Digital Twin for Virtual Learning - Industry Case

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This paper explores the implementation of a Digital Twin for Virtual Learning (DT-VL) system, developed by DAIM Research and KAIST, in a semiconductor manufacturing facility. Utilizing a reinforcement learning algorithm within a Massive Fleet Robot Agent (MFRA) framework, the system optimizes robot routing and allocation in Automated Material Handling Systems (AMHS), particularly addressing Overhead Hoist Transportation (OHT) challenges. The deployment demonstrated significant improvements, including a 32% enhancement in delivery times and a 20% increase in operational capacity, enabling the facility to operate efficiently with fewer robots and achieve substantial cost savings, thereby highlighting the efficacy of integrating advanced digital twins and machine learning technologies in industrial operations.

1. Massive Fleet Robot Agent (MFRA) – AMHS

Massive Fleet Robot Agent (MFRA) refers to extensive collaboration among autonomous robots, aiming to achieve a shared objective. The term ”massive” emphasizes the fleet’s size, with each ”robot agent” independently performing tasks. The Overhead Hoist Transportation (OHT) system, used in semiconductor fabrication facilities or FABs, is a prime example of a Massive Fleet Robot Agent (MFRA) based Automated Material Handling System (AMHS). These systems utilize numerous vehicles to lift and move batches between different machines. Modern FABs often employ over a thousand OHT vehicles, highlighting the vast scale and complexity of these operations (Hong et al. (2022)).

2. DIGITAL TWIN FOR VIRTUAL LEARNING

We introduce 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 including Hong et al. (2022) and Hwang and Jang (2020).

Q-learning, a reinforcement learning method, trains machine learning models through trial and error interactions with its environment, adjusting strategies based on outcomes Sutton and Barto (2018).

In high-tech manufacturing, especially with MFRA-AMHS, robots follow predefined routes to navigate efficiently and safely within spatial constraints. This setup, similar to urban traffic control, ensures both efficiency and safety, preventing accidents on the factory floor.

For modeling, MFRA-AMHS systems are seen as directional networks of nodes and edges, representing various points robots travel through. Control is managed node-by-node, where decisions on routing and task allocation are made based on the optimal path calculations using the Q-function, which estimates travel times between nodes. This process ensures smooth flow and effective task assignment within the manufacturing system.

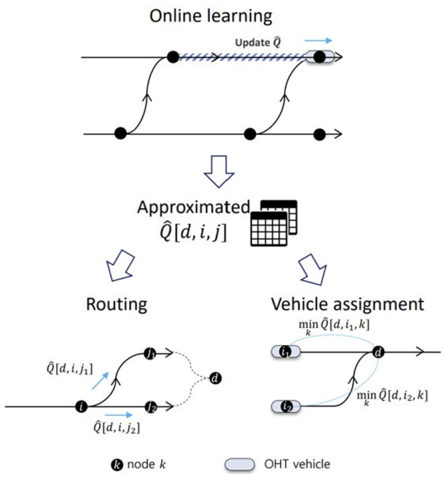

Figure 1. Overall Q-function value-based robot routing and control scheme

Routing decisions are guided by Q-function values to minimize travel time and efficiently allocate tasks, demonstrating an organized method for managing large fleets of robots within complex manufacturing setups. 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 $Q_i(d, j)$ and $Q_i(d, k)$ 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.

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 $c_i = \min_k Q_i(d, k)$ 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. Readers interested in a more comprehensive understanding of the methodologies and empirical results are encouraged to consult the following articles: Hong et al. (2022) and Hwang and Jang (2020). Factories are dynamic entities that must adapt quickly to shorter product cycles and new technologies. As machines are upgraded and new products launched, both the factory layout and the flow of parts change, requiring robots' paths to be adjusted. This adjustment is streamlined through the Digital Twin for Virtual Learning (DT-VL), which mirrors changes in the factory setup and updates the robots' Q-tables accordingly.

The DT-VL serves as a virtual model of the MFRA system, promptly reflecting changes like new machines or products that impact robot movement and operations. It simulates these updates in advance, ensuring that robots function seamlessly when production changes occur. This approach, known as Zero-shot Learning, emphasizes fast simulations to update learning parameters virtually before applying them in the real system, significantly reducing the costs and time associated with physical trials Haarnoja et al. (2023).

3. Industry Case

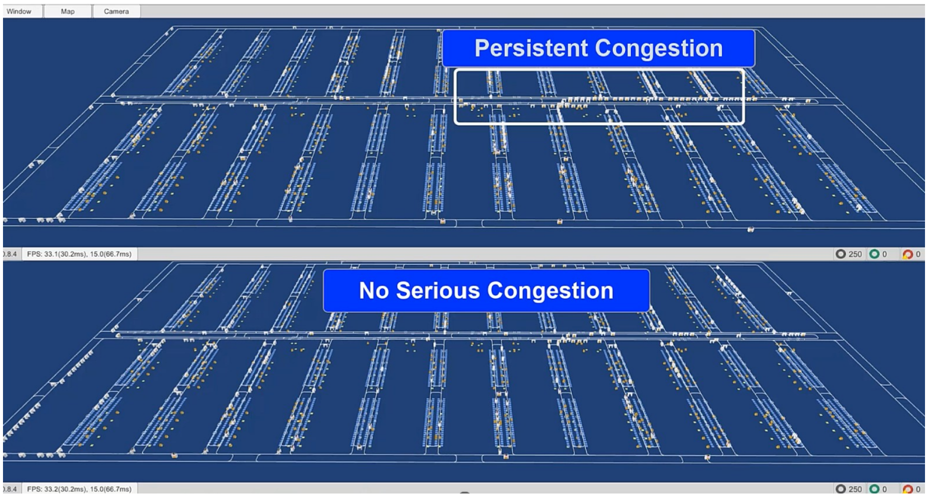

Figure 2. Movie clip of the system operating 1,000 OHT robots

DAIM Research and KAIST developed an Overhead Hoist Transportation (OHT) system for a Korean memory chip manufacturer, an application of the Massive Fleet Robot Agent (MFRA) system critical in semiconductor production. A movie clip 2 featured with this article shows the deployment of 1,000 robots and the traffic congestion challenges inherent in such dense robotic operations, where traditional manual interventions often failed.

To address these issues, the chip manufacturer collaborated with DAIM Research and KAIST, implementing a Reinforcement Learning (RL) algorithm coupled with a Digital Twin for Virtual Learning (DT-VL). This solution effectively managed robot assignments and alleviated congestion, as demonstrated in the movie clip (Screen shot depicted in Figure 2).

The DT-VL system's value is highlighted by the need for rapid adaptation in semiconductor factories, where updates are frequent. The implementation of the RL and DT-VL solution markedly improved robot efficiency with delivery times and capacity improving by 32% and 20%, respectively. This efficiency allowed the factory to reduce its robot fleet to 800, saving USD 16 million based on the cost of each robot.

References

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