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A Roadmap towards an Automated Warehouse Digital Twin: current implementations and future developments ⋆

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Abstract: Automation and digitization increase the effectiveness and efficiency of logistics processes. In warehousing, Automated Storage and Retrieval Systems (AS/RS) are largely adopted due to their considerable advantages over traditional warehousing, namely high space utilization, shorter cycle times and improved inventory control. To further enhance such advantages, warehouse operations can be digitized via a Digital Twin (DT) which retrieves data from the real-world industrial process, mimics its behaviour and feeds specific inputs back to the real-world process, after elaboration from a simulation-based digital model. This work presents a DT proposal for a real-world AS/RS system, highlighting its current implementations together with its future developments.

Keywords: Digital Twin, Agent-Based Simulation, Discrete Event Simulation, Hybrid Simulation, Industry 4.0, Automated Warehouse.

1. INTRODUCTION

In recent years, Automated Storage and Retrieval Systems (AS/RS) have become a widely used technology to store and retrieve goods. AS/RS are computer and robot assisted systems that can store items in specific locations and retrieve objects without the aid of a human operator. The main components of an AS/RS system are storage racks, storage and retrieval machines, Input/Output (I/O) points and conveyors (Lerher et al., 2010). Their main advantages over traditional warehousing systems are high space utilization, reduced labor costs, short retrieval times and an improved inventory control (Boysen and Stephan, 2016). A Digital Twin (DT) is a simulation-based virtual counterpart of a physical system, exploiting real-time data synchronization to optimize the actions undertaken by the physical system (Kritzinger et al., 2018). DT have been applied in several industrial contexts, such as predicting aircrafts fatigue and damages (Tuegel et al., 2011) or aiding cyber-physical production systems (Ding et al., 2019). However, literature on simulation-based DT concepts for industrial processes such as automated warehousing is still scant (Braglia et al., 2019; Coelho et al., 2021).

The objective of this work is thus to answer the following research objectives:

(1) Explore the value of an automated warehousing DT;
(2) Propose a formulation for its architecture;
(3) Investigate the main steps associated with its development.

The proposed DT implementation is based on a physical system installed in a university laboratory at the Politecnico di Torino and a Digital Model (DM) of the AS/RS operations, developed combining Discrete-Event Simulation (DES) and Agent-Based Modelling (ABM) paradigms. At its current formulation, the DT architecture does not intend to establish real-time cyber-physical communication, but rather to replicate the physical system in a virtual environment as a Digital Shadow (DS) (Kritzinger et al., 2018).

The remaining of this paper is structured as follows. In Section 2 we explore two streams of literature, namely simulation in AS/RS and DT applications to the warehousing context. Then, we present the physical and Information Technology (IT) infrastructure of the Logistics Laboratory. In Section 4 we highlight the proposed DT architecture, and in Section 5 we point out the relevant implementation steps. Finally, conclusions are drawn in Section 6.

2. LITERATURE REVIEW

2.1 Simulation in AS/RS literature

AS/RS are used for better operational efficiency, especially in operational contexts characterized by a high density of small and medium components or raw materials (Lagorio et al., 2020). Typical design decisions relating to AS/RS are about system choice, i.e. the type of handling machine, number of tiers/aisles and rack dimensions, as well

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as storage assignment rules and dwell points for vehicles (Roodbergen and Vis, 2009; Epp et al., 2017). The most widespread real-world setting is represented by an automated stacker crane operating on one aisle both horizontal and vertical movements (Boysen and Stephan, 2016), and thus this literature review focuses on such configuration. The most recognizable goal of AS/RS literature is to optimize storage/retrieval cycle times depending on the configuration of the afore-mentioned design decisions. To this end, simulation represents a way to generate accurate performance measures for a given system configuration (Epp et al., 2017).

A computer simulation model of an AS/RS with Rail-Guided Vehicles (RGV) as material handling tool has been used to examine the operational logic of the entire system and determine the optimal number of vehicles, the utilization of the narrow-aisle crane and the maximum throughput of the system (Lee et al., 1996). Another early work in simulation modelling is proposed by Linn and Xie (1993), who analyze the sequencing rules for retrieving parts from an AS/RS servicing a production line. In the automated warehouse context, models based on DES easily find application since this paradigm is useful to properly represent the operational level of a system (Barbosa and Azevedo, 2019). Gagliardi et al. (2015) used DES to analyze storage assignment policies for a unit-load crane configuration. Xu et al. (2016) combined DES and analytical formulation to explore the impact of different rules for transferring the load-units blocking the one being retrieved in a double-deep AS/RS with cross-aisle transfers. A similar configuration has been studied in the simulation model by Hahn-Woernle and Günthner (2018), albeit with the different objective of optimizing the energy consumption of the AS/RS. Finally, Gagliardi et al. (2014) integrated object-oriented programming concepts within their DES model.

