the 50s, given its risk-free way to test different scenarios without the need for physical resources [51]. However, with emergent Industry 4.0 technologies, state-of-the-art simulation platforms provide resources to better predict behavior both in terms of output and integration, such as the Internet of Things and cloud computing, providing extended interoperability and real-time data exchange [52].

Digital simulation is a key technology to optimize decision-making and the design and operation of complex and smart production systems. Simulation-based approaches allow gaining insight into complex manufacturing systems to develop and test new operating policies and concepts without disturbing the physical system. Besides, it also allows the experimentation and validation of products, processes, and system design to predict system performance in various abstraction levels [14, 53].

Many modeling and simulation methods exist, and a list of several of the methods can be found in an extensive literature review conducted by Diallo et al. [54]. Some of these methods are predominantly used in specific domains, while in manufacturing, discrete event simulation and 3D process simulation are seen as essential methods, especially for productivity analysis.

The 3D process simulation provides the ability to simulate different tasks for a given workplace, supporting analyses of dependencies such as collision avoidance and pathfinding for both workers and robots. Based on the layout, waypoints are generated for the agent to reach a target position. Generating realistic movements in the simulation is critical since they greatly influence operation cycle times. The implementation of well-established methods from the field of robotics for the movement calculation allows the generation of realistic behaviors for a worker, equipment, or robot, which grants precise insights to processing and cycle times without prior real-world implementation [55,56]. This method can be applied for individual processes but also to complex manufacturing lines, supporting validating manufacturing processes and interactions. Several recent studies have used 3D process simulation to explore the use of collaborative robots in a manufacturing context [57–61].

Discrete event simulation (DES), on the other hand, is process-oriented, i.e., the system is considered as a list of events to be processed or a flow chart in which the entities and resources flow through the processes [62,63]. These entities have a number of attributes and can be connected to resources, so they can be processed during an event if the necessary resources are available, and despite being a static representation, the DES inputs can be randomized to examine the impacts of different changes in the system [64,65]. This type of simulation is by far the most utilized in the manufacturing context, and it is commonly applied to investigate productivity, bottlenecks, line balancing, routing, scheduling, queueing, and supply chains [15].

Finally, hybrid simulation is characterized by the combination of two or more simulation methods or a combination of simulation with optimization approaches [66]. In this study, we take a hybrid simulation approach by combining 3D process simulation and discrete event simulation to evaluate the use of robot assistants as shared resources in smart factories while analysing the productivity for each scenario developed.

In the next section, we present our research design and detail how each simulation is used.

3. Research design

In this paper, we introduce a 3-step approach for simulating and evaluating the operation of robot assistants. The aim is to support simulation-based design and optimization of flexible resource utilization. The approach is composed of three main steps: (i) data retrieval and physical experiments to verify and obtain plug and produce related parameters; (ii) 3D process simulation for validation of manufacturing process and interactions; (iii) discrete-event simulation to analyse productivity and resource allocation. Each step and respective inputs and outputs are described below.

Step 1. The use of plug and produce systems requires knowledge about the system configuration and resource interaction. This first step focuses on verifying the technical implementation feasibility, considering both hardware and software integration. This includes interactions between the physical resources, system controllers, and resources planning/execution systems integration. Note that the integration of the robot can be both local at the given workstation or global with direct communication with higher-level system controllers. Thus, extensive integration with legacy systems is not required, and standalone robot programming can be utilized. Essential information should be retrieved from the physical experiments to be used later, such as the (a) setup time that involves the times for changing tools or any other needed manual work, (b) accurate calibration time that is difficult to estimate in the simulation, and (c) relocation parameters (e.g., speed) that vary depending on the assistant robot design and configuration. Furthermore, specific data related to the case (e.g., production demand, resource availability, operational hours) can be retrieved from the company systems in this step.

Step 2. This second step focuses on verifying the processes feasibility in different scenarios by using a 3D process simulation. This step supports analysing multiple scenarios taking into account the many resources and restrictions involved in the shopfloor dependencies. First, the simulation supports validating the process feasibility (e.g., robot reaching a target position or checking for interlock in process flow) even when a physical scenario is not available for testing; second, it supports gathering accurate processing and cycle times based on realistic movements, considering the robot and worker movements, the path for collision avoidance, interactions with other resources, and more. Essential information can be retrieved from this step to be used later, such as (a) accurate processing and cycle times, (b) detailed analysis of resources utilization in each process. Note this step also comprises the test and validation of new automation solutions, as described in Section 2.3 and exemplified in Section 4.2.

