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The Role Of AI In Warehouse Digital Twins

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Abstract

In the era of Industry 4.0, digital twins are at a pivotal phase. For a concept that is so inconsistently defined in the literature, it has been used for many applications, especially in manufacturing, production, and operations. DT not only allows for supervision and running simulations, but it also supports AI applications since it is mapped to all types of data and Intel on the physical object. On the other hand, warehouses have been subject to little digitization over the years. Warehouse management is at the very core of both manufacturing and retail operations, ensuring supply chain and production continuity. It is also a conjunction of uncertain material handling activities. It could easily benefit from the Information visibility and the smart features supplied by digital twins and machine learning. In this perspective, this paper examines the use cases of warehouse digital twins (WDT). This study aims to assess the maturity of AI application within WDT, namely techniques, objectives, and challenges. Consequently, inconsistencies are identified and research gaps are presented, making way for future development and innovation.

Keywords: Digital twins; warehouse; material handling; artificial Intelligence, machine learning

1. Introduction

Intralogistics is at the center of both manufacturing efficiency and customer satisfaction. Material handling could amount from 15% to 70% of production costs. In-store warehouse activities are also among the most hazardous industrial processes, causing up to 50% of all kinds of industrial injuries (Glatt et al., 2021). In a “post covid” world, companies had to adapt their strategies to stay financially above water and satisfy impulsive and unheard customer behavior. According to a survey done by LaserShip, more than 60% of consumers are willing to pay more for same-day delivery. They are also more demanding of product personalization and ethical and environmental beliefs. This requires a dynamic, straightforward, and completely transparent and visible process to one of the most unpredictable activities, flawed by supply chain structure change, demand seasonality, transportation cost change trends, and many other variabilities (Gong & de Koster, 2011). Digital twin (DT) is one of the emerging technologies gaining popularity over the last decade and having the potential to better warehouse management. The concept has stirred a lot of conflict in academia and industry as to how it should be defined. DT should ensure an ever-evolving, fully connected, and reasonably identical entities linked through IoT and allowing data analytics and simulation. The digital twin has "smart" capabilities allowing it to not only follow all the changes happening in the warehouse but also be the one suggesting modifications. Artificial Intelligence (AI) proposes a set of methods that can aid decision making, if not do it autonomously, based on collected information. Since DTs have undergone the trouble of collecting data and processing it, it only makes sense to go the extra mile and use advanced data analytics to grant it knowledge if not wisdom.

This paper aims to assess the maturity of AI application within the DT paradigm in warehouse management. Through a systematic review of scientific literature, we attempt to answer the following research questions: What are the AI techniques most used for Warehouse management under the DT paradigm? How is AI employed to ensure and elevate WDT functions? What are the challenges and barriers to adopting both WDT and AI in warehouses?

To do so the rest of the paper is organized as follows. Section 2 showcases the research methodology followed by section 3 that presents and details the analysis framework. Section 4 presents and discusses the findings of the review. Lastly, Section 5 presents conclusions and open research, with overall challenges and perspectives to conclude the paper.

2. Research methodology

This state of the art focuses on papers that have covered the use of both AI and DT technologies to optimize in-store warehouse activities. We have adopted the machine learning categories described by Usuga Cadavid et al. (2019) to construct our research query as follows:

TITLE-ABS-KEY ("digital twin" OR "digital twins") AND TITLE-ABS-KEY ("warehouse" OR "warehousing" OR "material handling" OR "inventory" OR "packing" OR "store" OR "storage") AND TITLE-ABS-KEY ("deep learning" OR "artificial intelligence" OR "machine learning" OR "AI" OR "ML" OR "neural networks" OR "regression" OR "clustering" OR "sarsa" OR "nearest neighbors" OR "Q-learning" OR "decision tree")

We've studied the results through the phases detailed in figure 1. An additional reference was added upon analysis of the selected articles. The selected references either display a fully embedded AI and digital twin framework or explain the possible relationships between both technologies and how one could exploit the other.

