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# WAREHOUSE DIGITAL TWIN: SIMULATION MODELING AND ANALYSIS TECHNIQUES

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## ABSTRACT

As an integral component of Industry 4.0, digital twin simulations have the potential to transform the material handling and supply chain industry. In this paper, we provide a digital twin framework for warehouse systems and the methodologies used to implement them. In addition, we present examples of practical digital twin applications in the warehouse environment. Finally we discuss some of the challenges that need to be overcome to ease implementation and expand adoption of warehouse digital twins.

## 1 INTRODUCTION

The material handling and supply chain industries are facing significant challenges. In February 2022, Forbes reported that during the pandemic, ecommerce grew 50% when comparing ecommerce sales in 2021 to ecommerce sales in 2019 (Goldberg 2022). As ecommerce continues to increase, additional pressure is placed on warehouses to meet these demands. To address this, companies are beginning to embrace Industry 4.0 which focuses on increasing automation through the application of the Internet of Things (IoT), sensors, advanced communication systems, and digital twins to achieve smart factories. For supply chain systems, this includes the development of smart warehouses with the goal of making better decisions that result in more efficient systems.

Digital twins in the form of a simulation provide one of the technologies that will make a significant impact toward advancing smart warehouses. In particular, digital twins can provide a dynamic virtual representation of the products, equipment, processes, and information involved in warehouse operations which can be used to make decisions that will help to maximize productivity, efficiency, and safety.

Although the benefits of digital twins are quite promising, technical challenges related to adoption and implementation persist. These needs include robust methods for synchronization between the digital twin and the physical system, methods for addressing system uncertainty, and computationally efficient methods for real-time decision making (Kuo et al. 2021). To address some of these challenges, specifically for warehouse systems, we provide a warehouse digital twin simulation framework and discuss the methodologies needed for implementation. In addition, we present examples of practical digital twin applications in the warehouse environment including dynamic simulation and visualization of kinematic movement of material handling equipment, warehouse design and planning, and artificial intelligence for real-time decision making.

The remainder of this paper in organized as follows. In section 2 we provide an overview of related work. A description of warehouse systems is discussed in section 3. A warehouse digital twin framework is presented in section 4. In section 5 we describe some digital twin modeling approaches for analysis and decision making. In section 6 we discuss the some of the remaining challenges associated with warehouse digital twin implementation. Finally, in section 7 we present our conclusions.

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## 2 RELATED WORK

The concept of digital twin was introduced by Grieves (2014) and defined as a virtual representation of a physical product which (with the advancements in technology) can provide a closed loop system for product management from time of manufacturing through the end of its life cycle. The digital twin encompasses three main components, a physical entity, its virtual representation, and bidirectional exchange of information between the two. The major benefit of this approach is leveraging both the virtual and digital components to passively impact the entire system by capturing, storing, evaluating and learning from both. The digital twin concept has been driven by initiatives such as Industry 4.0, big data and Internet of Things (Jones et al. 2020).

Digital twin simulation spans a wide range of application areas and industries. A digital twin architecture for manufacturing systems has been developed by Lin et al. (2020). Latif et al. (2020) present the application of digital twin to a manual manufacturing system, and utilize machine learning to improve decision making. Pu et al. (2021) construct a digital twin of indoor spaces to be used to aid rescue workers in obstructed areas of buildings. Park et al. (2022) present a digital twin application that utilizes reinforcement learning based production control in a job shop. Dehghanimohammadabadi et al. (2021) present a simulation optimization methodology for digital twins of production systems. Li et al. (2020) develop a digital twin framework for next generation ports and warehouse systems. Braglia et al. (2019) utilize RFID along with discrete event and agent-based simulation modeling tools to construct a warehouse digital twin. In addition, Leng et al. (2021) investigate an digital twin driven optimization for packing and storage in an automated warehouse system.

These are only a few examples of the growing number of digital twin applications. Leveraging these applications, we develop a digital twin simulation framework for warehouse systems.

## 3 WAREHOUSE SYSTEMS

Modern warehouses are complex systems with sophisticated equipment, tracking, control, and scheduling systems. In addition, warehouses are multi-functional with a range of supply chain related and support activities including shipping and receiving, storage and retrieval, picking, kitting, packing, palletizing, labeling, inventory management, vehicle maintenance, and vehicle charging, among others. Furthermore, material handling in a warehouse may be accomplished through one or a combination of alternatives such as manually operated forklifts, automated guided vehicles (AGV), conveyors, people, autonomous mobile robots (AMR), drones, etc. Although there are a wide range of warehouse sizes, the largest warehouses in use today occupy well over one million square feet and can have an extremely large number of stock keeping units (SKU) and extremely high volumes. The challenge for warehouse facilities is safe, robust and efficient operation.

