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CONCEPT OF DIGITAL TWINS FOR AUTONOMOUS MANUFACTURING THROUGH VIRTUAL LEARNING AND COMMISSIONING

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ABSTRACT

Autonomous manufacturing represents a paradigm shift in industrial operations, akin to autonomous driving. This paper explores the role of digital twins in enabling autonomous decision-making within discrete manufacturing environments operated by massive fleets of robotic agents. By integrating artificial intelligence (AI), particularly reinforcement learning, digital twins facilitate the management of complex automated material handling systems (AMHS), driving the transition towards software-defined factories (SDFs). In this paper, we demonstrate how digital twins support virtual learning, training the parameters for reinforcement learning, as well as virtual commissioning, optimizing system validation and testing through virtual and physical integrations.

1 INTRODUCTION

Autonomous manufacturing systems, much like autonomous vehicles, interpret the states of their environments and make independent decisions without human intervention.

The concepts of self-adaptation and self-learning in autonomous manufacturing systems have been proposed by many researchers in the past, including Žapčević and Butala (2013) Alam et al. (2020) Park and Tran (2011), and Wada and Okada (2002).

Central to this capability in the manufacturing context is the digital twin—a virtual representation of the physical world. This concept, first advanced by NASA, involves a real-time connection with the physical world through sensors and communication networks, enabling the simulation of various scenarios and the projection of future states to aid decision-making Barricelli et al. (2019), Semeraro et al. (2021).

The role of the digital twin in autonomous manufacturing was discussed in Ding et al. (2019), which introduced Cyber-Physical System (CPS) and Digital Twin technologies to establish a Digital Twin-based Cyber-Physical Production System (DT-CPPS). This study explored its configuration, operation, and real-time data-driven controls, aiming to advance shop floors toward smart manufacturing. In this paper, we also emphasize the role of the digital twin in autonomous manufacturing. The digital twin plays a central part in autonomously finding optimal parameter settings and fine-tuning the system configurations by connecting the real and virtual systems.

This paper focuses on digital twin applications for discrete manufacturing, specifically within systems operated by *massive fleets of robot agents (MFRA)*. Unlike traditional automated material handling systems (AMHS) that merely transport parts from one machine to another, the systems discussed here integrate machinery, data, and operations more comprehensively. By pairing digital twins with AI technologies, particularly reinforcement learning, we can control extensive fleets of robots and achieve truly autonomous manufacturing Hwang et al. (2020).

Digital twin technology provides a sophisticated simulation environment for reinforcement learning, allowing for the exploration of various scenarios and their outcomes without the need for physical trials. This process, known as virtual learning, optimizes agent behaviors by refining parametersHong et al. (2022)

Hwang and Jang (2020). We demonstrate the practical application of virtual learning through an actual industry case study.

Furthermore, this paper explains how digital twins support virtual commissioning—a process in which production lines are validated and tested by integrating virtual models with physical entities Pandey et al. (2023). This integration facilitates the comprehensive examination of potential issues in a simulated environment prior to physical implementation, significantly improving the efficiency and efficacy of manufacturing processes.

The ultimate goal of this work is to showcase how digital twins, in conjunction with AI and other digital technologies, actualize autonomous manufacturing and lay the groundwork for the software-defined factory (SDF), which represents the future direction of industrial manufacturing.

2 AUTONOMOUS MANUFACTURING

Autonomous manufacturing represents an advanced concept within manufacturing systems, utilizing cutting-edge digital and robotic technologies Žapčević and Butala (2013). This concept is best understood through a comparison between conventional automation systems and autonomous systems. Current automation systems in manufacturing excel at executing pre-programmed, repetitive tasks. However, they falter when faced with environmental changes, new product introductions, or unforeseen events, necessitating human intervention. For example, in a conventional automotive assembly line, the introduction of a new car model requires adjustments to the conveyor belt and reconfiguration of machines and tools. Additionally, unexpected machine errors necessitate human involvement to reset machines and re-plan production schedules. Similarly, most industrial robots in factories perform pre-programmed tasks and require reprogramming for new tasks.

