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A Digital Twin-Enabled Cyber-Physical System Approach for Mixed Packaging

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Abstract. Today's production plants are widely using automation tools to increase their productivity and improve their manufacturing process, reducing production costs and wastes. However, while fixed automation reduces cost in mass production, this is not the case in low batch size production, where the effort to re-program and test the automation in advance of being used in production is required. The connectivity of underlying subsystems with the increased use of software can, in turn, convert conventional production systems into smart cyber-physical ones, capable of demonstrating increased flexibility and adaptability to changing production demands, hence creating software-enabled industrial automation, which can be scalable and reconfigurable. This study discusses an approach for enabling an automated mixed packaging workstation supporting a different mix of products. IoT data of the entire robotic station allow the creation of a digital twin model. In turn, the connection of the digital twin model to machine learning methods allows for the automation of the entire mixed packaging process, starting from the objects' recognition to robot control for picking and placing up to the completion of the mixed package. The proposed framework is tested in a testbed coming from the food industry and related to the mixed packaging of dairy products. The preliminary results are provided in this paper and discussed, suggesting there is potential for future investigation and applications.

Keywords. Cyber-physical production system, Digital twin, Food industry, Machine learning, Reconfiguration

1. Introduction

Digitization and connectivity in production systems can facilitate a transition from traditional automation to a fully connected and flexible system, where a constant stream of operational data can facilitate its reconfiguration to new requirements and constraints. The increased interconnection of the cyber and physical parts of a manufacturing system, creating a Cyber-Physical Production System (CPPS), can result in a more efficient and resilient system. Nevertheless, enabling such a manufacturing system to autonomously adapt to newly-arrived demands and limitations under uncertainty with increased flexibility, requires a smarter and more holistic approach, with increased awareness of the working environment and its constraints. Looking at the shop floor, this moves beyond the notion of scheduling and planning to a distributed but holistic system governing the production operations while being supported by the continuous data flow.

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Digital Twins (DTs) of the manufacturing operations allow for increased visibility while enabling alternative strategies generation and validation upon disturbance of the process. Thus, DTs can be a key enabling technology for a reconfigurable CPPS, while facilitating the development of AI applications on top of it, such as real-time monitoring, reasoning, decision-making, analytics and predictive maintenance. Hence, it may contribute to an increase in the automation and resiliency [1] level of a CPPS even to enabling autonomous operations.

This work aims to discuss how the digital twin can serve as an orchestrator of production operations and support their transition to autonomous operations. An approach is presented to enable autonomous reconfiguration of a mixed dairy products packaging station, self-adapting to new packaging requirements autonomously and without human intervention. The proposed approach is tested in a use case coming from the dairy industry. The results support that the use of software tools and increased connectivity can enable such autonomous behavior.

2. Literature review

The digitization of production systems mandates a shift to the introduction of new Information and Communication Technologies (ICT) into existing systems improving their performance and flexibility. ICT along with IoT devices and applications generate a big amount of data that is difficult to be utilized and benefit production processes in manufacturing [2], [3], [4]. Their effectiveness is often held back by IIoT's reliance on older operational and information infrastructure [5], [6],[7].

Cyber-physical systems can be classified as closed-loop control systems where large-scale computer networks interact with and control physical components [8], [9], [10], [11]. These systems can facilitate the processing of an extensive amount of information generated on a shopfloor [12], [13].

In this context, one of the most promising technologies is considered the incorporation of real-world data into digital models capable of replicating in a virtual environment and through this digital thread partly or completely the behavior of the physical object, thus serving as its DT [14], [15], [16], [17], [18]. A DT can be used to bridge the gap between the physical and the cyber part of a CPPS as well as for the virtual testing and commissioning, alternative scenarios testing and verification, without the need to disrupt production [19]. The opportunity to test, simulate, predict and optimize manufacturing processes in a virtual environment ensures increased quality and efficiency [20], [15], [21] even at a lower production cost if used throughout the entire production process, as discussed in [22]. Besides flexibility, the DT can be used for any number and type of criteria [23]. Thus, the DT can enable a quick re-evaluation of core designs as well as the discovery of possible problems without having to start from scratch [24], [25]. Furthermore, the fact that DT models can bridge the gap between the design domain and operation domain of the smart manufacturing systems design process is also highlighted in [26], [27]. A DT model is used for real-time discovery of production systems structures and the automatic development of digital models, guaranteeing an updated model at any time within one minute and with minimal manual intervention [28]. In [29] a DT was built to test, help, and improve all the intelligent interfaces of a robot, which were selected to control the hardening process of a metallic profile, through induction. However, for more complex system structures, that can be easily adapted to environment changes, a 'living model' and a 'dynamic model' are proposed in [30], [31].

