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Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 232 (2024) 1121–1130
Procedia Computer Science
www.elsevier.com/locate/procedia

5th International Conference on Industry 4.0 and Smart Manufacturing

Exploring the limitations and potential of digital twins for mobile manipulators in industry

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Abstract

This paper explores the qualification of a digital twin (DT) for a mobile manipulator (MOMA) in industrial applications. We discuss the development of different DT models based on various industrial needs and highlight the dependence of model accuracy on online sensor precision. Limitations of DTs for MOMA are examined, including challenges in respecting qualifiers due to the inability to incorporate unstructured aspects of the factory environment. Through a case study and some examples, we show the latent potential and limitations of DTs for MOMA in industrial contexts. The challenges of fidelity, real-time operation, and environment modeling are discussed. It is emphasized that creating a true digital twin of a mobile manipulator is hindered by the inability to include the complete surrounding environment. Recommendations for future research focus on addressing these limitations to enhance the effectiveness of DTs for MOMA in Industry 4.0 and smart manufacturing.

Keywords: Digital twin; Mobile manipulator; Industrial applications; Robotics

1. Introduction

It is considered as established knowledge in manufacturing that robotic technologies such as cobots and mobile robots are enabling technologies for Industry 4.0 (I4.0) [1]. Alongside these innovations, the concept of the digital twin (DT) has gained significant attention for its potential to revolutionize industrial processes by providing virtual representations of physical systems [2, 3]. In particular, the use of DTs for mobile manipulators (MOMA), robotic systems capable of movement and manipulation, has shown promise in a variety of industrial applications [4, 5, 6]. However, the development and qualification of a DT for a MOMA is not without its challenges.

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1877-0509
10.1016/j.procs.2024.01.110

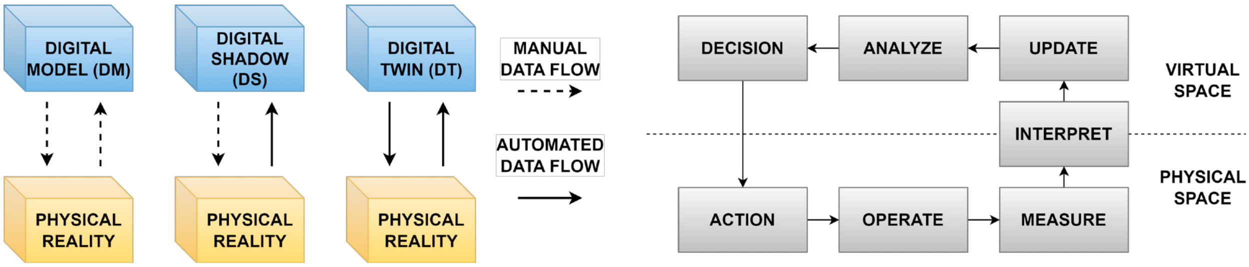


Fig. 1: Explicit description of the activities performed in physical and virtual space to achieve a fully functioning DT.

In this paper, we explore these challenges and discuss its potential and limitations in industrial applications. Some of the most relevant include the process of implementation, which is not straightforward and requires careful planning. The required level of accuracy for specific qualifiers might also change, and this currently represents one of the main points of discussion, and a topic we will address in this work.

It is worth defining the terms "digital model" (DM), "digital shadow" (DS) and "digital twin" to properly contextualize the goal of the study. The three definitions refer to the stages characterizing the digitization of a physical system. For years, a common definition of such terms has been elusive, also due to the variety of focused areas within disciplines. However, efforts of categorizing relevant literature offered a common definition prop, based on the contrast between the levels of integration [7]. The DM cannot send or receive data from the physical object, as it primarily comprises a 3D virtual representation. However, the scope can extend beyond geometry, including relational information, operational insights, and design-wise meta details, providing a more comprehensive understanding of a system's behavior, and interactions. This expanded concept of a digital model contributes to more accurate simulations, informed decision-making, and enhanced collaboration among teams. Data flow back to the real object is not possible at this stage. On the other hand, a DS can interface with the real system and receive and process information that has already been obtained, as well as manage information that is received in real time. A DT includes the final link between the virtual and real worlds, allowing data to be exchanged in both directions. It uses a combination of data, models, and algorithms that simulate the behavior, performance, and characteristics of the corresponding physical entity in real or near-real time, and is continuously updated to reflect the current state of the physical system [8]. Figure 1 provides a visual explanation of the three settings, and clearly shows the main differences.

