Data Synchronization in Digital Twin for a Lab-Scale Drone Factory

Master's thesis in Production Engineering

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Abstract

Industry 4.0 has introduced new technologies aimed at revolutionizing and digitizing the manufacturing sector. Among these, Digital Twin stands out as a leading technology for industrial digitalization. This thesis examines the integration of Digital Twin with an actual production system to achieve data synchronization. A lab-scale drone factory serves as the test bed for this research. Through an extensive literature review, the study identifies essential communication technologies and architectures that facilitate the connection between Digital Twin and real systems. The project's methodologies involve developing a Digital Model, selecting a communication protocol, establishing a connection between the Digital Model and the real system, importing and exporting data between the Digital Twin and a server, and verifying the control of the real system via the Digital Twin and vice versa. The findings demonstrate that the Digital Twin can replicate and control the real system, offering suggestions for production parameter improvements. The study concludes by discussing the implications of future research on this thesis and detailing the steps and advantages of integrating event log data into PlantSim.

Keywords: Digital Twin, Industry 4.0, Real Time Data Synchronization, OPC UA, Internet of Things.

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Aniruth Vishwanath Nagarajan

Gnyaneshwar Janaswami

Gothenburg, June 2024

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AI	Artificial Intelligence
CAD	Computer Aided Design
DES	Discrete Event Simulation
DT	Digital Twin
ICT	Information and Communications Technology
IoT	Internet of Things
KPI	Key Performance Indicator
ML	Machine Learning
MTTR	Mean Time To Repair
MUs	Movable Units
OEE	Overall Equipment Effectiveness
OPC UA	Open Platform Communications United Architecture
PLC	Programmable Logic Controller
RFID	Radio-Frequency IDentification
RTDS	Real Time Data Synchronization
SII Lab	Stena Industry Innovation Lab

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Introduction

1.1 Background

In the era of the fourth industrial revolution, often referred to as Industry 4.0, the rapid evolution of technology is leading to a great transformation in the manufacturing industry (Barton et al., 2022) (Negri et al., 2017). This transformation is moving towards achieving smart manufacturing through the integration of state of the art technologies such as the Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), Digital Twins (DT), Virtual Reality (VR) and cloud computing into production processes (Datta, 2022). These advancements aim to provide better control over business processes, enhance operational efficiency, facility management and overall productivity, providing a competitive edge for the manufacturing companies in the market (Reddy et al., 2021).

DT is a virtual replica of a physical object or a system characterized by an automatic data exchange between the physical system and digital model in real-time and is considered as a vital component of Industry 4.0 (Jones et al., 2020). A DT enables simultaneous simulations of multiple processes which provides a comprehensive and flexible approach to optimize the production, in contrast, traditional simulations focus on discrete event simulations (DES) on individual processes (Wright and Davidson, 2020). The integration of DTs in production systems not only improves system efficiency, productivity and product quality but also provides effective maintenance strategies as well as facilitates sustainable practices by reducing raw material use (Franciosi et al., 2022).

The advantages and benefits of integration of DT in a production system according to (Jiang et al., 2021) are that it can help in detecting and locating faults in processes, visualizing the system statistics, and improves security and performance of the monitoring and control network. DT can predict the lifecycle of components, tools and machines by using real-time data communication and optimization of the maintenance strategies. A DT can be used to maximize asset serviceability by improving the production flexibility, system reliability, and reducing the operation cost (Liu et al., 2021a). A DT can also be used for providing a platform for cooperative maintenance and resource allocation.

Despite the above mentioned benefits of DT, there are significant practical challenges in integrating a DT with real production systems (Sharma et al., 2022). One of the challenges in integrating is real-time synchronization of data between the physical and virtual models (Botín-Sanabria et al., 2022). There are many digital models that serve as digital shadows of physical systems. Often, these models lack a real-time link to their physical counterparts or maintain only a one-way flow of data, primarily from the physical system to the digital model. (Schuh et al., 2021). In contrast, a DT requires data to flow in bi-directional in real-time to make decisions and optimize the production systems.