Consequently, this paper focuses on the design and development of a DT of a mixed packaging station which facilitates the evaluation and reconfiguration of the cyber process according to newly-arrived constraints mandated by a different packaging requirement in terms of product types. In other words, the DT provides a real-world reference model to orchestrate the process of mixed packaging, dynamically and in an autonomous approach, in an existing workstation with already installed robotic and non-robotic automation. Thus, the main contribution of this work is a DT-centered end-to-end software solution of increasing the flexibility and reconfigurability and finally making autonomous an existing process of mixed packaging of dairy products using software automation.

3. Approach

The proposed approach focuses on the design and development of a DT centered cyber-physical production system capable of overseeing and orchestrating a mixed packaging workstation in a dynamic and self-adaptable approach (**Figure 1**). The DT of the suggested system aims to orchestrate the cyber part and its software components along with the physical part consisting of a robotic station for mixed packaging and other automation required for the packaging process, i.e., product packages arrival sensors, life beat signals from the various software modules, optical sensors, etc. The proposed CPPS aims at enabling the packaging of a different mix of products based on the demands of the user/customer in an autonomous way. To this end, a distributed software architecture is proposed, using a DT as the workstation living model for orchestrating the entire packaging process.

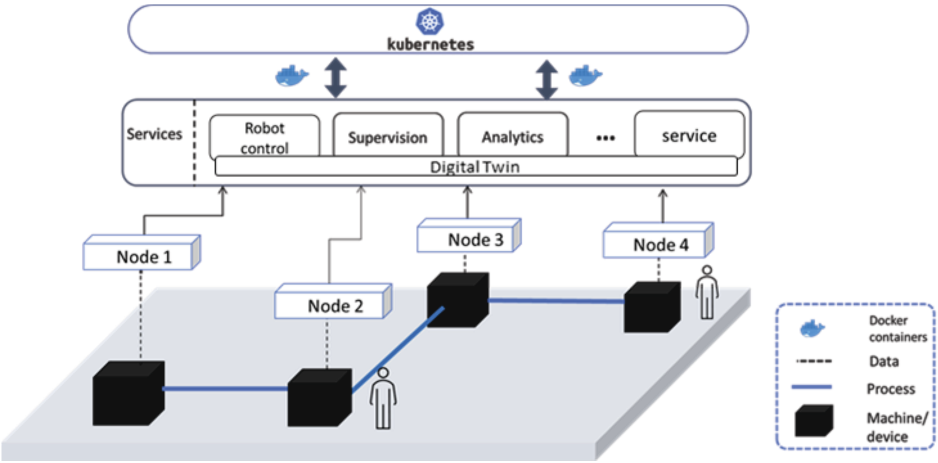

Figure 1. Approach schema.

The DT, includes the digital model of the workstation, its resources, sensors, and physical constraints, such as collisions, gravity, etc., and integrates the operational data of the workstation as collected by the sensors deployed, optical, vibration, proximity, etc. and software components in execution, robot control, analytics, production planning, supervisory control, etc. In particular, the mixed packaging station and the process is modelled in a suitable 3D environment. The 3D models of each component are then linked to its corresponding data source (integrated PLC, sensors on top of the conveyor belts, etc.) enriching the 3D models with real-world information and dynamically updating their status in the simulated environment. Each component in the simulated environment is also linked to a physics engine capable of replicating, to a point, the behavior of the real-world component. Thus, the fusion of real-world information in almost real-time to 3D objects capable of replicating the behavior of their real-world counterparts creates the DT of the mixed packaging station.

The arrival of a new package of products is detected by a set of proximity sensors. The objects to be packaged are recognized and enumerated, through their center identification, by processing 2D images captured by optical sensors when delivered to their final positions and before the packaging process begins. The optical data, acquired by camera sensors, enable object recognition, which is instantly validated against a list of predefined products as well as the coordinates of the object that is detected. However, this study also considers the possibility of new product arrival. If a product is either not recognized properly or not included in the list, then the DT uses the acquired, from the optical data, 3D dimensions of the new product to build a suitable 3D model of the object not mapped to the existing list in the DT environment (**Figure 2**). The newly created 3D model is then linked to an existing component behavior, which is dynamically updated in runtime based on data collected from the sensors capturing the behavior of the new object in the real-world environment. This method allows the system to manipulate and import in the DT environment different and unknown objects and approximate their behavior until sensor data allow for their update.