The purpose of this paper is to discuss the qualification process of a DT of a MOMA for industrial applications. A case-study at the Department of Management and Production Engineering at the Polythecnic University in Turin is brought as an example. An example is shown in a laboratory setting to study the accuracy in different qualifiers and to test a variety of environmental settings where the MOMA could operate in real-life scenarios. While the concept of a MOMA serves as the motivating aspect of this study, it's important to clarify that this paper's focus will be specifically directed towards the mobile robot component. This work aims to present the mobile robot aspect, to stir potential future research that can address the broader scope of a full MOMA system. Section 2 presents different applications of DTs to examine the current state of the art; Section 3 outlines the hardware and software utilized in the experimental setup; Section 4 describes the case-study and briefly covers the accuracy question; Section 5 discusses the limitations of employing DTs; Section 6 concludes the paper with a brief summary of the topic.

2. Digital Twin models for different applications

Digital twin models have emerged as a valuable tool for enhancing the efficiency of production systems in industrial settings. DTs bridge the gap between the physical and virtual worlds, enabling real-time monitoring, analysis, and optimization of performance. In this section, we describe some applications, specially focusing on mobile manipulators. We explore how each needs the development of models with distinct characteristics and examine the potential of combining them with other Industry 4.0 technologies. The applications in robotics overlap with the applications of robot simulation, whether kinematics or dynamics. However, a key difference between a DT and a simulation lies in the representation of the state of a physical system. While a simulation predicts future states based on a set of initial assumptions, a DT tracks the actual states of a specific instance of the system in operation [8]. The computational models used to infer the current state of a DT are often the same used in simulation to predict future states – and the application can extend beyond industrial production [9]. This highlights the close relationship between digital twins and simulation models, and the potential for these two approaches to complement each other.

Van Der Horn (2021) [8] lists the mandatory qualifiers of DTs: the virtual representation is a single instance of a physical system. The information from the real world is used to update the state of the virtual representation over time. There are other qualifiers that are important in specific applications: the fidelity to the physical twin, the possibility to operate in real-time, the level of detail in the reproduction of the operating environment. The process of implementing DTs is not straightforward, requires careful planning and consideration, and high-level design decision making. It should include parallel steps such as outcome-driven design: the implementation should be guided by specific outcomes to determine the required level of accuracy for specific qualifiers. Therefore, the assessment of indicators depends on the searched outcomes: reducing costs and risk, improving efficiency and service offerings, security, reliability, resilience, and supporting decision-making, to name a few. Real-time capabilities may not be necessary, and fidelity may be limited in certain aspects. While the representation of the environment is necessary, its level of detail can be limited, and not consider mobile or non-permanent objects. Without any intention of being exhaustive, we mention some industrial applications of evident utility employing a MOMA.

Martinez (2021) [10] proposes a Digital Twin Demonstrator to supervise flexible manufacturing with robotics, using Human-Computer-Machine Interaction. A case study evaluates the approach to show the enabling of close-to-real-time supervision, allowing the system to adapt to changes. Antonelli (2022) [4] implements an intelligent monitoring system of a MOMA on board, utilizing data gathered online and Machine Learning (ML) for the optimization of energy recharging cycles. Similar objectives of optimizing energy efficiency have also been studied without utilizing a MOMA [11]. Zhou et al. (2022) [6], develop an initial prototype of a DT with integrated dynamics for an industrial mobile manipulator, and couple it with a dynamic model to consider the interactions between the physical robot, human, and the environment. Several other industrial applications lead to the development of models, which may or may not involve a MOMA or comparable configurations. To exemplify, predictive maintenance involves a DT that can be used to monitor the condition of physical resources and predict potential failures. By analyzing real-time sensor data from the physical counterpart, the DT provides insights into the health and performance of the system, enabling proactive maintenance and minimizing downtime [12]. It is possible to achieve on-line monitoring of the robot's speed for safety measures to predict failures and safe stops, by monitoring the robot's parameters during collaborative activities through machine learning algorithms, thus increasing the reliability of the task and limiting the down times [5].

