POLITECNICO DI TORINO

Department of Management and Production Engineering

Master’s Degree in Engineering and Management

Integration of Digital Twin with UR and AMR for Real-Time Adaptive Material Handling Systems

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Abstract

Traditional manufacturing systems were static, rigid and disconnected and they were designed for mass production with low flexibility. Those systems had predefined schedules and fixed processing speed. Therefore, they were not able to adapt in real time data which leads to unbalanced workflows, excess inventory. With the fourth industrial revolution, new manufacturing systems, especially Smart Manufacturing systems, can respond fast to global competitiveness and customization. Smart manufacturing systems gather real-time data with improvement in decision making, increasing efficiency and performance and total production.

By emerging Digital Twin, it is considered as a core component in smart manufacturing. Digital Twin through the virtual component of physical assets, is updating the systems based on real-time data. As smart manufacturing needs quick decision based on real-time data, Digital Twin enables this process and makes the manufacturing process more reactive and smarter.

However, in the real world, the capacity of the warehouses is limited and imbalances between workstations and warehouses can create bottlenecks and disrupt the production flow. Therefore, Having the synchronization between warehouse capacity and workstations is necessary to have stable manufacturing process. Increasing the speed of robotic systems in workstations does not always guarantee better performance as it causes congestion, so it is important to keep the processing speed of the processing and warehouse availability balanced and prevent blocking or overflow.

The proposed solution is to integrate a Digital Twin framework to adjust the speed of the robot manipulator with respect to the limited capacity of the warehouse. This study is done in Mind4Lab at Politecnico di Torino by utilizing FlexSim simulation software, a UR3e collaborative robot for picking and place applications, a mobile robot MiR100 for moving the items to a warehouse and the Modbus communication protocol for exchanging data between physical and digital components.

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Acronym List

AMR Autonomous Mobile Robot

AGV Automated Guided Vehicle

DT Digital Twin

MiR Mobile Industrial Robot

UR Universal Robot

HRC Human-Robot Collaboration

PLC Programmable Logic Controller

TCP/IP Transmission Control Protocol / Internet Protocol

HMI Human-Machine Interface

CAD Computer-Aided Design

IoT Internet of Things

KPI Key Performance Indicator

3D Three-Dimensional

GUI Graphical User Interface

FMS Flexible Manufacturing System

ERP Enterprise Resource Planning

ROS Robot Operating System

MSP Microsoft Project

BOM Bill of Materials

AI Artificial Intelligence

ML Machine Learning

Glossary

Autonomous Mobile Robot: A robot capable of navigating its environment without fixed paths or human intervention, using sensors and onboard intelligence.

Automated Guided Vehicle: A mobile robot that follows predefined paths, typically using wires, magnets, or tracks on the floor.

Cycle Time: The total time required to complete a process or transport task from start to finish.

Digital Shadow: A one-way data flow from the physical system to the digital system, used for monitoring and analysis but without interaction.

Digital Twin: A dynamic digital representation of a physical system that is continuously updated with real-time data and can interact with the physical system.

Physical Reality: The actual robotic and mechanical components in a system, such as the mobile robot and manipulator.

Interarrival Time: The time between the arrivals of two consecutive items in a system.

Throughput: The number of items or tasks completed in a system over a given period.

1 Introduction

Today, manufacturing is evolving thanks to the new technologies which are introduced by Industry 4.0. Designing and managing production systems is being reshaped due to new concepts like cyber-physical systems, real-time data analytics and smart automation. Among these innovations, Digital Twin technology has emerged as a powerful tool to create a dynamic connection between physical and virtual reality. This enables real-time monitoring, decision-making and performance optimization. (Glaessgen & Stargel, 2018; Tao et al., 2022)

A Digital Twin is not just a digital model. It is a virtual representation of a physical system that mirrors its behavior based on real-time data and it is continuously updated (Negri et al. 2017). This technology is widely used in different industries from manufacturing to healthcare and where it helps improve throughput, reduce downtime and manage variability (Soori et al., 2023;Cimino et al., 2019)

While many studies focus on using Digital Twins for predictive maintenance or optimization, fewer have looked at how this technology can support real-time decision-making in production systems. In particular, the challenge of synchronizing robot behavior with warehouse capacity has not been fully addressed in the literature. (Attaran & Celik, 2023)

One common challenge in production lines is managing the mismatch between workstation speeds and storage capacities. When warehouse space is limited, processing items at a constant high speed can lead to bottlenecks, idle robots, and inefficient use of resources. It is important to note that increasing speed does not always lead to better performance as it can actually cause congestion and reduce the stability of the system.

This study addresses this challenge by proposing a Digital Twin framework that adjusts the robot manipulator's speed in real time based on warehouse capacity. The goal is to create a more balanced and responsive material handling system that avoids bottlenecks and improves overall process flow. In this framework, a UR3e collaborative robot and a MiR100 mobile robot are used along with a virtual model built in FlexSim and synchronized via Modbus TCP/IP. This study is developed and tested in a laboratory setting in Mind4lab in Politecnico di Torino and, and the model offers practical insight which can be extended to more complex industrial environments.

The structure of the thesis is organized as follows: section 2 provides a historical overview of the industrial revolutions and the definitions of industry 4.0. Section 3 presents a general overview of Digital Twin and explores its application and challenges in the real world. Section 4 focuses on collaborative robots and their applications in manufacturing. Section 5 studies the mobile robots and the differences between Autonomous Mobile Robots (AMR) and Autonomous Guided Vehicles (AGV) and their development with manipulators. Section 6 discusses motivation for this study and describes the physical setups, including the UR3e and mobile robot and presents the virtual model developed in FlexSim with detail about 3D model and process flow. Section 7 explains the implemented logic and analyzes scenarios and results.

2 Industry 4.0

The first industrial revolution (F.I.R) was the transition to new manufacturing processes in Europe, the United States and the rest of the world.

In 1760 with the invention of steam engine, the first industrial revolution occurred. In that time, train which consumed coal as the main source of energy, was considered as the main transportation system and second industrial revolution begins with the invention of combustion engines where run by oil. This leads to mass production. The third revolution started in 1960 with using information technology and electronics to automate production. The industry 4.0 started with a project by German government in 2011. The key goal of this revolution is interconnection, information transparency and decentralized decision. Figure 1 shows the industry revolutions and the main reason behind them over time. (Rahman et al., 2023)

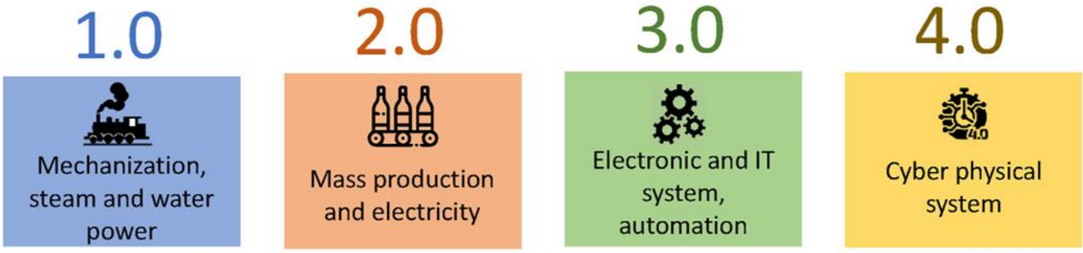


Figure 1. Industrial revolutions

The term industry 4.0 stands for the fourth industrial revolution. The main objective of industry 4.0 is to satisfy customer needs by affecting order management, research and development, delivery up to utilization and recycling. Vaidya et al. (2018) Industry 4.0 is characterized by a combination of new technical components and main principles to design and form this concept. The main components of industry 4.0 are:

1. Identification (RFID system): the first step is to identify how to process good.
2. Locating (RTLS): identification used with location or recording the place of identification.
3. Sensing or Cyber-physical system (CPS): the physical production is with computed based process. A CPS includes sensors which can collect and send data.
4. Networking or Internet of things (IoT): with IoT companies can control their product in real time. IoT is part of the CPS.
5. Data collection and analysis (Big Data and Data mining): With industry 4.0, the variety, volume and velocity of data has increased, which is due to advances in sensor technology.
6. Business Service or Internet of Services (IoS): this service helps service providers to offer their services through the Internet. (Mohamed, 2018)

In table 1, there are some definitions of industry 4.0.(Mohamed, 2018)

Table 1. Definiation of Industry 4.0

Authors	Definition of Industry 4.0
Koch et al. (2014)	“The term Industry 4.0 stands for the fourth industrial revolution and is best understood as a new level of organization and control over the entire value chain of the life cycle of products, it is geared towards increasingly individualized customer requirements”.
MacDougall (2014)	“Industry 4.0 or Smart industry refers to the technological evolution from embedded systems to cyber-physical systems. It connects embedded system production technologies and smart production processes to pave the way to a new technological age which will radically transform industry and production value chains and business models”.
McKinsey Digital (2015)	“Industry 4.0 seen as a digitization of the manufacturing sector, with embedded sensors in virtually all product components and manufacturing equipment, ubiquitous cyber physical systems, and analysis of all relevant data”.
Deloitte AG (2015)	“The term Industry 4.0 refers to a further development stage in the organization and management of the entire value chain process involved in manufacturing industry”
Geissbauer et al. (2016)	“Industry 4.0 - the fourth industrial revolution, focuses on the end-to-end digitization of all physical assets and integration into digital ecosystems with value chain partners”.

**Adapted from Mohamed (2018)*

Groumpos (2021) In their study, they grouped the impacts of industrial revolutions into positive and negative categories. After the first industrial revolution, the GDP per capita increased for the first time in history. By shifting from work by hand at home to factories, the average income increased. Moreover, technological innovations like mechanized spinning, weaving and locomotives paved the way for future industrial advancement. There was a start to form a middle class of skilled workers and shape modern capitalist economies. As is mentioned, industrial revolutions had also negative impacts like poor and unsafe working conditions, no job security, increase in child labor and inequality in social classes.

AS shown in figure 2, the nine pillar technologies that form the modern industrial production under the fourth industrial revolution are:

1. Additive manufacturing (AM): Nowadays, companies can produce small batches of customized products with the help of 3D printing instead of prototyping components.
2. Augmented Reality (AR): AR systems help to do a variety of tasks like guiding operators in training courses with smart devices.
3. Autonomous Robots: Autonomous robots can communicate with each other and work alongside a human in a safe environment.
4. Big Data and Analytics: As digitalization grows and creates more datasets, data and analytics are crucial to industrial and digital economy. Analytics is the process of creating information from raw data by filtering, categorizing, contextualization and processing.

5. Cloud: Cloud manufacturing is a combination of existing advanced manufacturing models with enterprise information technologies like cloud computing.
6. Cybersecurity: By increasing cyber-attacks and threats, the demand for protection of industrial system and manufacturing are increased.
7. Horizontal and vertical system integration: The totally automated value chain is due to the evolution of cross-company and universal data integration network.
8. The Industrial Internet of Things (IIoT): With I4.0, devices can communicate and interact with each other under the IIoT.
9. Simulation: Simulation tools and techniques are used in smart factory operations to create the digital counterpart of the physical asset. (Mourtzis et al., 2024)

Figure 2. The nine pillars of Industry 4.0.

With the emergence of the industry 4.0, there is a significant shift in the technological advancements and their application in industry. During this phase of revolution, the use of data analyzed, advanced automation, machines and smart factories helps to enhance efficiency and productivity of production throughout the value chain. The concept of smart manufacturing is focused on integration of information technology which includes IoT, cloud computing and artificial intelligence. Currently factories are focused on deploying Digital Twin technology to facilitate the adoption of smart manufacturing strategies which can enhance production speed and quality and overall system efficiency. (Ebni et al., 2023)

Horváth & Szabó (2019), proposed the driving forces and barriers to adopting industry 4.0 technologies in manufacturing. Figure 3 shows the forces and barriers. They categorized the driving forces into 5 groups:

1. Human resources: with the labor shortage, companies want to automate the repetitive task and assign workers for higher value task but on the other hand there was a lack of skilled employees and also retraining them was time-consuming and expensive.

2. Financial resources and profitability: Through digitalization, companies could decrease the cost like labor cost and inventory cost, but digitalization needs a higher initial investment, and many companies worry about return of investment.
3. Market pressure: Companies for survival in the market and being competitive must digitalize which allows new business models and strengthen customer relationships. While those do not digitize, they will fall behind.
4. Management expectations vs reality: Management wants real-time control and performance data through smart systems while lack of planning and leadership, causes unsuccessful implementation.
5. Productivity and efficiency: Industry 4.0 reduces errors, lead times and improving efficiency and product quality but in order to achieve improved performance, it needs optimized processes and flexible structures. Moreover, there might be the resistance of workers in change due to fear or uncertainty.

<table>
<tr><th>Driving force</th><th colspan="2">Factor</th><th>Barrier</th></tr>
<tr><td>Increasing labour shortages
Reducing human work
Allocating workforce to other areas (higher added value)</td><td colspan="2">Human resources</td><td>Lack of appropriate competences and skilled workforce
Longer learning time (training of staff)</td></tr>
<tr><td>Reducing costs e.g. human resources, inventory management and operating costs</td><td colspan="2">Financial resources and profitability</td><td>Lack of financial resources
Return and profitability
Shortcomings in tendering systems
Long evaluation period for tenders</td></tr>
<tr><td>Market competition
Follow market trends
Increasing pressure from competitors
Business model innovation</td><td>Market conditions and competitors</td><td rowspan="2">Management reality</td><td rowspan="2">Lack of a leader with appropriate skills, competencies and experience
Lack of conscious planning: defining goals, steps and needed resources</td></tr>
<tr><td>Demand for greater control (from top management)
Continuous monitoring of company performance</td><td>Management expectations</td></tr>
<tr><td rowspan="2">Reducing the error rate
Improving lead times (compliance with market conditions)
Improving efficiency
Ensuring reliable operation (e.g. less downtime)</td><td rowspan="2">Productivity and efficiency</td><td>Organizational factors</td><td>Inadequate organizational structure and process organization
Contradictory interests in different organizational units
Resistance by employees and middle management</td></tr>
<tr><td>Technological and process integration, cooperation</td><td>Lack of a unified communication protocol
Lack of back-end systems for integration
Lack of willingness to cooperate (at the supply chain level)
Lack of standards incl. technology and processes
Lack of proper, common thinking
Unsafe data storage systems
The need for large amounts of storage capacity</td></tr>
</table>

Figure 3. Driving forces and barriers of Industry 4.0.

One of the pillars of the industry 4.0 framework is simulation. The new simulation modeling paradigm is based on the concept of Digital Twin (DT). It combines real-time data with simulation models for better performances in productivity. In the next session, the concept of Digital Twin will be discussed in detail.

3 Digital Twin

3.1 General Overview of Digital Twin

The concept of the Digital Twin (DT) was introduced by Glaessgen and Stargel during the 53rd Structures, Structural Dynamics, and Materials Conference for the first time. They described it as a powerful simulation framework that combines multiple physical models, real-time sensor data, and historical information to mirror the life of a physical system like a vehicle or machine. A Digital Twin acts as a virtual replica of a physical object, which allows engineers and decision-makers to understand better the performance and therefore leads to smarter and more efficient decisions. (Glaessgen & Stargel, n.d.)

The term "Digital Twin" is often used interchangeably with "Digital Model" and "Digital Shadow". while these concepts are different based on the level of data integration between the physical and digital objects. Some digital representations are manually created and not linked to real-time data; others are fully synchronized with the physical object. Therefore, the authors classify Digital Twins into three subcategories as can be seen in figure 4: Digital Model, Digital Shadow, and Digital Twin, based on the extent of data integration. (Kritzinger et al., 2018)

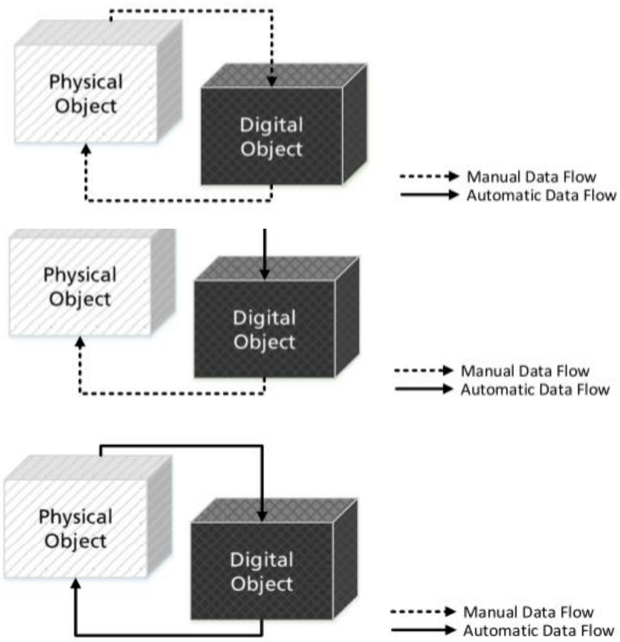


Figure 4. Digital flow in Digital Model, Digital Shadow and Digital Twin

AS it can be seen in the figure 5, there are differences in capabilities of performing different functions between Digital Twin, digital shadow and digital model. It should be notable that Digital Twins are not replacing digital models or digital shadows.(Iranshahi et al., 2025)

Functions	Digital Model	Digital Shadow	Digital Twin
Automatic data flow; from physical object to digital model.	☒	☑	☑
Automatic data flow; from digital model to physical object.	☒	☒	☑
Predictive analysis; Testing scenarios in a virtual environment before applying them to the physical system.	☑	☑	☑
Real time monitoring of its real-world counterpart.	☒	☑	☑
Decision-making; Real time analyzing the data, testing predictive scenarios and making decisions.	☑	☑	☑
Control; Real time interaction and optimization of the behavior of its real-world counterpart.	☒	☒	☑

Figure 5. Comparing the capability of Digital Twins, Digital Shadow, Digital Model

Fuller et al. (2020) in their studies, they categorize the research on Digital Twins into three primary areas: manufacturing, healthcare, and smart cities. They highlight that many of studies are concentrated within the manufacturing sector, which shows that the industry considers Digital Twin technology for enhancing operational efficiency and predictive maintenance. They also recognize several important challenges that interrupt the implementation of Digital Twins. These challenges include the need for stable IT infrastructure, the availability of useful and high-quality data, concerns regarding privacy and security, and the necessity for trust and standardized modeling practices. Responding to these challenges is important for having a successful integration of Digital Twins across different areas, as they represent both a technological advancement and a paradigm shift in how industries operate and interact with data.

According to Jones et al. (2020), the definition of a Digital Twin is linked to 13 key characteristics that shape its operation and interaction with the physical world. These characteristics include elements such as the physical and virtual entities, the twinning process, state, and fidelity, among others. All together they form the foundation of how a Digital Twin functions, emphasizing its role in synchronizing the physical and virtual environments to accurate monitoring, simulation, and optimization.