Although a warehouse may have many functions as previously described, we will illustrate the application of digital twins to warehouse systems by focusing on the primary functions of shipping/receiving and storage/retrieval. However, digital twin modeling and analysis techniques described in the next sections can be extended to all warehouse operations.

## 4 WAREHOUSE DIGITAL TWIN FRAMEWORK

A warehouse digital twin provides a virtual dynamic replica of the physical warehouse system as the system operates over time. The goal of a digital twin simulation is to provide continual analysis and decision making support to enable control and management of warehouse system resulting in operational efficiency. A conceptual warehouse digital twin framework is shown in Figure 1. The framework includes the physical warehouse system, the warehouse data and control systems, the digital twin simulation of the warehouse system, and an experimentation/analysis component.

The physical warehouse system includes all of the components within the four walls of the warehouse and the components that interact with the warehouse providing inputs and outputs (e.g., inbound/outbound

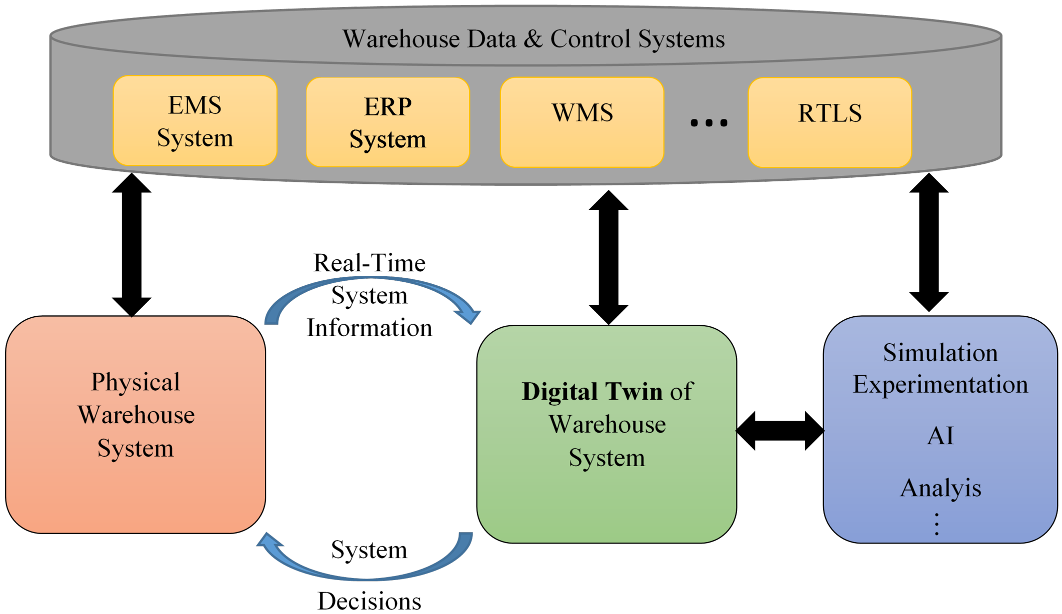


Figure 1: Warehouse digital twin framework.

trucks). Within the warehouse are racks/storage locations, the layout of aisles, docks, etc., material handling equipment, people, scanners, communication network, pallets, products, boxes, etc. Although some of the components are passive, many of the components utilize sensors to actively generate (or can be set up to generate) data. For example, forktrucks equipped with sensors can track their position, velocity, pose, angular velocity, height, load, etc. Units loads can be tracked using scanner, bar codes, and RFID. People can also be tracked in terms of their task, location, pick rates, movement, etc. In general, these sensors can provide very detailed information about the current state of the warehouse.

Warehouse data and control systems store information about the warehouse system and the supply chain. Although these systems can vary from company to company, some typical systems include an enterprise management system (EMS) and/or an enterprise resource planning (ERP) system for tracking asset and operational information; a warehouse management system (WMS) for tracking and managing warehouse operations; and a real time locations system (RTLS) for asset location tracking and telematics; among others. Data and information are exchanged between the physical warehouse system processing customer orders, dispatching people/material handling equipment for fulfilling customer orders, tracking inventory location, and other operational activities.