3. Analysis framework

Our analysis differentiates what qualifies as a DT and how it was used in collaboration with AI. We have also taken into consideration the data used in both AI and DT to represent warehousing activities.

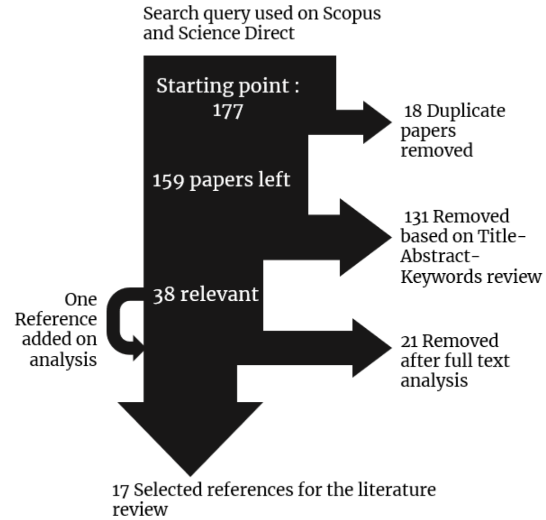

Figure 1. Research strategy

3.1. Digital twin

DTs are comprehensive digital representations of the physical assets, comprising their design and configuration, state and behavior (Hribernik et al., 2021). Fuller et al. (2020) provided a more grounded interpretation of the concept. They defined DT as the effortless integration of data between a physical and virtual machine in either direction. Instead of focusing on the definition, Fuller et al. made the distinction of what is not a DT and why. This led to identification of the following:

1) Digital Model: There is no automatic data exchange between the physical model and digital model. This means once the simulation is created, a change made to the physical object has no impact.

2) Digital Shadow: A digital shadow is a digital model with a one-way flow between the physical and digital objects. A change in the state of the physical object leads to a change in the digital representation but not vice versa.

3) Digital Twin: the data flow is bidirectional. A change made to the physical object automatically changes the digital object and vice versa.

In order to further differentiate the maturity level of the studied papers we also identified the characteristics of DTs, detailed in the literature. Zheng et al. (2021) synthetized and identified the characteristics of cognitive digital twins as DT-based, Cognition, Full lifecycle management, Autonomy capability, and Continuous evolving. On the other hand, Hribernik et al. (2021) described digital twins as autonomous, context-aware, and adaptive. We have identified DT characteristics relevant to our study, which are a conjunction of the two visions presented previously. Through our research, we've identified how AI could be incorporated. Each characteristic is defined as follows:

Context-awareness (CA) is the ability to distinguish incoming stimuli clearly. It does not stop at the use of IoT and Information systems (IS), but also the way they are utilized.

Autonomy (Auto) is the DT's ability to conduct autonomous activities without human assistance or a minimum level of human intervention.

Continuous evolving (CE) is the ability to grow with the real system along the entire lifecycle. DT updates itself according to the change of relevant data, information, and knowledge from the real system and all other interconnected software.

Full lifecycle management (FLM) allows the model to cover different phases across the entire lifecycle of the system, including the beginning of life (BOL, e.g., design, building, testing), middle of life (MOL, e.g., operating, usage, maintenance) and end-of-life (EOL, e.g., disassembly, recycling, remanufacturing).

3.2. Artificial Intelligence (AI)

AI was originated in 1956 at the Dartmouth Summer Research Project on Artificial Intelligence and had a tardy and rough evolution. To this day, there is still no consensus on what is properly considered as AI. According to Mehmood et al. (2019) the AI methods include Analytic Hierarchy Process (AHP), fuzzy logic (FL), Genetic algorithms, Neural network (NN), and Simulated Annealing (SA). Modern subsections of AI include machine learning (ML) and deep learning (DL). The three terms are often used interchangeably in the literature. DL generally refers to deep artificial neural networks and sometimes deep reinforcement learning, both are primarily ML techniques; hence it is considered a specific type of ML. Many developers of AI systems now recognize that it can be far easier to train a system by showing it examples of desired input-output behavior than to program it manually by anticipating the desired response for all possible inputs (M. I. Jordan & T. M. Mitchell, 2015).