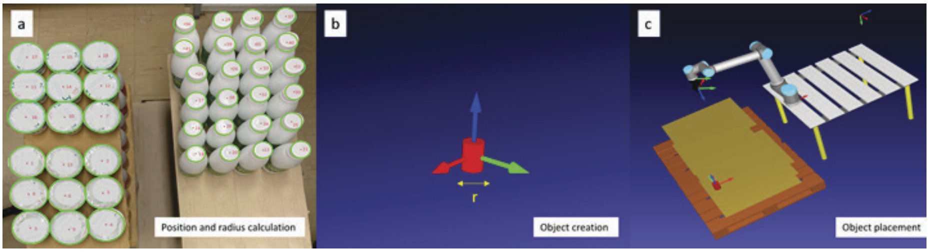

Figure 2. DT methodology.

The DT evaluates dynamically the process of mixed packaging before the actual operation takes place, and based on the orders received and the products recognized, and through dynamic simulations generated the required parameters for starting the execution of the mixed packaging process in the physical world, such as the proper robot motions, gripper force and approach to grasp the product, etc. The simulated scenario is evaluated against fully achieving a mixed packaging order. After the successful validation of a mixed packaging scenario, the scenario parameters are communicated from the cyber to the physical part for configuring the physical process accordingly. For example, if a task is a pick and place, the robot waits to receive the appropriate parameters from the DT. Then, the DT evaluates the newly arrived data for dynamically adapting the process flow and reconfiguring it if needed. The simulation process for validating newly arrived constraints is performed during the placing operation of the robotic manipulator and requires an average of 1.2 to 1.3 seconds. The time is enough for the robot used in this study, UR10 CB2, but may not be enough for a delta robot more suitable for a packaging process in an industrial environment.

In addition, supervisory control is enabled in the overall CPPS in terms of life beat signals of every component being part of the CPPS. Based on the operational status of each component, alternative configuration and execution scenarios are selected towards either fulfilling the production order or attempting a recovery by introducing to the CPPS the human factor for manual recovery. Moreover, supervisory control uses ultrasonic sensors to check the availability of products and their packages. Furthermore, and towards making the human factor aware of the mixed packaging process status semantic technologies were adopted, mapping the human expert knowledge to a knowledge graph. A knowledge graph of the mixed packaging process has been developed using as a based the ontology of [2]. The knowledge graph is used to correlate process data to specific events towards providing meaningful information to the user concerning the production status and its analytics. In particular, the analytics component uses knowledge from experts as well as historical data to reduce the amount of data that are needed to be analyzed. This approach aims to provide better insight to a human operator or engineer supervising the mixed packaging process.

The proposed architecture allows for the loose coupling of various software and hardware components, through virtualization, with the data flow managed by and going through a central communication broker. The broker provides basic information to the connected apps, stores the main data model used, and includes the routing map containing the apps specific IPs. Moreover, the broker can record the requests from each application, hence ensuring that all the requests are answered. The purpose of the broker is to provide an agnostic middleware among the services of the system, enabling horizontal and vertical scalability.

4. Implementation

A prototype software system has been developed to test the applicability of the proposed approach. A high-level conceptual architecture of the implemented system is illustrated in **Figure 3**.

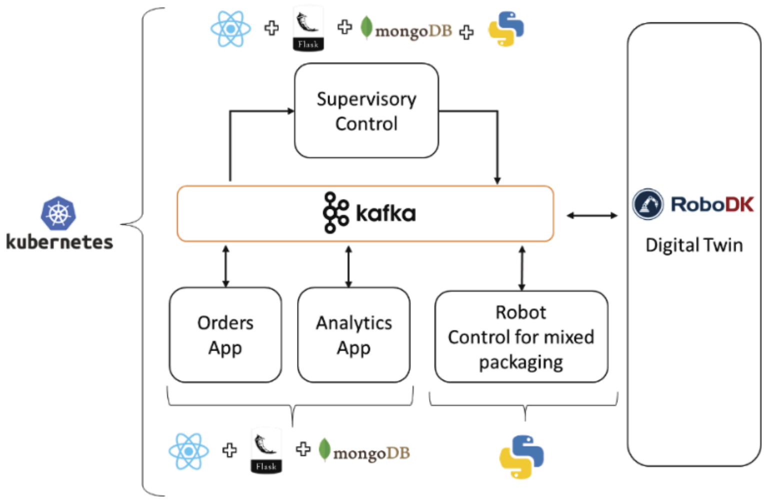

Figure 3. System's implementation.

