Cooperation and Synchronization of Robotic Tasks Using a Digital Twin

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Abstract: Industry 4.0 marks a significant advancement in the manufacturing process by integrating advanced digital technologies. Robotics is one of the nine pillars defining the contours of Industry 4.0. These robots must be able to perform tasks safely, especially when working simultaneously in shared areas. However, robots only have a partial view of the production environment and need to communicate with each other to obtain more extensive information. To facilitate the exchange of information and ensure safety during the process, we can use a digital twin that contains information on the layout of the production system and is tasked with converting and transmitting part position information from one robot to the other. The communication between the robots is realized thanks to the OPC UA communication protocol. The effectiveness of this strategy is illustrated on a robotic platform constituted by two 6-axis Niryo Ned robots associated with their digital twin.

1 INTRODUCTION

Industry 4.0 represents a significant leap forward across the entire manufacturing chain (Wanasinghe et al., 2020), (Bajic et al., 2021). This new era is characterized by the integration of advanced digital technologies, to control cyber-physical systems for example, to enhance operational efficiency but also to redefine the capabilities of industrial automation. Cooperative robots are components of Industry 4.0, which work alongside human operators to enhance productivity and efficiency. Robots are designed to be highly adaptable allowing them to perform various tasks ranging from simple repetitive actions to complex, precision-oriented processes.

In the framework of Industry 4.0, robots are integrated into a smart factory environment where they can communicate with a network of interconnected machines and systems. This connectivity allows for real-time data exchange and decision-making, leading to more efficient production processes. For instance, robots can automatically adjust their operations based on their sensor's data, ensuring optimal performance and minimizing errors.

Moreover, the use of robots in manufacturing can address the growing demand for customized products. Indeed, by rapidly reprogramming robots, manufacturers can switch between different product lines without significant downtime. Resource management and optimization of robot arm trajectories to minimize energy consumption contribute to more environmentally friendly production processes (Barenji et al., 2021), (Mohammed et al., 2014). In addition, robots can perform repetitive or hazardous tasks for human workers, improving workplace safety and reducing the risk of injury.

Cooperation and synchronization among robots hold significant potential across various industries. By working together, robots can complete tasks more efficiently and accurately than a single unit. This collaborative approach allows for task division, where each robot can specialize in specific tasks, leading to enhanced productivity and reduced completion times. Additionally, by sharing real-time data, robots can adapt to changing conditions and correct errors more quickly by defining new tasks according to this new situation. This robotics cooperation leads to faster, more accurate results and increased productivity across various applications.

However, with several robots operating in a shared work area, the various production tasks must be synchronized to avoid collisions. This constraint complicates the design of the controller and extends the development time, which is problematic in Industry 4.0, where production changes are frequent and con-

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trol configuration changes must be made as quickly as possible to limit production downtime.

In this context, the use of a digital twin for coordinating tasks among multiple robots offers many advantages. A digital twin is a virtual replica of a cyber-physical system that allows real-time monitoring and simulation (Barricelli et al., 2019). By employing digital twins, robots can be coordinated more effectively, as the virtual model provides a comprehensive overview of the entire operation. This enables precise task allocation, ensuring each robot performs optimally. Real-time data from the robots is fed back into the digital twin, allowing for dynamic adjustments and continuous improvement. This enhances synchronization among robots, reducing downtime and improving overall productivity. Furthermore, digital twins can facilitate better resource management by optimizing robot trajectories and minimizing energy consumption. Integrating digital twins in robotic coordination and synchronization leads to more efficient, accurate, and adaptive manufacturing processes.

In this work, a digital twin approach is used to improve synchronisation and information exchange between two robots using the same work area. A pallet containing two types of parts arrives at the robots via a conveyor belt to be disassembled. Each robot is responsible for one type of part and only one robot at a time can operate in the area. In addition, there is only one camera on one of the robots, so the other robot must receive information about the parts' position to carry out its task.

To facilitate the exchange of information and ensure safety during the process, we use a digital twin that contains information on the production system layout and is tasked with converting and transmitting part position information from one robot to the other. The digital twin provides an overall view of the production area, unlike robots, which only have a partial view based on information from their sensors. The contribution of this paper is to show how a digital twin can be used to facilitate the cooperation and synchronisation of robots thanks to its overview and the use of the OPC UA communication protocol.