According to Negri et al. (2017) , the Digital Twin (DT) is defined as a virtual and computerized counterpart of a physical system which is linked with the concept of Industry 4.0 and cyber-physical systems (CPS). In the beginning it was conceptualized by NASA for aerospace which DTs offer real-time synchronization between the physical and virtual worlds through sensors and data integration. In manufacturing, DTs help optimize production systems, enhance decision-making, and support predictive maintenance by continuously updating virtual models based on real-time data from their physical objects.

Jeremiah et al. (2024) in their study, they explore different applications of DT and their security challenges and also categorized it into five different groups based on application and characteristics. **Product Digital Twins** are digital replicas of physical products which mostly are used in manufacturing for simulations, design, and testing. **System Digital Twins** represent larger systems like factories or cities, integrating multiple products and processes to provide a whole view. **Process Digital Twins** focuses on simulating and optimizing workflows or processes, especially in industries like manufacturing and logistics. **IoT-Enabled Digital Twins** leverage real-time data from IoT sensors to create dynamic models. Finally, **Human Digital Twins** are used in the healthcare area for personalized medicine, health monitoring, and predicting health outcomes.

In the context of manufacturing, the concept of a Digital Twin by Dr. Michael Grieves is defined as a virtual representation of a physical product that enables a comparative analysis between the designed product and its actual object. This iterative feedback loop between design and execution has an important role in enhancing the manufacturing process, as it allows for real-time data and adjustments that align production outcomes with design specifications. By facilitating this comparison, Digital Twins contribute to improved efficiency and quality in manufacturing operations. (Grieves, n.d.)

AS Shao and Helu explain, the scope and constraints of a Digital Twin depend on three key factors: **application**, which defines its fidelity and objectives; **viewpoint**, determining whether it focuses on a product, process, or system; and **context**, which influences how information is presented, and which data is needed for decision-making. These factors ensure the Digital Twin is specified to unique use cases while maintaining cost-effectiveness. (Shao & Helu, 2020)

According to Liu et al. (2024) the most important difference between DT and conventional digital models is the dynamic nature of DT. This means that any changes happening in the DT are synchronized in real-time with the physical objects it represents. Additionally, DTs form a closed loop with these physical objects which means that analyses and decisions made based on the DT are fed back to the physical object in real time and influencing its behavior

A Digital Twin offers various benefits in Industry 4.0/5.0 technologies, including data acquisition, modeling, integration, analytics, visualization, and maintenance. (Asranov Mansurand Aliev, 2024). In the next section, the application of Digital Twins has been discussed.

3.2 Application for Digital Twin

After the first definition of DTs in aerospace, the concept has expanded over the past decade to other areas such as manufacturing, healthcare, and construction.

Digital Twin technology can support a wide range of functions across the manufacturing system. As shown in figure 6 one of the important applications is improving equipment reliability through a “Machine Health Twin” which uses sensor and process and monitor data and predicts potential failures. This reduces downtime machine. Another application is production planning optimization to decide what to produce, when and with which resources. A digital Twin can collect real-time data from different systems like ERP and analyze them and based on this analysis it can adapt the production plan automatically. This enables better coordination, reduced cycle times and increase efficiency of machine usage. Additionally, during equipment commissioning a “Commissioning Twin” allows manufacturers to test and validate system virtually which reduce costs. (Shao & Helu, 2020)

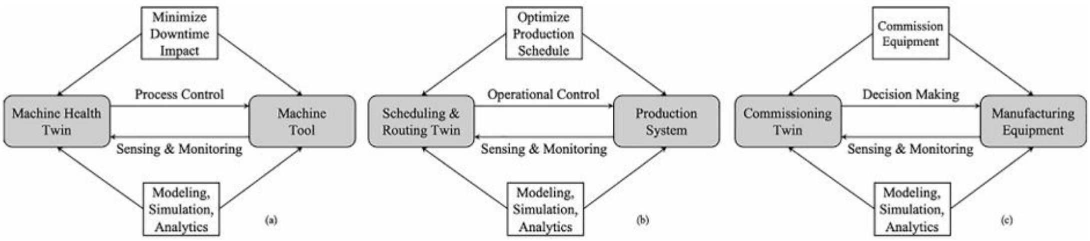


Figure 6. The use of Digital Twin in manufacturing

They reviewed the papers of Digital Twin application in the product life cycle which most of the studies are related to production, prognostics and health management and design. (Dzedzickis et al., 2021)

Figure 7 shows Percentage share of research areas in Digital Twin application.

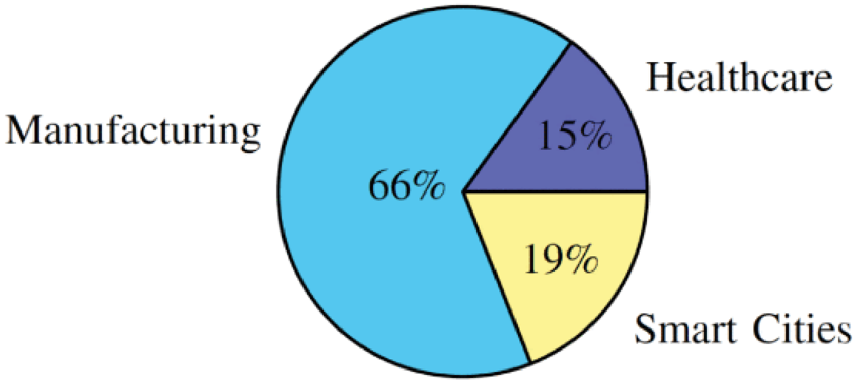


Figure 7. Percentage share of research areas in Digital Twin application

In the context of Manufacturing, Digital Twins can be used to optimize the production process, predict and prevent equipment and machine failures, and improve efficiency and quality of production. (Soori et al., 2023).

Soori et al. categorize the use of Digital Twins in a manufacturing system into three phases:

A) **System Design Phase**: In the system design phase, the Digital Twin is utilized to validate and test the manufacturing system, identifying inefficiencies and evaluating the feasibility of physical manufacturing solutions. Real-time monitoring data helps predict potential failures and optimize system operations before serious problems happen.

B) **System Configuration/Reconfiguration Phase**: During this phase, the Digital Twin is designed based on the physical system's specifications, such as geometry, material properties, and operating conditions. It simulates system behavior under different conditions, including changes in input parameters or the introduction of new components. The semi-physical simulations by the Digital Twin allow for validation of the system's performance and help identify potential failures.

C) **System Operation Phase**: In the operation phase, Digital Twins continuously monitor the manufacturing system's performance in real-time. They provide important feedback and adjustment instructions to the physical system and enabling manufacturers to predict and resolve issues before they lead to downtime. This reduces waste, enhances efficiency, and optimizes the production process and improves production performance.

Digital Twins have emerged in manufacturing and providing virtual representations of physical systems that enable real-time monitoring, predictive maintenance, and optimization. However, despite the extensive theoretical framework of DTs, there is significant gaps between their conceptualization in literature and their practical implementation in real-world cases. (Cimino et al., 2019)

Cimino and colleagues found that many existing DT applications are not fully integrated with manufacturing systems, particularly in their ability to interact with Manufacturing Execution Systems (MES). A critical finding is that most DTs cannot control physical systems from the digital environment which decrease their effectiveness in optimizing manufacturing processes. This gap suggests a need for enhancement of communication between digital and physical objects to facilitate real-time adjustments and decision-making. To address these issues, a practical implementation of a DT was conducted in a laboratory setting at Politecnico di Milano by focusing on a mobile phone assembly line. This application specifically studied the monitoring of energy consumption and machine states in real time and demonstrating how DTs can improve operational efficiency. They propose a structured approach to developing a DT that aligns with the operational needs of manufacturing systems. This framework includes three key aspects:

(I) Real-Time Data Acquisition: Using protocols such as OPC UA to ensure effective communication and data exchange between the Digital Twin and the physical manufacturing environment.

(II) Energy Consumption Monitoring: Developing functionalities within the DT to track energy usage across different machine states.

(III) User-Friendly Interfaces: Creating graphical user interfaces (GUIs) that enhance interaction with the DT which make it accessible for operators and decision-makers.

By focusing on these aspects, the proposed framework aims to decrease the gap between theoretical models of Digital Twins and their practical applications and finally improve the integration of DTs into manufacturing systems.

Caputo et al. (2019) studied on a Digital Twin (DT) framework for evaluating ergonomic performance in assembly line stations. They show how DT can improve workplace design. This framework helps to identify and correct design errors which could lead to ergonomic issues and delays in production. This approach reduces costs and time if the potential problems are considered during the early design stages, rather than after the start of production. The authors applied their framework to a Fiat Chrysler Automobiles (FCA) assembly line, utilizing a Concurrent Engineering (CE) approach to create the Digital Twin. CE allowed the simultaneous evaluation of ergonomics alongside the design and engineering phases, rather than performing ergonomic checks after the start of production. This integration helps to be sure that ergonomic considerations are embedded into the process from the outset. The DT replicated the workstation in a virtual environment, simulating the tasks performed by workers. This helps to assess ergonomic conditions during the design phase by analyzing worker postures and material handling requirements. The use of Virtual Reality (VR) technology and digital human models (DHM) within the Digital Twin made it possible to simulate workers performing tasks and providing a detailed assessment of how ergonomic factors would affect real-world performance. This study shows the value of Digital Twin technology as a tool for considering ergonomics into the design phase, ensuring safer and more efficient workplaces while avoiding costly design corrections later in the production process.

Karanjkar et al. (2018) developed a Digital Twin to optimize energy consumption in an automated Surface Mount Technology (SMT) assembly line. The main aim of the study was to enhance energy efficiency while simultaneously improving production throughput. To achieve this, they employed an IoT-driven Digital Twin. They installed sensors throughout the assembly line to monitor energy consumption and collect comprehensive data on machine performance over a three-month period.

Using SimPy, an open-source discrete-event simulation library, the authors constructed the Digital Twin of the SMT-PCB assembly line. This model helps them to do "what-if" analyses which helps to study scenarios and the evaluation of different parameters to assess their impact on energy consumption. The Digital Twin helps this simulation to evaluate the optimal buffer size for enhancing energy efficiency. The results showed that through the buffering, they could achieve a 2.7 times reduction in energy consumption without negatively impacting production throughput. This study highlights the potential of Digital Twin technology in manufacturing, particularly in optimizing energy use while having operational efficiency.

In recent advancements in healthcare technology, the concept of Digital Twins has emerged as a transformative approach, particularly in emergency departments dealing with anonymous patients who lack accessible health information. The proposed model by Aluvalu et al. (2023) leverages Digital Twin technology to enhance patient care by integrating several key components: digital health records, smart devices health trackers, expert advisors, and blockchain communication.

When a patient arrives at the emergency department, this model enables healthcare providers to quickly access the patient's digital health records, even in cases where the patient is unable to provide their medical history. Additionally, real-time data from wearable devices is made available, allowing for continuous monitoring of the patient's vital signs and health metrics.

With immediate access to comprehensive health information, medical professionals can make more accurate and timely decisions regarding treatment. This capability is crucial in emergency situations where every second counts. The implementation of this Digital Twin model has demonstrated a remarkable 95.6% improvement in the detection and treatment of patients within the emergency department. Overall, the integration of Digital Twin technology in healthcare not only streamlines the process of obtaining critical patient information but also significantly enhances the quality of care provided to patients in urgent medical situations.

The manufacturing sector is under a fast transformation which is because of technological advancements, particularly in the decision-making and monitoring tools that facilitate the implementation of Digital Twin technology. This innovation makes it possible to monitor and optimize manufacturing processes in real time. Using virtual objects to monitor, simulate, and remotely control physical assets is one use for Digital Twins. Moreover, this technology helps us to understand customer need better and therefore improves customer satisfaction. With these predictive techniques, factories can predict machine failures, plan repairs, enhance machine performance, increase the useful life of machines, and redesign systems for higher efficiency. (Attaran & Celik, 2023)

Kumbhar et al. (2023)They proposed a Digital Twin framework for detecting and improving bottlenecks throughput in manufacturing systems. The framework utilizes a utilization-based method for detecting bottlenecks, which has demonstrated the capability to achieve a minimum throughput improvement of 10% in existing systems. This approach not only enhances operational efficiency but also provides a robust mechanism for real-time monitoring and decision-making, allowing manufacturers to respond swiftly to changing conditions on the shop floor. Furthermore, the integration of process mining techniques within the framework facilitates the generation of dynamic process maps, enabling a comprehensive understanding of resource interactions and dependencies. The findings underscore the critical role of data-driven methodologies in modern manufacturing, particularly in the context of Industry 4.0, where digital transformation is essential for maintaining competitive advantage.

Attaran & Celik (2023) Studied on the use cases and application of DT. DT technology in manufacturing is used by designing products and optimizing production lines and predicting the maintenance needs. In Agriculture, it is used for making better decisions related to resources, weather conditions, soil health and reducing waste. In the healthcare sector, it is used for personalizing treatment, drug development and designing smart hospitals. In the automative sector, it is used to improve design and monitor performance. Also, in the construction and real estate sector, it is used for tracking the project, managing resources and assessing quality. Digital Twin use cases and applications can be seen is figure 8.

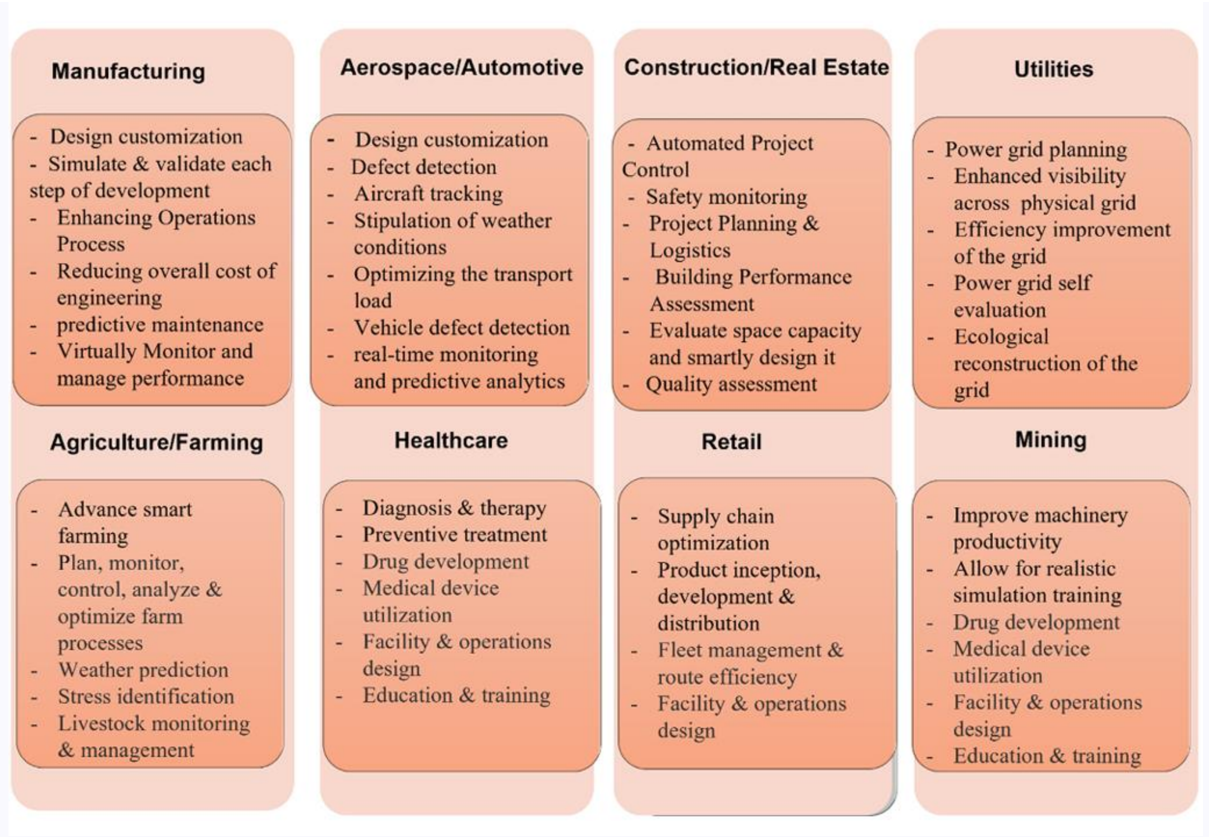


Figure 8. Digital Twin use cases and applications

3.3 Challenges of Digital Twin

Although Digital Twin is used in a wide range of industries, it has its own challenges which depend on the domain the DT is being implemented. These challenges are mainly technical:

1. High fidelity 2-way synchronization is difficult especially for large factories that require resources and high-steam IoT.
2. Interoperability with the software which is used in a production lifecycle: factories use different software for tasks like inventory, operations and product management. One of the issues is the compatibility of DT with this software.
3. Cybersecurity and IoT security: with the DT operating across multiple industrial partners and inventory sites, the security becomes more important.
4. Add-Ons: using Dt entails add-ons like cost, resources and research. DT can be costly if the duration of the project is short. Moreover, DT needs to be in line among different components, real-time tools and big data resources, therefore, putting all these together might be time consuming. (Sharma et al., 2022)

Kober et al. (2024) studied the challenges of the Digital Twin in manufacturing. They group the main challenges into 3 main groups, technical, organizational and methodological and many of the challenges overlap as is shown in figure 9. The definition of each of challenges is on table 2.

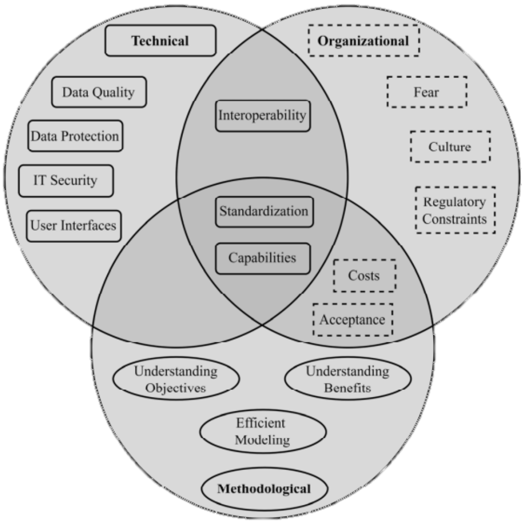


Figure 9. Challenges of Digital Twin application

Table 2. Main challenges of Digital Twin

Main Challenges	**Characteristics**	**Definition**
Technical	Standardization	Lack of unified protocols, interfaces and process causes delay in system integration and real-time data exchange
	Data Quality	Incomplete data from older machines are hard to integrate or interpret
	Data protection	Concerning privacy and legal restrictions, limit data collection and storage
	IT security	Risk of cyber attacks
	User interfaces	Difficulty in creating minimal and simple interfaces
	Interoperability	Difficulty in integration of data from different systems with different formats
	Capabilities	Lack of skilled personnel to develop and assess DT systems
Organizational	Costs	Needing high initial investment and recurring costs
	Acceptance	Lack of trust of employees and unclear expectations
	Fear	Fear of loss of jobs in employees
	Culture	Resistance to data-driven decision making and internal politics
	Regulatory constraints	Internal and external objections due to regulatory requirements
Methodological	Understanding Objectives	Difficulty in understanding the objective of the DT
	Understanding Benefits	Difficulty in understanding the benefit of the DT
	Efficient Modeling	Efficiency in modelling

4 Collaborative Robot

4.1 Overview

Market globalization and demand growth are pushing industries to move from mass production to new technologies with humans. Therefore, by changing in demand of customers, manufacturing systems are moving towards customization. Moreover, these days human factors are considered important for improving the work conditions and reducing the risks which are because of new technologies. Industry 4.0 offers new ways to improve human-machine interactions through using Collaborative Robots (cobots).