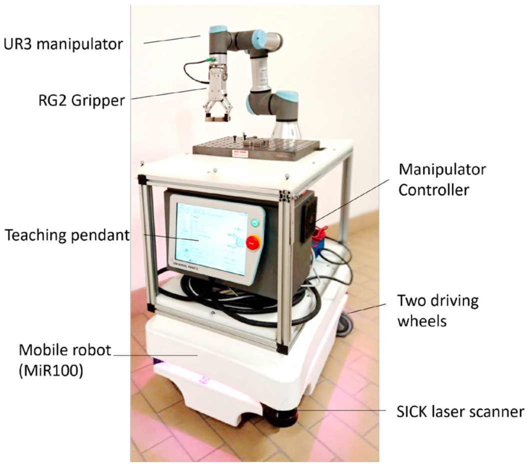


Fig. 2: Mobile Manipulator (MOMA) platform components at the Mind4Lab laboratory of Polytechnic University in Turin

All the previous application ultimately aim at process optimization, where the DT is employed to simulate and optimize manufacturing processes. By creating a virtual replica of the equipment and its surrounding environment, users can evaluate different parameters and configurations to identify the optimal process settings. On the other hand, they can also be utilized for training and simulation purposes: by creating realistic virtual environments, operators can acquire hands-on experience in operating robots and other machines in a safe and controlled setting. This approach minimizes the risk of accidents and allows for the refinement of operational procedures prior to implementation in the physical environment [13]. Also, this approach can be followed in combination with one other Industry 4.0 enabling technology, namely Augmented Reality (AR), or in some cases Virtual (VR) or Mixed Reality (MR), to provide industrial operators with an enhanced training experience that closely resembles the physical system. The main advantages are the reduction of the risk of potentially costly accidents and errors in real-world operations. Operators also gain familiarity with the characteristics of the system by interacting with its digital counterpart, and optimize their performance before taking action on the real industrial application [14].

DT models presents several applications where they can potentially improve production systems capabilities in industry. In robotics, particularly mobile manipulators, they are the first choice for companies to enable real-time monitoring, and optimization of performance. However, to fully unlock their potential, it is crucial to address the key challenges associated with them, that we briefly presented in this literature review. In the following section, we describe the critical aspect of accuracy in the case-study, and how we achieve the most accurate possible representation of the physical MOMA in that setting.

3. Experimental setup and methods

The MOMA system in Figure 2 consists of a robotic manipulator installed on a movable platform. The MOMA includes a six-dof robotic arm [15] with a two-finger gripper [16], and a mobile robot with sensors for object detection and environmental perception [17]. The mobile robot MiR100 includes four passive universal wheels and two active drive wheels with a DC motor. The perception system includes a SICK laser scanner and movement-based Inertial Measurement Unit sensors. The control system of the MOMA runs on an INTEL NUC PC and is responsible for the navigation control of the robot using an integrated algorithm to detect objects and obstacles.

ROS (Robot Operating System) includes tools and libraries that enables the programming and control of robots, and an interface for real-time communication between digital and physical devices. It supports 2D and 3D simulations through RVIZ and Gazebo, allowing the emulation of different scenarios to identify errors and potential risks. ROS Noetic is employed on the Ubuntu 20.04 operating system, on an Oracle VirtualBox. By designating the virtual machine as the master and the MiR100 as the slave, a connection is established, with bi-directional communication. This facilitates real-time commands to the mobile robot, as well as the displaying of data through specialized messages, such as current speed or position. Within ROS, methods are available to control the MiR, including: (i) *RVIZ*, with real-time mapping and elements detected by the sensors and laser scanner to indicate the presence of obstacles, allows the user to set a destination on the map and observe the representation of the robot moving in real-time, while the actual robot replicates the trajectory in reality; (ii) *Command line*, allows the posting of messages to relevant topics, such as a specific angular or linear speed, or a desired destination, by providing [x, y, ϕ] coordinates; (iii) *rqt_robot_steering* controller, enables the variation of speed using a joystick-like graphical interface. Figure 3 shows the MOMA's DT as represented in RVIZ, where yellow and red lines represent obstacles and walls. In the center of the map stands the MOMA and the green lines illustrate the path or trajectory within the environment.