Step 3. The final step focuses on verifying the processes implementation viability for utilizing a shared resource. For such, discrete-event simulation is used to investigate multiple scenarios in terms of resources utilization, resources allocation, and productivity. By using the data gathered on Step 1 and Step 2, this simulation supports analysing the resources needed to cope with the demand in the several workstations. Note that data exchange between the 3D process simulation and discrete event simulation tools can be done either manually or automatically (eg, through PLM systems). Stochastic behavior can be applied to avoid biased results, and layout aspects must be taken into account to ensure relocation feasibility.

In the following section we introduce the case study and describe how the 3-step approach was applied and tested, while the feasibility and benefits of using robot assistants are analysed.

4. Case study

The case study was held at one business segment of the global Danish group Danfoss A/S, the Danfoss Drives A/S. The company is the global leader in the variable speed control of the electric motors segment. The company has approximately 5.000 employees, having as core products low- and medium-voltage AC drives used to control electric motors' speed, convert energy from natural or renewable resources, and transmit it to the electrical network. Given their strategy of providing highly customized products to their clients, their production line is also focused on keeping a high degree of flexibility.

At the time of this study, most of the assembly lines, apart from testing and material handling, are semi-automatic throughout different plants. However, the company aims to transition towards Mixed-Product

Assembly Lines, a type of assembly line that, while flexible, contributes to creating product variety and absorbing volume fluctuations [67]. Therefore, over the last years, Danfoss implemented collaborative robots to increase automation while keeping the needed flexibility. However, cobots have been mainly adopted in fixed stations, and since they usually are not planned to be flexible enough to move among stations, the utilization rate is usually low.

We expect that the 3-step approach proposed in this paper enables adopting robot assistants as a shared resource in the Danfoss context. The procedure for collecting and analysing potential cases involved the following steps: (i) we identified cases in which cobots are used in fixed stations and their idle times are high, thus the remaining capacity could be used elsewhere if adapted to a mobile solution; (ii) with potential cases identified, we selected processes that happen similarly in different lines, which facilitates implementation given the reduced types of tasks; (iii) finally, we selected the process with the highest combined cobot idle time.

Therefore, our unit of analysis consists of three similar cells in the company, each of them tasked with preparing components that are used on nearby assembly lines. These sub-assembly stations are today partially automated, in which a worker and a collaborative robot work simultaneously. The process consists of a thermal paste application into a component used later in the production line. Currently, the human worker performs the product placement in a fixture plate, while dispensing the thermal paste is the robot's only task. Thus, currently, three collaborative robots are required for such an operation. However, since the majority of the time the cobots are awaiting part delivery or conclusion of the human tasks, the utilization rate remains low.

Therefore, our goal is twofold in this case study. First, automate the process further to reduce the number of person-hours needed, and; second, evaluate the adoption of robot assistants, to increase the flexibility of resources while increasing cobots' utilization rate by allocating the remaining capacity for different activities in the factory. For such, the application of the 3-step approach is now detailed for this specific case study.

4.1. Step 1: Physical experiments and data retrieval

The first step in our approach is to gather data that cannot be determined from the simulation, but rather serves as input for the simulations in Steps 2 and 3. This data consists of two main parts, (i) data on the plug-in and plug-out procedure of the robot determined using physical experiments, and (ii) scenario-specific production data.

4.1.1. Physical experiments

The purpose of the physical experiments is to first validate the technical feasibility of the integration of robot assistants in the scenario, and second to accurately determine the timing of the plug-in and plug-out procedures, including setup time, calibration, etc. When using our 3-step approach to estimate the potential of a currently manual task, as it is the case here, the experiments cannot be carried out on the real production equipment, as this has not yet been prepared for integration with the robot assistant. To overcome this, the experiments can be carried out on a mock-up of the intended setup in a decoupled environment, or results from similar tasks may be applicable. Here in this study, we make use of experiments carried out in a previous study [6] by the authors on comparable production tasks.