The digital twin of the warehouse system is a simulation model that replicates the behavior and state of the physical warehouse system. As the state of the system is captured over time by the digital twin, warehouse system performance can be analyzed. In particular, the digital twin can be used conduct simulation experiments such as simulating the near term future of the system to forecast potential issues so action can be taken to avoid them. In addition, by capturing the history of the system, the digital twin can be used to analyze how and why various situations occur. The digital twin of the warehouse can be used for support of both off-line and on-line decisions such as resource planning or dispatching. Furthermore, artificial intelligence (AI) methods can be designed, trained, and tested utilizing the digital twin model, and then used in the operation of the physical system.

As the digital twin is integrated with the physical system, real-time system information is transferred between the physical system and the data and control systems. As the analysis takes place in the digital twin simulation, systems decisions and adjustments are transferred back to the physical system and the warehouse data and control systems are updated.

### 4.1 Data Driven Digital Twin Model Creation

The warehouse digital twin simulation model needs to be created using a flexible modeling approach. Object oriented discrete-event or agent-based simulation methods are often used for warehouse models. By creating object class definitions where object instantiation and behavior are data driven, changes to the system and experimentation can be easily accommodated. Bhisti and Kuhl (2021) demonstrate the development and use of a data driven warehouse simulation approach in Simio. In this approach, data tables are used to create all of the objects in the simulation including bulk and rack storage locations, forktrucks, travel paths/aisles, dock locations, etc.

In addition for a data driven model, a robust, low-latency communication system is needed to exchange information between the warehouse and digital twin. A publisher-subscriber framework is often used to accomplish this.

## 5 DIGITAL TWIN MODELING FOR ANALYSIS AND DECISION MAKING

Digital twin simulations enable the ability to make smarter decisions Warehouse decisions can typically be thought of in terms of their time horizon. Strategic decision are long-term decisions often involving capital investment such as the size of the warehouse to build or how many forktrucks to purchase. Short term decisions are often referred to as planning decision such as warehouse scheduling and inventory management decisions. Real time or near real time decisions involve operational choices such as task assignments for forktrucks when they become available. The fidelity of the digital twin can vary depending on the types of analysis, controls, and decisions needed/wanted for the warehouse systems under consideration. In the next sections, we present three examples of digital twin model methods that could be used for warehouse analysis and decision making.

### 5.1 Dynamic and Kinematic Models in Digital Twins

In some warehouse modeling and analysis situations, there is a need to have access to and explicitly capture vehicle movement and sensor information within the digital twin. In such cases, a high fidelity representation of the traveling speed, turning radius and maneuverability, object detection and avoidance capability, etc. of warehouse vehicles may be critical to addressing some operational and planning problems.

For example, one may be interested in evaluating the capabilities and performance of alternative types of autonomous mobile robot under various warehouse conditions. For these types of decisions, programs such as ROS (a common robot operating system language used for AMRs) can be used in conjunction with Gazebo (a visualization/animation tool) to develop a dynamic simulation/visualization of the kinematic movements of the AMR as well as the AMR sensor readings such as LiDAR or other sensors. Figure 2 is an image captured using ROS and Gazebo depicting the kinematic model of a forktruck in a warehouse aisle where a single-channel LiDAR is being used to aid in navigation. Figure 3 shows the 3D point cloud data produced by a 16-channel LiDAR mounted on the forktruck which can be used for navigation and warehouse mapping. These types of models can provide great insight into the movement and control of material handling equipment in a warehouse.

Including the kinematic models for warehouse vehicles is particularly important for detecting and solving conflicts in navigation. The kinematic model can include detailed characteristics that impact the travel path and maneuverability of the vehicle. For example, the differential drive models for forklifts can take into consideration the track width of the forklift, turning radius, speed, acceleration, etc. These models can also simulate the sensors (e.g., LiDAR, cameras, RFID, etc.) that may be installed on the vehicle and their parameters such as scan angles, range, etc. of the sensor. To demonstrate the implementation of a kinematic model on a forktruck, we construct a simple warehouse simulation model in MATLAB. Figure