The physical system of the lab scale drone assembly factory is installed at Stena Industry Innovation Lab (SII Lab), Lindholmen, Gothenburg. The SII Lab is a national test bed and an international digital innovation hub (Lab, 2024). The focus of the test bed is Smart Industry and primarily in final assembly. The drone assembly factory is a Simulated Work Environment factory set up for education and research within Industry 4.0 which demonstrates different technologies such as HRC robots and strategies for increased automation and digitalization (Factory, 2024). The drone factory consists of four different areas: Training, Internal logistics, Final Assembly and Quality Control. Currently there are multiple projects going on at SII Lab with the drone factory focused on cognitive and physical automation.

1.2 Aim

This thesis focuses on investigating the drone factory production system in Stena Industry Innovation Lab (SII-Lab) by producing a 3D model for a DT in Tecnomatix plant simulation software and to improve the digitalization level in production systems. The thesis aims to find the feasibility of bi-directional data synchronization to the digital model in real-time. The intended outcome of the thesis is to demonstrate the benefits that bi-directional communication has on production, such as improvements in throughput and cycle time.

1.3 Research Questions

RQ1: How can data connectivity be effectively established between a digital model and a real production system to improve data synchronization utilizing existing industrial infrastructure?

RQ2: How does bi-directional communication between a physical system and its digital twin influence the efficiency and performance of production systems?

1.4 Delimitations

The project does not include the technical detailed analysis of SII-Lab's drone factory, nor does it concern with the available technologies for data collection. It does not benchmark the created DT with the real drone factory. Due to multiple projects running on the same system, there was a time restriction for this project. The drone assembly production volume was arbitrary, and the data collected during production differed from a well structured and supervised data collection that can be seen in a typical real system. Instead, the data collected was unstructured and contained much irrelevant information for this project. Lacking the expertise in server setup and IoT platforms, we needed assistance from lab personnel, whose availability was limited due to their involvement with other projects which were running simultaneously on the same system. Consequently, process optimization was not possible under these circumstances.

2

Theoretical Background

The objective of this section is to provide the overview about basic concepts needed for the reader to understand the main contributions of this thesis. As this paper explores the concept of DTs and its benefits, the topics such as Industry 4.0, DT, Real-Time Data Synchronization (RTDS), etc. and how these concepts are related to each other have been discussed in the following section.

2.1 Industry 4.0

The evolution of industrial manufacturing systems over the period of time have been divided into four industrial revolutions. The path of evolution of industry is depicted in Figure 2.1.

Introduction of steam power and mechanization in the late 18th century kick-started the First Industrial Revolution where manufacturing processes were improved and transitioned from manual work to steam powered (Sharma* and Singh, 2020). Electricity enabled the concept of assembly lines which paved a way for mass production but with no product customization. Electric energy set off the era of the Second Industrial Revolution in the late 1800s. The Third Industrial Revolution, in the 1960s, started with the integration of computers and microelectronics, that is the automation or digitalization of the manufacturing industry. Automation made the production flexible, allowing for mass customization. Fourth Industrial Revolution, also known as the Industry 4.0 is the integration of intelligent digital technologies into the manufacturing and industrial sectors to bring forth the digital transformation era. Industry 4.0 or i4.0 is synonymous to smart manufacturing (Asadollahi-Yazdi et al., 2020).

2.1.1 Key Components and Benefits of Industry 4.0

The development in the Information and Communications Technologies led to the automation of cyber-physical systems with advanced connectivity and gave birth to the concept IoT. Other key components of i4.0 include DT, AI, Big Data and Analytics, Cloud Computing, etc (Barton et al., 2022).