In [6] the robot assistant used was composed of a Universal Robots UR5 manipulator mounted to a manually movable platform and equipped with a 4TECH Kelvin tool-changer, a calibration tool, an OnRobot RG2 gripper, a 4TECH pneumatic gripper and an AIM Robotics glue dispenser tool. The scenario included an assembly station and a glue-dispensing station which could be controlled by either a human operator or a robot assistant. The communication between the robot assistant and production line in this case was facilitated using MODBUS. The scenario was set up in an industrial-like lab environment at Aalborg University, see Fig. 2.

The plug-in and plug-out procedure included retrieving the idle robot from within 15 m or the target station. The results of the physical experiments conducted in [6] verified the technical feasibility of the integration, and the plug-in and plug-out timing is summarized in Table 1.

4.1.2. Data retrieval

Case-specific production data is retrieved at the company. The demand per station to fulfill the production of each line was extracted from the enterprise resource planning (ERP) system based on the average demand of the previous year. Note that although the three stations selected for this case are similar in terms of processes, they differ in the number of units produced given the different line demands. Table 2 shows the daily demand per line.

Other general parameters, such as maintenance and availability (mean time before failure and mean time to repair) was also collected, as shown in Table 3. Note that both programmed and non-programmed maintenance is already considered on the availability. Besides, the company production operates in three shifts. Therefore 24 h daily operation is assumed in this study.

4.2. Step 2: Simulation-based process automation and process feasibility evaluation

After demonstrating the technical feasibility in Step 1, this second step focuses on evaluating the process feasibility, analysing further process automations, and determining operation cycle times. Therefore, we first analyse the current scenario, and by using a 3D process simulation we evaluate feasible solutions to further automate the operation and later calculate their operations cycle times. The simulation software Visual Components is used to perform the analyses.

First, the current manufacturing process was mapped along with the company's production engineers to better understand the production requirements and restrictions. Then, the process sequence from the process mapping at the company was introduced in the 3D process simulation. Later, the tasks allocated to the robot and the worker were analysed in terms of times and restrictions. In this way, we proposed a new solution to convert the semi-automatic station into an automated process. We equipped the robot assistant with various tools and a quick tool changer that support automation of several pick-and-place tasks currently allocated to the human worker, while additional equipment for machine tending was used to substitute load and unload activities also currently executed by the worker. Fig. 3 illustrates the resources and tools used.

As shown in Fig. 3, for this case we simulated the robot assistant with similar tools as specified in the physical experiments (see Section 4.1.1), with additional and case-specific tools that support further process automation. The setup consists of a Universal Robots UR10 collaborative robot, a 4TECH Kelvin quick tool changer, and a manual trolley that carries three tools: an OnRobot RG6 gripper, a tailored tool to dispense thermal paste on the product, and a calibration tool (a vision-based system can be a substitute for the calibration tool if needed). The Profeeder X is a licensed product by EasyRobotics with ten flexible trays that accommodate the parts to be produced. Finally, a tailored fixture plate that has both an automatic dispenser that deposits thermal paste on a robotic tool and a base for part placements.

The simulation-based proof of concept was robust, showing the feasibility of automating almost the entire process. The new process now requires human interactions only for relocating the robot assistant between stations and loading the ProFeeder. The processes at the station run step by step as follows:

1. **Loading the ProFeeder**: This process is done manually, where an operator loads the ProFeeder X with parts before the operation starts. The parts to be processed come in cardboard boxes that can be