According to the study the main market for cobots is small and medium-sized enterprise which are responsible for 90% of the world's enterprises and have an important role in economic growth. SMEs are using the cobots to produce low-volume with high variant products in a minimum time as they are safe, low cost and easy-installation. (Kumar et al., 2023)

The main aim of cobot is to work alongside a human worker without fences to perform tasks. There are different types of interactions between cobot and worker, where there are coexistence, synchronization, cooperation and collaboration. Coexistence interaction, the workers and robots are close to each other, but they do not work in the same workspace. Synchronized interaction, both are using the same workspace but not at the same time. Cooperative interaction, they are working closely and interacting but on different tasks at the same time. In Collaborative interaction, they are in direct contact and working at the same time and on the same task. (Dzedzickis et al., 2021) Figure 10 shows the five typical level of human-robot cooperation.

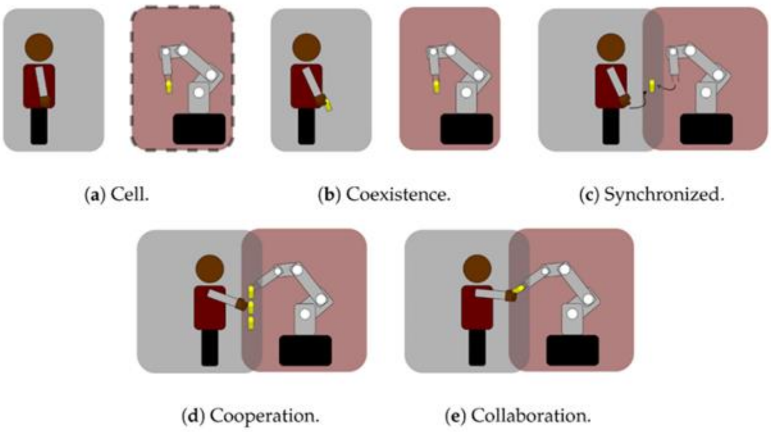


Figure 10. Five typical level of human-robot cooperation

There was a gradual transition of robots from caged robots to human robot teaming. Figure 11 illustrates the Different types of shared workspace in human robot collaboration (HRC) systems. Zafar et al. (2024) introduce a brief overview of the important stages during this transition:

Caged robots: in the early years of industrial automation, robots were in protective cages. The main objective of these cages was to ensure safety in the workplace.

Collision coexistence: with the advancement of technology, robots equipped with sensors and cameras which helped them to detect the presence of humans close by them and respond appropriately in order to prevent potential collisions or accidents. This was a significant step in enhancing safety and reducing the risk of injuries and accidents.

Human-robot interaction (HRI): with progress in robotics, they are equipped with natural language processing and speech recognition. These technologies enabled robots to respond verbally. This phase introduced interactive and responsive robot behavior which makes it easier for humans to work alongside robots effectively.

Human robot collaboration (HRC): In this phase, human and robots collaborate with each other on tasks.

Physical HRC (pHRC): In the next phase of evolution of robotics, they are not only collaborating with humans but also physically interacting with them. This interaction includes passing objects, jointly manipulating.

Human-Robot Teaming (HRT): In this stage, robots are integrated into human ream as partners rather than tools. These robots are equipped with AI and machine learning algorithms which enable robots to adapt human behaviors, preferences and decision-making processes. Therefore, in this stage, robots are not just passive instruments, they are active and adaptive.

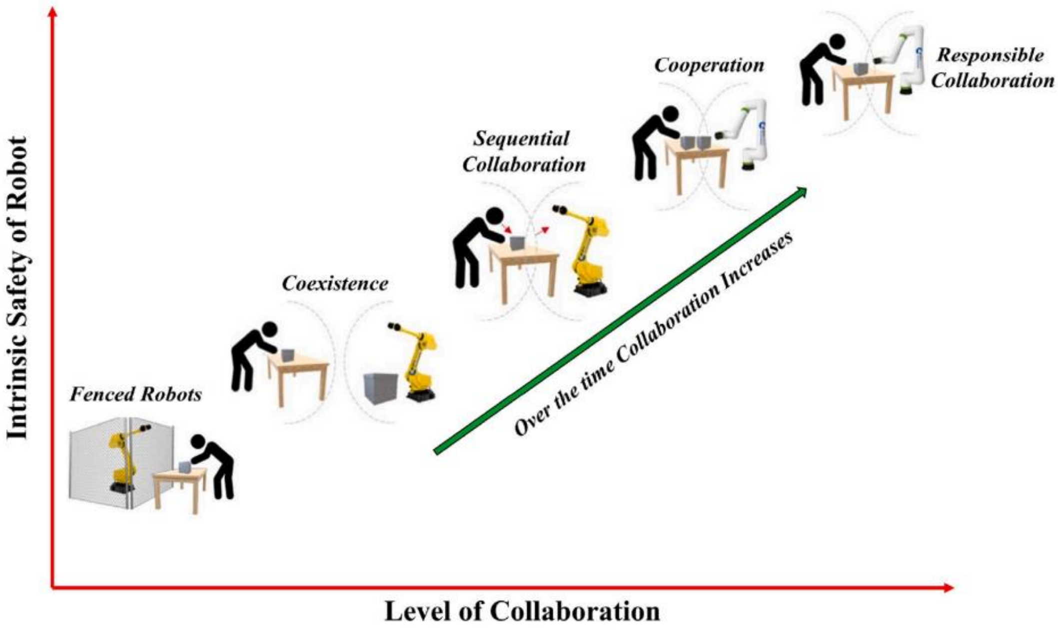


Figure 11. Different types of shared workspace in HRC systems

4.2 Application of Collaborative Robots in Manufacturing

Cobots have a wide range of features and capabilities which enable them for industrial use. They are used for picking and placing tasks, inspection, assembly and co-manipulations.

The application of cobot in manufacturing is various. In Assembly line, they are used to assist workers by doing various tedious and repetitive tasks, which help to increase the speed of the process. In this way, workers can focus on more skilled tasks. These are used for quality check of the products through camera and sensors. (Javaid et al., 2022)

They identified 5 main categories as the challenges for introducing collaborative robots in SMEs. In the following, the challenges are presented:

Safety: Since workers and collaborative robots are working closely together, safety is one of the main concerns. cobots must follow safety rules like SO/TS 15066, but some researchers are mentioning these current standards are not enough.

Performance: it is expected to improve the speed, quality and efficiency by using the collaborative robots but in some cases, cobots are too slow especially when they are close to humans.

Strategy: cobots are a long-term investment for companies. Therefore, companies need a clear plan for production. Many of SMEs have difficulty in choosing the right cobot and right task for it.

Involvement and training: workers must understand and accept the usage of cobots to be used effectively. Therefore, training is important.

Smart technology: While researchers are excited about smart technologies, many SMEs aren't as focused on them—often because of concerns about cost, complexity, or simply not being fully aware of what's possible. That said, some companies do recognize the value of smarter systems, especially when it comes to automatically spotting defective products and improving quality control. (Schnell & Holm, 2022)

According to the study of European Parliament, collaborative robotics technology has benefits and disadvantages. cobots are safe for humans as they are working together, which reduces the commissioning costs as they do not need fencing or being isolated. They are easier to program and can be relocated. By entering cobots into industry a new paradigm of automation introduced in which the operator is not replaced by machine. It assists the operator to improve and complement his/her capabilities like accuracy, endurance and power and make their work more productive. They play a main role in agile production and can contribute to deploying new business models. On the other hand, cobots do not have a high payload, long reach and high productivity, which limits their use especially in a high-volume production. Gambao (2023) In the table 3, the main benefits and disadvantages are shown:

Table 3. Benefits and disadvantages of cobots

Benefits	Disadvantages
Easy installation and relocation	Short reach
Maximum flexibility in production	Low payload
Low risk for operators	Need acceptance by workers
Higher process quality	Need safety assessments
Increased productivity	

In terms of application, as is shown in figure 12, based on the data from Statistica in 2023, almost a third of the collaborative robots are used for material handling, assembly and pick and place. This result shows that cobots are now mainly for handling parts to reduce the workload of the workers. Today, cobots are not used in quality control specially in SMEs where they prefer traditional methods. (Puttero et al., 2025)

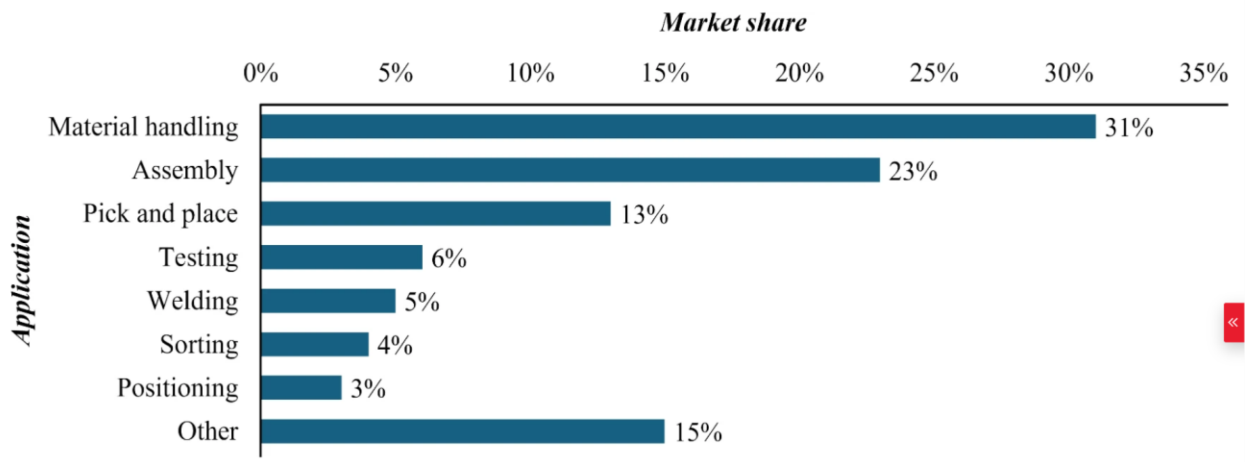


Figure 12. Percentage size of the collaborative robot market by application

5 Mobile Robots

5.1 Autonomous Mobile Robots

Barrett Electronics of Northbrook introduced the first Automated guided vehicles (AGV) in 1953. The structure was complicated as it was a tow truck that followed on a wire in the floor instead of a rail. They were inflexible, expensive, difficult to install and unreliable. It was used in warehousing and logistical activities.

Table 4 shows the complete development schedule and different types of AGVs which are integrated with different technologies. (Zhang et al., 2023)

Table 4. An overview of AGVs completions over the time period

Year	Products	Accomplishments
1950s		Some of them used optical sensors and colored bars and some of them used magnetic sensor
1960s		In the food industry, it is used these vehicles with electric and magnetic sensors. They followed a fixed path and when they reached a stop sign, they stopped automatically.
1970s		AGVs have a computer and control system. They often follow special wires on the floor, which guide them using an active magnetic signal. This method is commonly used to help them stay on the right path.
1980s		AGVs use lasers and infrared sensors to find their way. They're equipped with smart electronics and microprocessors which help them know exactly their locations.
1990s		AGVs use special wheels that let them move in any direction and have sensors for navigation. They can also spot and fix small errors. This makes their movement more accurate, especially for long-distance travel.
2000s		AGVs now use artificial intelligence to help them find their way and see their environment. They often use wireless networks to track their position and can even work together as a team to do jobs more efficiently.
2010s		Open-source software is used in AGVs, especially ROS (Robot Operating System), which helps control and manage robots.
2020-present		These vehicles can move in any direction, which increases productivity. They can also connect easily with a company's IT systems at different levels. They're flexible, easy to upgrade or reconfigure.

AGVs were originally used in transporting goods in warehouses and logistics industry. They are using tracks or predefined routes and also it needs the operator supervision. By advancement in technology, Autonomous mobile robots (AMRs) evolved. They are an evolution of AGVs which can understand and move independently in the environment.

There are some differences between AGV and AMR. AGVs work on fixed routes through wires, magnetic strips or sensors. These predefined routes need installation which can be expensive and disruptive to production. AGVs can detect objects in their ways but they cannot navigate around them. Therefore, they stop until the obstacle is removed. While AMRs are equipped with intelligent navigation capabilities. They use cameras, sensors and laser scanners. They are able to detect obstacles and without removing the obstacle, choose the best alternative route. They are also different in the case of applications. AGVs have limited applications because they are dependent on fixed routes and need infrastructure therefore it is difficult to change the production line and make them less adaptable. On the other hand, AMRs are much more flexible as if the production cells are relocated or new processes are introduced, they can re-map the site and upload the new map. Safety in AMRs and AGVs are different. As AGVs follow fixed route, in case of being obstacles on their way, they detect through their sensors, and it needs a manual intervention to resume operation, and it makes disruptions on workflow. While for the AMRs, as they are using 3D cameras, LiDAR and AI-detection of obstacles, they are able to navigate dynamically. It can be concluded that AMRs are an ideal choice for modern facilities as they can continuously analyze and react in real-time and keep operations running safely. (Mobile Industrial Robots, n.d.)

As shown in figure 13, there are several methods and techniques of navigation and localization of AMRs that have been developed and each of them has its own principal and accuracy performance. Localization techniques can be categorized based on positioning algorithms as follows: trilateration/triangulation, scene analysis/fingerprinting, and proximity detection. Trilateration and triangulation approaches use measurements like Time of Arrival (TOA), Time Difference of Arrival (TDOA), Received Signal Strength (RSS), and angle-based methods like Angle of Arrival (AOA) and Angle of Departure (AOD). These are typically used with technologies such as UWB or Wi-Fi. Scene analysis and fingerprinting involve techniques like LiDAR, radio wave mapping, and vision systems, including SLAM (Simultaneous Localization and Mapping). These methods build and refine maps of the environment in real-time, making them suitable for dynamic and unstructured settings. Proximity detection includes simpler techniques based on RFID, QRCode, ArUco markers, or line-following, which are cost-effective but less flexible for dynamic navigation. (Semborski & Idzkowski, 2024)

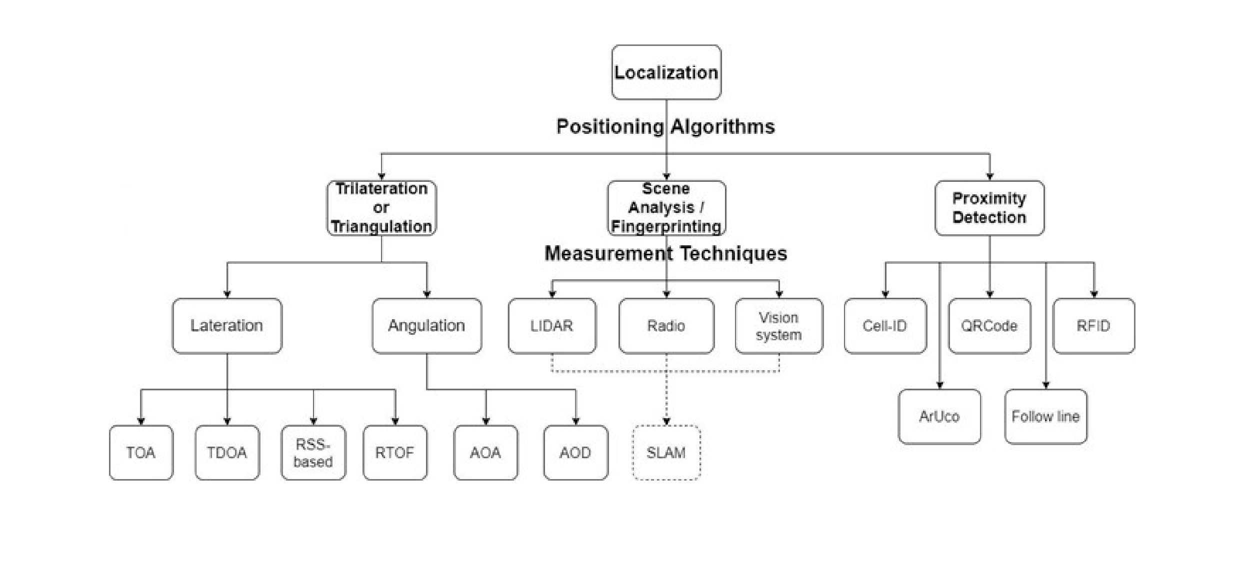


Figure 13. The classification of methods for localizing a mobile robot

According to the data from Statistica as it is shown in the figure 14, the global market for Autonomous Mobile Robots (AMRs) was valued at approximately 2.4 billion USD in 2021. With a projected annual growth rate of around 23%, it is expected to surpass 10.5 billion USD by 2028, reflecting the increasing demand for intelligent automation in industries such as manufacturing, logistics, and warehousing.