ML can be primarily categorized into three types. The main discrepancy between these types lies in whether they are trained with labeled datasets or not (M. I. Jordan & T. M. Mitchell, 2015):

a) Supervised learning (SL): The training set provides clearly distinguished input features X and the corresponding output labels Y.

b) Unsupervised learning (UL): the algorithm is provided only input features X. It is up to the model to classify all data in the sample space using techniques such as cluster analysis.

c) Reinforcement learning (RL): The learner performs a specific action in an interactive environment. Based on experiments, the program can be rewarded or punished. The goal is to obtain the maximum cumulative reward value through trial and error.

3.3. Data

This section details how data is used to describe warehouses in the virtual space. Almost every feature or application of AI and DTs can be traced back to data. It is one of the key components to enable real time connection, contextual information, and training the AI algorithms … It is also distinctively used depending on the application, availability and the source. According to Leung et al. (2022), three different types of data, sourced from manufacturing information systems, IoT or manually entered are collected in a warehouse:

- Environmental data: include temperature, humidity, and light intensity … These data could be useful in decision making, depending on the types of goods stored in the warehouse.
- Product data: include the inventory levels and storage locations of goods. For instance, Radio Frequency Identification (RFID) technologies can be used to keep track of storage locations and quantities linked to the warehouse management system (WMS) and then the DT for replenishment and stock-keeping purposes.
- Handler data: include data related to both equipment and workers, such as their real-time locations. It can be data collected from workers' handheld devices given to workers to track their locations or measure some other physical variable.

It is also important to take into consideration data sources (WMS, IoT …) so as to judge the level of DT Interoperability and connectivity to other software.

3.4. Warehouse activities

In the scope of this study, we have distinguished two types of warehouses : Mechanical warehouses with automatic systems and mechanical tools that require minimal human intervention (e.g., conveyors, stacker crane …) and non-mechanical warehouses in which operators fulfil all processes through manual labor or while using machines and lifting tools (e.g. AGVs, Forklifts …).

Warehousing activities depend on the product, industrial sector and the type of the warehouse itself. We have chosen to use Gong & de Koster's (2011) adaptation of warehouse logistics. The general material flow of In-house logistics goes through the following activities: product/order arrival, put-away and preparation for storage, storage, order picking, and preparations for shipping (packaging, accumulation, sortation) and shipping.

4. Results

In the analyzed literature, AI applications in WDTs range from processes, strictly done in a warehouse, to warehouse-related activities in other fields such as asset management and synthetic sensing (Bányai et al., 2019; Corneli et al., 2019; Minerva et al., 2021; Zacharaki et al., 2021). The papers studied here present a mix of both manual and automatic stores which proves that we don't need a highly automated, fully mechanical system to make a DT or use AI. Table 1 summarizes the finding of this literature review.

4.1. What are the AI techniques most used for Warehouse management under the DT paradigm?

4.1.1. *Artificial Intelligence*

ML has been used either for classification or forecasting. For classification, neural networks (NN) are abundantly exploited. Melesse et al. (2022) used convolutional NN to analyze thermal images of bananas to monitor fruit freshness in stores. Zhan et al. (2022) used a sparse autoencoder to differentiate abnormal stationary in cold storage warehouses. Corneli et al. and Hayward (2019) both used YOLOv2 for object detection, allowing inventory and asset inspection applications in buildings. Wu et al. (2022) withdrew by long short-term memory (LSTM) network (deep learning) dependencies inside time series of the received signal to estimate locations online. In the same manner, Zhao et al. (2021) used the same resource with k-nearest neighbor to make indoor location estimation for warehouse safety management. Bányai et al. (2019) utilized Black Hole Optimization-Based Clustering to group the available supply demands based on time frame related objective function.