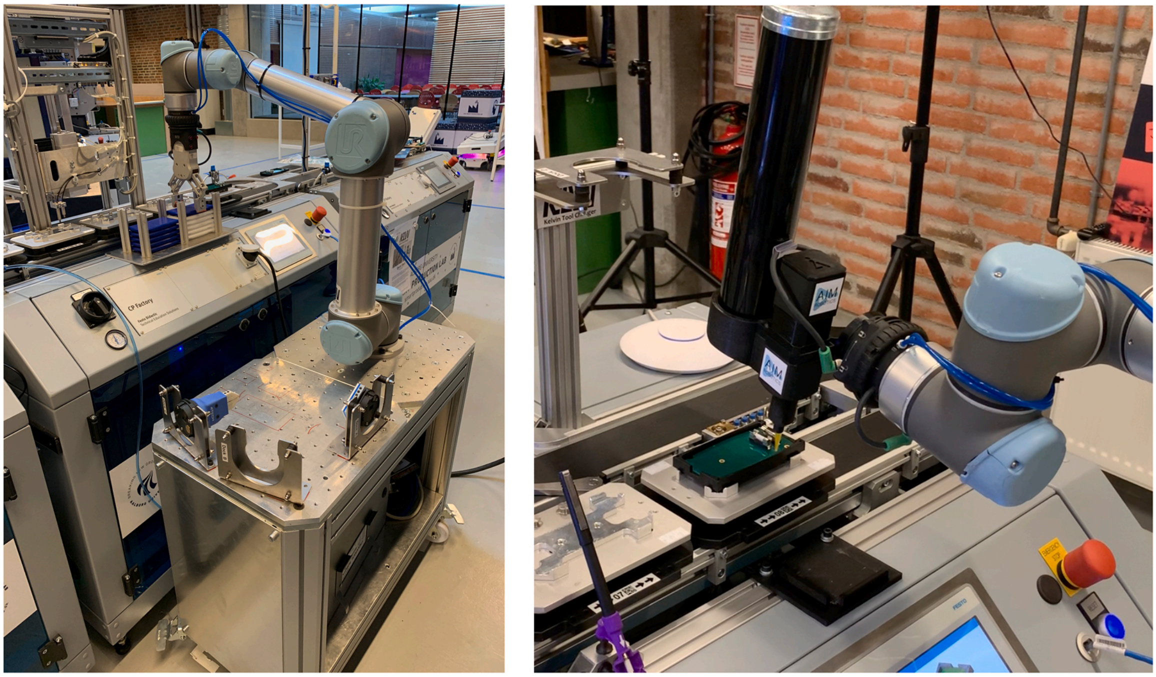

Fig. 2. Physical experiments. Left: The robot assistant shown at the assembly station. Right: The robot assistant operating at the glue-dispensing station.

Table 1
Timing of the plug-in and plug-out procedure determined using physical experiments in [6].

Activity	Timing [seconds]
Plug-in	187
Plug-out	62

Table 2
Average daily demand per line.

Production line	Demand [units]
Line 1	1408
Line 2	496
Line 3	352

Table 3
Production parameters.

Maintenance parameters	Values
Availability	99.5%
Mean time to repair (MTTR)	600 s
Operation hours	24 h/day

directly placed in the trays. Product models vary in size, but each tray accommodates six cardboard boxes with 12 products each, regardless of the model. Therefore, the ProFeeder accommodates up to 720 parts at a time.

2. **Production request**: The robot assistant receives the order from the manufacturing execution system (MES). This determines which tool the robot assistant should select and from which tray the parts should be picked. Alternatively, if the company does not want to connect the robot assistant with the MES, different pre-configurations can be set to determine the tool and materials to be used. In this case, we used the manual configuration for simulation purposes.
3. **Robot calibration**: The robot assistant performs an autonomous calibration using the calibration tool. This calibration procedure works by placing the tool to a reference point at the station, from which all the task-relevant poses are described from. After the robot has been calibrated, the poses expressed locally in reference to the station are now expressed by the robot world-frame. Thus, the same robot can be quickly calibrated when moved to a different cell.
4. **Operation**: The robot attaches the gripper to pick the part from the ProFeeder and place it on the fixture plate. Next, it changes the tool from the gripper to the tailored dispenser tool. The automatic dispenser deposits thermal paste on the tool, which is then applied to the part. This tool is needed for process quality reasons and cannot be replaced only by the automatic dispenser. Next, the robot assistant changes the tool again, now to pick the part from the fixture plate and place it back to the cardboard box. Note that the robot assistant can operate autonomously until all parts are finished since the robot assistant can also be programmed to open the trays with the same gripper, either when parts in a tray are concluded or when the MES request a different model placed in a different tray.

Operational processing times were obtained from the 3D process simulation that uses the in-built robot controller to calculate processing times for each operation following the robot motion planning. Within the simulation software, the Universal Robot connectivity plugin enables connecting to a Universal Robot controller and running a simulated robot with realistic movements. That allows calculating cycle times accurately with low variance compared to a real-world setup. Besides that, the 3D process simulation allows testing path sequencing, collision detection, reachability analysis, and more that support analysing the process feasibility without replicating all designed scenarios in the real world. Given the different reach points in the ProFeeder, minor differences in cycle times can be observed. Therefore, a triangular distribution is used in the simulation. Table 4 shows the operation cycle times.