This paper is organized as follows. Section 2 provides a brief overview of the use of a digital twin in robotics applications. Section 3 describes the robotic platform, the digital twin and its relevance to this application, as well as the communication protocol between the digital twin and the platform. Section 4 is devoted to experiment results, illustrating the strategy's effectiveness. Conclusions and future research are given in the last section.

2 DIGITAL TWIN AND ROBOTICS

The development of digital twins for robotics is one of the areas that has seen growing interest from researchers and manufacturers, particularly for modelling and simulation, data management, and bringing intelligence and connectivity to production systems to support the transition to Industry 4.0 (Liang et al., 2022).

The authors in (Wu et al., 2022) propose the use of a digital twin to compensate for the positioning errors of a robotic arm. A position sensor is added to the robotic arm to communicate to the digital twin the actual position via Websocket. By comparing the information from the robot and the sensor, the digital twin can adjust the position if it detects a significant deviation.

A digital twin integrating resource information, sensor information and layout information is proposed in (Kousi et al., 2019) to adapt the behavior of mobile robots in real time. The authors have defined a data model to reconstruct the 3D environment and enable real-time trajectory adaptation. However, the components exchange information via the Robot Operating System (ROS) interface, making it more complex to integrate non-robotic components into the digital twin.

Digitilization and simulating a robot in a software environment makes it possible to use artificial intelligence (AI) techniques to train or optimize before or during task execution. Reinforcement learning is used in (Matulis and Harvey, 2021) to train a robotic arm with six degrees of freedom for a pick-and-place application. In (Bansal et al., 2019), the authors have developed an ant colony algorithm to avoid collisions in an assembly task performed by an industrial robot. A genetic algorithm is used in (Liu et al., 2022) to optimize the trajectory of a mobile robot using real data from the physical robot. Several partial models are integrated into a common model in (Erkoyuncu et al., 2018) to provide information for a learning model. The model embedded in the digital twin enables the exploration of various scenarios and real-time decision-making.

A digital twin of a 6-axis robotic arm has been developed in previous work to perform virtual commissioning and improve robotics learning (Sow et al., 2023). This paper extends the functionality by including the digital twin in real-time production for synchronisation and information transmission. The new architecture of the digital twin is described in the next section.

3 METHODOLOGY

In this section, we briefly present the robotic platform, the digital twin and the network protocol, as well as the Environment Layer required for robotic tasks.

3.1 Robotic Platform

The robotic platform consists of two 6-axis Niryo Ned robots (Niryo, 2024) and a conveyor belt (see Figure 1). Each robot has a suction cup at the end of its arm, enabling it to pick up an object. A camera is placed on just one robot to observe its environment. Using image processing, it is then possible to detect objects and determine their characteristics. The robots have different tasks to perform depending on the type of object.

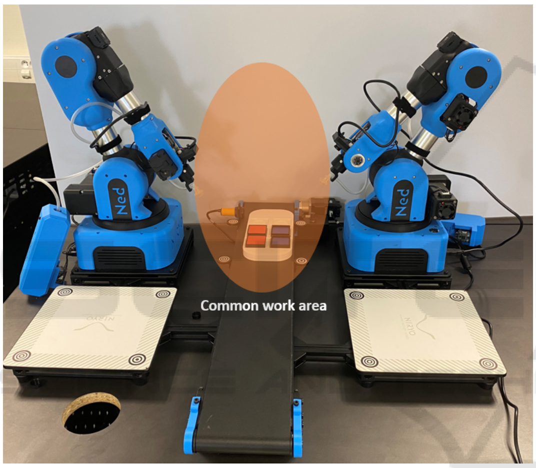

Figure 1: Flexible manufacturing system.

Table 1 shows the ranges and speed limits of the six Niryo Ned joints. In the case study presented in Section 4, the speed is voluntarily limited to 60% of the maximum value to reduce mechanical wear, particularly on the belts, which is one of the main causes of failure.