On the other hand, forecasting applications provide a wider range of ML technics. Neural networks still take the lead, having been used trice. Leung et al. (2022) used a neuro-fuzzy model (a combination of NN and fuzzy logic) to forecast the future arrivals of PI-SKUs. Xiuyu & Tianyi (2018) used backpropagation NN to make sales predictions. Other ML technics comprise Gradient-boosting decision tree (GDBT) to monitor anomaly detection and maintenance (Huang et al., 2021), proximal policy optimization (PPO) to make inventory predictions (Kegenbekov & Jackson, 2021). Wang et al. (2020) used a combination of both time-weighted linear regression method (TWMLR) and Non-dominated Sorting Genetic Algorithm (NSGA-II) to predict the remaining time of processes and find an optimal allocation of trolleys for the material handling tasks. DT could curate multiple algorithms in the same platform and subject problems to this set of optimization tools. Gao et al. (2022) implemented multiple ML techniques, in the "algorithm center". The appropriate algorithm is selected to match the problem from the Algorithm Center. This architecture thus allows for multiple adaptations and solutions, which ensures optimal problem-solving.

SL is the most used ML method having been used in twelve papers, either on its own or combined with other types of learning. UL was used trice, while RL was only used once. There's also a big interest in deep learning, namely deep neural networks, for it presents more computational power and is very compatible with the emergence of big data (Corneli et al., 2019; Kegenbekov & Jackson, 2021; Melesse et al., 2022; Zhan et al., 2022). These algorithms were either approved through tests and are envisioned to be used in a DT framework (Hayward, 2019; Kegenbekov & Jackson, 2021; Melesse et al., 2022; Xiuyu & Tianyi, 2018; Bányai et al., 2019) or are already applied in a case study presenting a united DT/AI embedded system.

4.1.2. *Data*

Except for Kegenbekov & Jackson, (2021) and Bányai et al. (2019), all DTs and AI/ML algorithms were trained using real product data. They are also the only ones that discussed the disadvantages of running AI algorithms in a simulate environment. Using simulated data and environments might lead to unexpected results. RL is known for finding loop holes in virtual models, in this case, it terminated ordering additional inventory closer to the end of the simulation to minimize holding costs.

Handler data is primarily used for online location tracking. Environmental data, though heavily talked about in the literature, is not subject to much application. Temperature plays a heavy role in safety monitoring (Zhan et al., 2022). Minerva et al. (2021) states that we can exploit all data types for object identification through AI. The DT develops auditory and visual signatures based on all kinds of data collected to identify changes in an environment and act accordingly.

A common goal among all DT adaptations in literature is to access information in real-time, this is often not the case for real life implementations. Real-time monitoring is necessary for safety applications requiring immediate responses (Zhan et al., 2022). Leng et al. (2021) and Leung et al. (2022) opted for more realistic, periodic, and synchronized data updates, which are both efficient and effective for their applications. This proves that real-time data acquisition is not always necessary depending on the level of abstraction and the objective.

4.2. How to ensure DT characteristics through AI ?

There is no standard mold for a DT. Before the clarifications of Kritzinger et al. (2018) and Fuller et al. (2020), the term DT was used interchangeably with simulation or cyber-physical systems. Even now, this is still the case for some studies that reduce DT's potential to simply be a CAD model. AI Programs are becoming fundamental to the proposed models and frameworks of DTs. Almost all the studied papers developed models and architectures that use ML in the DT platform or cloud. Otherwise, these algorithms are closely linked to the virtual counterpart in order to