The orders app oversees creating the mixed packaging order consisting of one or more recipes. On the server-side of the application, the Flask framework and Python 3.9 were used. The front-end has been developed using React JS, a JavaScript library for user interfaces developments. Moreover, the front-end has been integrated with a Mongo

Database for the data storage and the communication accomplished through JSON format.

Python 3.7 and OpenCV function Hough Circles have been also used for the image processing software module using a camera to detect circles in an image.
Furthermore, the analytics' component is based on a Single-Page Web Application as well as on a client-server architecture that uses the technologies. The development of the supervisory component has been accomplished with error handling functions which have been developed in Python 3.9.

For the communication of the components, Apache Kafka 3.0.0 is used as a communication broker where the applications of the system exchange formally defined MQTT messages. Kafka is responsible for realizing the digital thread that will feed the implemented DT.

Finally, the digital model of the digital twin responsible for the pairing of virtual and physical processes has been implemented in RoboDK 5.3. The DT through the dynamic simulation tools of RoboDK and with the data arriving from the workstation through Kafka realized the DT which orchestrates the entire process through their docker containers which are deployed in a Kubernetes 1.9 cluster.

5. Case study

The implemented prototype has been tested and validated in a case study coming from the dairy industry. The challenge faced by dairy industries as well as by many food industries is the mixed packaging process of different products included in many sales packages and product bundles that include a mix of different products that can vary based on the customer. The current practice in the considered case study is that human operators select and place different types of food products in appropriate packages.

This work aims to enable an autonomous robotic station for mixed packaging of versatile dairy products, resulting in increased productivity and efficiency. Moreover, a rather old robot has been selected to investigate the feasibility of granting advanced features and autonomy to existing industrial automation that do not inherently possess such smart features and autonomous capabilities. In particular, for testing and validation purposes, an industrial UR10 CB2 collaborative robot, safe for testing and demonstration, has been used with a 2F-85 gripper by Robotiq.

The scenario concerns the autonomous mixed packaging of two different dairy products, with a vision system to monitor the packaging process. The user can create an order and multiple recipes through a user interface the Mixed Packaging Orders UI, choosing the order the packaging size, the number of the packages and the number of each specific product and then, in collaboration with the tracking camera on the robot, it will place the products in the correct position inside the product bundle, after picking them up with the robot gripper. Ultimately, each product package will contain a specific number of products with classic and fruits flavors. Finally, the DT will be used to initialize the entire system, with all its software components, generate the initial robot trajectories, control the operational status of all connected components of the testbed and orchestrate the overall procedure. This is performed offline in a matter of 5-7 minutes and when the products to be packaged arrive at their initial picking position.

A high-level design of the testbed area created for the automated mixed packaging of dairy products of a different type, signified with different colors, fruits (red) and classic (green), is illustrated in **Figure 4**.

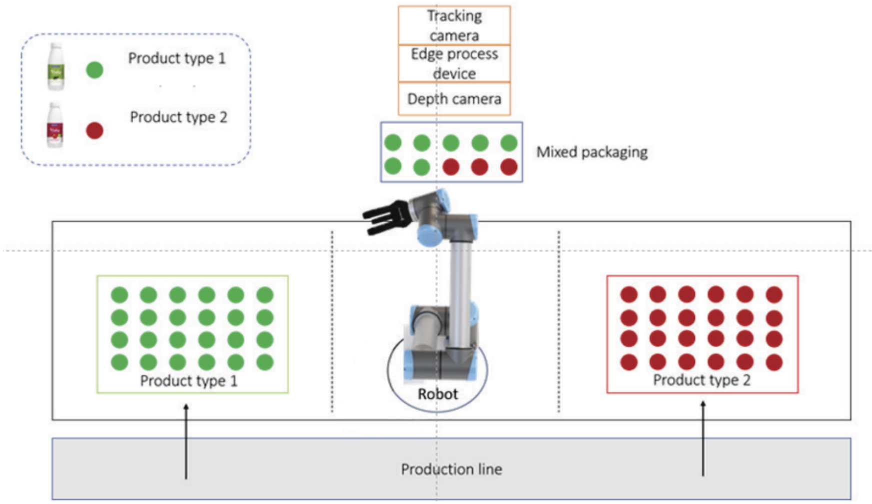

Figure 4. Case study schema.