3.2 Digital Twin and Protocol Network

Figure 2 shows the architecture of the digital twin, which consists of three layers:

- The Simulation Layer acts as an interface with the user, who can visualise robot movements in a simulated environment. It receives the position of the physical robot joints and copies the trajectories in real time.
- The Environment Layer contains information about the layout of the flexible manufacturing system. By receiving information about the position

Table 1: Parameters of the robotic arm.

Joint (type : rotation)		
N°	Range	Speed limit
1	$-170° \leqslant \theta_1 \leqslant 170°$	$\dot{\theta}_1 \leqslant 150°.s^{-1}$
2	$-120° \leqslant \theta_2 \leqslant 35°$	$\dot{\theta}_2 \leqslant 115°.s^{-1}$
3	$-77° \leqslant \theta_3 \leqslant 90°$	$\dot{\theta}_3 \leqslant 140°.s^{-1}$
4	$-120° \leqslant \theta_4 \leqslant 120°$	$\dot{\theta}_4 \leqslant 180°.s^{-1}$
5	$-100° \leqslant \theta_5 \leqslant 55°$	$\dot{\theta}_5 \leqslant 180°.s^{-1}$
6	$-145° \leqslant \theta_6 \leqslant 145°$	$\dot{\theta}_6 \leqslant 180°.s^{-1}$

of the parts on the pallet, it updates this information for all the robots according to their reference frame.

- The Communication Layer provides the interface between the robots and the digital twin's layers thanks to an OPC UA server.

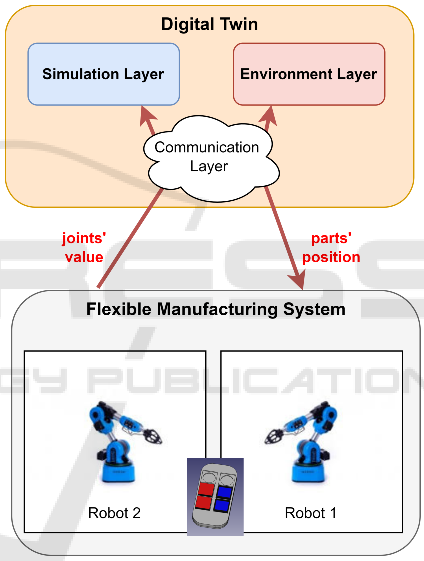

Figure 2: Global architecture.

Unlike many articles that used ROS services to communicate between the physical robot and the digital twin, we use the OPC UA protocol, which is increasingly used in industrial automation. This protocol uses the client-server and publish-subscribe principles and offers a high level of interoperability for communication between systems from different suppliers. In our case study, the production system is composed entirely of robots, but a cyber-physical production system is composed of heterogeneous components which may have different communication protocols. OPC UA's advantage over ROS is that it is easier to integrate non-robotic components such as conveyors or cylinders into the digital twin, which better reflects a real production system. In addition, one of the major problems in integrating digital twins is designing the data model to enable communication. OPC UA offers the possibility of creating information models, and working groups are developing them to create standardisation. In robotics, there is the OPC UA Robotics Companion Specification, which defines a data model for describing the motion device system, so that information from a robot can be passed up to the upper layers of a manufacturing system, such as the cloud.

Finally, the authors in (Profanter et al., 2019) find that the OPC UA protocol is faster in real-time communication than ROS, which is a significant advantage in our use of the digital twin for information transmission.

3.3 Environment Layer

The Environment Layer is fundamental to our approach to synchronizing and transferring information between robots, thanks to its global vision of the system. The robots' perception is restricted by their sensors: they only know their arm position thanks to the joints' value, but they do not know where they are located concerning the other components of the system. The controller authorises all movements within the limits of the joint angles, although there may be common working areas where there is a risk of collision if there is no synchronization.

Moreover, in our example, one of the robots is under-equipped with a sensor, as it does not have a camera that can locate parts for its pick-and-place task. Therefore, cooperation is not only limited to authorizing access to the work area but also to transmitting the position of parts from the robot with the camera. However, each robot has its reference frame, which means that the position of a part sent by one robot to another requires a change of reference frame.

The Environment Layer overcomes these problems by incorporating robot positions with production system layouts, making it easier to design the control system and quickly identify conflict areas. Figure 3 shows the Environment Layer flowchart. Initially, a file containing the location of all system components is imported into the application when the system is designed, to calculate the changes in robot reference points. During production, the Environment Layer receives the parts position from the robot with the camera and converts it into the frame of the robots that need it. Then, the layer synchronizes the robots' tasks according to their states.