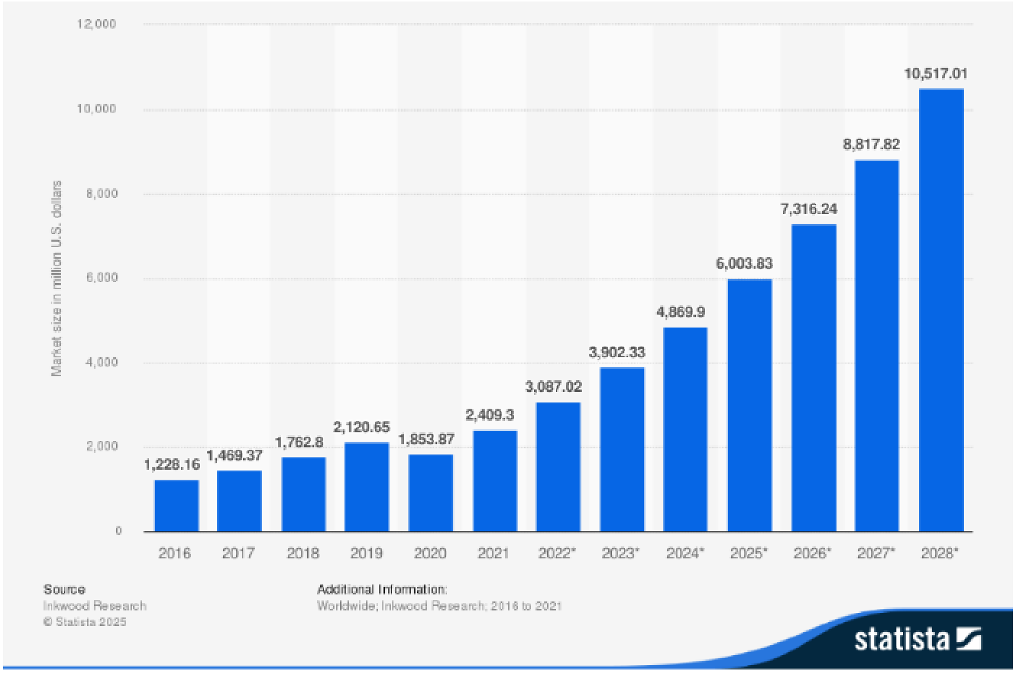


Figure 14. Size of the global market for AMR

5.2 Mobile Manipulators

In the age of mass customization, companies with a high mix volume production need to adopt a flexible manufacturing system in order to survive. As customized products are popular, traditional industrial robots may not be suitable for these applications as they are inflexible and have a high cost in reprogramming of new tasks. Therefore, a possible solution is using combination of autonomous mobile robots (AMR) and lightweight collaborative robot arms (cobots) which are mobile manipulators. (Gros et al., 2023)

The background of mobile manipulators goes back to 1984 with the development of the MORO (MObiler ROboter). The main idea behind this approach comes from making standard manipulator robots more flexible which are stationary and fixed.

The architecture of Autonomous industrial mobile manipulators (AIMM) is an integrated and battery-driven robotic system which includes a robot manipulator mounted upon a mobile platform extended by a sensor and tooling system. The local running software (distributed or central) is responsible for control and coordination. (Hvilshøj et al., 2012)

Figure 15 shows the conventional architecture of an AIMM robot system.

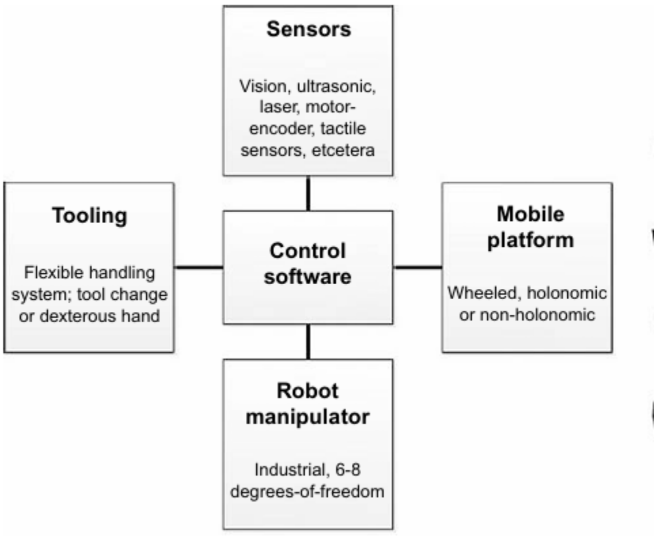


Figure 15. The conventional architecture of an AIMM robot system

The application of autonomous mobile manipulators in industrial robots include assistive tasks, logistics tasks and service tasks. The logistics tasks refer to the transporting items between workstations and stations and the process of loading components into machines. The assistive tasks include the processes of loading/unloading items into machines for assembling, observing and comparing the items in order to identify and correct defects and actual processing like welding, bending, etc. The service tasks include maintenance, repair and overhaul of production machines and cleaning. (Hvilshøj et al., 2012)

Bøgh et al. (2011) provided an overview of the history of mobile manipulators from 1984 to 2010 as can be seen in figure 16.

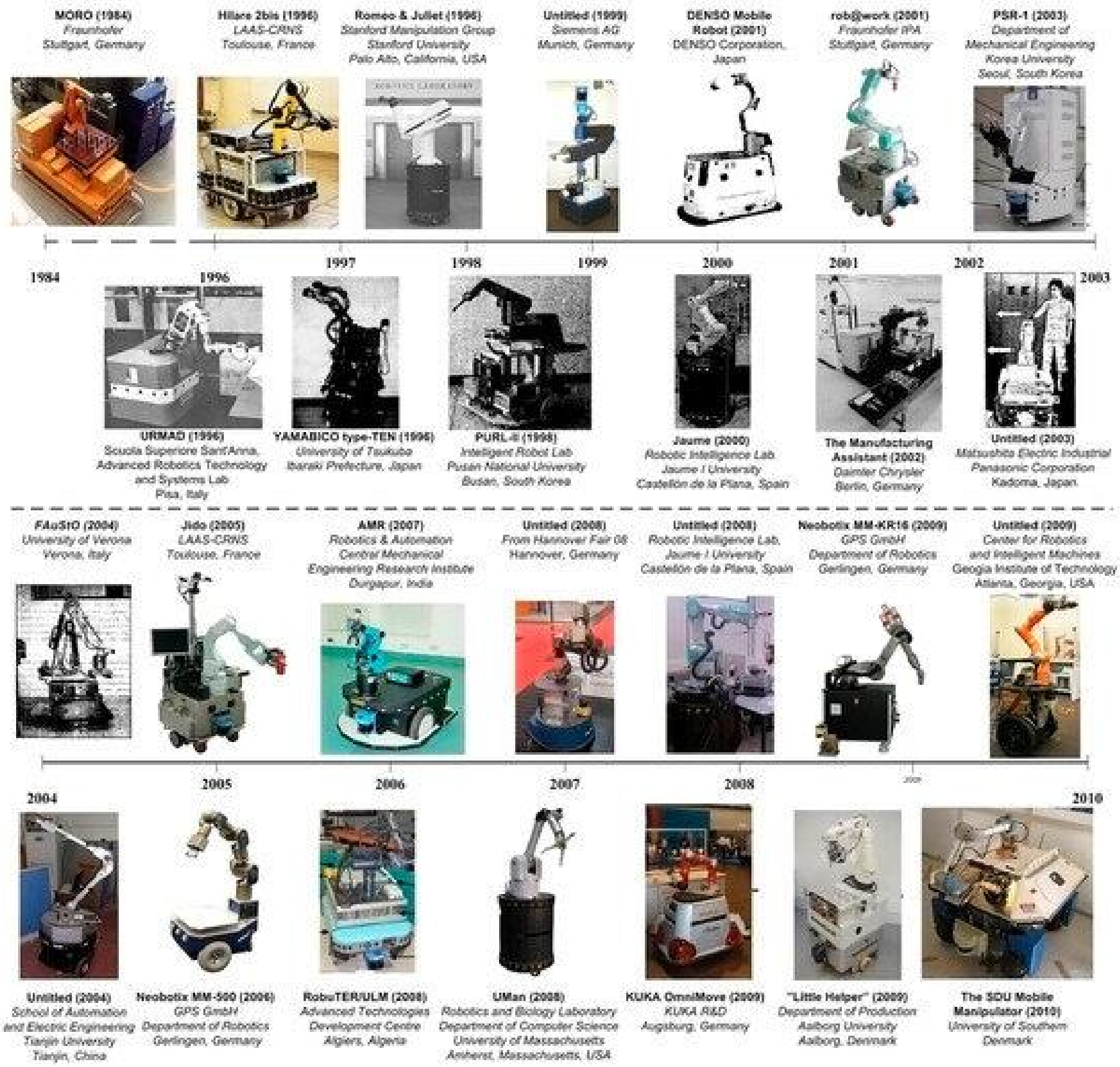


Figure 16. An overview of the history of mobile manipulators

According to the report of market segment analysis of mobile manipulators, the warehouse and distribution segment has the largest market share in 2021, and it is anticipated to grow at a CAGR of 11.5% by revenues over 2022-2027 which is due to the increase in demand. With flexible automation and mobile manipulators, the changes related to the warehouse infrastructure are minimal and less expensive. Therefore, there is an upsurge in demand for these robots. (IndustryARC, n.d.)

Thakar et al. (2023) present an overview of where mobile manipulators are used in practice as it is demonstrated by figure 17. It shows examples from different fields like transportation, warehouses, machine tending, assembly and farming. Each application has different needs when it comes to making decisions. For example, in warehouses it is important for the base and the arm to work together smoothly for picking and placing items while in healthcare the robot needs to move safely around people and deal with unexpected situations.

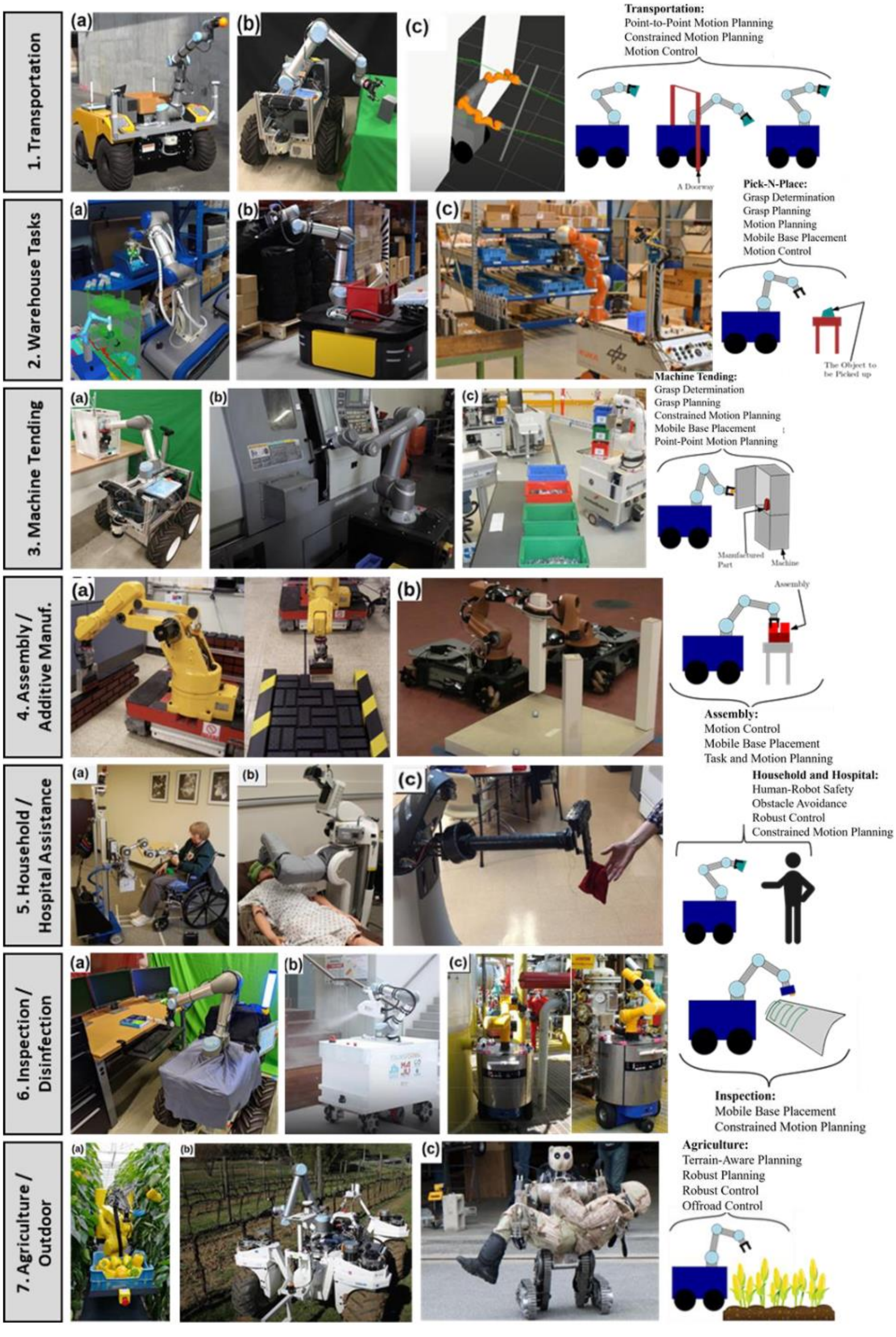


Figure 17. Example of mobile manipulators in various applications

6 Dynamic Speed Allocation Digital Twin

6.1 Motivation

Industry 4.0 shows the revolution of computers, machines and human interconnectivity which results in higher manufacturing efficiency, and a larger production scale. The main idea behind the fourth industrial revolution is its capability to automate decision-making and problem solving. It enables both operations of asset real-time performance management and engaging all stakeholders equally through vertical and horizontal integration. In vertical integration, through interconnection network of the digital and physical process within different departments of an organization, it responds to unexpected order changes due to demand fluctuations, equipment shortage or stock shortage, while in the horizontal integration, through the networking of the different processes, entities forming the global value chain of any product, ensure coordination of operation and information flow.

In the real world of manufacturing and warehousing, capacity is limited. Products cannot be processed and stored at a constant rate as the warehouse becomes full. If products are processed at maximum speed without considering warehouse limitations, there would be problems like having queues, inefficiencies in systems, and having delays. In many industrial systems, the speed of the robot is predefined and fixed, but this rigidity leads to bottlenecks especially in warehouses. A dynamically adaptable robot speed based on the warehouse availability introduces responsive and automation. To address these problems, it is necessary to have adaptable systems where the speed of product processing is dynamically adjusted based on the number of the products in the warehouse. The proposed solution is embedded in the values of smart manufacturing by avoiding unnecessary production and synchronization of the process flow with real-time warehouse capacity.

Digital Twin technology enables dynamic and responsive systems. By modelling physical representative and integrating with simulation environments, Digital Twin helps to dynamically control robot behavior based on actual conditions. While simulation models are used for planning and testing in manufacturing, their effectiveness is limited due to the lack of real-time response. This thesis aims to enable two-way communication between virtual and physical entity through Digital Twin. By integrating FlexSim software with real robots via Modbus TCP, the system responds in real-time based on the actual condition.

This work aims to show that by embedding Digital Twin logic into AMR and cobot, manufacturing systems can achieve higher efficiency, reduce waiting time and increase utilization rate. The motivation lies not only in improving logistics but also in aligning with broader goals of industry 4.0.

While this study is done in a controlled lab environment, the logic and framework are scalable and can be done in large and real-world manufacturing settings.

6.2 Physical Reality

Physical system includes one collaborative robot (UR3e), shown in figure 18.b, which performs tasks and then the mobile industrial robot (Mir), shown in figure 18.a, moves to load the item and unload them into a warehouse.

(a)

(b)

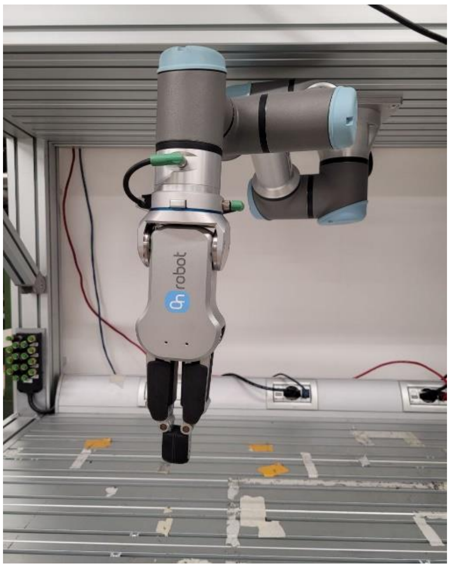


Figure 18. (a) Mobile Industrial Robot, (b) UR3e

6.2.1 An Overview of UR3e Collaborative robot

UR3e is a light collaborative robot which is developed by Universal Robots. It is part of the e-series and as it is small, it is a good solution for small scale automation. Payload capacity is 3kg (6.6lbs) which means the arm of this robot can lift to 3 kg. Reach arm is 500 mm which means the arm can extended to 500mm. This cobot is 11.2 kg which is very light and easy to move. Based on the specifications, this robot is ideal for assembly, material handling and screwdriving. (Universal Robots, n.d.)

The programming of the robot is through the Polyscope as shown in figure 19 graphical interface which is user-friendly without requiring coding knowledge for basic programs. The red button is used to stop the robot in case of emergency stop. There is a black button which is behind the screen, and it is used to move the robot freely while the user is holding the button.

Figure 19. Teach pendant

In the tab of the program, there are 3 sections which are used for defining the program of the robot:

1. Basic: The most common commands are “Move”, “Waypoint”, “Wait”, “Set” and “Halt” as it is shown in figure 18. Move controls the motion of the robot through the waypoints. Waypoints must be under the Move command. It is possible to define the speed and acceleration of the moves. 3 types of the moves can be defined. MoveJ which results in a curved path, MoveL which results in linear movements and MoveP which performs linear movements with circular. Wait and Set are used for communicating with other devices. The Set command assigns a value to a variable or output, while the Wait command is used to pause the operation of the robot until an event occurs, such as an input or a variable reaching a specific value, or a set amount of time passing. Halt command is used for stopping the program.

2. Advanced: This section includes complex command for controlling the robot, like if, thread, script, loop, wait and etc. If and if … else commands change the robot’s behavior based on sensor inputs and variable values. If a condition is evaluated as True, the statements within this If command are executed. An If statement can have only one Else statement. Use Add Else If and Remove Else If to add and remove Else If expressions. A thread is a parallel process to the robot program. A thread can be used to control an external machine independently of the robot arm. A thread can communicate with the robot program with variables and output signals. In this application, if and loop are used. In figure 20, the advanced commands are shown.