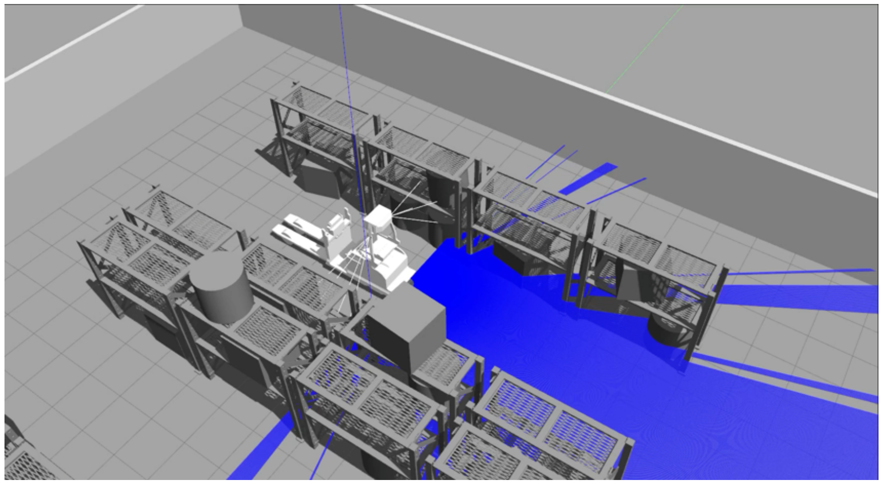

Figure 2: AMR in a warehouse with one dimensional LiDAR projection.

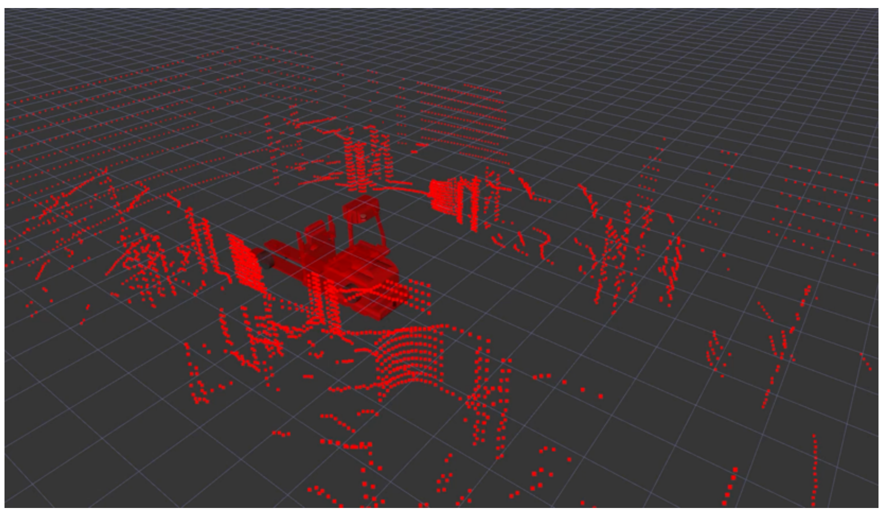

Figure 3: AMR in a warehouse with 16-channel LiDAR scan.

4 shows an example of a path plan generated for an autonomous forktruck to its destination compared with the actual path taken by the forktruck considering the kinematics and sensing capability of the vehicle. Available path planning algorithms typically take a more global (and thus coarser) approach than the motion control and navigation capability of a forktruck. In this example, A* is used for the path planning. The motion planning and navigation of the forktruck is done using a vector field histogram method (Borenstein, Koren, et al. 1991) and is dependent on the data obtained from an onboard LiDAR sensor. The pure pursuit controller (Coulter 1992) is used for controlling the wheels based on the planned motion. The resulting forktruck movements (in terms of angular velocity) is based on the desired linear velocity, maximum angular velocity and the look ahead distance. This calculation also takes into account the safety distance to be maintained from obstacles around the forktruck. As a result of its navigation capability, the forktruck deviates from the planned path. Although the extent of this deviation will be dependent on the particular situation, simulating travel paths including the kinematic models within the digital twin may help to identify potential conflicts or safety issues.