While this 3D process simulation has demonstrated the technical feasibility for process automation, the processing time to produce each part increased since operations now are performed only by the robot assistant without the support of a human operator. Hence, it remains unclear how the automation optimizes resource use and how the robot assistant should be allocated to deal with the demand for each line.

Fig. 3. Automated production setup with a robot assistant.

Table 4
Production parameters.

General parameters	Values [seconds]
Cycletime (min)	52
Cycletime (mean)	54
Cycletime (max)	56

Therefore, next we apply the discrete-event simulation to analyse how the system behaves in different scenarios to support the resources analyses.

4.3. Step 3: Simulation-based resource analysis

Finally, in this step we verify the processes implementation viability for utilizing a shared resource. Several scenarios are developed and analysed to evaluate how resource allocation influence productivity and utilization rate. The simulation uses the data retrieved from Step 1 (demand, robot assistant availability, mean time to repair, setup time, changeover time, and robot movement parameters), and Step 2 (operation cycle times). Note that data exchange between the simulation tools was done manually in this case due to the use of different platforms and the lack of features for integration. In total, seven scenarios are developed and tested, covering the use and relocation of one to three robot assistants with different workloads in three different stations. Since the simulation uses a stochastic approach, experiments for each scenario were run five times, and the average result was used for mitigating bias. The simulation software Enterprise Dynamics is used to conduct the experiments.

As seen in Table 2, demand varies between the production lines, which makes it important to investigate the availability of robot assistants to create a buffer of parts for production. Therefore, we investigate how many robot assistants are needed and how often they can be moved from one line to another. Note that the more often a robot can be relocated without risking the total production, the more flexible we turn the manufacturing system, avoiding high buffers. On the other hand, the movements are at the cost of production time, in which non-added time for relocation and calibration is spent. Thus, scenario-based analyses are conducted.

The scenarios consider the total number of robot assistants and the percentage workload per station before the robot assistant is relocated. We tested scenarios with up to three robot assistants – in which the three collaborative robots already available at the company can be used for – and three different workloads (25%, 50%, and 100%) before relocation. The workload means that after producing a percentage of the line demand, the robot assistant is relocated to the next line in which a robot assistant is not available. Note that in Scenario 3, one assistant robot is allocated for each line, consequently no relocation is needed. Hence, seven scenarios are explored in total, as illustrated in Fig. 4.

The results presented in the following sections aim to demonstrate that the described methodology is capable of (i) modeling, analysing, and improving process automation, and (ii) improving the utilization rate, which is critical to minimize costs and enhance future project viability.

4.3.1. Scenario analyses

The results presented throughout this section discuss the results of using a different number of robot assistants and workloads. Stochastic simulations were run multiple times for all scenarios to mitigate the risks of biased results.

First, we analyse the results for Scenarios 1.1–1.3 that uses only one robot assistant. Table 5 presents the results related to the total time spent to cope with the demand and the percentage of the time the robot assistant is busy, idle, not available, or traveling to a different station. All percentages are related to the total daily operation time.

As seen in Table 5, regardless of the workload strategy used, the total time to cope with the daily demand surpasses the 24 h available daily. This shows that more robot assistants are needed. Besides, because of the high availability and low setup time, the workload strategy accounts for a low difference in total time. This difference can also be seen as the required time from a human worker time to relocate the robot assistant from one station to another since the trolley, in this case, is manual. Next, we see the results of Scenarios 2.1–2.3.

As seen in Table 6, now with two robot assistants, the total required time is below the available time, showing the demand can be fulfilled with this setup, and the idle time indicates that the excess capacity could be used to handle an increase of up to 25% in demand. As expected, Scenario 2.3 outperforms the other two configurations needing only 21.37 h to fulfill the demand, while the 'travel to job' is highly minimized. Note that the indicator 'travel to job' indicates the time the robot assistant is being relocated to another station, and in this case study the three stations are relatively close to each other, which contributes to a low percentage compared to the operation. However, in cases where stations are far from each other, or the total availability in daily operation is lower (e.g., one shift), this will potentially have a greater influence on the results.