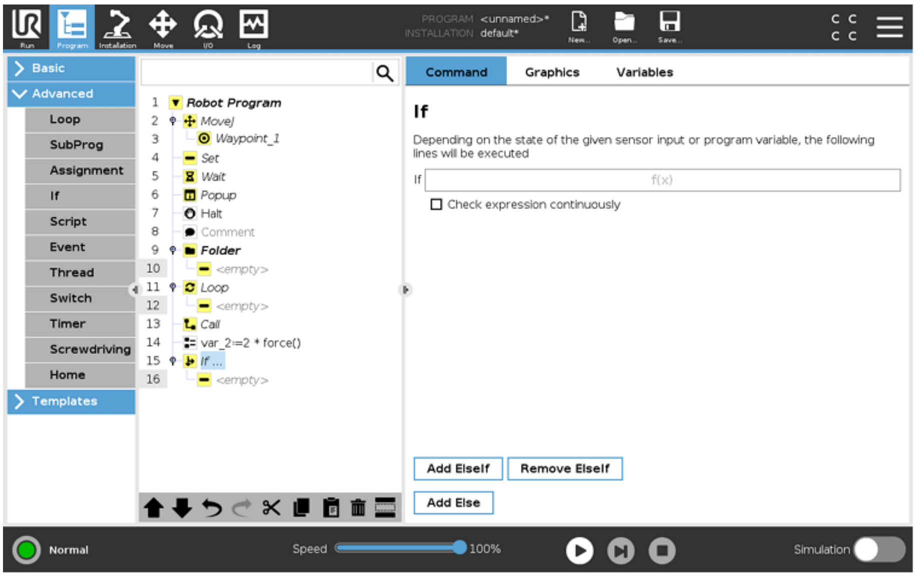


Figure 20. Advanced section of the programming tab

6.2.2 An Overview of Mobile Robot

An autonomous mobile robot which is used in this experiment is Mobile industrial robot 100 (MiR100) from the Company of Mobile Industrial Robot, one of the leading companies in Autonomous mobile robots. This robot is suitable for small and medium sized transport tasks in logistics and healthcare. The maximum payload that could be carried is 100 kilograms (220 lbs). It uses a Lithium-ion battery which offers up to 6 hours 53 minutes of active operation with full payload. It uses several safety mechanisms such as 360 personnel detection; emergency stop buttons and ultrasonic sensors. MiR 100 supports WI-FI, USB and Ethernet connectivity which makes it easy to integrate with Digital Twin platforms. It is compatible with Modbus TCP and can communicate with simulation software like FlexSim.

The programming of the Mobile Robot can be done through a PC, Tablet or Smartphone. First, the user needs to sign in with a username and password. To start programming, the Setup tab must be accessed and then Missions should be selected. A mission is a predefined series of tasks that the robot performs. There are some predefined tasks as is shown in figure 21, where tasks can be dragged and dropped to create a mission. The set of the tasks used are:

- Move: This Action includes several sub-actions like, docking, check position status, Move and …. in this model, Move is used to navigate to a predefined locations on the map which are set according to the map of the of Mind4Lab Laboratory at Politecnico di Torino figure 22.
- Logic: in the tab of the logic, there are several actions including if, loop, wait, while and …. In this model, the loop is used to run the mission continuously without stopping. The While action is also used to check if a PLC register is set to a certain value or not.
- PLC: this tab includes actions which are used for the connection between the FlexSim and mobile robot. The set PLC register action is used to set a value in a register address which must match with the register address in FlexSim. The Wait for PLC register

action is used to wait for a value and continue to the next action as soon as the value is found in the set register.

- UR: This action includes Run UR program which is used to communicate with a UR which is mounted on the top of the mobile robot. This action starts with a *.urp* file saved on the Universal robot (cobot which is mounted on the mobile robot).

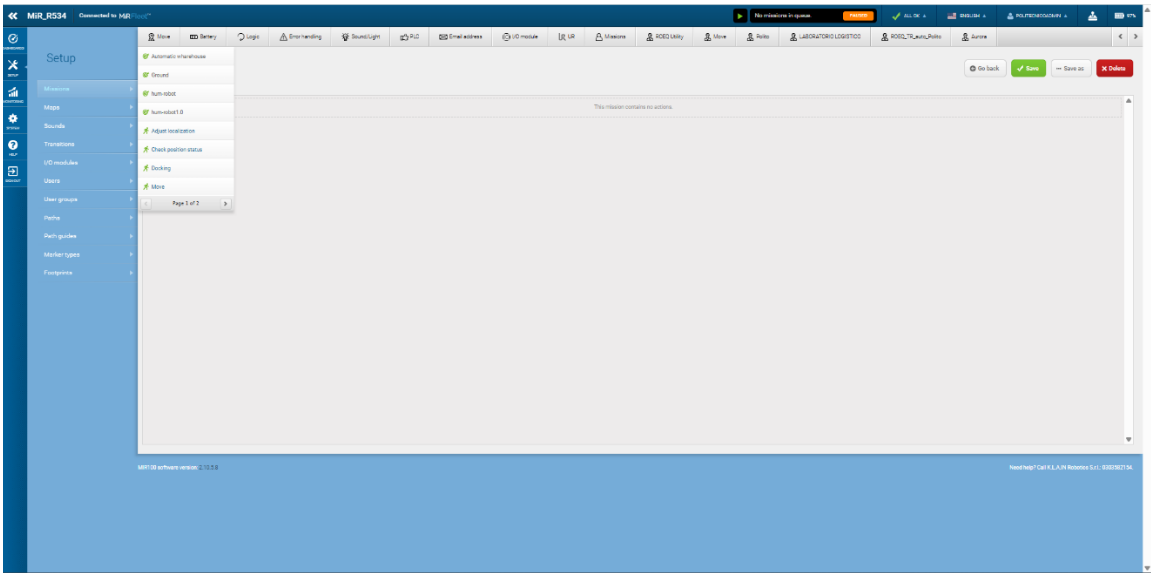


Figure 21. Predefined tasks to create a mission

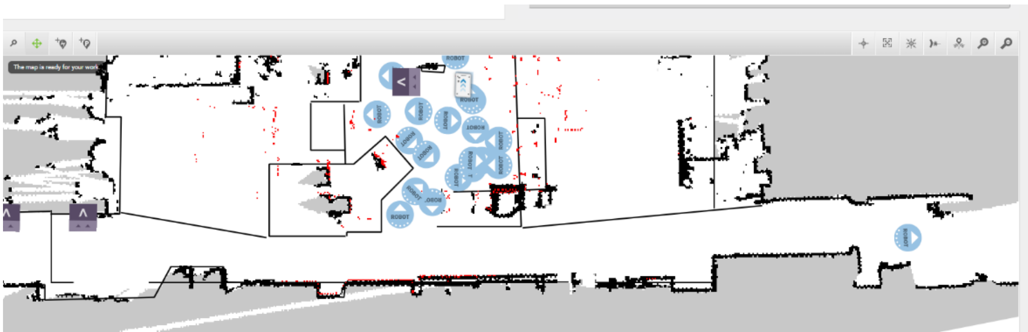


Figure 22. Map of Mind4Lab

6.3 Virtual Representation

In this study, FlexSim simulation is the virtual representation. FlexSim is simulation software which includes collection of tools for simulation applications. It is a mixture of modeling, artificial intelligence, 3D models and data processing. It has two modelling environments, 3D and process flow. It has a user-friendly interface to build a model even with limited knowledge of coding. Through emulation tool it is possible to connect the model to the real-world system to exchange data. This feature enables real-time synchronization between digital and physical system. Therefore, it is a key feature for the implementation of Digital Twin. The 3D model provides realistic visual, and the process flow environment allows to create logic. In some cases, it is not possible to use only the 3D model as it has some limitations. Therefore, along with the 3D model, process flow is used. FlexSim Software Products (n.d.)

In the following sections, the 3D model environment and process flow environment will be discussed.

6.3.1 3D Model

One of the main features which makes FlexSim unique is that there is a possibility to create a 3D system. 3D models are more visual and sometimes can be more effective, especially for decision makers who do not have a technical background. For creating a 3D model, objects are used. Some of the most common objects are as follows as also it is shown in figure 23:

1. Flow items: These objects move from one station to another station. They can be materials, customers or products.
2. Fixed resources: Objects which are static and interact with flow items. Each fixed resource is used for a specific function. The most common fixed resources are sources which are used to create flow items. Each source creates an item per inter-arrival rate, scheduled arrival list and can be labeled or colored. The queue is used to keep flow items when a downstream object cannot accept them and by default it is in a FIFO, but it can be LIFO or adjust it. It receives flow items until it reaches the maximum capacity. The processor simulates the processing of flow items, and the total time is summed up with the set-up time and a process time. The sink is used to destroy flow items which are finished.
3. Task executers: Objects that are moved in the 3D model and do tasks like transporting flow items. One of the common task executers is AGV which travel, load and unload flow items.

Figure 24 represents an example of a 3D model in which a source is creating items and in a processor is being processed and then are going to the queue.

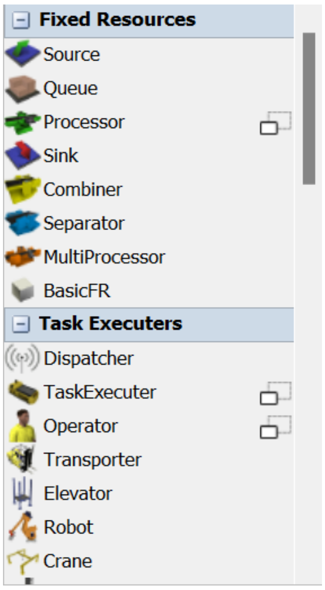


Figure 23. Common objects of 3D model

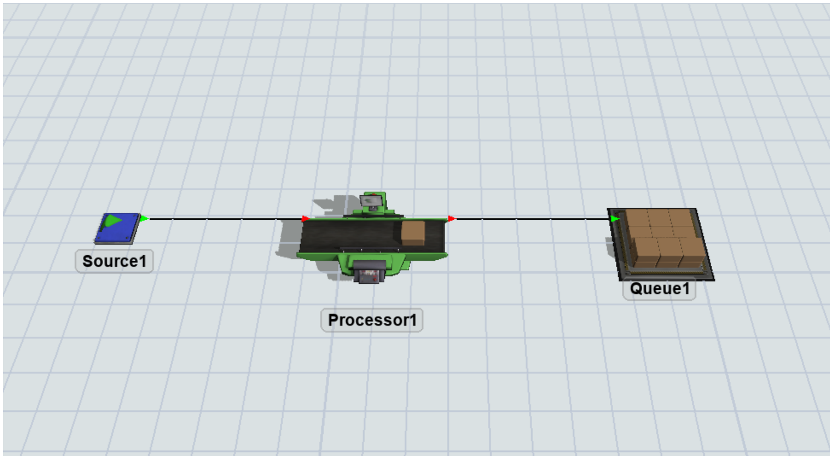


Figure 24. An example of a 3D model

6.3.2 Process Flow

The process flow environment is an environment where it is possible to create the logic of the model. There are a set of predefined elements which can be adjusted based on the required logic as it is demonstrated in figure 25. Tokens are the basic component which flows through activities in process flow when a simulation is running.

Their functionality is like flow items in 3D model. But tokens, unlike the flow items, can be more abstract. For example, they can represent a customer's order is ready. At the basic level each token has ID, Name and labels. In figure 26 an example of process flow is presented.

In this study the following components are used and in the following section it is discussed:

1. Event-Triggered Source: It creates a token in response to an event. When the event happens, it will create a Token. The Token can interact with activities in process flow like updating systems state. In this study it is linked to Source in 3D model.

2. Assign labels: It creates or modifies labels. Labels are used for storing important data about objects. Labels can be assigned to an incoming (entering) token. a parent token, flow items, 3D objects such as an Operator or Processor and ect. In this study 4 labels are considered, interarrival time, item color.
3. Create object: It creates one or objects in 3D model. In the study it creates boxes.
4. Decide: This activity sends a token to one of two or more possible activities based on defined conditions. Deciding can be based on a condition, case, time or percentage etc. In this study, the decision is based on the number of items in each floor storage on 3D model.
5. Wait for Event: When a token reaches this activity, the token will wait until an event occurs. In this study, when a token reaches it, it remains there until the physical robot is ready to start.
6. Custom code: with this activity, it is possible to create custom behavior in process flow. It is possible to use pre-defined options and write new code in FlexScript. As soon as the token enters this activity, it will evaluate the code and then release it to the next activity. Here, it is used for having the interarrival time and the type of the items in a global table.
7. Resource: These shared assets show an asset with limited capacity. A resource is acquired by an Acquire Resource activity and released by a Release Resource activity. For example, if there is one machine in the station which is shared between two other stations. When one station uses this machine, it would acquire that machine as a resource. When it finished in that station, it will be released. In this study, two resources are used to represent the UR3e and Mobile industrial robot which are shared between two stations.
8. Delay: This activity keeps the token for a certain length of time. It can be fixed or follow a statistical distribution.
9. Variable: This shared asset stores any kind of data and can read or change data. The variable can be used like a label on a Token or other object. The variable is changed by a Set variable activity and read by a Get Variable activity. Variable value can be a number, string, array, object, emulation connection or emulation variable. The Emulation tool is a tool which creates a link between FlexSim and external PLCs or clients/servers that communicate with PLCs. This tool supports multiple protocols like Modbus, OPC DA, OPC UA etc. Emulation tools are discussed in the following section. In this study, there are two variables as a connection for UR3e and Mobile industrial robot.
10. Set Variable: this activity sets the value of a Variable shared asset. They are used to track and manipulate data within the simulation.

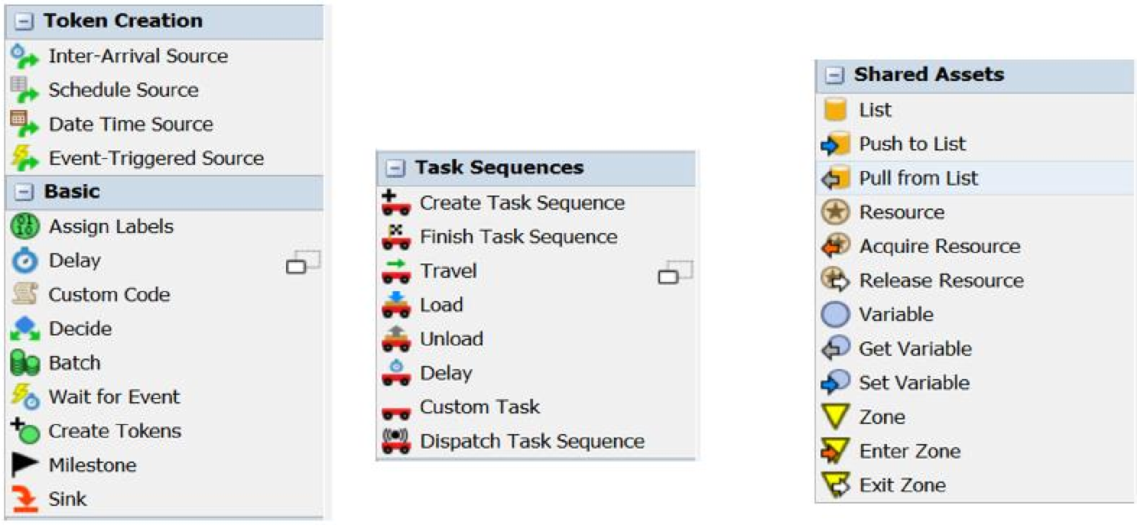


Figure 25. Predefined elements in process Flow

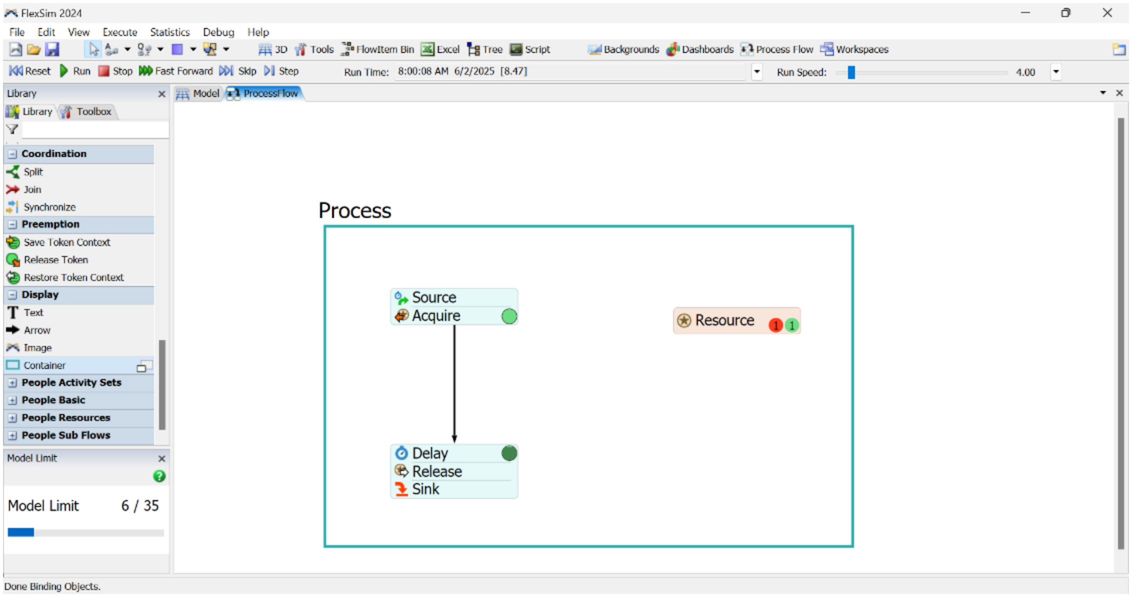


Figure 26. An example of process flow

6.3.2.1 Emulation Tool

As it is mentioned, Emulation tool creates a link between FlexSim and external PLC. It is supported by multiple protocols like Modbus, OPC DA, OPC UA etc. This tool is used for communication and interaction between physical systems and virtual models. In this way, data, signals and commands are sent and received in real time. In this study Modbus TCP protocol, which is Ethernet-based, is used. In figure 27 the properties of an emulation connection are shown. In this study 2 types of Modbus connection are used, one for connection of the UR3e and the other for the mobile industrial robot.