Autonomous manufacturing seeks to minimize human intervention by integrating various advanced digital and robotic technologies. It automatically identifies the environment and system states, such as machine conditions and processing parts, as well as production planning and inventory levels. Decisions are made autonomously, encompassing machine reconfigurations, robot guidance, and production planning from a holistic perspective. These decisions are then executed by autonomously sending signals to robots, setting machine parameters, or generating codes for manufacturing IT systems.

The key characteristics of autonomous manufacturing include:

- Sensing, decision-making, and actuation
- Integration of operations

As the term suggests, autonomous manufacturing involves sensing the environment, making decisions, and executing those decisions without human intervention. It also aims for complete operational integration. For instance, when a machine error occurs and causes a temporary stoppage, the Manufacturing Execution System (MES) and Supply Chain Management (SCM) systems exchange state information and autonomously adjust the production plan and optimal Work-in-Progress (WIP) levels in the factory. This alignment with the concept of an unmanned factory highlights the overarching goal of eliminating human intervention.

The concept of autonomous manufacturing has been discussed for decades but has only recently become feasible. The key enablers of autonomous manufacturing include:

1. Massive fleet robot operation
2. Cloud computing
3. Artificial Intelligence (AI)
4. Digital twin

In discrete manufacturing, robots play a critical role by handling parts and performing processes. Industrial robots have become more intelligent, capable of identifying objects through image processing and determining optimal movement paths based on the shapes of objects.

This advancement in robot technology underpins autonomous manufacturing. "Massive Fleet Robot Automation (MFRA)" emphasizes the collaborative effort of multiple agents working together towards a common goal Hwang et al. (2020). The term highlights the extensive scale of the fleet and the automation of robots within it, which is discussed further in the subsequent section.

Cloud computing serves as the second enabler, providing the necessary flexibility and scalability in manufacturing operations. As factories evolve, processing machines are continually upgraded, and new products are frequently introduced, necessitating computational flexibility and scalability.

The third enabler, AI, moves beyond rule-based operations by identifying environmental and production states and making decisions on behalf of humans. Machine learning algorithms, particularly Reinforcement Learning (RL) with simulation, evolve and enhance intelligence levels, enabling better policy decisions for the future, as illustrated in later sections of the paper.

Lastly, the digital twin is a crucial component of autonomous manufacturing. Combined with AI, it projects future scenarios and trains RL algorithms while also creating an environment that better integrates physical systems and provides virtual validation of decisions. The digital twin technology plays a pivotal role in the advancement of autonomous manufacturing.

3 MASSIVE FLEET ROBOT AGENT (MFRA) – AMHS

Massive Fleet Robot Agent (MFRA) is a term that underscores the collaboration of multiple agents working together to achieve a common goal (Figure 1). The word “massive" highlights the large scale of the fleet, while “robot agent" refers to the automation of individual robots within this fleet. Each agent acts as an independent entity capable of performing tasks autonomously. Historically, the concept of coordinated, large-scale industrial operations can be traced back to Henry Ford’s implementation during the mass production of the Model-T in the 1910s. However, unlike Ford’s rigid assembly lines, modern manufacturing demands greater flexibility and adaptability. An example of contemporary application is the new electric vehicle assembly line by Hyundai Motors, which utilizes AGVs (Automated Guided Vehicles) and AMRs (Autonomous Mobile Robots) to create a highly adaptive assembly system. This advanced line is also referred to as a “beltless line," indicating the absence of traditional conveyor belts, which underscores the shift towards more dynamic and flexible production methods.