One of the main benefits of implementing the IoT and other technologies of industry 4.0 is that it is highly customizable based on customer requirements, it brings upon high resource productivity and efficiency with more flexibility and also aids in

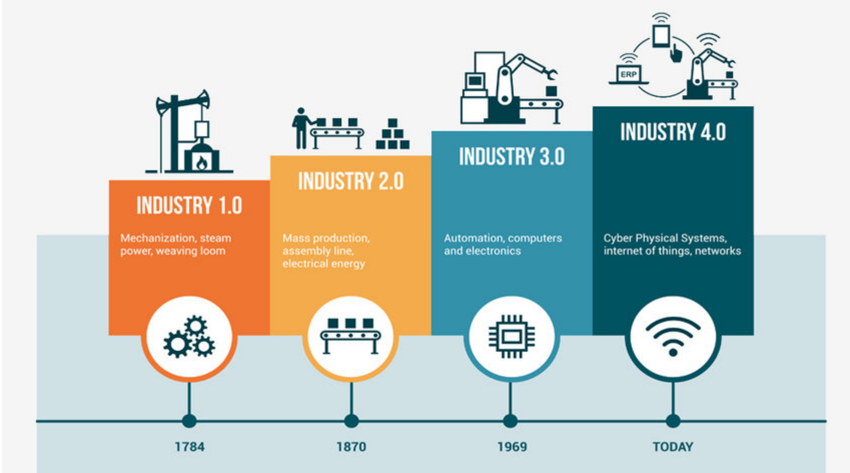

Figure 2.1: Industrial Revolution Timeline

optimized decision making (Kagermann et al., 2013). There are multiple case studies on made in Italy Small and Medium-sized Enterprises presented in the article (Matarazzo et al., 2021) on how digital technologies are used for understanding future trends and for developing value co-creation (Bravi and Murmura, 2021). These articles (Saebi et al., 2017) (Volberda et al., 2017) shows how digitalization of business can modify the structure of business models, other added benefits to business digitalization include cost reduction due to deployment of 3D digital models during prototyping phase of products, quality improvement as a result of using RFID on parts for quality control throughout the process and delivery time reduction (Moeuf et al., 2018). Further benefits include maximizing efficiency, cutting operational costs and remaining competitive in the business and manufacturing cost mapping (Kiel et al., 2017).

With the advent of Industry 4.0, newer smart manufacturing technologies and tools are growing rapidly in the various sectors of industry. These technologies allow manufacturing enterprises to monitor, analyze, and control their environmental and carbon footprint more effectively and participate in modern supply networks to regain and retain their competitiveness on a global scale (Sinha and Wuest, 2021).

2.2 Digital Twin

A DT is a virtual replica of a physical system or an object which has the ability to link both physical and virtual worlds in real-time with automatic data flow between them (Figure 2.4) that provides a realistic and holistic view on what-if scenarios prediction (Jones et al., 2020). DT is considered as an important component of industry 4.0 for gaining a competitive edge over competitors and its main applications includes designing, decision making, optimizing, maintenance, remote access and training among others (Singh et al., 2021). The concept of DT came into recognition in 2002 in relation to Product Lifecycle Management at the University of Michigan by Michael Grieves. The model proposed was referred to as "Mirrored Spaces World" (Figure 2.2) which had three components: real space, virtual space and a link for data / information sharing between them (Grieves, 2005). This "Mirrored Spaces World" had no practical applications at that time due to the lack of supporting technologies such as low connectivity with devices, low computing ability, data storage and management, etc.

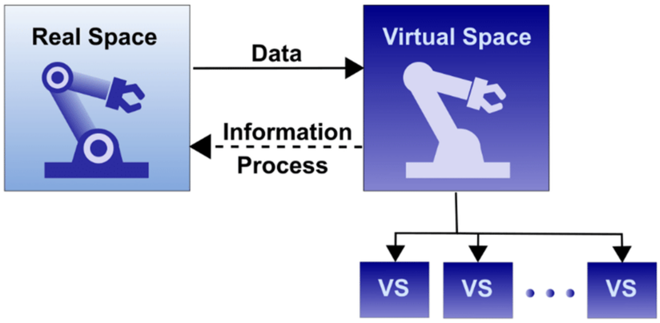

Figure 2.2: Mirrored Spaces Model proposed by Michael Grieves (Singh et al., 2021).