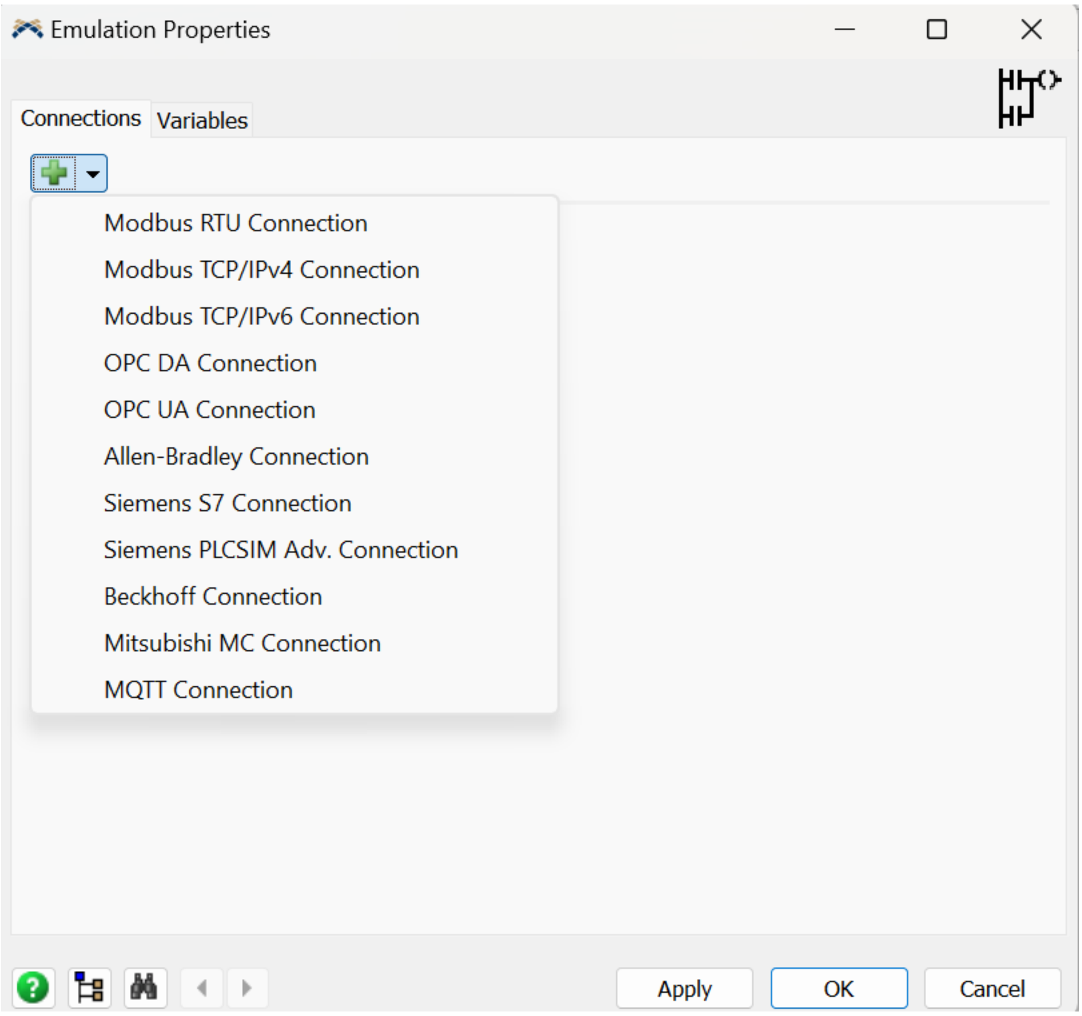


Figure 27. Emulation properties

6.3.3 Dashboard

Dashboard of the FlexSim is one of the tools for collecting data during the running of the simulation. Users can choose different types of visualizations like charts and graphs. It is a useful tool which users can easily monitor the KPIs, and statistics during over the time. It helps with analyzing the simulated system and taking corrective actions if needed or adjusting inputs or outputs. Dashboard supports data from simulation models like variables, output and attributes. Figure 28 shows an example of a dashboard with different types of charts.

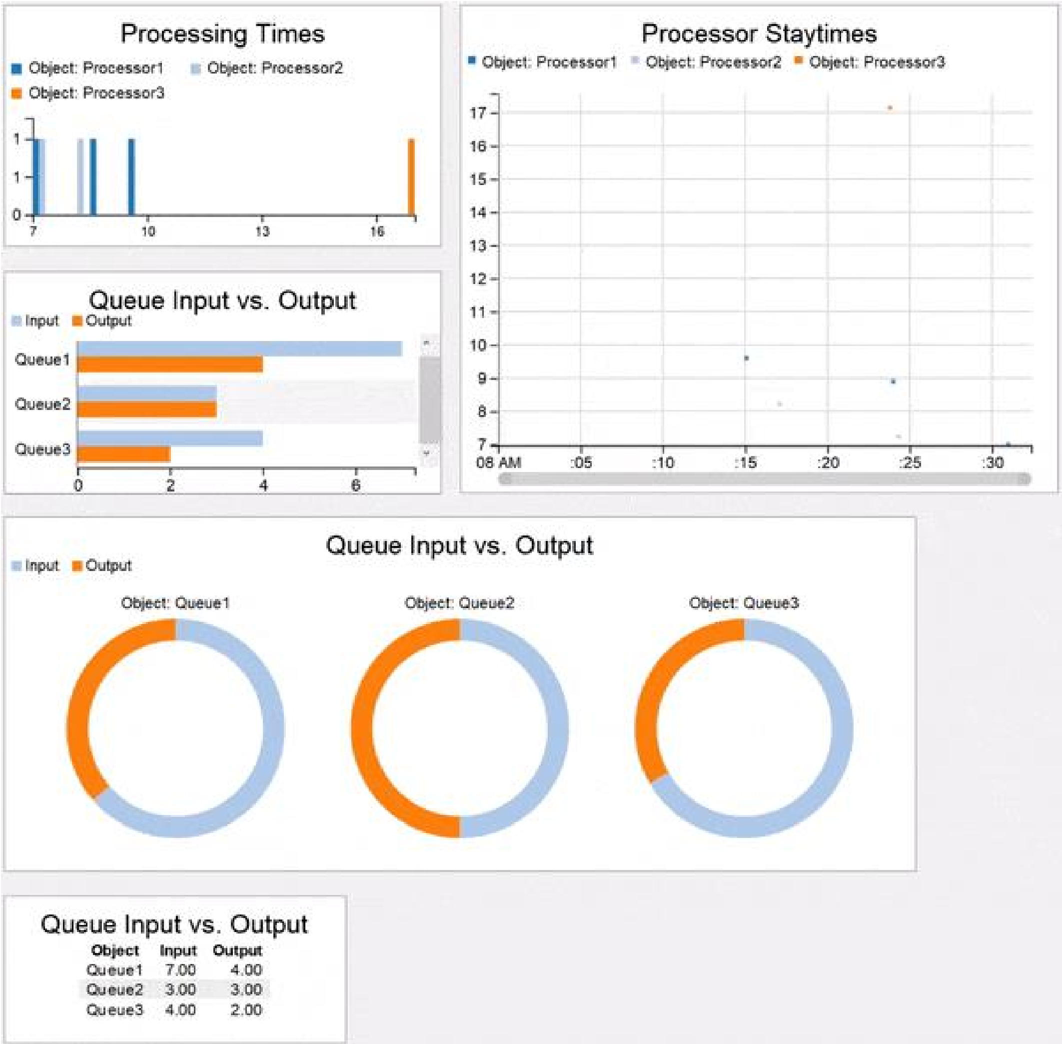


Figure 28. An Example of the dashboard

7 Case Study and Result Description

7.1 Process Description

Before describing the model, it is necessary to introduce the key elements of the proposed solution:

- 1 source which creates 20 items and arrives at the start station
- 1 Robot: which is responsible for picking and placing items from Start station to Station 1 and Station 2.
- 2 Stations: Station 1 and Station 2 where item 1 and type 2 are being stored temporarily and waiting for pick up by mobile robot.
- 1 Task executor as mobile robot for transporting the items from station 1 and 2 to the 2 warehouses.

The proposed Digital Twin framework is designed for a process involving 2 types of items. In total, 20 items are generated; 70% of them are item type 1 and 30% are item type 2. These items enter the system in a random order with an interarrival time of uniform distributed between 20 and 40 seconds. As soon as one item arrives at the system, the robot immediately starts its task to put the item in station 1 or station 2 based on item type. Once an item is placed at either station, the mobile robot is triggered to start and transport item to the corresponding warehouse. Reflecting the real-world constraints, each warehouse has a limited capacity, and this is modeled in the simulation.

Before the robot starts its tasks for picking and placing, it checks the current capacity of the warehouses; if the warehouse is close to reaching its maximum capacity, the robot adjusts its speed through the sensor variable which sends the command to robot and operates at a slower pace to allow time for stored items to exit. Consequently, the robot dynamically adjusts its speed based on the number of items in the warehouse to avoid congestion and ensure continuous flow.

Figures 29 and 30 show the 3D model of the proposed solution and process flow. The logic behind the model is discussed in the following section.

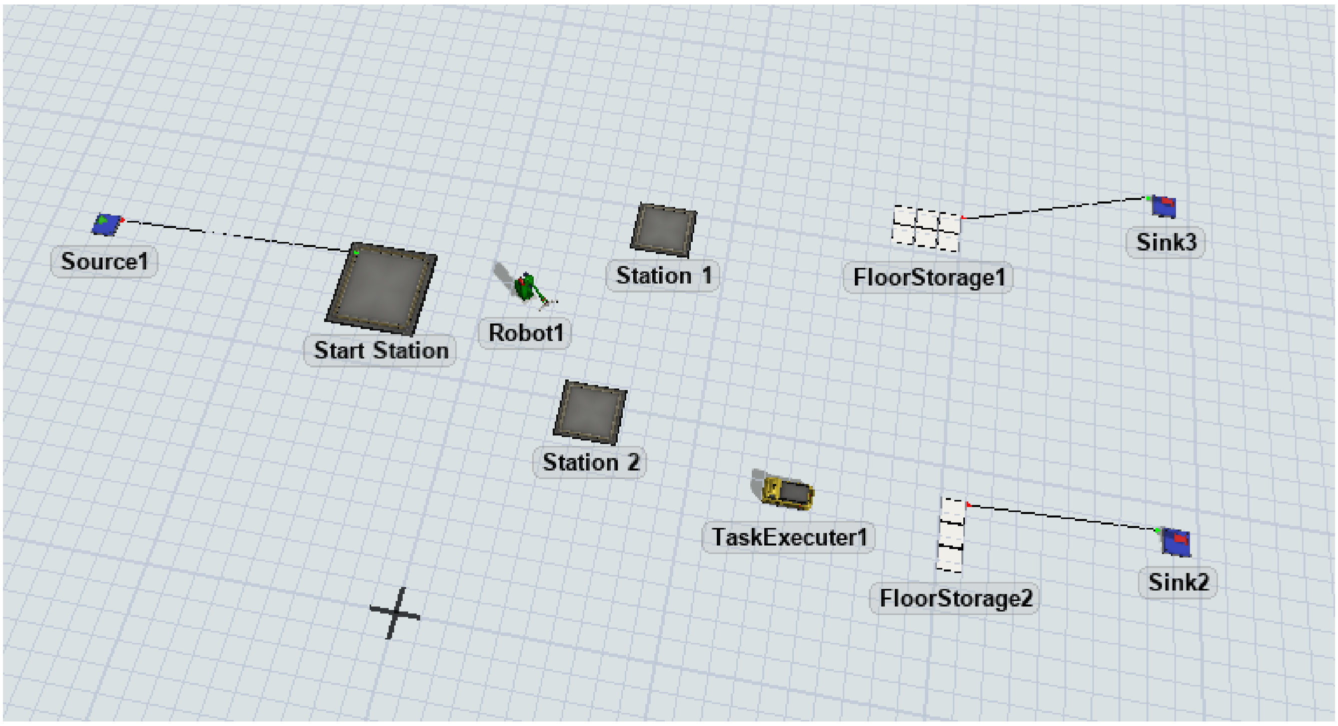


Figure 29. 3D model of proposed solution

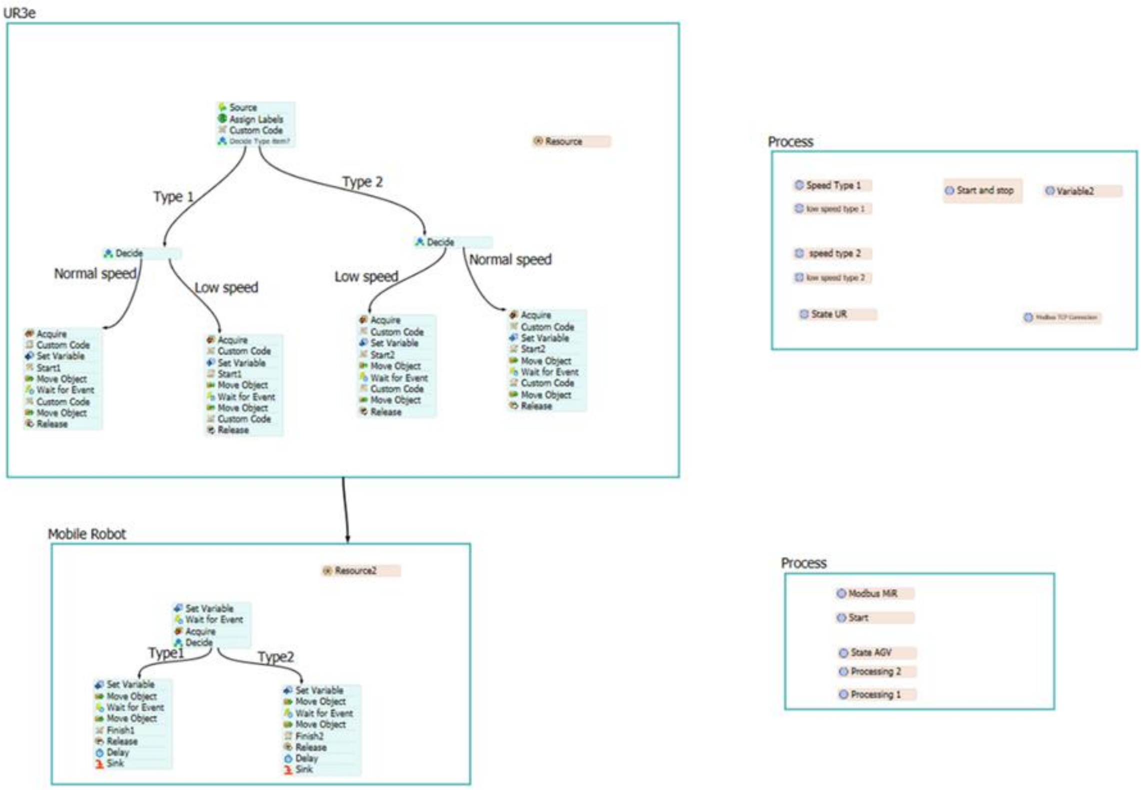


Figure 30. Process flow of proposed solution

7.1.1 Logic within the 3D Model and Process Flow

The process starts with the arrival of 20 items to the system. This is done by one Source element. The arrival of items is random based on the uniform distributed between 20 and 40 seconds. Moreover, it is added a condition as in figure shown, in order to just create 20 items as it is shown in figure 31.

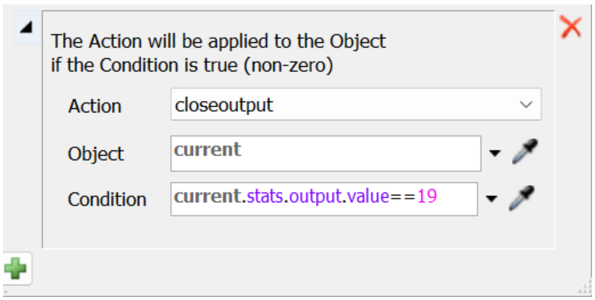


Figure 31. Condition of arrival items

The *source* is connected to the *Start Station* where the items are grouped into 2 types randomly. 70% of them are type 1 and 30% are type 2. When the items arrive here, the robot starts its task to pick and place the item to put in Station 1 and Station 2. As it is shown in the figure 32, when first item is available, by enabling the "**Use Transport**" option, *Robot1* is responsible for picking item up and delivering to the next destination.

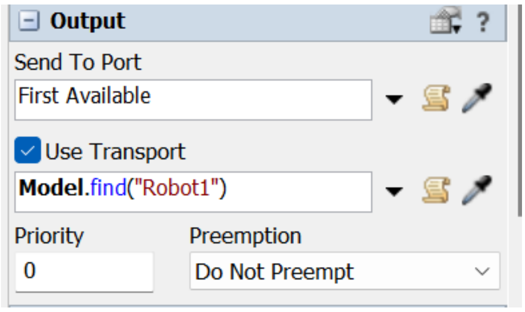


Figure 32. Properties of Start Station

In *Station 1* and *Station 2*, the label of *Type* is defined to determine 2 types of items. Label *Type* in *Station 1* has the value of 1 and in *Station 2* has the value of 0 as it is shown in the image. Figure 33 shows the properties of the labels.

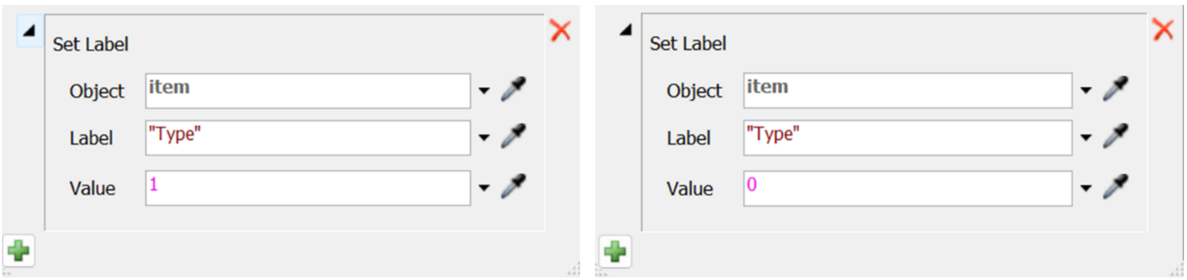


Figure 33. Properties of Station 1 and Station 2

FloorStorage 1 and *FloorStorage 2* are the places where the items arrived by Task executer. “***Max Content***” defines how many flow items will be allowed to hold at a given time. For the FloorStorage *1* is 6 *and FloorStorage 2* is 3 items. ***“Minimum Dwell Time”*** show how long a flow item must stay in the rack before it is released to continue downstream. For *FloorStorage 1* and *FloorStorage 2 are* 170 and 200 seconds respectively. In figure 34, the properties of *FloorStorage* 1 and *FloorStorage* 2 are shown.

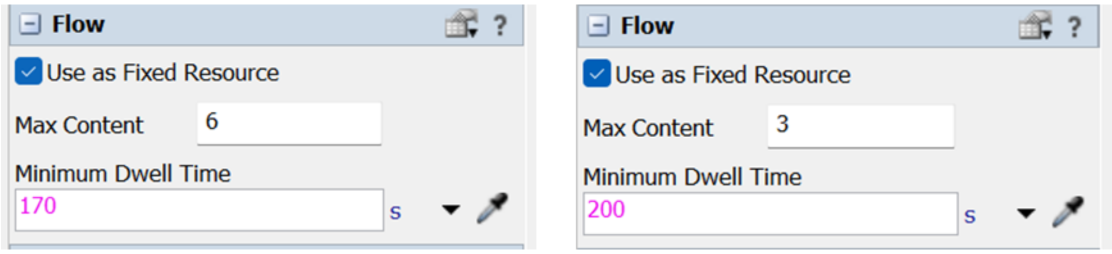


Figure 34. Properties of FloorStorage 1 and FloorStorage 2

In the process flow, the *source* listens for the “On Entry” event from the 3D object of Start Station as can be seen in figure 35. When an item enters that station, it triggers the activity and assigns the entering item to a label named item. This label is used for further operations.

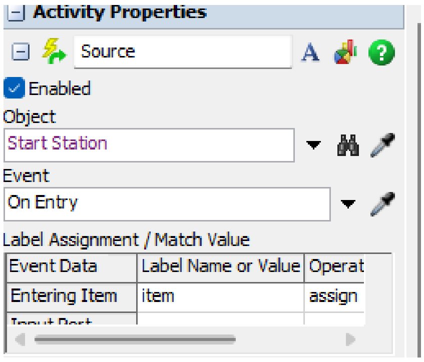


Figure 35. Properties of source

Assign label block, assigns label to the tokens as more details can be seen in figure 36. The first label is *interarrivaltime* which shows the time when the item exits from the source.