Fig. 3: Map of the experimental area in RVIZ

Fig. 4: MOMA model in Optitrack Motive

Optitrack Motive provides a real-time 3D position tracking system. It uses markers on rigid bodies whose data are needed, along with eight infrared cameras, to capture and calculate the position relative to the Optitrack reference system, established through prior calibration. To ensure accurate identification, a minimum of three markers is required. The MOMA determines its position based on its map, which may not precisely reflect the measurements of the actual environment. In our case study, the Optitrack Motive serves as the verifying tool for the accuracy of digital and real models, since with proper calibration it reaches an error of approximately 530 μm, the most accurate representation that aligns with real-world measurements. Figure 4 illustrates the designed digital model of the MOMA within Mind4Lab, which is specifically created for conducting experiments. The figure showcases the digital representation of the MOMA system, capturing its structure, components, and overall layout in the laboratory environment.

Matlab with Simulink and Simscape is used to create the digital model. Simscape Multibody allows for a virtual 3D simulation environment using CAD models. An approximate replica of the lab and the MOMA is developed. Simulink is used to execute the appropriate actions, such as orienting or moving the robot. Simulink and Simscape are connected, allowing for the observation of the effects of signals sent by the controller on the 3D simulation environment. The digital model uses Stateflows to create a state machine, with a scheduler that coordinates the movements of the MiR and UR robots based on the case study. In our case, a pick-and-place operation is deployed, where an object is moved from A to B and then returned to the A. The two macro blocks controlling the MiR and UR are implemented in Simulink using MATLAB Robotics System Toolbox and Mobile Robotics Simulation Toolbox. MATLAB and Simulink enable communication with the ROS system through the 'ROS Toolbox', which facilitates real-time acquisition of MiR data, allowing to save and analyse them. By configuring the network settings to establish a connection between the control machine and the hardware on the same network, it is possible to publish messages on the topics shared with the MiR100, enabling it to perform precise actions in real time, such as reaching a specific point in the lab. Similar functionality can be achieved with the command line in the ROS virtual machine. Figure 5 displays the simulation environment within Matlab Simulink, where blocks, components, and connections are visualized. It provides a representation of the simulation and the interactions between elements within the Simulink environment.

Through the experiment we evaluate the accuracy of the DT, and assess the consistency with the real robot, and check the robustness of the system when obstacles are found. In a first set, we deploy a free of obstacles environment, and the robot is programmed to follow a trajectory, navigating between three specified positions in the environment (charging station, loading station, unloading station). The robot performs pick and place and then returns to its initial position at the charging station. During test runs, we collect data to evaluate the accuracy and correspondence between the real object (tracked with OptiTrack) and the virtual model (simulated and traced with data collected by ROS). By comparing the trajectories of the robot from the real tracking system and the virtual model, we evaluate the fidelity of the DT and assess any discrepancies. In a second set, we introduce obstacles, randomly placed on the trajectory to mimic realistic scenarios where the robot might find unexpected objects on its path. The robot is programmed to