NASA referred to DT as 'Virtual Digital Fleet Leader' and they were the first organization to give a definition for DT - it defined as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin" (Zhou et al., 2022). The US Air Force after NASA used DT for the design, maintenance and prediction of their aircraft. They used DT to simulate physical and mechanical properties of aircraft to forecast fatigue or cracks in the structure .

By definition it can be referred to that DT is different from digital models such as CAD/CAE and simulation. Many organizations refer to 3D models when using the term 'Digital Twin', however, a 3D model is just a part of DT as a DT reflects the data from real world systems at any given point in real-time thus aiding in monitoring and understanding the performance of the system for its predictive maintenance (Singh et al., 2021).

A 2D/3D model created using any software with the purpose of just simulating a process or system is termed as a 'Digital Model'. When a digital model has a unidirectional flow of data and information from physical system to the virtual model in real-time it is termed as a 'Digital Shadow' (Al-Sehrawy and Kumar, 2021). Manufacturing industries use digital shadow for monitoring the physical system in real-time. A digital model with a bidirectional data flow between physical and virtual systems in real-time is termed as a 'Digital Twin' .

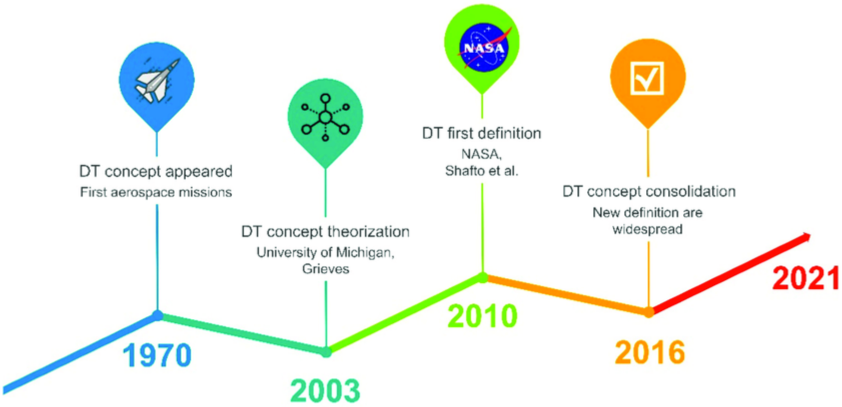

Figure 2.3: Evolution of Digital Twin

A definition of DT is proposed here that can be applied irrespective of the industry or its application:

"A Digital Twin is a dynamic and self-evolving digital/virtual model or simulation of a real-life subject or object (part, machine, process, human, etc.) representing the exact state of its physical twin at any given point of time via exchanging the real-time data as well as keeping the historical data. It is not just the Digital Twin which mimics its physical twin but any changes in the Digital Twin are mimicked by the physical twin too" (Singh et al., 2021).

2.2.1 Benefits of Digital Twin

This subsection will explore the advantages of utilizing digital twins in the context of management, reliability, and data integration across various departments within the manufacturing industry.

Real-Time Operations Management: DT technologies use historical data to provide users with a comprehensive understanding of the physical systems. To provide the comprehensive view DT requires bi-directional flow of information between physical and virtual systems. DT provides users recommendations and aids them in decision-making by simulating multiple "what-if" scenarios (Stupar et al., 2023).

Improving Reliability: DTs have the ability to enhance physical facilities and processes by identifying potential problem areas within the system. This is done to give users a global perspective on safety, reliability, and availability of the system (Stupar et al., 2023).

Data Integration Across Repositories: DT has the ability to consolidate data from various company repositories into a universal repository for users to easily access and write data. Traditional industries maintain separate units to store data, however DTs aggregate data from different sources like sensors, actuators, PLC's etc into a single data source. This allows users to understand relationships among these diverse data points, thereby facilitating a holistic approach to data management (Stupar et al., 2023).

Simulations and Predictive Analytics: DTs leverage virtual environments to simulate and experiment different scenarios thus reducing the need for physical trials. With real-time data DTs can perform predictive analysis. These analyses can be applied to foresee potential failures and optimize business operations. Insights derived from the analyses can inform users of changes to the physical system, enhance performance and reliability of the system (Galar and Kumar, 2024).