Another label is *itemtype* which is specified by percentage, 70% of items would have value 1 as Type1 and 30% of them have the value 0 as Type2 and randomly are assigned.

The reason for having this percentage is to show item type 1 is the high demanding items in manufacturing while type 2 are low demanding.

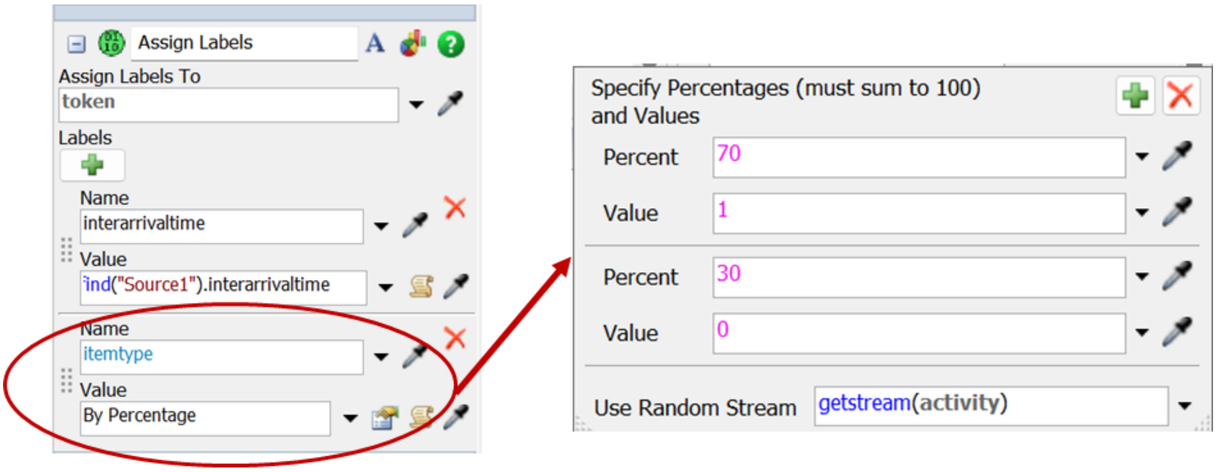


Figure 36. Properties of assign labels

A custom code is used in order to have some data of the tokens inside a global table. As it is shown in figure 37, in the table, by entering the items, there would be the interarrival of each item and the item type.

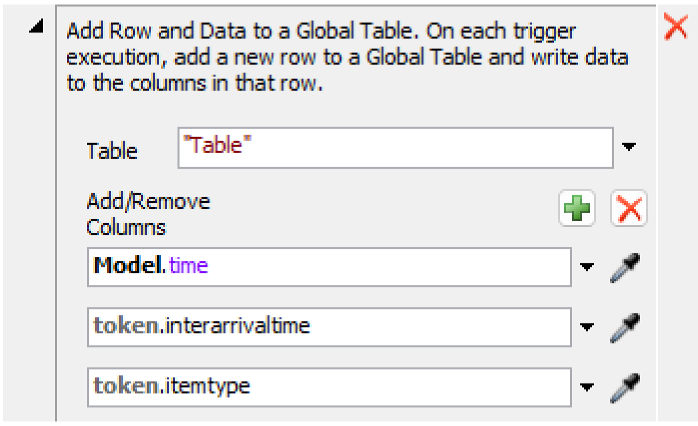


Figure 37. Properties of custom code

The first decide block is used for distinguishing between item type. It checks the condition if the *Token.Itemtype==1*, it means that item is type 1, otherwise it means that it is type 2. The two next decide blocks are used for deciding if the UR should move the items at normal speed or low speed. This decision is based on the number of the current items of *FloorStorage 1* and *FloorStorage 2*. If the number of stored items exceeds a certain threshold, the robot adjusts its speed to low, in order to prevent congestion. Otherwise, it continues operating at normal speed. Figure 38 provides properties of the decision.

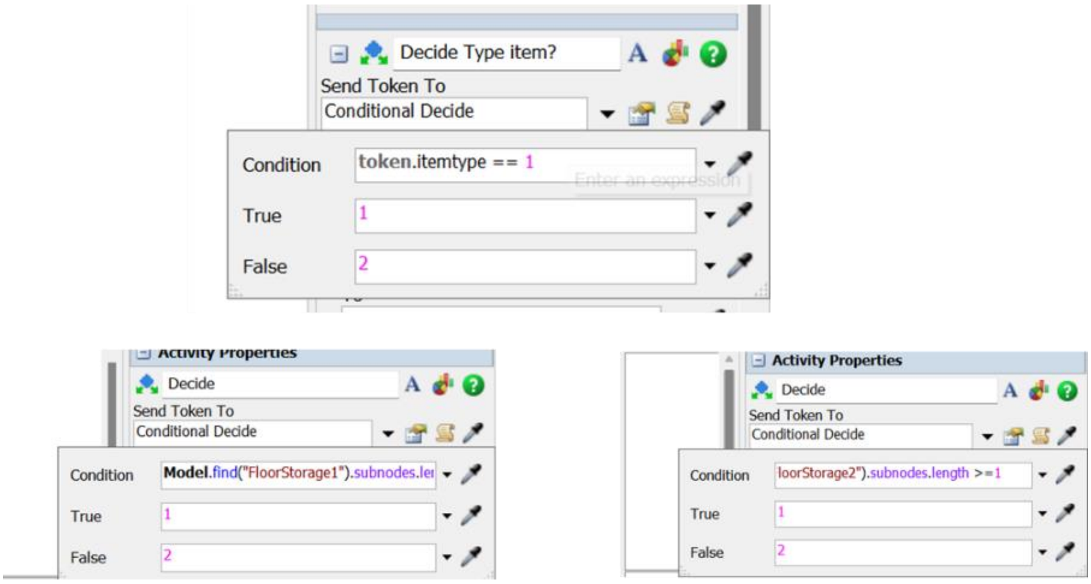


Figure 38. Properties of decide

When the item is in one of the stations, the Mobile Industrial Robot starts its task and moves to the station. There is a *wait for Event* block which is connected to the variable of state Mir. This block is used to pause the process while the robot is busy. It waits specifically for the robot's state to change from busy (1) to available (0) as can be seen in figure 39 As long as the robot is working on another task, the process is on hold. Once the robot finishes its job and becomes free, the process continues, and the robot can be assigned a new task.

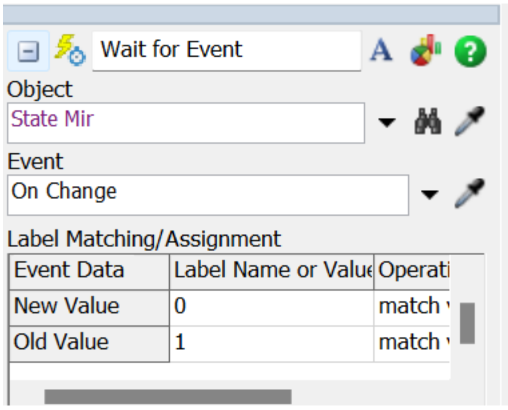


Figure 39. Properties of Wait for Event

7.1.2 Variables of the Process Flow

7.1.2.1 Emulation properties

In the proposed Digital Twin, the connection between physical reality and virtual representation is through TCP Modbus communication protocol which is Ethernet-based.

The IP address of Mobile industrial Robot is *192.168.12.20* and for the UR3e it is *192.168.81.97*. Port 502 is the default port for Modbus TCP/IP communication. The Modbus TCP Client of FlexSim connects to the server's IP address on port 502 to send requests like "read register," "write register” …. Change Interval is 1.00 seconds which means the client polls the server every 1 second. Both connections are active, which means the system will attempt to communicate with both servers. Figure 40 shows the details of the connections.

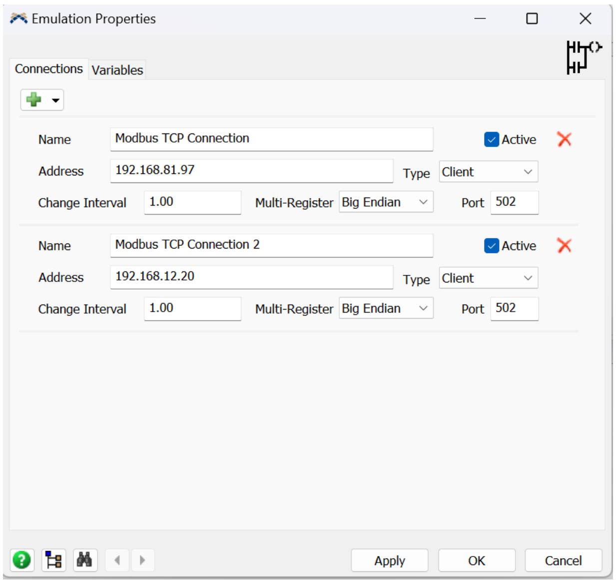


Figure 40. Emulation properties

7.1.2.2 Variables of UR3e

The proposed solution is to use variables as shown in figure 41 for sending and receiving commands to or from the robot. For the UR robot, 5 sensor variables are considered. Start and stop are sensor variables which send a signal on the start of the simulation to start the UR robot. When the signal is no longer received robots stop working and the program is stopped.

Each type of the item has 1 sensor variable for speed. Normal speed Type 1 and normal speed type 2 are for adjusting the speed of the UR. Here it is considered the constant speed for all items without considering the capacity of the warehouse. If these 2 conditions are not correct, then items are moving at a low speed through sensor variable of low-speed type 1 and low speed type 2.

State UR is the control variable which receives a signal when the robot picks an item and stops once the robot placed the item. It controls the movements of robots in simulation.

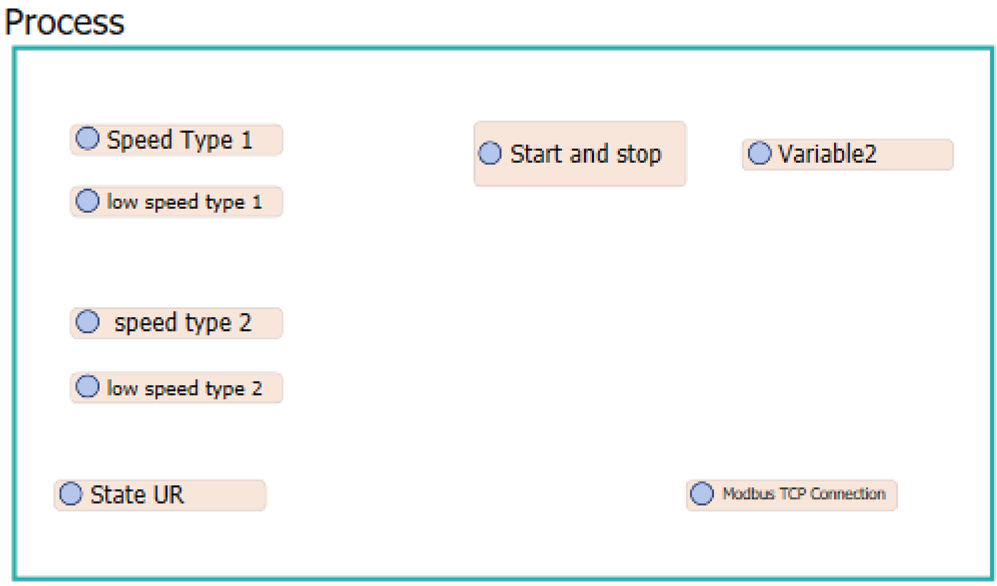


Figure 41. Sensor and control variable of UR3e

7.1.2.3 Variables of MiR

For the MiR variables, as shown in figure 42, are also used for sending and receiving command. Two sensor variables and one control variable are used in the model. *Start* sensor variable is used for sending the command to start the MiR as soon as the token arrives this block in the process flow with the register type of coil and address 0. The control variable of *State MiR* is used for receiving the data from the MiR in FlexSim to know if the robot is busy or not. This helps to keep the tokens in process flow until the robot is available. This variable is a 32-bit integer holding register with register number 1194. The sensor variable of Processing is used to send the command to robot to move to the station to pick the item. It is also a 32-bit integer holding register with register number 1196.

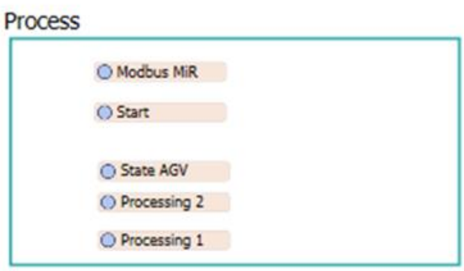


Figure 42. Sensor and control variables of MiR

7.1.3 Logic in the UR3e

To ensure the accurate execution of Pick and place by UR3e, logic according to the figure 44 was developed. This program is structured based on the conditional statement and predefined waypoints which allows the robot to adapt its movement based on digital output signals.

The logic starts with a waiting mechanism which holds the robot idle until it receives a trigger signal *From Robot 1*. Once it is activated, the robot enters a continuous loop where it monitors the state of the digital outputs (DO [0], DO [1], DO [2], DO [3]). Each signal corresponds to a different task.

DO [0] is corresponds to when the token inside the virtual model is item type 1 and the storage has enough capacity therefore, robot pick and places the item with normal speed to the Station 1, while DO [1] is corresponds to the item type 1 where the warehouses it reaches to the threshold and therefore, robot must do the pick and place task with low speed. In virtual model, the register address of DO [0] and DO [1] are 16 and 17.

On the other hand, for item type 2, Do [2] is on, it means the token in virtual model where there is enough capacity in warehouse so the UR can do the task with normal speed but if DO [3] is on, this means there is not enough space in warehouse and UR must work with slower speed. In virtual model, the register address of DO [0] and DO [1] are 18 and 19.

DO [4] is used in order to control the robot whether it is busy and processing an item or free and ready to do the task. When the token enters one of the active branches, DO [4] is set to Off. This sends the signal to FlexSim that the robot is busy now and therefore, no new item should be released into the system. When the robot has completed the placing operation and is ready to start a new task, DO [4] is turned back on. This update notifies the FlexSim that the robot has finished its task and is ready to accept a new item.

Additionally, the digital output register that originally triggered the action (DO [0], DO [1], DO [2], DO [3]) is also reset and set to False. This ensures that the system clears the previous condition and prepares for the next signal, preventing unintended repetitions of the same task. Table 5 provides a summary of all the variables with corresponding digital outputs.

Figure 43 shows the process flow of how the digital outputs are working in the proposed solution.

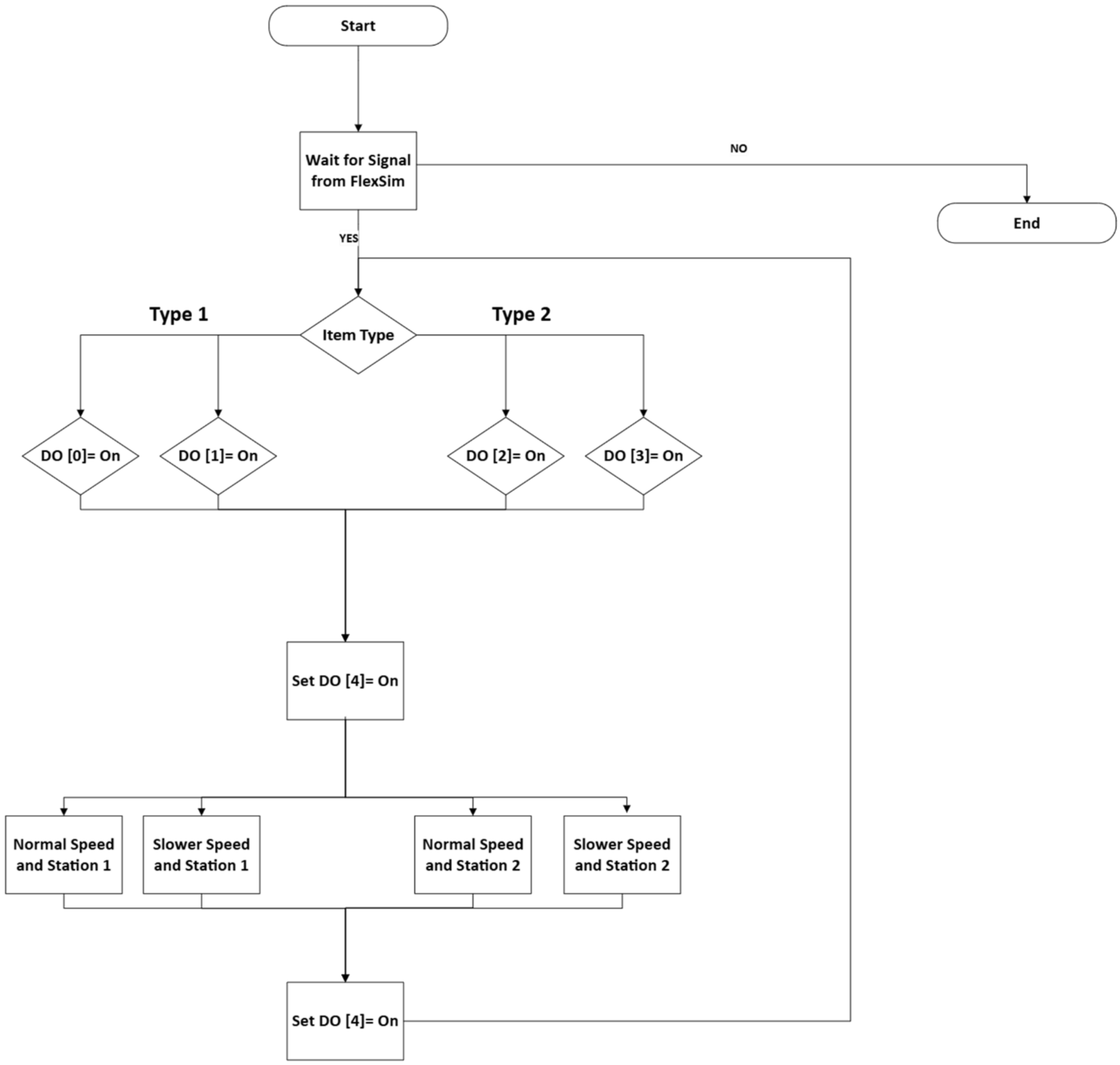


Figure 43. Process flow of UR3e

Table 5. Variables of the virtual system and signals of the physical System

Variable of Virtual System	UR3e Signal
Start and stop	DO [From Robot 1]
State UR	DO [4]
Speed Type 1	DO [0]
Low Speed Type 1	DO [1]
Speed Type 2	DO [2]
High Speed Type 2	DO [3]