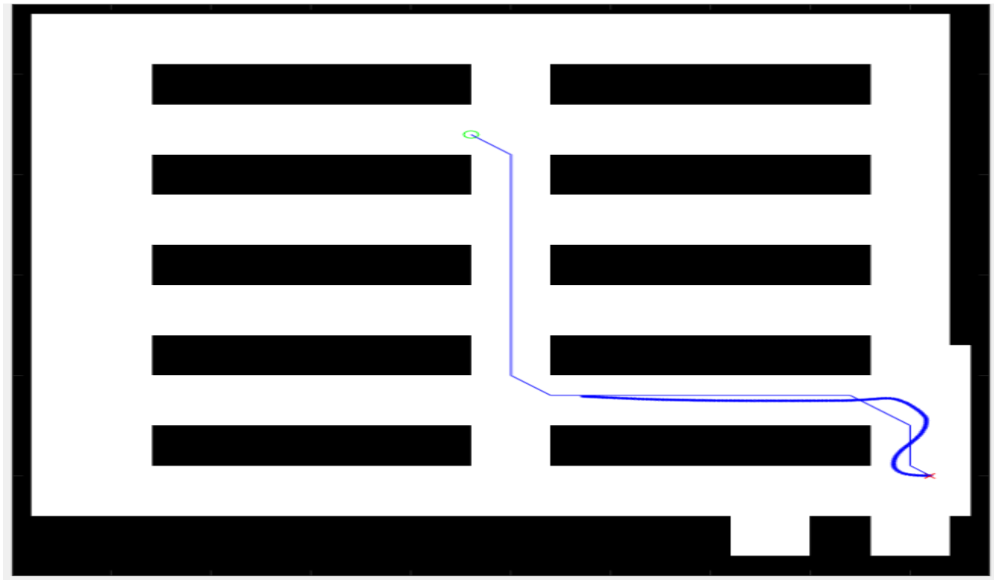

Figure 4: Example of a path planned using A* (thin line) vs. the actual path by the forktruck (thick line)

In addition vehicle selection and path planning, we are currently investigating the use of kinematic models in conjunction with dispatching rules and the impact on system performance. Figure 5 shows an example model of a warehouse constructed in MatLab which enables this capability.

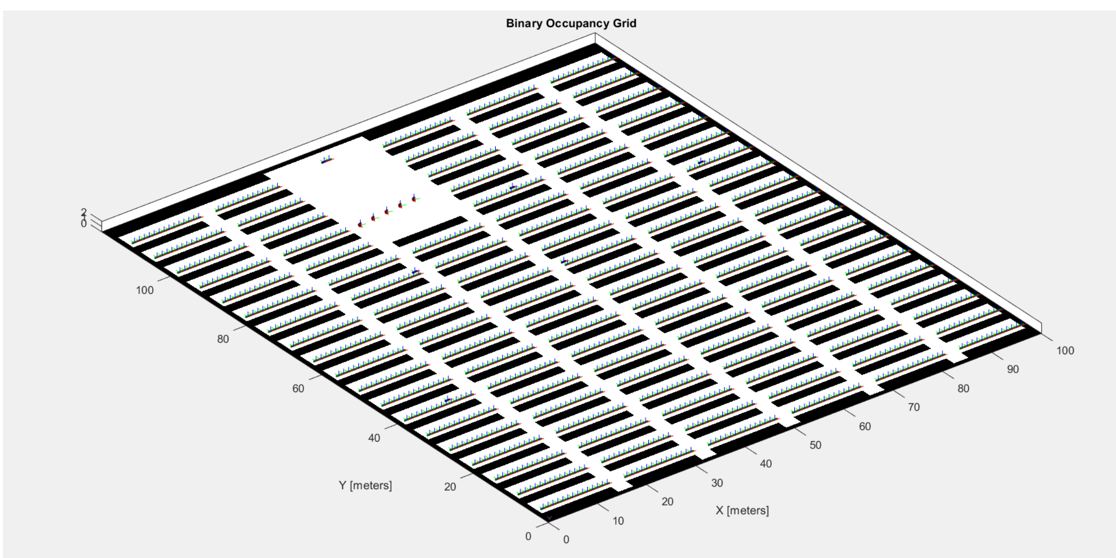


Figure 5: Warehouse model in MatLab which includes AMR kinematic functionality.

## 5.2 Warehouse Design and Planning

Warehouse planning and design decisions are critical to warehouse operational success. To adapt to the changing demand for goods, warehouse must agile and able to change. Under current supply chain conditions, these decisions are occurring more frequently than they may have occurred in the past. In this case, a company can utilize a warehouse digital twin simulation to analyze alternative warehouse designs and compare them with the current system configuration and operational performance.

Bhisti and Kuhl (2021) present a data-driven discrete-event simulation modeling approach to serve as an analysis tool for determining the appropriate mix of bulk and rack storage locations to utilize warehouse space effectively. In particular, a simulation-based methodology is used to determine the optimal mix of racks and bulk lanes for a warehouse layout considering inventory quantities and turnover rates. The model is designed to evaluate system configurations including the number of racks and storage locations, the number of bulk lanes and lane depth, and the velocity mapping of products based on demand. The goal of the warehouse simulation methodology is to conduct experiments and evaluate the trade-offs of key performance metrics for various system configurations. An example of a warehouse simulation model using this approach is shown in Figure 6.