Facilitating Collaboration: DT technologies facilitates collaboration between different cross-functional teams by providing a unified digital representation of the physical objects. This shared data enhances team efforts to improve operations and drive innovation within the company (Galar and Kumar, 2024).

2.2.2 Key Technologies for Digital Twin

The improvement in IT and 5G technology has improved the effectiveness of DTs as it needs to get, process and send data back and forth to the physical system in real-time which requires a reliable network with high data transferability and safety (Liu et al., 2021b). Machine Learning and AI plays a vital role in improving the efficiency of the DT for effective decision making and for formulating maintenance strategies (Tao et al., 2018). Other technologies that help in enabling DT include Big Data Analytics and Cloud based solutions. Enabling DT requires integrated hardwares such as the sensors, gauges, RFID tags and readers, cameras, scanners, etc. to collect data for DTs and transmit them in real-time through servers like OPC UA (Liu et al., 2021b).

2.2.3 Digital Model

A digital model is a virtual representation of a physical system or an object which does not have any kind of automatic data exchange between them (Fuller et al., 2020). All the data exchange between the physical system and virtual model are manual as illustrated in Figure 2.4. Any change is physical system will not have any direct impact in the digital model and vice versa. Digital models are primarily used for discrete event simulations, analysis of processes, designing and prototyping.

2.2.4 Digital Shadow

A digital shadow is a real-time representation of a physical object or a system where the information flow is automatic only from the physical system to the virtual model

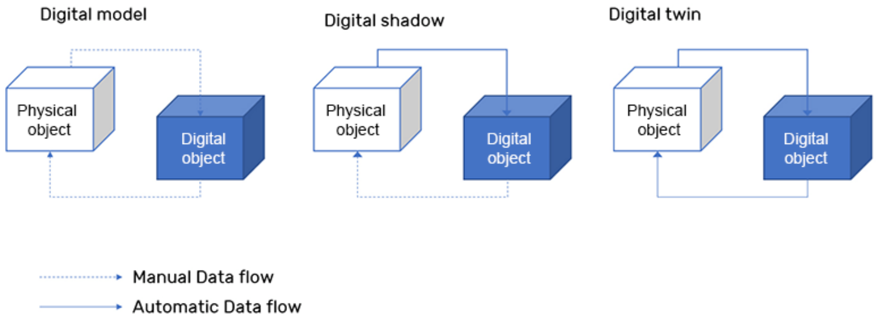

Figure 2.4: Data flow in Digital Model, Digital Shadow, and Digital Twin

as illustrated in Figure 2.4 (Kassen et al., 2021). A digital shadow collects and processes data from various sources such as sensors to aid in monitoring the system in real-time and to support decision making and also improves the decision quality (Liebenberg and Jarke, 2020). It can also provide future states of the system by generating prediction models and running simulations of what-if scenarios (Stecken et al., 2019). In production, they are widely used for production planning, forming maintenance strategies and order processing (Liebenberg and Jarke, 2020). A digital shadow can be converted into a DT by establishing an automatic data flow connection from virtual model to physical system in real-time.

2.2.5 Real-time data synchronization

Industry 4.0 uses information and communication technologies and follows a structured approach to digitalize the manufacturing sector (Ashton et al., 2009). A key component of this approach is the cyber-physical power system (CPPS), which plays a crucial role in real-time monitoring and synchronization of real-world events through the internet (Lee et al., 2015). DT technology is a central part of CPPS, by continuously integrating real-time context and feedback from the system a DT can enable a constant control and enhance production processes, optimize and simulate production lines (Uhlemann et al., 2017) (Sakr et al., 2021).

The primary purpose of DT is to create a digital replica of a real manufacturing system. DT leverages simulation features to select and adapt the digital model to the physical system. DTs surpass Discrete Event Simulation (DES) in real-time synchronization, thanks to Industrial Internet of Things technologies (AboElHassan et al., 2021). DES is primarily used for offline optimization of a digital model and to produce a production plan. DTs on the other hand represent the next evolution by enabling real-time synchronization, execution, and modification of systems. DES helps understand "what may happen," whereas DTs provide insights into "what is happening" and facilitate immediate responses (Sakr et al., 2021).