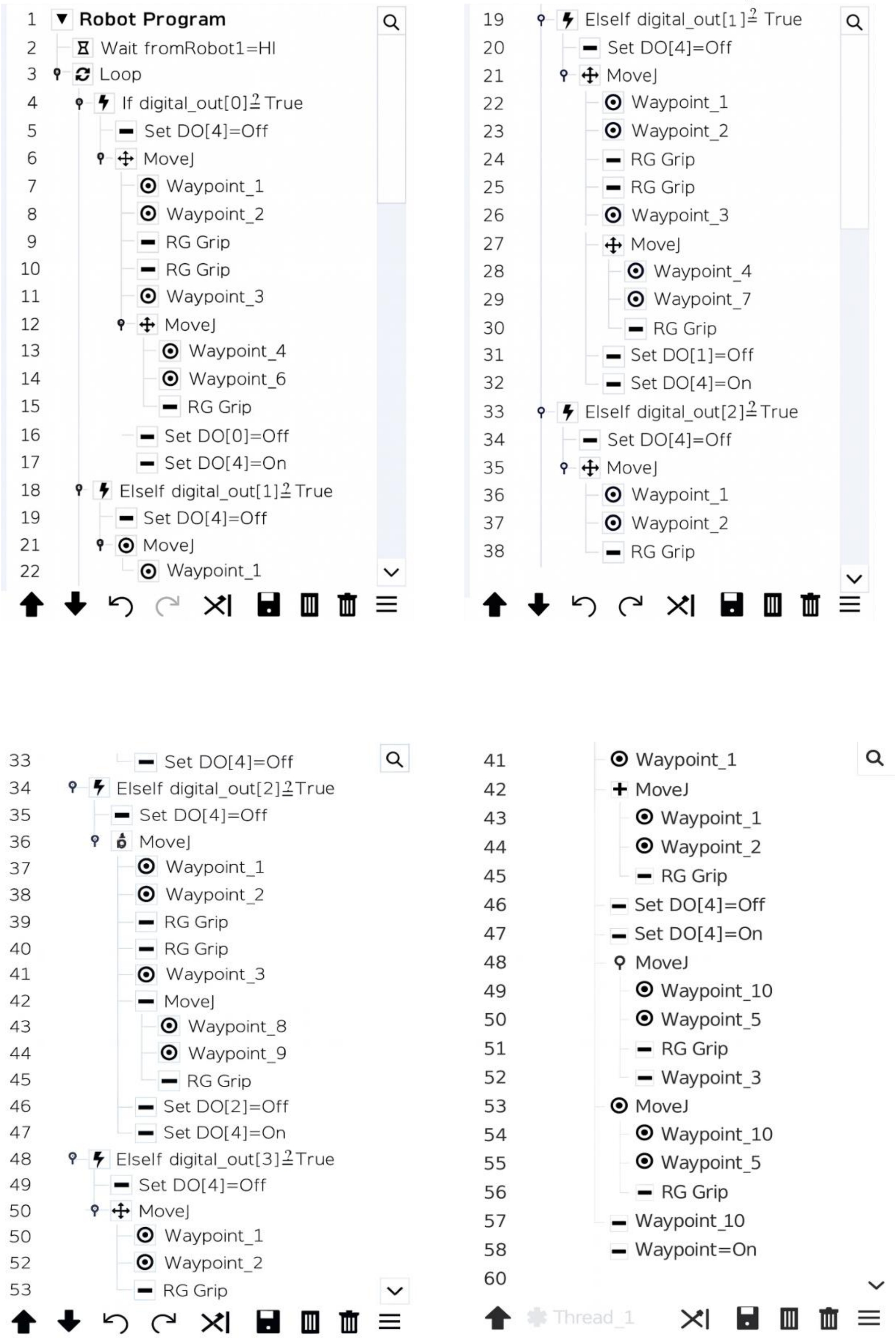


Figure 44. Logic of UR3e

7.1.4 Logic in the MiR

In this system, tasks are defined on the MiR portal for moving items from Station 1 and Station 2 to Storage 1 and Storage 2. These tasks are controlled by a set of conditional rules. To synchronize FlexSim with the MiR robot and send commands to it, three PLCs are used as it is shown in table 6.

- **PLC register 98** indicates the robot's current state. When its value is 0, it means the MiR is available to pick up an item from one of the stations. Once an item is placed in a station, the MiR moves to the loading point to grab it, and **PLC register 98** changes to 1.
- **PLC register 99** and **PLC register 97** are used to track items at Station 1 and Station 2. When **PLC register 99** is equal to 1, it indicates that an item is waiting at Station 1. Similarly, when **PLC register 97** is equal to 1, it means an item is waiting at Station 2.
- After the MiR loads an item, it moves to the unloading location. Once the item is unloaded, **PLC register 99**, **PLC register 97**, and **PLC register 98** are all reset to 0, signaling that the robot is ready for the next task.

This loop continues until all 20 items are moved to the storage, then the MiR will stop.

Table 6. PLC and register address

PLC	Register Address
PLC register 97	1194
PLC Register 98	1192
PLC register 99	1196

AS it can be seen in figure 45 the logic of mobile robot starts with a unlimited loop and this loop continues until all 20 items are moved to the warehouses. Once all items are moved, the mobile robot stops automatically.

Inside this loop, there is conditional logic, and this conditional logic will be checked all the time. When the mobile robot is available, it receives the signal from FlexSim and moves to the loading point. At this moment, the robot is busy and set the PLC 98 to 1.

FlexSim sends a signal to determine the pick-up station either Station1 or Station 2. This is communicated by setting one of the PLC 97 or PLC 99 to 1. Based on this signal, the appropriate UR program runs. If Station 1 is selected, UR program 2 is launched and if Station 2 is selected, UR program 1 runs. These programs control the collaborative robot arm which is mounted on top of the mobile robot and enable it to pick the item.

Once the item is picked up, the mobile robot proceeds to the unloading point.

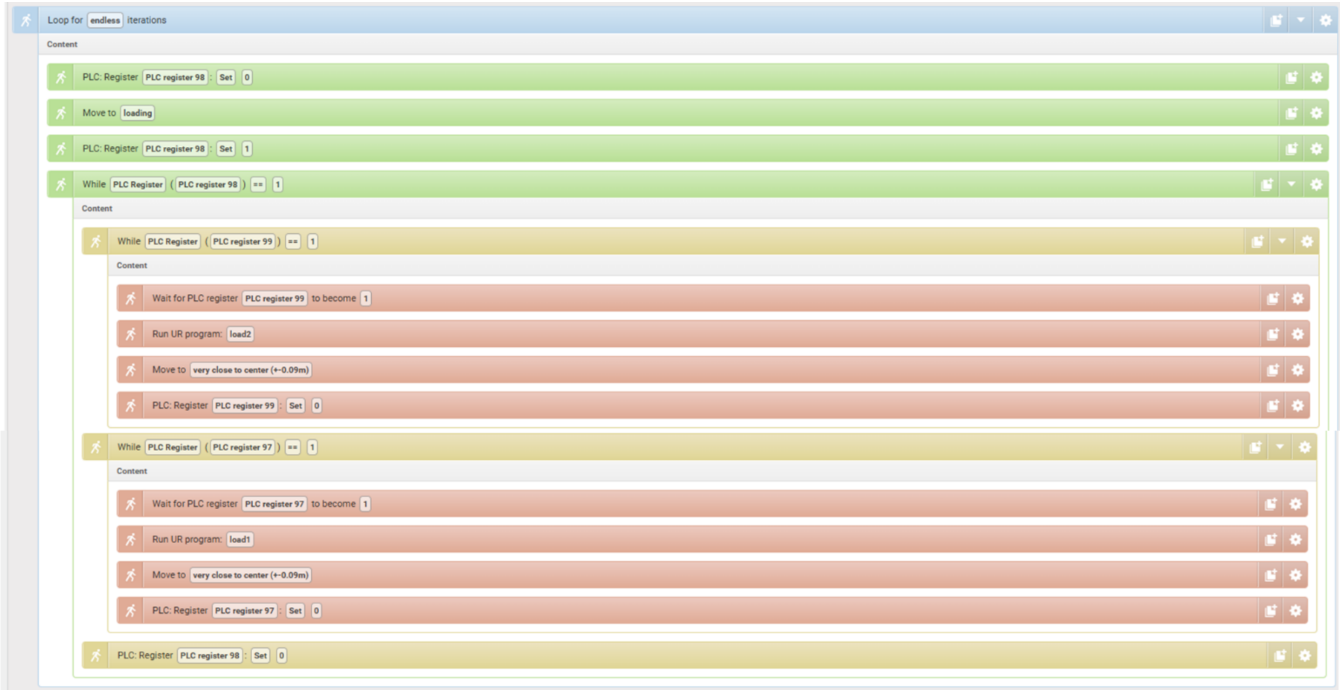


Figure 45. Logic of MiR100

In the following section, 2 scenarios are discussed to see the impact of speed adjustment of system performance.

In scenario 1 the UR3e works at a constant speed without considering the capacity of the warehouse. In contrast, scenario 2 shows the application of Digital Twin technology where the speed of the UR3e is adjusted dynamically based on real-time status of the warehouse.

7.2 Scenario 1

In this scenario, the UR3e robot picks and places items at a steady speed, without considering how full the two warehouses are. It continues working at the same pace, placing items into Station 1 and Station 2. Meanwhile, the MiR robot transports the items one by one to the warehouses. But once the warehouses are full, the items can't be moved right away as they have to wait in the stations until space becomes available.

The whole process takes 856 seconds, and during this time, the UR3e is active only 23.63% of the time. On average, items of type 1 wait about 106.8 seconds in Station 1, while type 2 items wait around 97.4 seconds in Station 2. These waiting times show how long the items are stuck in the stations before the MiR can move them. At most, there were 5 items waiting in Station 1 and 2 items in Station 2. The UR3e continues operating without considering downstream bottlenecks. As a result, even though the robot can work faster, the full warehouses reduce overall efficiency. This mismatch leads to unnecessary waiting times and underutilization of resources. These results suggest that introducing logic to adapt the UR3e's speed based on warehouse availability could improve resource utilization and reduce item wait times. This insight forms the basis for the next scenario, where speed adjustment is explored. Figure 46 shows the result of this scenario in FlexSim dashboard.

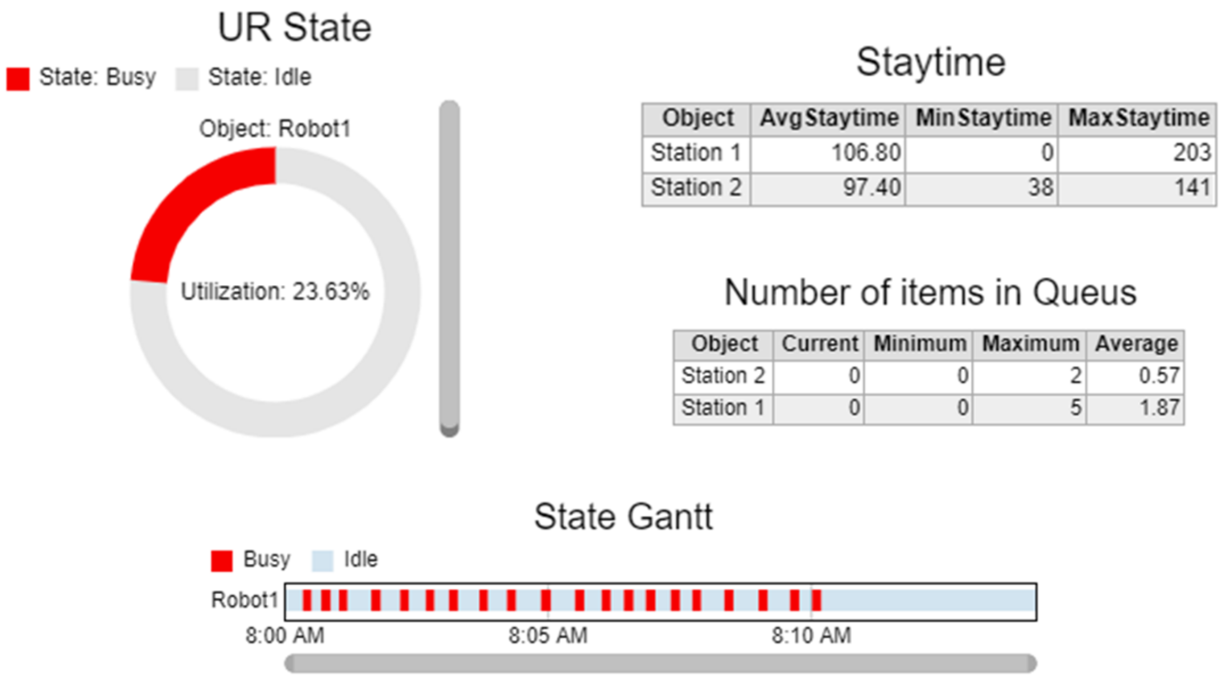
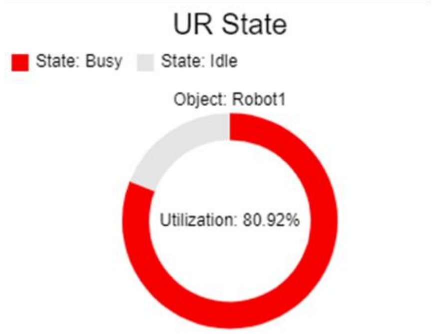


Figure 46. KPIs of Scenario 1 without DT

7.3 Scenario 2

In this scenario, the system uses a Digital Twin approach to keep the process running smoothly. It constantly monitors how full the warehouses are, and when they're getting close to maximum capacity, it automatically slows down the speed of the Universal Robot (UR). The important part is that the process doesn't stop.

By adjusting the robot's speed instead of halting everything, we can avoid creating bottlenecks at the stations. Normally, when the UR runs at a constant speed, items tend to pile up at the stations and have to wait for the robot to pick them up. But in this case, by slowing the robot down when needed, the system gives itself more time to clear space in the warehouse. This helps keep the manufacturing flow continuous and balanced, even under changing conditions. The whole process takes 879 seconds in total with the utilization rate of 80,92% of the robot. On average item type 1 and type 2 are waiting in station 1 and station 2, 22,67 seconds and 40.00 seconds respectively. The maximum number of items in station 2 and station 1 while they are waiting for the mobile robot are 1 and 2. Although in this scenario the cycle time is slightly longer than the scenario without Digital Twin, the system avoids congestion and interruptions by dynamically adjusting the speed based on the warehouse capacity. In figure 47, the results of the adaptive speed of UR3e are shown.



Staytime

Object	AvgStaytime	MinStaytime	MaxStaytime
Station 1	33.67	8	48
Station 2	40.00	32	48

Number of items in Queus

Object	Current	Minimum	Maximum	Average
Station 2	0	0	1	0.23
Station 1	0	0	2	0.57

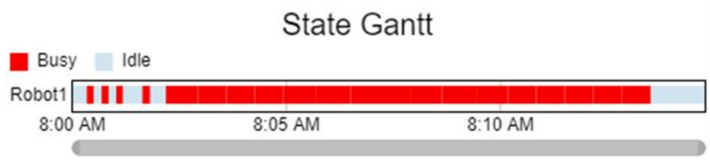


Figure 47. KPIs of Scenario 2 with DT

7.4 Discussion

Comparing the results of the two scenarios clearly shows the effectiveness of the proposed Digital Twin framework. It not only enhances the overall system performance but also helps prevent bottlenecks, leading to a smoother and more efficient process flow. In Scenario 1, the UR3e robot is working at a constant speed no matter what is happening in the rest of the system. At first glance, it might seem efficient as the process finishes in 856 seconds which is shorter than scenario 2. Moreover, items spend a long time waiting in the station for over 100 seconds on average for type 1 and nearly 97 seconds on average for type 2, which is due to the unavailability of the warehouses. On top of that, the UR3e is underutilized with 23,63% which shows that a faster robot does not guarantee better performance when downstream resources become bottlenecks.

On the other hand, scenario 2 with introducing a Digital Twin speed adjustment, allows the system to react in real time to changes in warehouse availability. When storage is close to being full, the UR3e robot automatically slows down and gives more time to be free space. This adaptive behavior reduces the waiting time in station 1 and station 2 to 22.67 seconds for type 1 and 40 seconds for type 2 respectively. This leads to a higher utilization rate of 80.92%.

Although the cycle time increases slightly to 879 seconds, the system avoids congestion, reduces idle time and keeps a more stable workflow.

This suggests that constant speed is not always beneficial in logistical processes. System responsiveness and coordination between robots, stations and warehouses are important factors for efficiency of systems.

Table 7 shows the key results of both scenarios:

Table 7. Result comparison

<table>
<tr><th colspan="2">Performance indicators</th><th>First Scenario</th><th>Second Scenario</th></tr>
<tr><td colspan="2">Number of processed items</td><td>20</td><td>20</td></tr>
<tr><td colspan="2">UR3e Utilization rate</td><td>23,63%</td><td>80,92%</td></tr>
<tr><td colspan="2">Total process time (seconds)</td><td>856 Sec</td><td>879 Sec</td></tr>
<tr><td rowspan="2">Average Stay time in Stations</td><td>Station type 1</td><td>106,80 Sec</td><td>33,67 Sec</td></tr>
<tr><td>Station type 2</td><td>97,40 Sec</td><td>40,00 Sec</td></tr>
<tr><td rowspan="2">Maximum number of Items in Stations</td><td>Station type 1</td><td>5</td><td>2</td></tr>
<tr><td>Station type 2</td><td>2</td><td>1</td></tr>
</table>

8 Conclusion and Future Studies

This thesis showed how a Digital Twin can improv the performance of internal logistics using a collaborative robot UR3e and an Autonomous Mobile Robot Mir100. By analyzing 2 scenarios, it becomes clear that when UR3e is working at a constant speed without considering system conditions as seen in scenario 1, it leads to inefficiencies in system like long waiting time, low robot utilization rate and bottlenecks at stations.

In contrast, scenario 2 showed that with logic based on warehouse capacity through Digital Twin can make a difference in system efficiency. By adjusting the speed of UR3e in real time, system decreased idle time and waiting time while increasing utilization rate and a more continuous flow. Although the process time was slightly longer, the overall system was more balanced.

These results highlight the importance of adaptability and real time decision making. Digital Twin is a powerful tool that enables smart manufacturing and brings flexibility into operations.

Another factor that can be considered is the speed of the mobile robot as well as the UR3e. Since both robots are working together, considering their speeds could lead to even better system performance.

Moreover, predictive logic where decisions are not just based on current situations can be studied. Using past data to forecast helps the system to make smarter and productive adjustments.

Another area which is valuable to consider is energy consumption optimization. While this thesis focused on timing and process flow, energy consumption is also important. Balancing speed and energy consumption of UR3e and MiR100 can bring environmental and operational benefits.

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