Table 1. Overview of literature regarding digital twins and related concepts

	ML			Other AI technics		Level of DT			DT characteristics				Data types				Data source			Warehouse activities					
	SL	UL	RL	FL	GA	DM	DS	DT	CA	FLM	Auto	CE	Nature	ED	PD	HD	IS	IoT	Manuel input	Arrival	Put away	Storage	Picking	Preparation	Shipping
Melesse et al. (2022)	X							X	X	(X)	(X)		R		X		X	X	X			X			
Pan et al. (2022)								X		(X)	(X)														
Leung et al. (2022)	X			X				X	X				S		X	X	X	X		X		X	X		X
Huang et al. (2021)	X						X					X	R		X			X							
Leng et al. (2021)							X		X		(X)		R		X		X	X			X	X			
Kegenbekov et al. (2021)			X				(X)		X				S		X							X			
Zhan et al. (2022)		X						X	X		(X)	X	R	X		X	X	X			X	X	X		
Zacharaki et al. (2021)								X																	
Minerva et al. (2021)	X	X						X						X											
Sacks et al. (2020)								X																	
Hayward & Portugal (2019)	X X					X							R		X			X	X			X			
Corneli et al. (2019)	X					X							R		X	X	X	X	X			X			
Xiuyu & Tianyi (2018)	X						(X)						R		X		X	X		X					
Wang et al. (2020)	X				X			X	X		X		R		X		X	X			X		X		
Gao et al. (2022)	X				X			X	X		X	X	R		X		X	X			X	X	X		
Wu et al. (2022)	X							X	X		X	X	R		X		X	X			X				
Zhao et al. (2021)	X							X	X			X	R	X	X	X	X	X				X			
Bányai et al. (2019)		X						X	X		X		S		X	X	X	X			X		X		

DM, DS: digital model, shadow, FL: Fuzzy logic, GA: genetic algorithms, CA: context awareness, FLM: full lifecycle management, Auto: autonomy, CE: continuous evolving, ED, PD, HD: environmental, product and handler data, R: real, S: simulated, IS: Information system.

compare the results of the AI program with the expected status recorded in the DT's database (Corneli et al., 2019; Hayward, 2019).

4.2.1. Context awareness

AI objectives, namely classification, and forecasting, go beyond data collection by IoT and structuring. They were used for the elaboration of contextual information that DTs act on. Melesse et al. (2022) used image classification to define banana quality. Depending on the results, the DT can decide on the actions to be taken moving forward: preserve, put on sale or donate the goods before they are borderline inconsumable. Leung et al. (2022) used machine learning to predict order arrivals within the hour, allowing the system to organize the total inbound synchronization strategy accordingly. RL is by nature to a degree context-aware. The set of rules and interactions from the environment makes for a predefined interactive, situational setting. Neural networks were used to detect abnormal stationary, regarded as dangerous when warehouse operations requiring urgent interventions, from false alarms. Wang et al., (2020) used AI to predict the remaining processing times. The results are compared to the current status to optimize the material handling method proactively.

4.2.2. Autonomy

When it comes to autonomy, DT adaptations still require (and depend on) human presence in the loop to procure modifications in the physical system (by requesting a change or through notifications). Autonomous control and data acquisition has been

facilitated through IoT and the interconnectivity of the DT with other software in the cloud, namely with information systems (Leng et al., 2021; Melesse et al., 2022; Wang et al., 2020; Zhan et al., 2022). Through AI DT are an even more pertinent, perceptive, and to a degree autonomous decision-making systems, in the sense that it could even exceed human perception in finding optimal solutions. But when it comes to acting on solutions, the literature is still lacking. Hribernik et al. (2021) defined autonomy from an architecture point view, where the DT is made of multiple autonomous, interconnected, singular sub-systems. This usually influences the DT's architecture to make it able to access data singularly if need be.

4.2.3. Continuous evolving

Warehouses are fast-evolving environments, prone to daily if not hourly drastic changes. DTs need to adapt to these changes and allow an accurate representation regardless of the degree of abstraction. The structure of the DT should allow for a continuously evolving adaptation of the system so as not to make false predictions and flawed hypotheses. This is still not very explored in the literature. When it comes to adaptive DTs, collected data should be reintroduced into the cloud to reevaluate the virtual counterpart (Huang et al., 2021; Zhan et al., 2022). Huang et al. (2021) created two data streams, one that goes to the edge layer which allows high performance data processing and deployment of the ML algorithm (real time application) and the second goes through the edge for preprocessing and feature extraction and then to the cloud to reevaluate and update the model when necessary. This also makes the DT aware of the contextual changes in the warehouse. Zhan et al. (2022) stated having designed an online self-adapting mechanism to ensure that the model is in line with the environmental changes of the warehouse. Zhao et al. (2021) used a closed-loop structure that permanently updates the datasets and regenerates the programs following gene structure. From this perspective, the algorithms are self-conscious and self-modifying.