In particular, the procedure starts with a human user creating a mixed packaging order with two different recipes through the corresponding UI **(Figure 5)**, choosing for each recipe the packaging size, the number of the packages and the number of each specific product type in the final package, the user chooses to make 5 packages with the size of 6x3, indicating that each package will contain 6 dairy products with fruits flavour (red bottles) and 12 dairy products with classic flavour (green bottles).

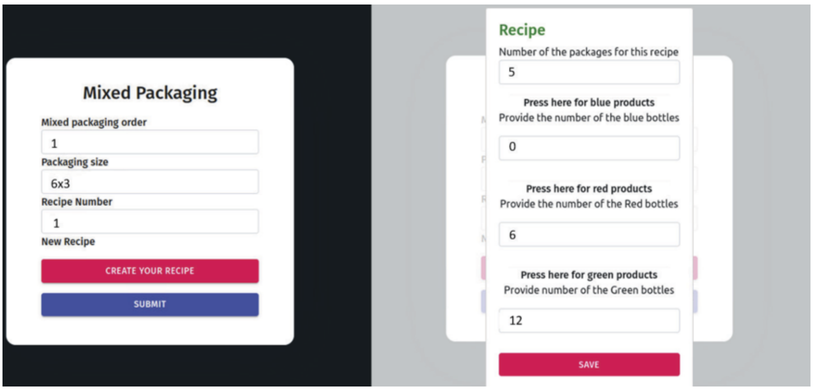

Figure 5. Orders UI.

A depth camera is used to recognize two different products in boxes containing product types 1 and 2. After the bottles' identification and their coordinates' extraction from the software module, the DT evaluates and reconfigures the mixed packaging process accordingly **(Figure 6)**. The DT simulates the entire process according to the defined recipe and the given coordinates, making the entire system flexible, providing the ability for the system to be adapted to different types of products.

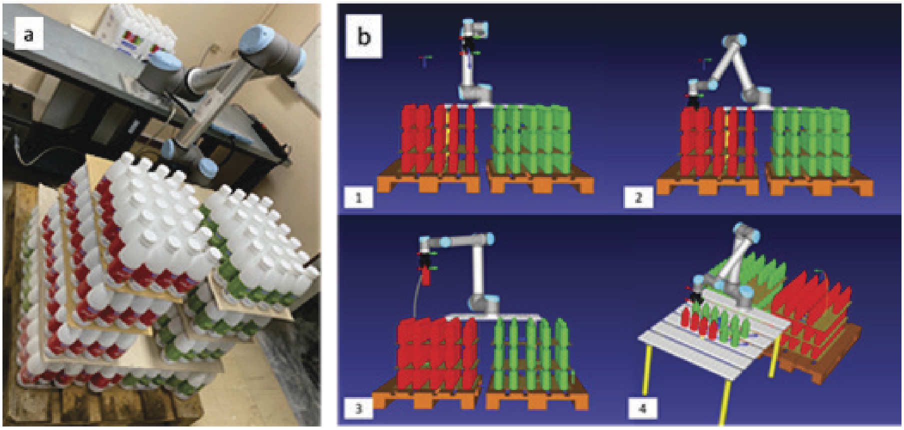

Figure 6. a) The physical environment b) The DT environment.

Through DT simulation, the gripper can be easily reconfigured before making any mistake in picking and placing in the real world. Consequently, the robot starts the packaging procedure only after a successful simulation.

After the simulation and validation of the mixed packaging procedure by the DT, the process starts. Next and as data arrive at the digital twin through the digital thread, implemented by the Kafka broker, new actions may be generated by the DT self-adapting to newly-arrived constraints, such as selecting a faster trajectory based on the actual time that was consumed by the robot.

6. Results

The approach performance was evaluated based on a) the percentage, of products that fell during mixed packaging with and without the use of the DT component facilitating for the gripper reconfiguration and adaptation to the new product and its position and b) whether it was feasible to switch from kefir bottles to yoghurts autonomously and without human intervention.

The results concerning a) are depicted in Table 1. In particular, the first two columns indicate the order number and the order id. Then, the last two columns indicate the percentage of bottles that fell during the mixed packaging process with and without using the DT.

Table 1. Percentage of bottles fall with and without the use of the DT.