2.2 Warehouse DT

Few studies on DT application to warehousing contexts are available in recent literature. The DT by Braglia et al. (2019) revolves around a warehouse simulation model built in AnyLogic, and collects data from the physical system by means of Radio-Frequency Identification (RFID) sensors. The aim here is to optimize the flow of pallets of tissues inside a warehouse. Coelho et al. (2021) also propose a simulation-based decision support tool for an in-house logistics DT, covering logistics activities such as Receiving, Storing, Order picking, Cross-docking and Shipping. The decision-support system connects the physical system to the virtual system via a layer of services, including Warehouse Management System (WMS) and Enterprise Resource Planning (ERP). The DT by Leng et al. (2021) focuses on the storing and distributing tobacco. The DT system implemented in this case study consists of two parts: the joint optimization model and the semi-physical simulation engine. The cyber-physical synchronization is carried out by a middleware platform that deals with the integration of public protocols and interfaces with the database. Likewise, the focus of the DT by Leung et al. (2022) is on the Machine Learning (ML) models for jointly optimizing replenishment operations with order picking in the context of urban logistics. Here, the physical system only comprises the order picking process. Finally, a warehouse DT is proposed by Chen et al. (2020), who focus on tracking the activities of an Unmanned Aerial Vehicle (UAV) inside a physical laboratory system, where data collection and transmission is aided by RFID sensors and 5G communications protocol.

2.3 Research gap and main contribution of this study

With this study we intend to contribute filling two research gaps, that lie in an unexplored field of DT and in the modelling and simulation approach used for its implementation. In a nutshell, extant DT literature focuses on optimizing warehouses operations such as replenishment and order picking, as well as on data collection systems. However, there are no studies that aim to apply these concepts to an AS/RS based warehousing system. Furthermore, existing simulation approaches allow AS/RS simulation models to be more easily scalable and to store more information such as the perishability of a product. Despite this, DES lacks of effectiveness when the level of complexity increase. Thus, the aspects of the system that cannot be modelled only with DES can be integrated in the model exploiting a lower level simulation paradigm, namely ABM (Braglia et al., 2019). A diminished abstraction can be achieved through ABM because the behaviour of the system analysed is not modelled directly, but it emerges from the interactions of its constituent agents, that is autonomous decision-making entities that individually assess their situation and take decisions based on a set of rules. The integration of DES and ABM, or rather two simulation modelling paradigms, is called Hybrid Simulation (HS) (Mittal and Krejci, 2015). This approach consists of the combination of two or more simulation methods in order to exploit the potentialities of each simulation method and to finally develop more straight-forward and more efficient models (Scheidegger et al., 2018).

3. THE LOGISTICS LABORATORY

In this section the physical and IT infrastructures installed in the Logistics Laboratory are presented.

3.1 Physical Environment

The AS/RS system installed in the laboratory has a total surface of 68,6 m^2 and is equipped with:

(1) A Maxi-Shuttle (MS) aisle-captive system, similar to a mini-load stacker crane (e.g., see the Schäfer Miniload Crane (SMC) for comparison), able to move totes (or boxes) along three axes using single, double and multiple commands;
(2) A single-aisle storage rack composed of seven tiers and eight columns, with single, double, and multiple depth storage locations;
(3) An I/O roller conveyor system;
(4) Two working stations installed within the storage rack with gravity flow racks for parts-to-picker operations.

The I/O points are parallel to the aisle and located in columns four and eight respectively. The working stations are adjacent to the AS/RS and thus all parts are accessible

Fig. 1. The working stations with pick-to-light system and MR interface

from a single front, a design configuration deemed to be beneficial for reducing order times (Bortolini et al., 2020). Moreover, the working stations are equipped with pick-to-light systems for parts-to-picker operations. Finally, through the I/O roller conveyor system the AS/RS connects with Mobile Robots (MR) responsible for material handling processes outside the AS/RS (Fig. 1).