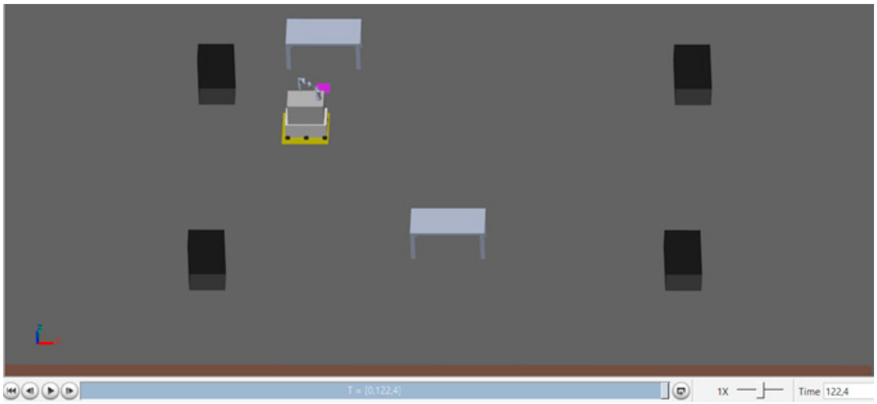


Fig. 5: Matlab Simulink environment

adjust its trajectory and still reach its final destination, the charging station. We collect data from twelve runs on the robot's pose at the charging station. The reference position is provided by the MiR100 system itself, the final real position is obtained from OptiTrack, and the DT estimation comes from data collected in ROS. By comparing them, we evaluate the accuracy of the model for the robot's final pose, despite the presence of obstacles.

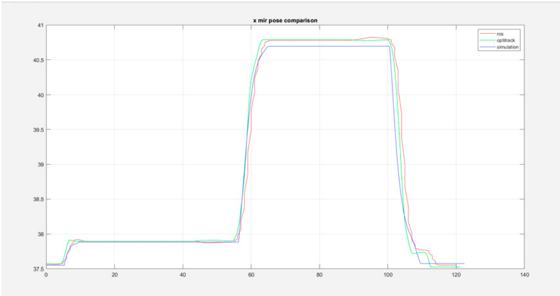
4. Results on the accuracy of the Digital Twin

For both experimental setups, we present a non-exhaustive list of preliminary results that represents the work produced so far, and will be expanded in the future, when more sets will be added, and more extensive results will be published. However, for the discussion for the present manuscript, they already represent a sufficient starting point; so, they are presented here and highlighted with some accompanying figures, and a preliminary discussion is reported.

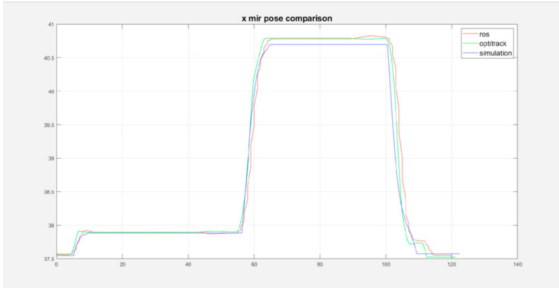
In the first set of experiments, we aim to assess the correspondence and accuracy between data acquired via OptiTrack (representing the real object) and ROS (representing the virtual object) for the MiR100. Figures 6(a) and 6(b) depict the x and y coordinates of the MiR100 over time, while it is moving in the lab environment to perform the programmed pick and place activity. Figure 6(c) has the ϕ orientation coordinate over time. The plateaus represent the three designated stations: the charging station, loading station, and unloading station. The acceleration and deceleration ramps connecting the plateaus are the MiR100's movements as it transitions from one station to another. In both figures, the graph lines representing the data acquired from OptiTrack and ROS follow the same pattern and are almost overlapping. This alignment suggests that the virtual model, traced using ROS data, accurately follows the movements and positions of the real physical object tracked by OptiTrack. The close resemblance between the two data sets provides initial indications towards the fidelity and reliability of the DT in representing the MOMA.

However, it is worth noting that the pattern observed for the simulated environment in MATLAB and Simulink does not follow the real path as closely as the ROS data. This once again highlights the inherent limitations and hazards of relying solely on a simulated environment to accurately represent the real-world conditions. Nevertheless, this result is not as concerning as the previous findings are uplifting, because the control signals and data transmitted to the actual robot, utilizing the virtual environment, are sent through the ROS platform rather than the simulation.