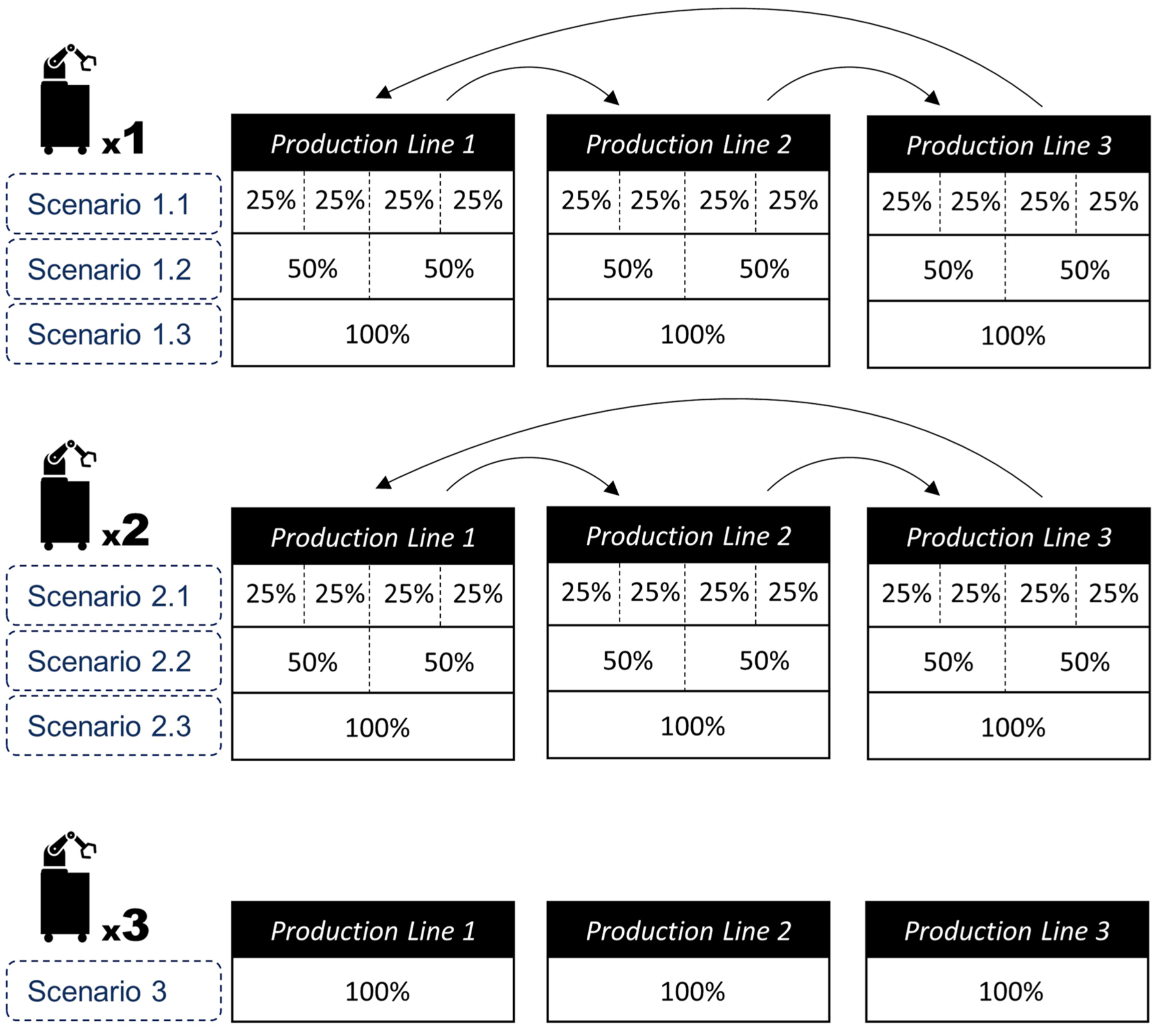

Fig. 4. Description of scenarios.

Table 5
Results of Scenario 1.1–1.3.

		Scenario 1.1	Scenario 1.2	Scenario 1.3
	Number of robot assistants	1	1	1
	Workload per station	25%	50%	100%
Robot assistant 1	**Busy** (%)	99.20%	99.35%	99.44%
	Idle (%)	0.00%	0.00%	0.00%
	Not Available (%)	0.48%	0.48%	0.47%
	Travel to Job (%)	0.32%	0.17%	0.09%
	Time for production (hours)	33.92	33.76	34.14

Table 6
Results of Scenario 2.1–2.3.