3.2 IT infrastructure

Both the physical and IT infrastructures have been installed by a third-party company specialized in system integration and logistics automation systems. The IT infrastructure of the laboratory AS/RS revolves around the use of a WMS and a Warehouse Control System (WCS). A WMS is a computerized information system for the preparation, monitoring and execution of warehouse activities of a transactional nature. The WCS instead is a software application that directs the real-time activities of the AS/RS. For instance, picking orders are built on the upper-level host represented by the WMS and are then transmitted to the WCS. The WCS then optimizes the AS/RS operations and movements applying a Dijkstra algorithm based on the list of totes to retrieve. This results in an activity list for the MS to be completed. This information is then delivered to the physical system via the Programmable Logic Controller (PLC), which sends signals to the actuators installed on the mini-load stacker crane and the conveyor belts.

4. THE LOGISTICS LABORATORY DT

Talkhestani et al. (2019) proposed the architecture of an Intelligent Digital Twin, namely the DT according to the definition used by the authors in this paper. Starting from this theoretical framework, the architecture of the Logistics Laboratory DT has been developed. A Unified Modelling Language (UML) class diagram has been created, since this type of diagrams can be used to effectively describe DTs and the connection between the various entities involved (Azangoo et al., 2020). In the class diagram developed (Fig. 2), it is possible to observe the presence of three layers, characterized by different colours:

(1) The physical environment (yellow), which refer to the entities that have a physical location inside the Laboratory and that have been previously described in sub-section 3.1.
(2) The IT infrastructure (green), which includes the classes representing the IT elements that work as a bridge between physical and the virtual space and analysed in sub-section 3.2.
(3) The virtual environment (blue), which contains all the entities that are placed in the virtual space, namely the Digital Model (DM).

In this section we define the third layer of the UML diagram more deeply, given that the physical environment and the IT infrastructure have been already introduced in Section 3. In the DT architecture, the DM is used as a virtual replica of the physical Logistics Laboratory. It is also composed by an Artificial Intelligence (AI) class, which offers the possibility to perform optimizations on the replicated system through the definition of new policies. This requires a huge amount of data to be used as input for ML algorithms. Once it accurately replicates the physical system, the DM can be also used as a data source, performing a high number of simulations in a short time. Before applying the new policies defined by the AI in the real system, the model executes a validation to compare the behaviour of the system with the old policies. In case the expected improvement is found, the new policies automatically apply without the need for intervention by an operator. This enables one of the core characteristics of a DT, namely the bidirectional connection between physical and virtual space (Kritzinger et al., 2018).

The UML class diagram proposed also provides the connections and the relationship of the different classes within the aforementioned three layers. For a reason of practicality, some of the classes included in the model have been simplified. For example, all the elements making up the automated warehouse and that have been precisely described in sub-section 3.1, have been summarized in a single UML class, namely the Automated Area class.

5. IMPLEMENTATION STEPS

The high level of complexity associated with logistics systems results in a complex realization process of a complete DT in such context (Korth et al., 2018). Thus, in order to develop the DT structure, it is fundamental to proceed with sequential implementation steps.

5.1 DM implementation

The creation of a proper DM is a crucial aspect for a successful DT implementation (Fei et al., 2018). In relation to the objectives of each DT application, a specific type of virtual model can be developed (Neto et al., 2021). The objectives of this research require a DM able to precisely replicate the real system functioning, with a very low level of abstraction. Thus, the development of a hybrid model based on DES and ABM has been selected as the best choice to achieve an effective DT implementation. The environment selected to build the DM is AnyLogic, a Java based multi-method simulation software employed in various industries (Borshchev et al., 2014).

At the current level of implementation of the DT architecture, the DM only replicates the automated area of the Logistics Laboratory and the movement of totes. Elements like the MR fleet, the operators and the products are still