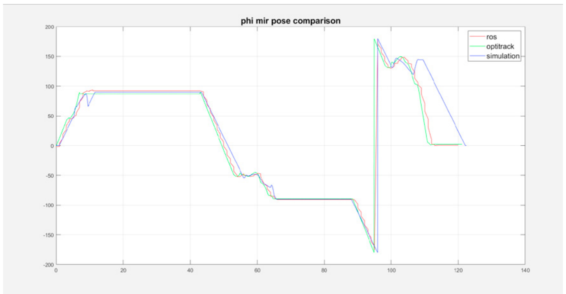
In the second set of experiments, we introduce obstacles randomly into the MiR100's trajectory to evaluate the accuracy of its pose at each station. We collect data for each of the twelve test runs, for each of the three stations individually, and plot Figure 7, representing the reference position for the station provided by the MiR100 system, the actual poses of the MiR100 acquired by our digital system, and the observed real poses captured by OptiTrack. The majority of the data obtained from our system, representing the virtual model, and the one observed by OptiTrack, fall within our goal range of 0.05 to 0.1 m, showing close similarity to reality in the accuracy of the DT model, and aligning with the data-sheet accuracy of the MiR100, 0.05 m. The compatibility derives from the calibration, continuously improved through several iteration, and synchronization between the real physical object and the virtual model, obtained through the integration of accurate sensor data, motion control algorithms, and time synchronization.



(a)



(b)

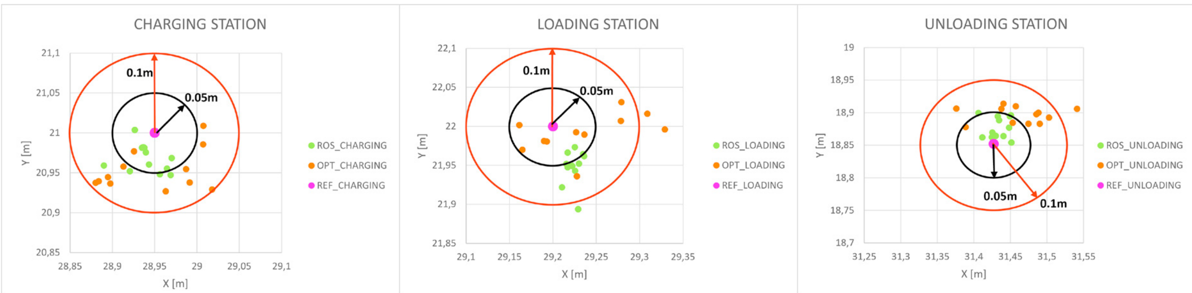


(c)

Fig. 6: (a) Comparison of x position of MiR100 (b) comparison of y position of MiR100 (c) comparison of ϕ orientation of MiR100 over time between data captured with the simulation environment, with ROS, with OptiTrack (x-axis = [s], y-axis = [m; DEG])

The consequence of these observations is significant, as the more accurate representation of the mobile manipulator's motion and pose in the DT moves the field one step further towards achieving reliable decision-making, optimization strategies, and predictive maintenance. With a high-fidelity DT, industrial applications can leverage the benefits provided by DTs to enhance efficiency and productivity, and improve overall performance.

The results of the first set of experiments show a convincing correspondence between the data acquired from OptiTrack and ROS, showcasing the fidelity of model in representing the real object. Figure 6 shows the alignment and overlapping patterns of the two data sets. In the second set of experiments, the close agreement between the virtual and real poses, along with the adherence to the MiR100's accuracy specifications, emphasizes the reliability of the model, and once again exhibit a compatibility between the real object and the twin. These findings allow for evaluation of the potential of such setups in industrial applications: bearing in mind the usefulness of DTs, in the following



(a) (b) (c)

Fig. 7: Pose of the MiR100 as taken with ROS and OptiTrack, with respect to the reference position, for (a) the charging station; (b) the loading station; (c) the unloading station

Section we argue about their limitation, and provide discussion about how to handle such a powerful tool, which is still unreliable and dependant on a variety of qualifiers and factors. One such factor is that the discrepancies between ROS and OptiTrack, which show the accuracy of the representation, are influenced by the localization accuracy of the MIR. This reflects the interaction between the model and the navigation system. It's important that these results affirm the capability of the twin to reproduce the robot's position within its navigation algorithms, while showcasing the potential for further improvements in localization accuracy to enhance the overall precision of the digital twin's representation.

There is an additional consideration that needs to be made regarding this experiments: to enable real-time communication between the physical and digital devices, synchronization between the two requires adjusting the time and date settings on the MiR interface to align with the network settings. Once the synchronization is established, the two devices can be connected using the ROS interface and the MiR driver. To assess the delay between the exchange of messages and information over the network, a specific command line in the ROS system can be used.