Control adaptability is enhanced by the automatic conversion of part position from one robot to another. When a robot's location is modified, the Environment Layer must be updated to reflect the new system configuration. Knowing the relative position between the robots, the layer then adjusts the reference frame change to the new robot position, which resumes its pick-and-place task without having undergone any code modifications.

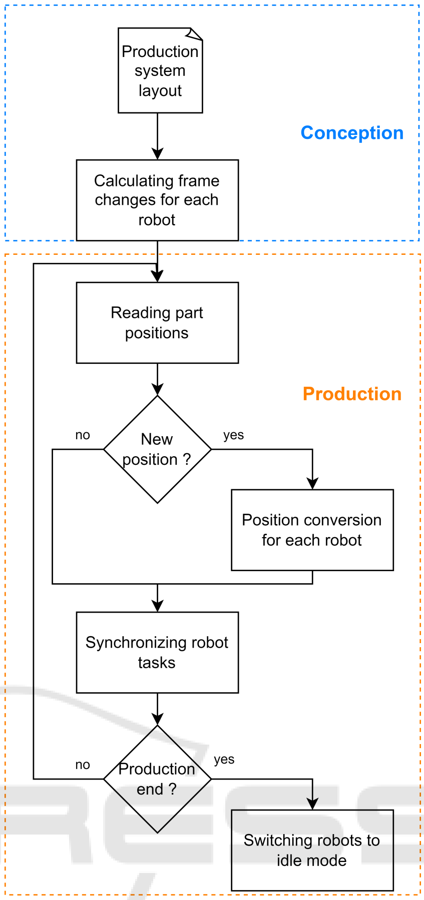

Figure 3: Environment layer flowchart.

4 RESULTS AND DISCUSSION

In this section, we present different scenarios to illustrate the gains in production time and energy consumption of the real system that can be achieved by using the digital twin.

4.1 Case Study

This section shows the results obtained using the robotic platform presented in the previous section. Figure 4 details the hardware and software components for implementing the cyber-physical production system:

- The flexible manufacturing system consists of two

Niryo Ned robots, a conveyor and a presence sensor. Each robot is controlled by a Python program developed using the PyNiryo library and executed by their Raspberry Pi;

- The digital twin's Simulation Layer is implemented on the Webots software to monitor the robots' movements in real-time using an OPC UA client (Webots, 2024) ;
- The digital twin's Communication Layer is implemented using Prosys OPC UA Simulation Server software. This layer establishes the interface between the various elements of the system by implementing an OPC UA server (ProsysOPC, 2024) ;
- The digital twin's Environment Layer is implemented with a Python script that converts the robots' positions and synchronises the robotic tasks.

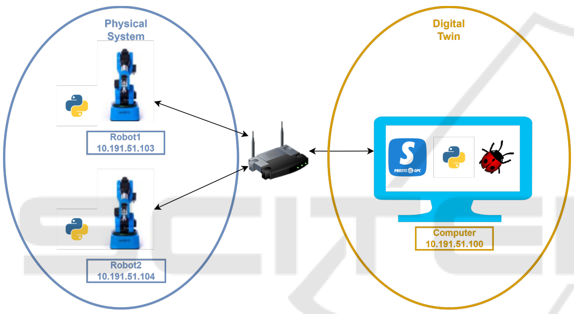

Figure 4: Architecture implementation.

Three scenarios are evaluated to illustrate the interest of the approach proposed in this paper. Four different parts are arranged on a pallet and forwarded to the robot work area on a conveyor belt. In the three scenarios described below, the aim is to pick-and-place some parts according to their characteristics. For all figures, the plots start when the presence sensor detects a pallet and stops the conveyor belt. In an inertial reference frame associated with the base of i-th robot, $\overrightarrow{O_iM_i}$ represents the position vector of i-th robot between the origin of the reference frame and the point associated with the suction cup tip of i-th robot. $||\overrightarrow{O_1M_1}||$ and $||\overrightarrow{O_2M_2}||$ denote respectively the magnitude of the position vector of Robot 1 and Robot 2.