		Scenario 2.1	Scenario 2.2	Scenario 2.3
	Number of robot assistants	2	2	2
	Workload per station	25%	50%	100%
Robot assistant 1	**Busy** (%)	92.38%	89.65%	88.46%
	Idle (%)	7.02%	10.04%	10.95%
	Not Available (%)	0.40%	0.27%	0.54%
	Travel to Job (%)	0.20%	0.04%	0.06%
Robot assistant 2	**Busy** (%)	48.16%	54.23%	53.39%
	Idle (%)	51.20%	45.25%	46.13%
	Not Available (%)	0.53%	0.40%	0.40%
	Travel to Job (%)	0.17%	0.11%	0.07%
	Time for production (hours)	22.34	21.59	21.37

The total time difference between Scenario 2.1 and Scenario 2.3 is almost one production hour, which illustrates that the flexibility increased, but often relocation is not for free. However, idle time is identified in all three scenarios, which potentially allows new strategies, such as relocating for a different line/operation to use the remaining capacity or modifying the workloads for more often relocation if higher flexibility is required.

Note that, even though the simulation already considers both programmed and non-programmed maintenance, the immediate worker availability is not considered. Thus, when choosing a manual trolley for relocation, a security margin (e.g., 90% utilization rate) is preferable to absorb times regarding possible unavailability of human workers for immediate robot assistant relocation.

Next, we see the results of Scenario 3, which uses three robot assistants, making no robot assistant relocation needed among the three production lines.

As seen in Table 7, now with three robot assistants, the total busy time is high for the station with the higher demand, while the other two robot assistants are idling most of the time. The production time of 21.17 h daily accounts for the highest utilization (robot assistant 1),

Table 7
Results of Scenario 3.

		Scenario 3
	Number of robot assistants	3
	Workload per station	100%
Robot assistant 1	**Busy** (%)	87.94%
	Idle (%)	11.78%
	Not Available (%)	0.28%
	Travel to Job (%)	0.00%
Robot assistant 2	**Busy** (%)	30.99%
	Idle (%)	69.01%
	Not Available (%)	0.00%
	Travel to Job (%)	0.00%
Robot assistant 3	**Busy** (%)	21.99%
	Idle (%)	78.01%
	Not Available (%)	0.00%
	Travel to Job (%)	0.00%
	Time for production (hours)	21.17

while the demand for the other two lines can be fulfilled in less than 7.5 h, that is, less than one shift time. In other words, it demonstrates a resource waste that can be potentially used elsewhere in the factory.

4.4. Case summary and key takeaways

This section summarizes the key takeaways for the case study focusing on analysing the feasibility of implementing the robot assistant in a Danish company. The 3D process simulation showed that process automation is feasible, and the human worker that was needed over the entire process is now needed only shortly a few times a day to feed the trays and move the robot from one station to another. The total time required by the human worker will depend on the strategy used, but it is similar to the results of the 'travel to job' indicator, summed to the filling process that can take up to 15 min per shift. One of the main requirements to make it feasible was autonomous calibration. A manual robot calibration was previously evaluated as very time-consuming, making it unfeasible from a financial point of view. With the autonomous calibration provided by a plug and produce approach, the process is simplified, making it possible to make better utilization of resources, both person-hours and the number of robot assistants needed to cope with the demand.

From the seven scenarios analysed, those with two robot assistants have shown to be the most appropriate. Results demonstrated that two robot assistants are enough to fulfill the demand while keeping a significant idle time as a security margin. Therefore, bottlenecks would not be created even if a more flexible approach that relocates the robot assistants more often is employed. Among the three strategies with two robot assistants, the most appropriate one will be based on the company needs in terms of flexibility and human-worker availability, which can vary depending on the order.

Although the number of cobots can be reduced when used as a shared resource, new equipment is needed, both for further automation and to convert the collaborative robot arms into mobile robot assistants. For instance, developing the new setup would require grippers, calibration tools, quick tool changers, tailored 3D printed fixture plates, manual trolleys, and the Profeeder X. It is critical to consider the additional equipment since it highly influences payback analysis. The payback analysis is made by analysing the initial acquisition cost of equipment subtracted the person-hours and a collaborative robot arm that is now available to be used elsewhere in the factory. Note that the exact payback number was not calculated because it involves worker salary and cost of tailored tools, which is out of this project's scope.