The results of the delay analysis shows if achieving near real-time communication for updating the data in the digital twin is possible: on average, the observed delay in our system is approximately 0.030 s, with a maximum delay of 0.084 s, which corresponds to an updating frequency from 12 Hz to 30 Hz. These can indicate a good level of performance for standard applications where real-time correspondence between the digital twin and the physical MOMA is not as critical. Achieving exact correspondence in positioning and localization of all the MOMA's parts in real-time would require even higher update frequencies, which might exceed the current capabilities of the laboratory setup. Such high-frequency updates would demand significantly higher computational power and may be computationally expensive to implement effectively at this stage. In applications where precise and instantaneous correspondence between the physical and digital systems is critical, such as high-speed or highly dynamic environments, the current capabilities may fall short. The potential consequences include reduced accuracy in the digital twin's predictions and recommendations, particularly during rapid changes or complex scenarios.

Nevertheless, these results are a promising step forward in leveraging such systems, considering the current state of technology and computational resources. As advancements in computational power and network capabilities come, higher update frequencies and tighter synchronization between the physical and digital systems become attainable, enabling even more precise and real-time decision-making support for MOMAs in diverse industrial settings.

5. Limitations of Digital Twins

The adherence of DTs to qualifiers plays a role in their effectiveness and the achievement of the outcomes. An representative DT enables monitoring and analysis of the physical system, highlighting inefficiencies and easing the implementation of optimization strategies. Real-time operability provides timely feedback and intervention, improving system performance. An optimal fidelity to the physical counterpart opens simulation scenarios to test configurations, to identify optimal process settings. Achieving high accuracy in DTs is therefore vital for organizations seeking to maximize productivity and operational efficiency. However, realizing it poses a non-trivial challenge, as the simultaneous fulfillment of qualifiers with optimal results remains elusive. Nevertheless, for enterprises to make informed decisions and reach desired outcomes, it may not be imperative to pursue such a level of accuracy. Balancing the qualifiers with practical considerations can still yield valuable insights and enhance operational efficiency.

Developing DT models for MOMA present as well several challenges: fidelity to reality is a critical aspect that affects accuracy and reliability of the twin. High fidelity requires understanding the MOMA's dynamics, sensor characteristics, and interaction with its environment. Real-time operation is another challenge, as it requires to exchange data with the physical system in a timely manner. Delays in data transfer and processing can hinder the effectiveness of the DT in supporting real-time decision-making and control. Despite the potential that our developed DT shows, the obstacle lies in the environment in which the MOMA operates. The inability to include unstructured parts of the factory environment, such as moving or non-permanent objects (operators, other non-connected AGVs, and so on), restricts the ability to accurately represent the physical world. This hinders the ability to account for potential collisions or changes in the surroundings, which is crucial for the MOMA's and the surroundings' safety and to realize reliable operative motion. Mobile manipulators operate in dynamic and unstructured environments, such as factory floors, where they interact with objects, obstacles, and humans. These unstructured elements pose difficulties when it comes to modeling and incorporating them into the DT. The DT primarily focuses on the MOMA itself and its internal components, but it often lacks the ability to include the complete representation of the factory environment, including non-permanent objects, movable obstacles, or transient conditions.

Consider a scenario where a DT of a MOMA is developed to optimize material handling in a dynamic factory environment. The DT accurately represents the MOMA's kinematics, dynamics, and task planning algorithms. However, due to the inability to include the movements of other objects and workers in the factory, the DT cannot account for potential collisions or disruptions caused by external factors. Consequently, the DT's optimization recommendations may not align with the reality of the physical system, leading to sub-optimal performance in real-world scenarios. Lacking an accurate representation of the environment may fail to anticipate or account for the presence of these obstacles. Consequently, the DT's path planning algorithms or collision avoidance systems may not provide reliable guidance to the physical MOMA, potentially resulting in collisions or inefficient trajectories. Without a comprehensive representation of the environment, the DT's insights and recommendations may be limited or misleading.