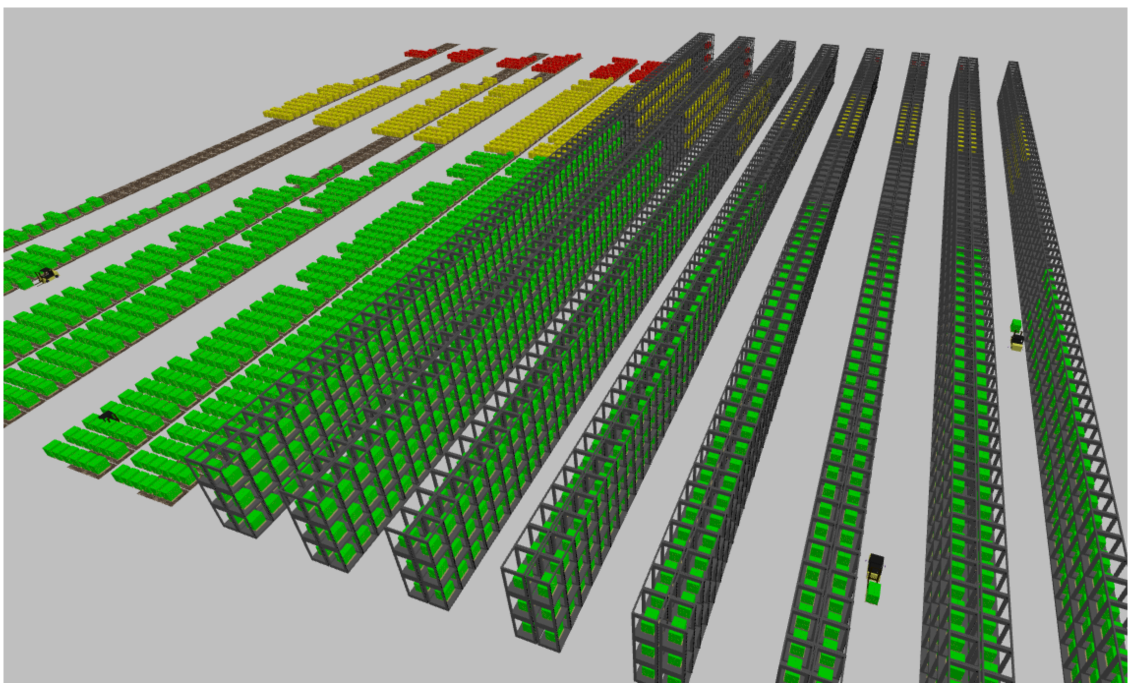

Figure 6: A view of the simulation model of a warehouse with 5 AMRs, pick up and drop off locations.

### 5.3 Artificial Intelligence and Real-Time Decisions

Warehouse operational decisions are often addressed with heuristic rules or policies that result in the same decision even if conditions in the warehouse change. By utilizing a digital twin with tools such as artificial intelligence, smarter decisions can be make based on the current state of the system.

The task assignment and path planning (TAPP) problem is an operational decision problem that must be addressed hundreds or thousand of times per day. Each time a forktruck completes a task and becomes available, the forktruck needs to be assigned to one of the pending tasks. Given a warehouse with fleet of forktrucks, the goal is to assign the task that will result in the most efficient operation of the system. As the state of the system is never quite the same, an accurate picture of the current state of the system is important. This information can be provided by a warehouse digital twin.

Li et al. (2019) propose a deep reinforcement learning method, namely a deep Q network (DQN) that solves the task assignment and path planning problems, simultaneously. A overview of the methodology is shown in Figure 7. The methodology is intended to enable real-time dispatching for available AMR. In particular, when an AMR becomes available in the physical warehouse, a dispatch request is sent to the digital twin of the warehouse system along with warehouse state information including the task assignments and path plans for the other active AMRs in the system and the pending task list with associated pickup and dropoff location data.