Orders	Orders ID	Without DT	With DT	Results
1	101	30%	10%	-20%
2	102	2%	5%	-17%
3	103	32%	12%	-20%
4	104	35%	18%	-17%
5	105	31%	30%	-1%
6	106	18%	20%	+2%
7	107	30%	12%	-18%
8	108	27%	20%	-7%
9	109	33%	23%	-10%
10	110	34%	15%	-19%

In addition, the suggested approach has been tested and validated in a second mixed packaging scenario. In particular, the experiment concerning the packaging of two different types of products, especially yoghurts and kefir bottles. The purpose of this experiment is to present the gripper's adjustment to different products and whether the DT will reduce the amount of dropped products by simulating the gripper's opening. Table 2 presents, in the third and fourth columns, the percentage of dropped products with and without the DT. The fourth column calculates the difference.

Table 2. Percentage of products (yoghurts or kefir bottles) that fall without the use of the DT.

Orders	Orders ID	Without DT	With DT	Results
1	311	40%	26%	-14%
2	312	36%	31%	-5%
3	313	22%	23%	+1%
4	314	55%	31%	-24%
5	315	21%	17%	-4%
6	316	33%	21%	-12%
7	317	14%	18%	-4%
8	318	29%	21%	-8%
9	319	41%	28%	-13%
10	320	23%	14%	-9%

Regarding b_ and the autonomous transition from one mixed packaging procedure to the next one with different product and picking constraints it was performed after some dynamic simulations for selecting the best-fit robot and gripper parameters. This procedure required approx. 3.7 minutes which included the simulation and validation time in RoboDK along with the data transfer to the UR10 controller and until it started moving.

7. Discussion

Regarding the contribution of the software automation to the mixed packaging procedure, according to the results of the first experiment with the use of the DT model and the gripper's reconfiguration before pick and place in the real world, the percentage of bottles not getting picked properly and thus resulting in dropping can be reduced up to 20% approximately, thus reducing the cycle time of the packaging process. In the second scenario, a higher value regarding the reduction of dropped products was observed. Specifically, the value that has been observed was more than 24%. This result validates that the system is more efficient in the case where the type of the product is different. However, in some orders, an increase in the number of bottles that drop has been identified in both experiments. In these orders, the products were in the corners of the pallets so the authors assume that the products could not be recognized correctly from the object detection module and as a result, the digital model of the product differs from that of the real world.

Considering the second part b) of the experiment, the use of the DT as a real-world model for orchestrating and making autonomous the mixed packaging process was successful. Furthermore, the use of an increased number of software solutions could automate significantly a rather old robotic manipulator and interconnect it with several software solutions and IoT components, granting it with advanced features, such as flexibility, autonomy, and therefore increased resiliency.

To transfer the prototype to an industrial setup, little changes would be required to the software of the mixed packaging process, mostly due to additional real-world constraints that would need to be considered. These concern mostly the robustness and stability of the overall solution. On the other hand, the hardware will need to change significantly for any industrial application especially the robotic manipulator. A delta robot would be preferred whose speed could pose challenges for the software components, and especially their processing times.

Finally, it is noteworthy that with the use of Kubernetes the software can be directly deployed to production with minor changes as well as can be maintained remotely.

8. Conclusion

This work discusses a DT-centered methodology for enabling the autonomous and reconfigurable mixed packaging process. The DT focuses on the provision of a real-world model to orchestrate the process of mixed packaging of dairy products in an existing workstation equipped with a UR10 CB2 collaborative robot, granting it capable of autonomously performing mixed packaging operations. New constraints and requirements mandated by new product types and/or different production orders are mapped in the cyber part of the mixed packaging CPPS where different handling and packaging scenarios are evaluated by the packaging station DT. Upon validation, the system proceeds with the execution of the packaging process. A software system was implemented to test the proposed approach supporting scalability while being technology agnostic and neutral apart from core services. A testbed was implemented concerning a mixed packaging case study coming from a dairy industry with the preliminary experiments indicating the feasibility of the proposed approach as well as increased efficiency of the mixed packaging process with the use of the DT component as evaluated in terms of bottle falls, due to lack of proper handling processes.

Nevertheless, the capability of mapping newly arrived components to the DT environment is currently limited while their association to physical behavior is complex. In this direction, further experimentation and research are required.

As a next step, regarding the use case, the authors will focus on upgrading the DT and testing with a faster robot as well as a custom-made gripper, capable of handling multiple similar products simultaneously. Furthermore, regarding the DT, it is within the authors' intentions to use it for predicting and avoiding potential collisions of the robot during the pick and place procedure. Subsequently, further experiments performance, additional effort, and optimization are needed to be applied in the overall system so that it can be ready to be moved to the industrial environment of the corresponding industry and be tested in real-world conditions.

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