Finally, the purpose of sharing a resource that adapts to different stations is not only significant from a financial point of view, but also supports fast production adaptations when necessary. Thus, it also decreases the risk of technology obsolescence and support better reaction to sudden changes in demand, as resources can be quickly repurposed. Besides, for green-field automation projects, there is still potential to reduce initial investment since not every station would need to be fully equipped with robots and the required tools to operate. Combined, this reduces the pressure on operational efficiency for dedicated resources, often a trade-off with several manufacturing strategies.

On the other hand, as a shared resource, the failure of a robot assistant could negatively impact several production lines due to interdependencies. Therefore, backups or a more cautious maintenance strategy should be considered. Moreover, contrarily to this case study that used manually moveable robot assistants, it is highly important to notice that when evaluating autonomous robot assistants, the MTTR and availability measures gathered from the legacy system should not be straightforwardly used because the compounding risks of failures between the autonomous vehicle and the robot, which cannot be neglected and requires careful calculations.

5. Conclusion and future research

The majority of existing research on plug and produce robot assistants address technical development and integration aspects, and only very few researchers have addressed how to assess the operational aspects. Thus, we have in this paper addressed exactly this gap in research, and proposed a 3-step approach for evaluating the production performance and equipment utilization when applying robot assistants. The approach combines physical experiments on the technical feasibility and plug-in/plug-out timing with hybrid simulation evaluating first the process performance and finally the overall system performance. A case study at the large Danish manufacturer Danfoss has been used to both exemplify the application of the 3-step approach and also to preliminary verify its validity.

Our proposed approach is also valuable to practitioners, to whom it provides a tangible way to assess the potential of automating manual tasks using robot assistants prior to the technical investment. The exemplification of our approach shown through the case study at Danfoss furthermore provides a pragmatic view on how to step-by-step apply it and the level of results that it may provide. Although exemplified on a partly green-field scenario in the case study, the method does not favor either brown- or green-field setups, as long as the constraints imposed by the scenario are modeled accordingly in the simulation steps. Besides, the simulation supports obtaining accurate results for various scenarios without running physical experiments for all of them, reducing resource use.

However, in this study, we could identify three main limitations that could motivate further studies. First, data interoperability is a technical limitation that requires manual data input among the different steps. Although eased data sharing between simulation applications is promised by many Product Lifecycle Management system providers, in practice, such integration is still rare even when using a similar platform, and intensified when cross-platform solutions are needed. Platform independent standards will provide a solution to this, and the Functional Mock-up Interface (FMI) shows promise, that future work could investigate. Second, the case study proved to be not highly sensitive to the time associated with the relocation of the robot assistant. Therefore, for scenarios consisting of multiple micro-tasks, the time associated with the robot relocation would gain significance with regards to the productivity of the lines, which requires further investigations to understand the consequences and limitations. Lastly, data from lab-experiments comes with uncertainties. Since the lab itself can only emulate a fully operational production line to a certain extent, some uncertainty is attached to the results obtained in Step 1. Similarly, uncertainty is to be expected from the simulation results in Step 2 and 3 as these also are approximations of the real world. Consequently, decisions made based on final results obtained from the 3-step approach should factor the accumulated uncertainties in.

Therefore, the following future research directions are presented as possibilities to expand this research effort and surpass some of the aforementioned limitations. Firstly, the presented approach could be evaluated further by applying it to different industrial scenarios to provide a better understanding to practitioners about e.g. plug-in/plug-out time distributions rather than fixed values, which potentially decreased simulation uncertainty. Secondly, it would be of interest to investigate using the proposed approach for scenarios that mainly consist of micro-tasks and require frequent relocations since such times might have a greater productivity impact. Thridly, an investigation on how robotic solutions with increased autonomy minimize the time needed to relocate and calibrate the robot assistant to the various stations. Lastly, applying the presented approach to several, diverse tasks would create a data-foundation from which general indicators for successful deployment of robot assistants could be extracted. This would help practitioners set strategic directions for adopting robot assistants.

CRediT authorship contribution statement

Elias Ribeiro da Silva: Conceptualization, Methodology, Data curation, Validation, Formal analysis, Investigation, Simulation, Writing – original draft, Writing – review & editing, and Project administration. **Casper Schou**: Conceptualization, Methodology, Lab-experiments, Writing – original draft, Writing – review & editing, and Funding acquisition. **Sebastian Hjorth**: Conceptualization, Methodology, Lab-experiments, Writing – original draft, Writing – review & editing. **Finn Tryggvason**: Simulation, Writing – review & editing. **Michael Sparre Sørensen**: Simulation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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