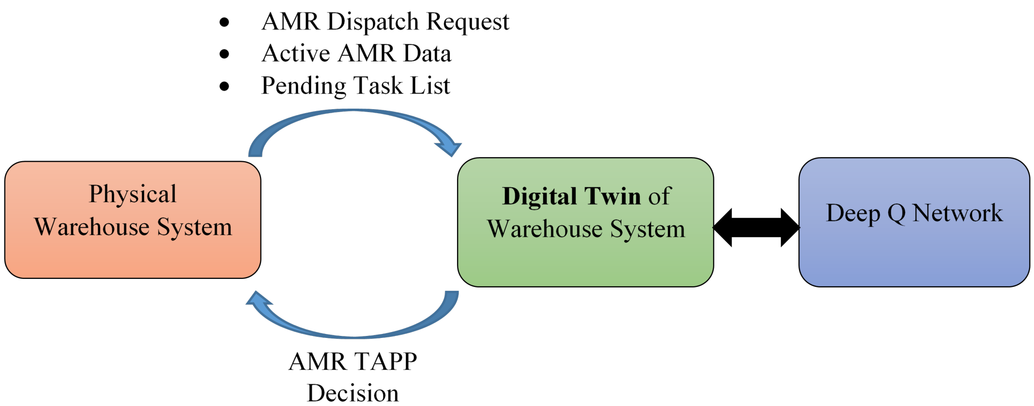


Figure 7: Overview of the TAPP solution method utilizing a digital twin and DQN.

To implement this approach to the TAPP problem, the digital twin is a type of agent-based simulation model where the warehouse layout is represented by a grid which indicates rack storage locations, aisles, AMR locations etc. An example of the grid layout is shown in Figure 8. A deep Q-network is trained on simulation data to quickly find a semi-optimal solution to the TAPP problem. The digital twin then sends the TAPP decision back to the physical warehouse to be executed by the AMR.

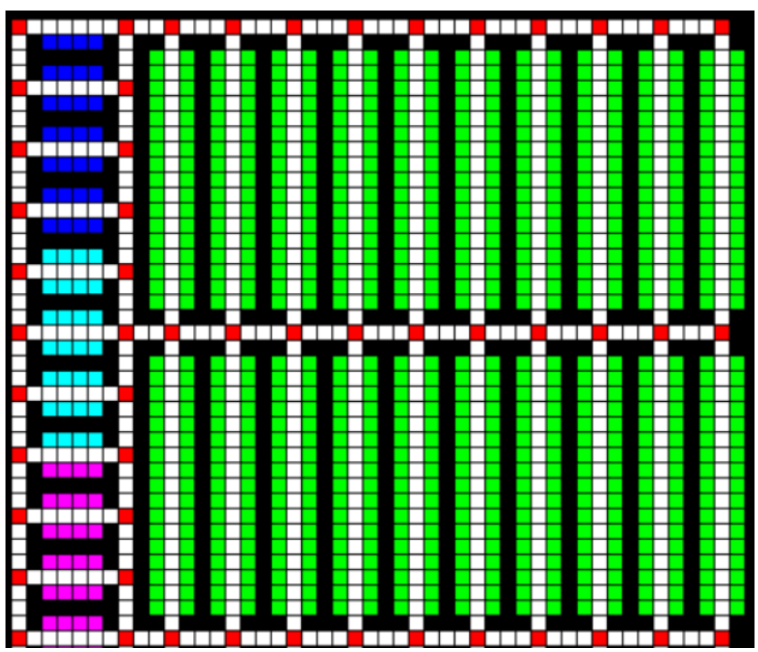

Figure 8: Digital twin grid layout for AI based TAPP solution approach.

## 6 CHALLENGES FOR WAREHOUSE DIGITAL TWIN IMPLEMENTATION

Although significant progress is being made in the development of software to implement digital twins in the warehouse environment, the are still a number of challenges. Some of the biggest challenges center around interoperability and the exchange of data and information between the physical warehouse system and the digital twin. Many warehouses today have a wide variety of technologies ranging from AMRs to manually operators material handling equipment to conveyor system. As such, collecting the right type of data from all of the various aspects of the system that are needed for quality decision making can be difficult.

A second challenge is filtering the data so the digital twin can be used to simulate the warehouse system for the problem at hand. Strategic decision, planning decision, and operational decisions require different levels of system abstraction and thus different levels and types of data. A methodology is needed to align the data requirements with the available data.

These are two of the major challenges that if overcome will enable the broader use of digital twins in warehouses.

## 7 CONCLUSION

In this paper we have provided a digital twin framework to warehouse systems. In addition, we have presented examples of practical digital twin applications in the warehouse environment. Finally we have presented some challenges to the implementation and adoption of digital twins. Overall, we conclude that digital twins will have a significant impact on the efficiency and productivity of warehouse systems and supply chains.