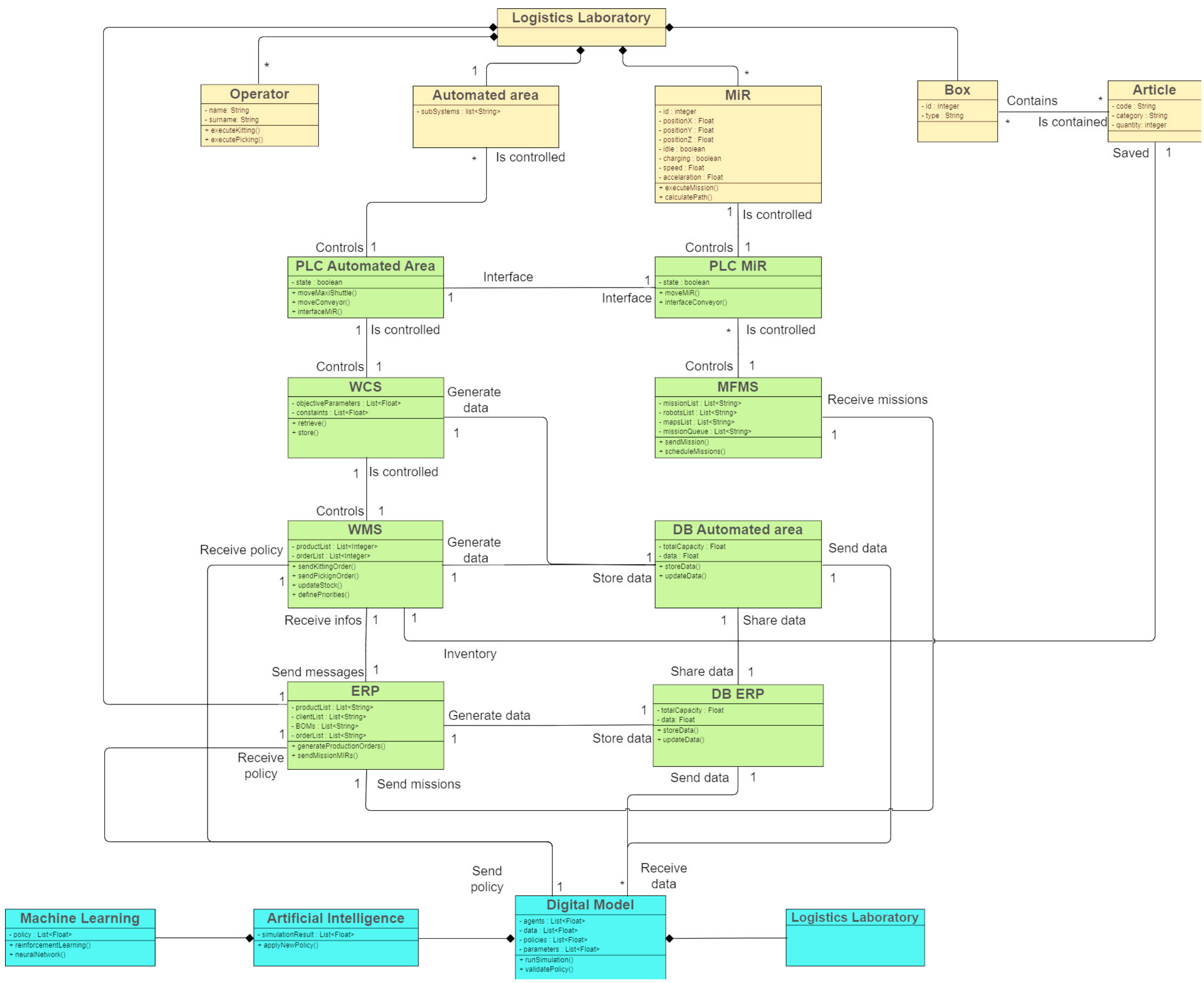

Fig. 2. Logistics Laboratory Digital Twin architecture

missing. The model has been built following a modular approach. This is due to the fact that the high degree of complexity present in a system as the one into analysis can be difficult to be modelled properly. Therefore, the main constituents of the Logistics Laboratory have been identified and separately modelled in AnyLogic as independent agents. Moreover, reproducing the single elements of the real system as independent objects is useful to model the specific functioning, rules, and exceptions and to reach a high level of detail in the virtual system. For instance, the storage rack of the automated warehouse has not been modelled as a unique, static, and rigid entity, exploiting the AnyLogic libraries dedicated to rack systems. On the other hand, a fully customised agent representing a single storage location of the rack has been created (Fig 3). Then, during simulation the whole storage rack generates as the consequence of the creation of a number of agents equal to the number of storage locations of the Logistics Laboratory storage rack.