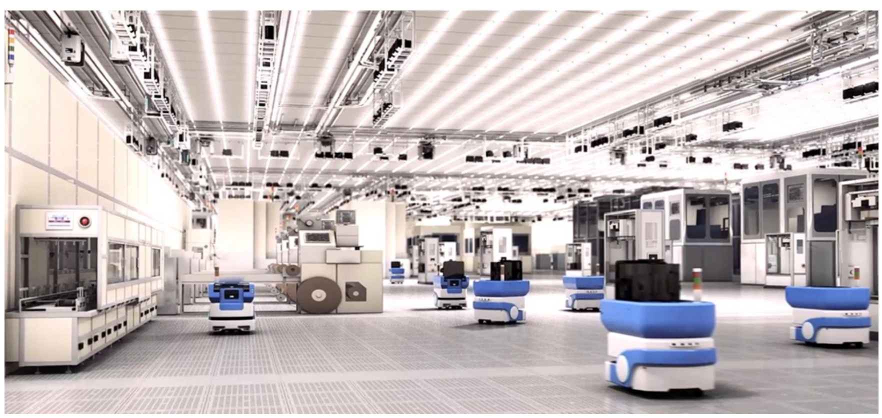

Figure 1: Illustrative image of Massive Fleet Robot Agent (MFRA) based AMHS.

The Overhead Hoist Transportation (OHT) system in semiconductor fabrication facilities, commonly known as FABs, exemplifies a MFRA based automated material handling system (AMHS). In these facilities, multiple vehicles hoist and transport lots from one processing machine to another. Modern FABs frequently operate with more than a thousand OHT vehicles, demonstrating the scale and complexity of these systems Hong et al. (2022).

Similar MFRA based AMHS (MFRA-AMHS) are prevalent in various industries. For instance, smartphone assembly lines at Samsung Electronics, home appliance production lines at LG Electronics, battery production lines at SK On and LG Energy Solution, and electronic parts production systems extensively utilize hundreds of AGVs or AMRs Hwang et al. (2020).

A primary challenge in MFRA involves the coordination and cooperation among the agents. Key operations include optimally assigning tasks to agents, navigating tasks such as path planning or routing to destinations, and resource planning like battery charging scheduling. Moreover, these operations must be synchronized with broader manufacturing processes such as scheduling and planning, inventory management, and workforce planning to effectively achieve production management goals.

Figure 2: OHT and AMR systems at KAIST (MFRA).

The operations of Automated Guided Vehicles (AGVs) and robot planning have been pivotal research topics within the domain of "Flexible Manufacturing Systems (FMS)" since the 1980s Gershwin (2018). While MFRA encompasses aspects of FMS, it distinctly extends and refines these concepts.

Firstly, MFRA-AMHS emphasizes scale-free agent control. Modern manufacturing lines, such as those in semiconductor FABs, which utilize over 1,000 OHT vehicles, exemplify the necessity for managing a vast number of agents. The critical challenge in such environments is minimizing computation time despite the scale of operations. This approach, known as "scale-free" agent control, ensures that computational efficiency is maintained irrespective of the number of agents involved.

Secondly, MFRA advocates for an integrated approach to manufacturing operations. Unlike conventional FMS research that often segregates material handling, production machine operation, and workforce management into distinct areas, MFRA adopts a holistic perspective. This integrated approach aims for globally optimal outcomes by considering all manufacturing operations collectively, rather than isolating individual components. Traditional FMS studies might focus on the management of AGVs as a separate entity from production scheduling or inventory management, but MFRA seeks to unify these and other aspects into a cohesive strategy.

Thirdly, the scope of research in MFRA surpasses the traditional confines of FMS, which primarily focused on algorithm design and operational analysis. Achieving integrated and holistic goals in MFRA requires interdisciplinary research. This includes not only traditional optimization, simulation, and machine learning techniques but also data-driven approaches. Additionally, a comprehensive understanding of conventional software design, such as database design, system architecture development, and network communications, is crucial. Knowledge in electro-mechanical system design and control system analysis also plays a significant role in advancing MFRA methodologies.

4 DIGITAL TWIN FOR VIRTUAL LEARNING

This section outlines the application of a reinforcement learning algorithm within the MFRA-AMHS framework, illustrating how digital twin technology enhances the effectiveness of the reinforcement learning process. The algorithms and approaches employed are based on previous research conducted by one of the authors, as detailed in Hong et al. (2022) and Hwang and Jang (2020). Readers interested in a more comprehensive understanding of the methodologies and empirical results are encouraged to consult these referenced articles.