While efforts are made to capture the components and behaviors of the MOMA, some complex dynamics or non-linear interactions may be challenging to model accurately. This introduces uncertainties and inaccuracies in the predictions and performance assessments. Moreover, achieving high accuracy to enable monitoring and optimization of physical systems comes at the cost of increased computational complexity: the more accurately a DT replicates the physical system, the more valuable insights and optimization possibilities it can offer, but at the same time the more computational resources and real-time operativity it requires. DTs need to process large amounts of data and perform complex simulations, leading to a significant computational burden, to be added to the required real-time operativity for timely feedback and decision-making. Indeed, companies often demand quick response times to enable effective control of operations, but this can introduce delays in data transfer, and consequently in decision-making, which can in turn reduce the opportunities offered by DTs. Balancing these factors involves finding an optimal level of accuracy that can be achieved within the available computational resources while maintaining real-time operativity, therefore making strategic choices on the complexity of the model, the level of detail, and the efficiency of the algorithms.

It is important to acknowledge the limitations and their potential impact on the reliability in industrial applications. However, it is worth noting that despite these challenges, DTs still offer valuable insights, optimization possibilities, and decision-making support. To mitigate these limitations, future research should focus on advancing techniques for environment modeling, incorporating advanced sensing technologies, and developing algorithms that can account for dynamic and unstructured elements. Additionally, efforts can be directed towards improving the fidelity and accuracy of DT models by integrating more sophisticated control algorithms, machine learning approaches, and data-driven techniques. By addressing these limitations, DTs for mobile manipulators can become more comprehensive, reliable, and useful tools for optimizing operations, reducing risks, and enhancing the efficiency of industrial processes.

DTs can nevertheless prove effective if utilized in applications with the intent to reach specific objectives; as such, they can overcome the limitations associated with environment modeling. TO exemplify, two implementation that clarify this statement include battery consumption optimization and predictive maintenance for MOMAs, or robots in general. Such examples show how tailored DT applications can effectively leverage the benefits of DTs while reducing the negative effects of the main challenges previously presented.

A DT can be employed to optimize the MOMA's battery usage: by receiving data from the MOMA's sensors, the DT can evaluate and predict the energy consumption required during different tasks and in various operating conditions identify potential energy-efficient strategies, acting on optimal path planning, task sequencing, and adjusting control parameters. Since the focus is primarily on the MOMA's internal components and energy-related aspects, the limitations related to environment modeling may not significantly impact the effectiveness of such a DT application.

Another valuable application is the use of DTs for predictive maintenance, which uses the received MOMA's performance and status parameters, and helps anticipate and detect potential failures, thus enabling maintenance scheduling, optimization of the MOMA's up-time, in turn reducing the unwanted, unplanned down-times. In this case, although the limitations related to environment modeling still exist, the primary focus is on the MOMA's internal components and their behavior and, as a result, the DT's predictions and maintenance recommendations remain reliable and effective.

6. Conclusions

In this paper, we have explored the limitations and potential of digital twins for mobile manipulators in industrial applications. We discussed the challenges associated with developing digital twin models for MOMA, including fidelity to the physical twin, real-time operation, and environment representation. It is evident that the inability to include unstructured parts of the factory environment in the digital twin model poses a significant limitation. By addressing the specific challenges related to environment modeling, and improvement in the DT's accuracy with future research, it would be possible to enhance the effectiveness of DTs of MOMAs, and better equip them to support companies' decision-making, optimization, and predictive maintenance in industrial applications. The advancements in these areas will further advance the paradigms of Industry 4.0 and smart manufacturing, facilitating improved operational efficiency, and increased productivity. The potential of digital twins for mobile manipulators is vast. By acknowledging the challenges, focusing on research directions, and leveraging advanced technologies, we can unlock the full potential of digital twins in industrial settings, paving the way for a more efficient and intelligent manufacturing landscape.

Acknowledgements

This work was partially supported by the DiManD Innovative Training Network (ITN) project, a European Training Network (ETN) programme funded through the Marie Skłodowska-Curie Innovative Training Networks (H2020MSCA-ITN-2018), grant agreement number 814078.

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