5.2 DS implementation

The DM alone does not constitute a DT. The intermediate step between a DM and a DT is the DS (Akbari, 2018). A DS can be defined as an extremely faithful virtual representation of a physical element capable of receiving and incorporating data. It is inserted in an infrastructure that allows the automated one-way data flow from the state of the physical object to the DM. This makes the DS perfectly synchronized with its physical twin and, as a consequence, any manual changes will be immediately reflected in the digital counterpart once implemented (Madni et al., 2019). From the above-mentioned definition, it comes to light that in order to implement a DS it is necessary to develop a data-driven model. Data-driven modelling is a technique in which dynamic elements of the DM are introduced in the virtual environment based on data derived from the physical system (Solomatine and Ostfeld, 2008). The choice to follow a data-driven modelling approach instead of a static one relies on the fact that the former does not need a manual update of the model since the dynamic elements are defined based on data fetched at occurrence (Janes and Yaffe, 2006). On the contrary, the latter requires a manual update to introduce a new item in the DM or to replicate the current state of the physical system. In addition, this results in a higher flexibility of the data-driven model in comparison to the static one. Finally, data-driven modelling allows

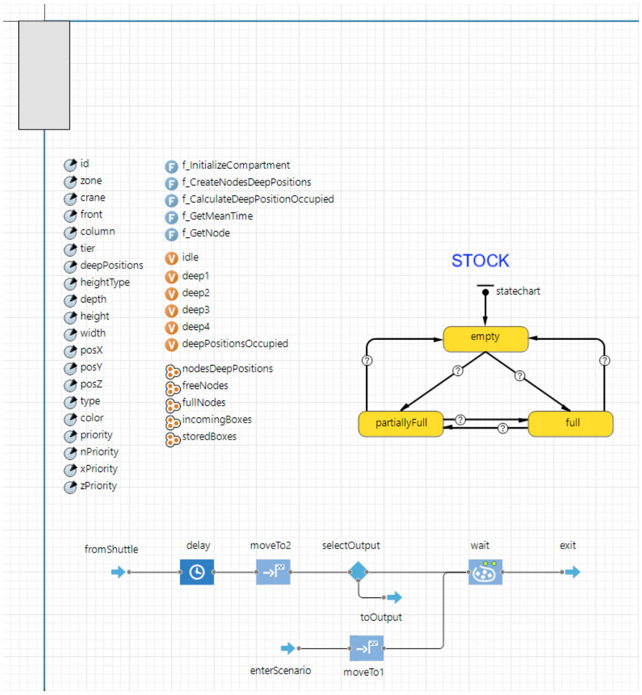

Fig. 3. AnyLogic storage location agent

the possibility to have multiple data sources from which to retrieve data to be inserted in the DM, while static modelling only admits a single data source (Hasenauer et al., 2015). All these aspects implicate that a data-driven model is much more difficult to develop in relation to a static model.

Once simulations can be run starting from the real system data, a procedure to retrieve and send them to the DM is needed. In this regard, the data sources to connect with the DM have been selected. They can be classified in two categories, namely structural and operational data sources (Fei et al., 2018). The first one refers to tables containing the information related to physical and static aspects of the Logistics Laboratory that do not change among simulations, namely the characteristics of the various totes, the coordinates and dimensions of the storage locations, and the parameters of the AS/RS machine. Despite the changeless nature of these data, they have been inserted in external tables to simplify the updating process of the DM in case a change in the physical system occurs. On the other hand, the second one consists of database tables including dynamic and operational data that changes from simulation to simulation, that is the position of each tote within the Logistics Laboratory, the level of stock for each product, and the list of kitting and picking orders to be completed. The connection between the DM and this kind of sources allows retrieving real data of a specific instant in time. As a consequence, at the start of each simulation the current data of the real system are fetched from the physical environment and used as a starting state of the DM. AnyLogic allows the connection with external databases and the creation of queries to retrieve data from the database tables when needed.

5.3 Current Results

The DM has been validated in order to test its reliability in replicating the functioning and performance of the real system. In particular, the storage process has been analysed. A Design Of Experiment (DOE) approach has been used (See table 1). Specifically, the total time to carry out the process has been selected as dependent variable, while the tote type and the total number of totes have been considered as independent variables. In all the experiments, the filling percentage of the storage rack has been fixed at zero. For each combination of factors, a replication has been performed. Since the tote type variable can have 4 levels, while the number of totes 3 levels, a total of 24 experiment have been conducted. Finally, the storage locations selected by the MS to store the totes have been recorded. Once conducted all the experiments in the Logistics Laboratory, the same DOE configuration has been exactly replicated in the DM.