The integration of digital twin technology allows for a sophisticated simulation environment where various scenarios and their outcomes can be explored without the need for physical trials. This virtual learning space enables the refinement of algorithms and the optimization of agent behaviors in real-time, ensuring that the learning process is both efficient and reflective of actual operational conditions.

4.1 Reinforcement learning for MFRA-AMHS

Q-learning is a type of reinforcement learning, a method used to train machine learning models alongside supervised and unsupervised learning. In reinforcement learning, the agent iteratively seeks the optimal solution through trial and error by interacting with its environment and making decisions based on available data Sutton and Barto (2018). It observes the outcomes of its actions and updates its strategy accordingly. This method is particularly advantageous for autonomous manufacturing for two reasons: firstly, it is well-suited to systems subject to continuous change, which typically lack steady-state properties. Secondly, reinforcement learning is effective for stochastic optimization with simulation, enabling the realization of learning-based optimization with advanced data-processing technologies Bertsekas (2019).

In high-tech manufacturing, most MFRA-AMHS operations involve robots traveling on predefined routes, despite their capability to autonomously navigate. This constraint is often due to spatial limitations within the manufacturing systems. Similar to urban traffic planning, where rules become necessary as vehicle numbers increase, predefined paths help manage the flow of numerous robots efficiently and safely. This is not only a matter of efficiency but also of safety, as these paths prevent robots from endangering human workers on the factory floor.

For modeling purposes, an MFRA-AMHS or MFRA system can be viewed as a directional network where a robot's path includes multiple branching and merging points. Thus, a robot's path can be represented as a graph $G(N,E)$, where N is a set of nodes including stations (where robots load or unload lots), branching, and merging nodes. The edges E connect these nodes consecutively.

Effective control within MFRA has been demonstrated through a node-based approach, where nodes act as decision-making entities guiding robots at critical junctures. Analogous to traffic signals in a roadway system, these nodes direct robots at intersections, deciding both the direction a robot should travel to reach its destination and the allocation of robots to tasks.

Routing decisions are made when a robot approaches a branch and needs direction to continue towards its destination, ensuring no delays in transportation occur. Allocation decisions involve assigning idle robots to new tasks or rerouting robots upon completion of their current tasks. The overall methodology for routing and allocation within this system is illustrated in Figure 3.

In the MFRA system, decision-making at node i utilizes the Q-function, denoted as $Q_i(\cdot)$, for routing and assigning robots at this node. The function $\hat{Q}[d,i,j]$ is defined as the estimated total travel time for a robot destined for node d, when it is currently at node i and selects node j as its next destination.

Routing decisions are made based on the values of the Q-function. For example, consider a scenario where a robot, destined for node d, approaches node i. The robot must choose between edge (i,j) and edge (i,k). The decision entity at node i compares $\hat{Q}[d,i,j]$ and $\hat{Q}[d,i,k]$ to determine which edge represents the shortest estimated travel time. The edge with the lower Q-function value is chosen, guiding the robot along the optimal route.