4.2.4. Full lifecycle management

None of the applications take into consideration the full lifecycle of the warehouses. The scope of the studies analyzed is mainly focused on the middle of life. Zacharaki et al. (2021) present through the RECLAIM project a framework that covers the whole lifecycle of the equipment. Their objective is to elongate through DTs the MOF. During that time and through data collection and analysis, we can prescribe refurbishment and remanufacturing actions on the machines, allowing to restore the functionality of the product or a part of it to an "as-new" state and optimize EOL.

5. Discussion and conclusion

ML technics have been highly applied in this literature review. Few articles that have not used AI explicitly still consider it as an important part of their future studies (Pan et al., 2022; Zacharaki et al., 2021). AI can help DTs reach maturity and wisdom throughout the entire product lifecycle by playing two roles :

- Reconstruction: AI can be an important tool for the reconstruction process; the process of creating and revisiting the virtual representation based on the raw data from the sensors;
- Application: Once the Digital Twin is reconstructed, another AI algorithm can be applied to the semantically rich representation of the Digital Twin to support the business goals (Slama, 2021).

Intralogistics are lightly covered in research relating to WDTs. None of the papers selected worked on optimizing package preparation (packaging, accumulation, sorting ...) and shipping. These activities present a research gap related to co-packing, prospective package preparations, testing the quality of packages based on clients appreciation, and finding links between the packaging and the shipping method.

DT has often been described as the perfect replica, being able to copy every change in the physical twin and anticipate it. This futuristic ambition is not very doable because we can neither have real-time connectivity yet (Fuller et al., 2020), nor can we capture all the states and minimal changes of a system. Such declarations presume that we have sensors everywhere to capture every shift in the air and omits connectivity and simulation times. This is at once impossible, costly, and unnecessary. With a certain level of abstraction and operational synchronization, it should be possible to effectively design and manage a stochastic WDT. It is important to keep realistic expectations when discussing DTs and AI. For the most part, ML algorithms are black box models that we do not fully comprehend the workings of. This can make the technic untrustworthy. However, this might actually help us discover patterns that we did not consider in the first place. Pan et al. (2022) discussed the field of data-centric engineering, leveraging the best of both physics, simulation, and data science. This helps ground AI and makes a little more predictable. AI has also proven Itself consequential to identifying contextual information and continuous evolving. Another potential research gap is the use of continual learning (CL) in a DT framework (Hashash et al., 2022). CL is in fact a branch of machine learning representing the capability of a model to continue evolving and regenerating from a data stream. this is also a degree of autonomy since it no longer requires human intervention. Nevertheless, autonomy is still poorly covered In scientific literature. Having autonomous systems presents more safety hazards in the workshop since we lose control over what and when actions happen.

DTs have been associated with product life cycle management since the very beginning. The first time the notion was ever explicitly used is by Grieves, during a PLM lecture (CoBuilder, 2018). None of the papers covered the entire lifecycle generally or focused on the end of life. None of the applications use artificial intelligence or simulation to model the beginning of life of a warehouse, revamping and redesigning the building, or discuss what would become of the warehouse by the end of its life.

IoT aside, warehouse operations can easily reach a huge amount of records and data used for management or assurance purposes. Tufano et al. (2022) used machine learning models to predict warehouse components design based on data and metrics collected through the life on a another storage system. The algorithms could be used to assess the effectiveness of the current, up and running warehouse to either duplicate or avoid making similar mistakes. Which brings us back to the ultimate research question of all time : What came first, the digital twin or the physical system?