Scenario 1 (Sc1): In this first scenario, each robot is equipped with a vision set to locate on the pallet the parts to be picked up and placed onto a dedicated platform. In this case, the two robots work independently to avoid any risk of collision. The first robot performs all its tasks before sending a signal to the second robot so that it can perform its tasks (see Figure 5). Each vision set associated with a robot checks

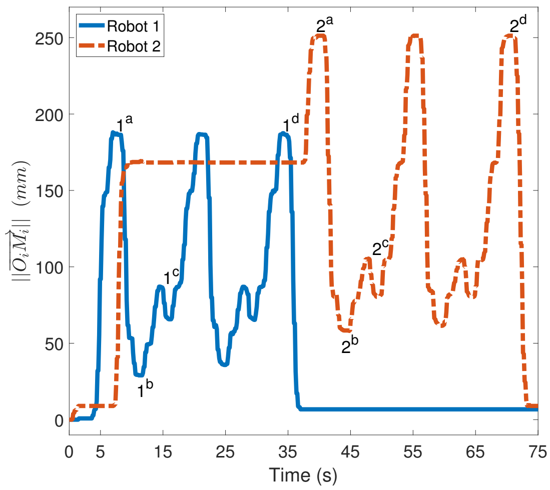

Figure 5: *(Sc1)* Robot 1 : $||\overrightarrow{O_1M_1}||$; Robot 2 : $||\overrightarrow{O_2M_2}||$.

to see if there are any parts left on the pallet, which means that the scenario takes a long time, with unnecessary movements and long image processing times. Figure 5 shows three cycles for Robot 1, followed by three cycles for Robot 2. Peaks 1^a and 2^a appear when the robots are in a high position, above the pallet, to locate parts. When the vision set associated with each robot detects a part with certain established characteristics, the suction cup at the end of the robot arm picks the component (peaks 1^b and 2^b) and places it on the dedicated platform (peaks 1^c and 2^c). For each robot, after peaks 1^d and 2^d, the robots return to their initial position, as no more parts are present on the pallet to pick. One can notice that to pick-and-place the four parts, the process time is about $75s$.

Scenario 2 (Sc2): In the second scenario, cooperation between the two robots is introduced to enable them to work simultaneously. A shared work area in which only one robot can operate at a time is defined to ensure that only one robot can pick up a part at a time and ensure collision-free synchronisation. If the area is occupied by the other robot, the robot must wait for authorization from the digital twin before picking up a part. Moreover, Robot 1 informs the digital twin of the parts presence to be picked up by Robot 2. Figure 6 shows that the robots take it in turns to pick up parts: while one robot places a part in the drop zone, the other picks up a part and so on until there are no more parts to pick up. This scenario minimizes the time during which the work area is not used by any robot and limits unnecessary movements, reducing process time by 40% compared to the first scenario.

Scenario 3 (Sc3): In the final scenario, we assume that only Robot 1 is equipped with a vision set. The level of cooperation has been increased compared to Scenario 2, as Robot 1 no longer simply informs the dig-

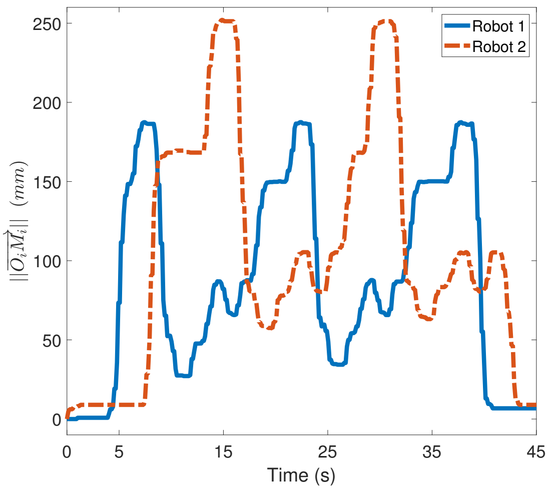

Figure 6: *(Sc2)* Robot 1 : $||\overrightarrow{O_1M_1}||$; Robot 2 : $||\overrightarrow{O_2M_2}||$.

ital twin that there are parts to be picked up by Robot 2, but also provides the position of the parts. This scenario uses the Environment Layer of the digital twin, as described in subsection 3.3, to transmit and convert part positions from Robot 1 to Robot 2. Figure 7 shows that the part picking alternates as in Scenario 2. The main difference is that the movements of Robot 2 are significantly reduced, as it does not need to scan the pallet using its vision system. In addition to the 56% reduction in process time compared with Scenario 1 and 27% reduction compared with Scenario 2, we can notice that Robot 2 consumes less energy than the previous scenarios by making fewer movements in this scenario (see Table 2).