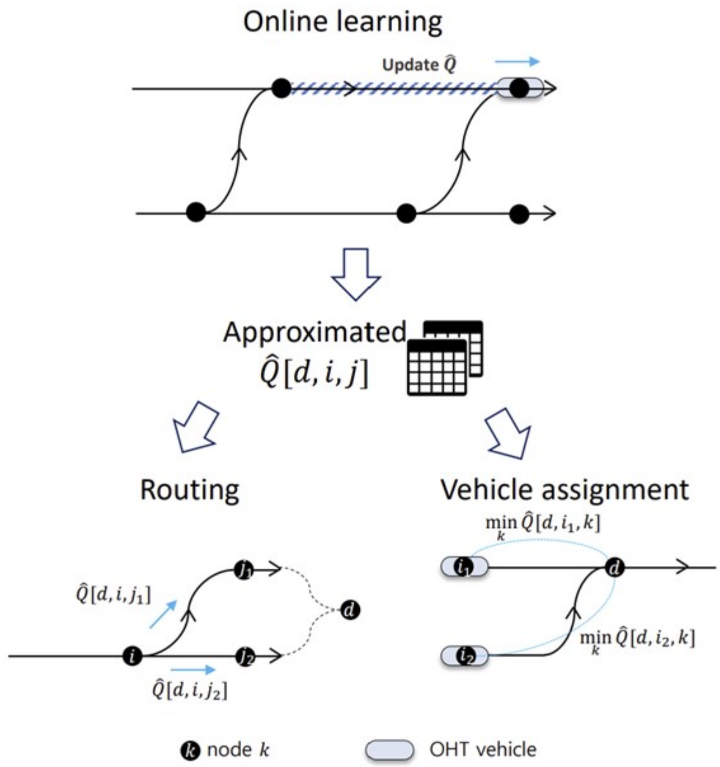

Figure 3: Overall Q-function value-based robot routing and control scheme.

Robot allocation also leverages the Q-function values. Suppose a new task at node d requires a robot for transportation. Node entities at nodes $i = 1,\ldots,n$, where idle robots are stationed, initially calculate $c_i = \min_k \hat{Q}[d,i,k]$ to identify which robot can reach the load in the shortest time. The optimal robot is determined by $i^* = \arg\min_i c_i$, and it is then assigned to transport the new load at node d.

4.2 Digital Twin for RL – Virtual Learning

A factory is a dynamic entity, constantly evolving to accommodate shorter product life cycles and the rapid introduction of new technologies. As processing machines are upgraded and new products introduced, the flow of parts and the layout of the factory undergo significant changes. Consequently, the paths of robots must be updated to reflect these changes. In the context of autonomous manufacturing, such updates necessitate immediate adjustments to the Q-values, a process facilitated by the use of a digital twin.

We refer to this application as the Digital Twin for Virtual Learning (DT-VL). Specifically, whenever a robot's path is updated, the corresponding Q-table must be revised. The DT-VL, a virtual replica of the MFRA system, mirrors any change in the factory that affects the tasks of the robots. For example, the introduction of a new machine may alter the factory layout, impacting robot movement, which should be promptly reflected in the DT-VL. Similarly, the introduction of a new product might necessitate different part flows, affecting robot operations within the MFRA system. Before the actual production of new products begins, the DT-VL simulates these changes, adjusting the Q-table accordingly.

The primary role of the DT-VL is to rapidly evaluate and update the optimal Q-values and transfer these updates to the actual MFRA system, ensuring that robots operate seamlessly within the updated environment. This method of updating learning parameters in a virtual system, which are then transferred to physical robots, is known as Zero-shot Learning Haarnoja et al. (2023). A key requirement for effective zero-shot learning is fast simulation, particularly crucial for MFRA systems, as the main objective is to minimize real-world learning costs through rapid virtual adjustments.

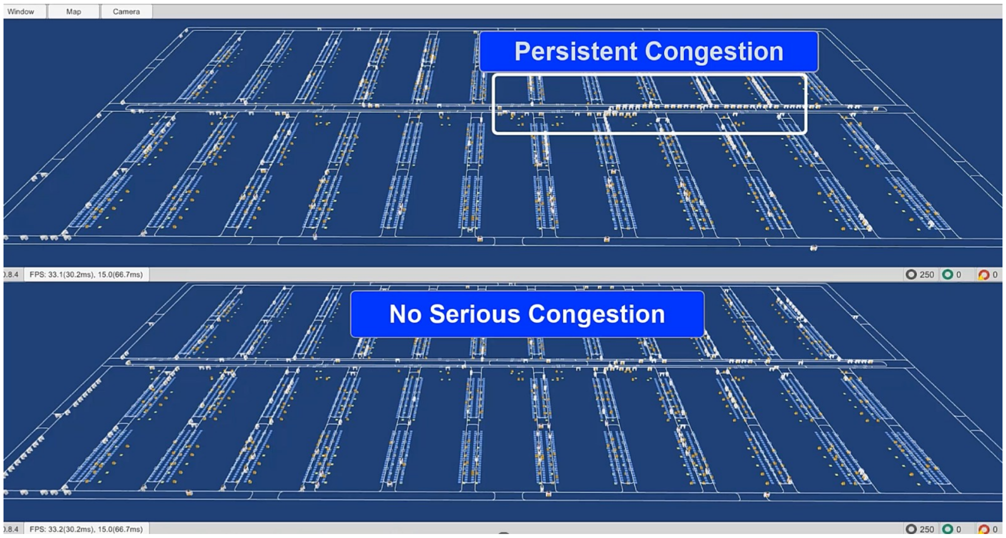

Figure 4: Movie clip of the system operating 1,000 OHT robots.