If we are to consider digital twins as a simulation based concept, then making of the digital twin doesn't necessarily need the physical counterpart. It is irrelevant whether the real counterpart already exists in the physical world or is about to exist.("Gesellschaft für Informatik (GI): Digitaler Zwilling"). Prior simulation will test if the soon to be warehouse can actually handle the stock, if resources are enough for ramp up, to test if we can get away with a traditional manual warehouse or if we ought to invest in a mechanical one ... All of these previous attributes are to be consolidated and evaluated, If not changed as both twins grow and evolve. Figure 2 showcases the warehouse twins evolution through time. This model was inspired by Sacks et al. (2020) representation of the lifecycle of the twins for building construction.

The model ensures information saving and visibility in a structured and evolutive configuration. Our vision for WDT will chronologically follow the natural evolution detailed in figure 2; From a digital model to a digital shadow and lastly, a twin. The concept is to be constructed based on simulation software allowing us

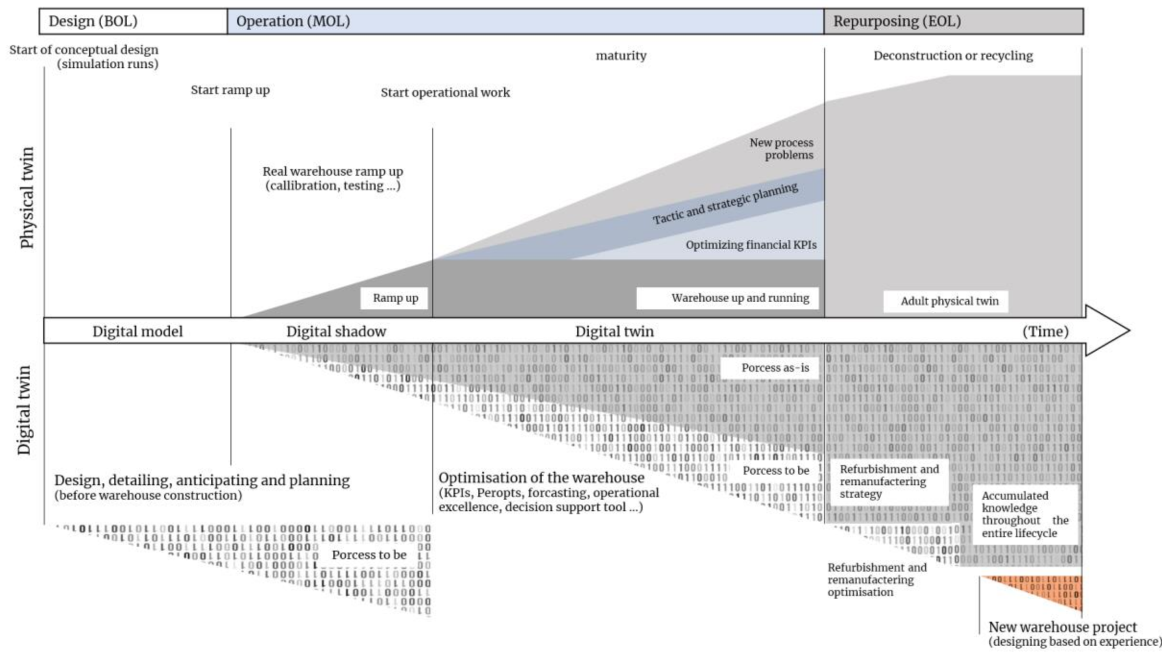

Figure 2. Full lifecycle management of WDT based on (Sacks et al., 2020)

to control the environment and run experiments in the first place, import datasets, and use machine learning based optimization and forecasts depending on the problematic at hand secondly. Also depending on the problem, we need to define the degree of synchronization required for the optimization to make sense. This way the “digital shadow” will be equipped with automatic data exchange and become a twin.

This literature review showcase the ever growing potential of both AI and DT to optimize warehousing. The algorithms are utilized in different ways to ensure WDT characteristics and potential. And on the other hand DT presents a mature and sophisticated and interactive modeling environment for AI.

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