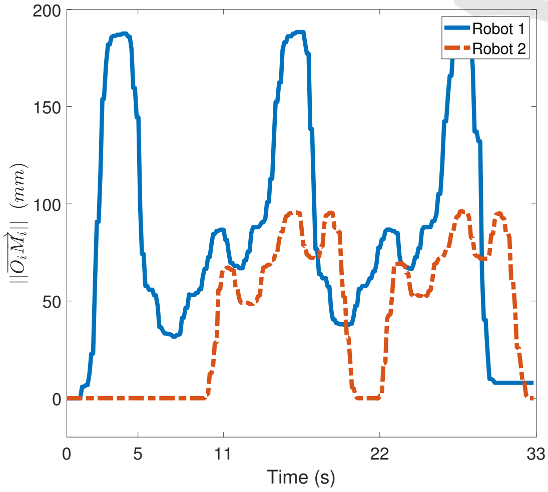

Figure 7: *(Sc3)* Robot 1 : $||\overrightarrow{O_1M_1}||$; Robot 2 : $||\overrightarrow{O_2M_2}||$.

Table 2: Distance comparison.

Scenario	1	2	3
Robot 1 (m)	1.1024	1.0881	1.0624
Robot 2 (m)	1.3984	1.0724	0.556
Robots 1 + 2 (m)	2.5008	2.1605	1.6184
Improvement (%)	-	-13.61	-35.28

4.2 Discussion

The sum of cooperation, the global vision provided by the Environment Layer and the data conversion carried out by the digital twin have improved productivity and reduced energy consumption in our pick-and-place application. Table 2 compares the distance covered by the end effector of the two robotic arms in the three scenarios presented in the previous section. The first two rows of the table provide the distance covered by each robot arm, and the third row shows the sum of these two distances. Finally, the last row shows the improvement in terms of distance covered in scenarios 2 and 3 compared to scenario 1. One can notice a decrease in the total distance covered by the two robot arms of 13.61% in scenario 2, and a decrease of 35.28% in scenario 3 compared to scenario 1. These results illustrate the effectiveness of the proposed approach.

In the customised production context, production systems are subject to frequent configuration changes, which may include layout rearrangements. These modifications lead to the development of new robot controllers by updating the new pick-and-place positions. In our approach, simply updating the locations of the robots in the Environment Layer is enough to adapt the control without modifying the robot code. More generally, the aim is to link information from the production environment to the control systems to simplify modifications using the Environment Layer.

The Environment Layer provides additional information to which robots have no access via their sensors. This information gives the robots a broader view, making them more robust to failures. There are two advantages to transferring decision-making to the digital twin: on the one hand, the robot can devote its computing capacity to optimizing its trajectory, and on the other, the digital twin can optimize tasks between the various robots in the system thanks to its higher computing capacity.

5 CONCLUSIONS

In this paper, we have proposed a methodology showing the benefits of using a digital twin for the cooperation and synchronization of robotic tasks. Our approach is fully in line with Industry 4.0, using technologies such as the OPC UA protocol, which enables interoperability and using machine vision with image processing. In fact, by centralizing all the data required to perform the tasks of each robot, the digital twin can reconstruct the working area and thus control each robot even if this last has a faulty sensor. Moreover, thanks to the knowledge of this working environment, the movement of each robot arm is minimized, thus reducing energy consumption and mechanical wear.

Future research will focus on developing a decision-making layer in the digital twin, which will be responsible for planning robot tasks and optimising image processing. In our case study, the robots receive the position of the parts to be picked and autonomously choose which one to pick. The decision-making layer currently under development will indicate the most efficient sequence of movements for each robotic arm, to save even more time and energy.

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