DAIM Research and KAIST developed an Overhead Hoist Transportation (OHT) control system for a memory chip manufacturer in Korea. The OHT system, an example of the Massive Fleet Robot Agent (MFRA) system, is instrumental in semiconductor fabrication. The movie clip 4 along with this article highlighted the facility's deployment of 1,000 robots and the challenges of unexpected traffic congestion that can occur with such a high density of robotic operations. Traditional methods of manually guiding and rerouting robots often proved ineffective and sometimes exacerbated the congestion issues.

In response, the chip manufacturer enlisted DAIM Research and KAIST to devise a solution, which led to the testing and implementation of a Reinforcement Learning (RL) based algorithm integrated with a Digital Twin for Virtual Learning (DT-VL). This innovative approach allowed for the effective assignment and guidance of robots, automatically alleviating unexpected congestion. The movie clip 4 clearly demonstrated the success of the RL and DT-VL solution in eliminating congestion.

The importance of the DT-VL system is underscored by the rapid pace at which semiconductor fabrication facilities must adapt, with processing machines and products frequently updated on a weekly basis. The impact of implementing the RL and DT-VL solution was substantial. As illustrated in Figure 5, data showed a notable improvement in robot performance, enhancing delivery times and capacity by 32% and 20%, respectively. Moreover, the efficiency enabled by the new system allowed the factory to operate effectively with 800 robots instead of 1,000, resulting in significant cost reductions. Considering each robot's cost of USD 80,000, this adjustment equated to a saving of USD 16 million.

5 DIGITAL TWIN FOR VIRTUAL COMMISSIONING

5.1 Virtual commissioning

The development and deployment of new MFRA-AMHS in factories are often time-consuming and costly. The AMHS is critical as it interconnects various components such as machines, manufacturing IT systems, and other facilities, necessitating extensive integration efforts with diverse hardware and software. Given that robot manufacturers, processing machine suppliers, and manufacturing IT system providers are distinct entities, the integration, testing, and system-level validation processes are fraught with risks. Consequently,

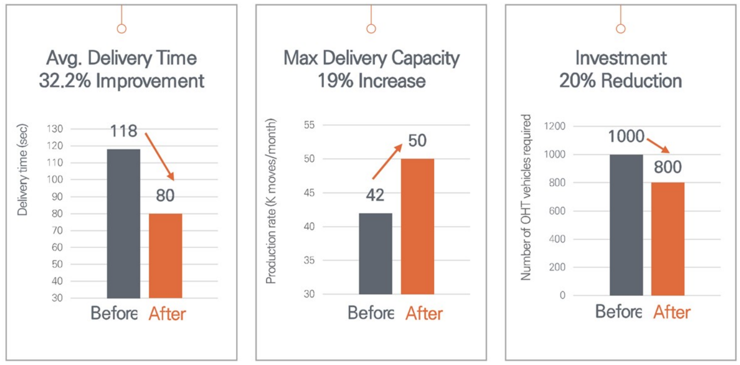

Figure 5: The result of using RL and DT-VL for the OHT system.

when a new factory is constructed, these integration challenges frequently delay the overall project, diminishing the return on investment (ROI), lowering morale, and reducing trust among teams and suppliers.

One effective solution to address these risks is the use of Digital Twin for Virtual Commissioning (DT-VC). DT-VC provides a virtual factory environment where hardware and software systems can be interconnected and tested virtually, without the need for physical setup at the factory site. This approach enables thorough testing and validation of system integration before actual deployment.