## REFERENCES

Bhisti, R., and M. E. Kuhl. 2021. "Simulation Analysis of Warehouses Utilizing Bulk and Rack Storage Systems". In *Proceedings of the 2021 IISE Annual Conference*, 734–739: Norcross, Georgia: Institute of Industrial and Systems Engineers.

Borenstein, J., Y. Koren et al. 1991. "The Vector Field Histogram – Fast Obstacle Avoidance for Mobile Robots". *IEEE Transactions on Robotics and Automation* 7(3):278–288.

Braglia, M., R. Gabbrielli, M. Frosolini, L. Marrazzini, and L. Padellini. 2019. "Using RFID Technology and Discrete-Events, Agent-Based Simulation Tools to Build Digital-Twins of Large Warehouses". In *Proceedings of the 2019 IEEE International Conference on RFID Technology and Applications*, 464–469: Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Coulter, R. C. 1992. "Implementation of the Pure Pursuit Path Tracking Algorithm". Technical report, Carnegie-Mellon University, Pittsburgh, Pennsylvania.

Dehghanimohammadabadi, M., S. Belsare, and R. Thiesing. 2021. "Simulation-Optimization of Digital Twin". In *Proceeding of the 2021 Winter Simulation Conference*, edited by S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo, and M. Loper, 1–10: Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Goldberg, J. 2022. "E-Commerce Sales Grew 50% to $870 Billion During The Pandemic". *Forbes* February.

Grieves, Michael 2014. "Digital Twin: Manufacturing Excellence through Virtual Factory Replication". https://www.3ds.com/fileadmin/PRODUCTS-SERVICES/DELMIA/PDF/Whitepaper/DELMIA-APRISO-Digital-Twin-Whitepaper.pdf, accessed 22 September 2022.

Jones, D., C. Snider, A. Nassehi, J. Yon, and B. Hicks. 2020. "Characterising the Digital Twin: A Systematic Literature Review". *CIRP Journal of Manufacturing Science and Technology* 29:36–52.

Kuo, Y.-H., F. Pilati, T. Qu, and G. Q. Huang. 2021. "Digital Twin-enabled Smart Industrial Systems: Recent Developments and Future Perspectives". *International Journal of Computer Integrated Manufacturing* 34(7-8):685–689.

Latif, H., G. Shao, and B. Starly. 2020. "A Case Study of Digital Twin for a Manufacturing Process Involving Human Interactions". In *Proceedings of the 2020 Winter Simulation Conference*, edited by K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and T. R., 2659–2670: Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Leng, J., D. Yan, Q. Liu, H. Zhang, G. Zhao, L. Wei, D. Zhang, A. Yu, and X. Chen. 2021. "Digital Twin-driven Joint Optimisation of Packing and Storage Assignment in Large-scale Automated High-rise Warehouse Product-service System". *International Journal of Computer Integrated Manufacturing* 34(7-8):783–800.

Li, H., X. Cao, P. Sharma, L. H. Lee, and E. P. Chew. 2020. "Framework of O2DES.NET Digital Twins for Next Generation Ports and Warehouse Solutions". In *2020 Winter Simulation Conference*, edited by K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and T. R., 3188–3199: Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Li, M. P., P. Sankaran, M. E. Kuhl, R. Ptucha, A. Ganguly, and A. Kwasinski. 2019. "Task Selection by Autonmous Mobile Robots in a Warehouse Using Deep Reinforcement Learning". In *Proceedings of the 2019 Winter Simulation Conference*, edited by N. Mustafee, K.-H. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, 680–689: Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Lin, W. D., and M. Y. H. Low. 2020. "Concept Design of a System Architecture for a Manufacturing Cyber-physical Digital Twin System". In *Proceedings of the 2020 IEEE International Conference on Industrial Engineering and Engineering Management*, 1320–1324: Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Park, K. T., S.-W. Jeon, and S. D. Noh. 2022. "Digital Twin Application with Horizontal Coordination for Reinforcement-learning-based Production Control in a Re-entrant Job Shop". *International Journal of Production Research* 60(7):2151–2167.

Pu, G., P. Wei, A. Aribe, J. Boultinghouse, N. Dinh, F. Xu, and J. Du. 2021. "Seeing Through Walls: Real-Time Digital Twin Modeling of Indoor Spaces". In *Proceeding of the 2021 Winter Simulation Conference*, edited by S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo, and M. Loper, 1–10: Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

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