Table 1. Design of Experiments

Tote type (Length, Height)	Number of totes
Type 1 (short, low)	6
Type 2 (short, high)	13
Type 3 (long, low)	20
Type 4 (short, low)	

As it is possible to observe in table 2, results show that the model accurately replicates the performance of the real system. In fact, on average the model underestimates the total storage time by 1.38 percent. Furthermore, in 90 percent of cases the storage locations selected by the DM correspond to the ones chosen by the AS/RS machine.

Table 2. Validation results

Id.	Tote type	Num. of totes	Laboratory Cycle time [s]	Model Cycle time [s]	Delta
1	Type 1	6	125.46	125.6	0.11%
2	Type 1	6	124.99	126.9	1.51%
3	Type 1	13	267.47	261.31	-2.36%
4	Type 1	13	263.31	262.15	-0.44%
5	Type 1	20	403.85	400.45	-0.85%
6	Type 1	20	399.81	400.75	0.23%
7	Type 2	6	128.26	126.13	-1.69%
8	Type 2	6	127.1	125.4	-1.36%
9	Type 2	13	267.03	261.5	-2.11%
10	Type 2	13	265.46	259.15	-2.43%
11	Type 2	20	407.36	413.43	1.47%
12	Type 2	20	406.54	411.1	1.11%
13	Type 3	6	127.34	124.65	-2.16%
14	Type 3	6	126.84	123.15	-3.00%
15	Type 3	13	266.6	258.5	-3.13%
16	Type 3	13	265.63	259.15	-2.50%
17	Type 3	20	409.09	401.15	-1.98%
18	Type 3	20	410.09	399.4	-2.68%
19	Type 4	6	127.7	120.55	-5.93%
20	Type 4	6	127.99	120.29	-6.40%
21	Type 4	13	277.39	272.45	-1.81%
22	Type 4	13	268.09	273.3	1.91%
23	Type 4	20	424.19	423.45	-0.17%
24	Type 4	20	418.8	425	1.46%

5.4 Future Developments

Despite the implementation steps and the results already achieved, some aspects are missing in order to complete the creation of a DT of the Logistics Laboratory.

Physical environment. From the physical system point of view, the implementation of an ERP system will support the coordination and management of all the processes (Umble et al., 2003). Furthermore, it will be an additional data source to integrate within the DM, to inject more detailed, comprehensive, and consistent data in the virtual environment.

Digital Model. The DM will be integrated with the missing elements of the physical environment that have not yet been modeled in AnyLogic, namely the MRs, the operators, and the products to be inserted within the totes. Moreover, AI and ML algorithms to leverage simulation data to automatically take decision will be explored. The outcomes of this step are twofold. Firstly, by studying the application of AI in the logistics and warehousing sector it is possible to better understand which elements needs addressing for an effective implementation. Secondly, analyzing the use of AI in such a context might support the selection of proper algorithms to develop.

Cyber-physical communication. Only when the data flows between a physical system and its digital replica are fully integrated in both directions, it is possible to refer to it as DT. In this way, the DM might also have the ability to control the physical object (Kritzinger et al., 2018). To achieve this objective, part of the current IT infrastructure will be redefined and restructured to ensure two-way communication with the DM.

Testing and application scenarios. Finally, possible testing and application scenarios of the DT could be defined. For instance, such technology might support the synchronization of arrivals and departures of the MR fleet in relation to the warehouse operations. Another promising field can be the introduction of a dynamic allocation policy of the totes following the already scheduled orders of the ERP, finalized to the reduction of the cycle time and maximisation of the throughput rate. Then, the DT might be applied in the prioritisation of kitting and picking orders aimed at reducing material take-backs and improving warehousing operations.

6. CONCLUSION

This work provided a contribution to the existing literature on DT warehouse applications via the adoption of an HS approach combining ABM and DES for the DM of an automated warehousing system. Furthermore, the current and future implementations steps of a full-fledged DT based on the afore-mentioned HS and a data-driven DS architecture were explored. The proposed DT is still a work-in-progress, and future developments will aim at strengthening the existing physical and IT infrastructure as well as develop communications protocol between the DM and the physical system.

We envision the proposed DT to support logistics companies in dynamically assessing their operational needs and improve their warehousing operations through better process synchronization, storage allocation policies and order picking.

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