Figure 6 and Figure 7 illustrate the virtual commissioning process for an OHT vehicle at KAIST. In this setup, the actual physical OHT vehicle is linked to the DT-VC, which in turn connects to other software systems, such as the Material Control System (MCS) and the OHT Management System (OMS). While the OHT is physically suspended on a testbed, it interacts with these systems via DT-VC, receiving and sending signals as depicted in the figure. Through this system, the OHT undergoes rigorous testing and validation of test procedures and protocols, ensuring that they fulfill the necessary requirements and specifications.

5.2 Industry case for DT-VC

The deployment and stabilization of the Massive Fleet Robot Agent-Automated Material Handling Systems (MFRA-AMHS) typically require a significant amount of time, often extending up to six months in total. This duration includes two to three months for deployment followed by an additional two to three months for system stabilization, which involves parameter tuning and validations.

However, one of the industry partners of DAIM Research, operating in the battery manufacturing sector, faced a critical requirement to expedite this process, needing both installation and stabilization to be completed within a month. Leveraging the capabilities of Digital Twin for Virtual Commissioning (DT-VC), which allows for the testing and optimization of all parameter settings in a simulated virtual factory environment, DAIM Research successfully met this challenging one-month deadline. The DT-VC solution enabled the efficient anticipation and resolution of potential integration issues, thereby significantly reducing the overall setup time.

6 CONCLUSION

In this paper, we initially define autonomous manufacturing and emphasize the importance of MFRA-based AMHS in modern production lines pursuing autonomous manufacturing concepts. We then discuss the role of the digital twin in MFRA-AMHS, highlighting two applications: virtual learning and virtual commissioning. The digital twin for virtual learning (DT-VL) employs a reinforcement learning (RL) algorithm to find optimal parameters in a virtual environment. Whenever changes occur in the real world, the virtual system representing this reality provides an environment to rapidly learn optimal settings for the new environment, thereby expediting the learning process.

Figure 6: Virtual commissioning for an OHT system.

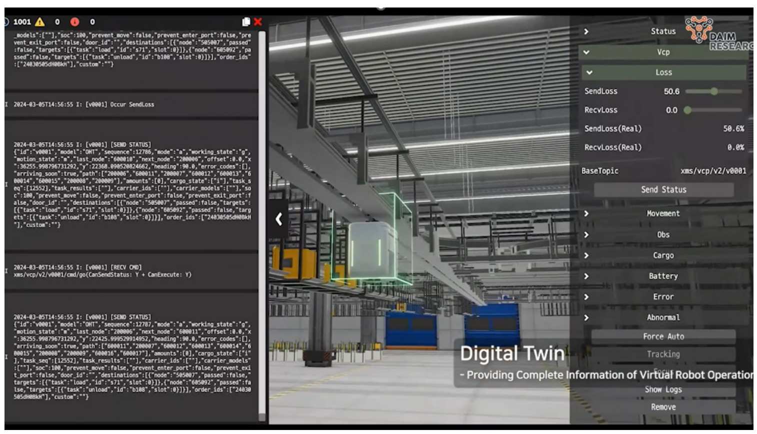

Figure 7: Screen shot for the virtual commissioning for an OHT system.

Virtual commissioning involves testing and validating the system. We present an industry case that integrates physical system hardware and manufacturing IT systems within a virtual factory environment provided by a digital twin. This case demonstrates how digital twin for virtual commissioning (DT-VC) is efficiently and effectively used to integrate systems.

It is important to note that true autonomous manufacturing is still far from being fully realized. However, the direction toward an autonomous manufacturing concept is clear. While this paper focuses on the AMHS aspects of autonomous manufacturing, applications related to the operations of processing machines are also pertinent, which we reserve for future research.

Additionally, a viable approach to achieving autonomous manufacturing is the software-defined factory (SDF), where the software concept is architected and then hardware components are laid out based on the software architecture. This concept, first introduced in smartphones and later adopted by Tesla for their automobiles, is provided as a direction for future research in autonomous manufacturing. One of our industry partners, Hyundai Motor Group (HMG), has designed and built a newly opened factory in Singapore using this SDF concept. Although it is still in the early stages, this is not just a future concept but is currently being investigated in the industry. We also reserve research on SDF for future exploration.

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