2.2.5.1 Open Platform Communications United Architecture (OPC UA)

The DTs is a crucial part in the Industrial Internet of things. One of the challenges of DTs is to establish communication and access information from various devices in the factory which are made by different manufacturers (Deng et al., 2022). For managing and analyzing massive datasets effectively a DT must be able to resolve, format, and unify multiple data types. And to establish real-time communication and interaction between a DT and its real-world counterpart, DT requires stable, rapid, and secure communication methods.

Open Platform Communication Unified Architecture (OPC UA) is an industry standard for information exchange, known for its safety and reliability (Salunke et al., 2023). To share real-time information on individual actuators and sensors, manufacturers can use OPC UA in a platform-independent manner and facilitate integrated communication. Additionally, OPC UA can be used in other areas where real-time data synchronization is required. The softwares such as ERP systems can use OPC UA to produce independent solutions for automating industries, improving flexibility, and enabling industry 4.0 standards.

OPC UA operates as a socket-based communication protocol enabling bidirectional machine-to-machine communication (Kumar et al., 2023). This type of communication protocol enables IoT devices to send and receive data at high speeds and frequencies. OPC UA requires a well-established server-client communication mechanism for effective communication. Once OPC UA is connected to the server, the OPC UA client can retrieve data from the server both wired or wirelessly and store it in the cloud, and access it for further analysis.

2.2.6 Traceability

To identify and access all available information about an object throughout its life cycle is called traceability (Schuitemaker and Xu, 2020). Traceability requires a unique identifier or tag to an object for recording and tracking its movements. These movement data are converted into historical data to track the object from its inception to disposal.

Traceability is a crucial tool for product lifecycle management and risk management for a manufacturing company. Its purpose is to monitor any changes and events that occur during production (Schuitemaker and Xu, 2020). Traceability's role in implementing industry 4.0 within a factory is to trace and enhance production efficiency and accuracy by integrating smart IoT technologies (Zhong et al., 2017b).

Traceability involves collecting data from IoT devices like RFID sensors and tags, including location and timestamps of each occurred event. For instance, when a logistics operator uses a handheld RFID device to scan a material tag the tracing system records the object's timestamp and location (Zhong et al., 2017a). To effectively trace different and large numbers of such discrete events occurring throughout a factory at various times and locations, it is essential to establish a well defined tracing logic. Without a proper programming logic for tracing, data integration and achieving traceability becomes challenging.

2.3 Discrete Event Simulation

Discrete Event Simulation or DES is a virtual model representing a real world world system that performs experiments with the virtual system on an event-by-event basis to generate detailed performance reports for analysis using computational and mathematical techniques which assist in the decision making process (Babulak and Wang, 2010).

2.3.1 Discrete Event Simulation Software

Tecnomatix Plant Simulation or just PlantSim is a computer application developed by Siemens Digital Industries Software for modeling, simulating, analyzing, visualizing and optimizing production systems and processes (PlantSim, 2024). Plant Simulation allows users to optimize material flow and resource utilization and logistics for all levels of plant planning from global production facilities, through local plants, to specific lines.

2.3.2 Key Performance Indicators

In a manufacturing company, production control has a multitude of key figures and figure systems; these are known as Key Performance Indicators (KPIs) (Joppen et al., 2019). KPIs in a manufacturing company are used by different departments. It is used as a management tool to provide a rapid analysis and reflects processes in the company. For example the most used KPI in production is OEE, throughput time, productivity and cycle time, etc (Lindberg et al., 2015).

2.3.3 KPIs Selection

The information content requirement states that selected KPIs need to allow for a comprehensive measurement of system performance, meaning that changes in any unselected KPI must be detectable in selected KPIs (Stricker et al., 2017). For this thesis work, the data of KPIs which can be obtained through event logs and also can be used to determine the system efficiency have been selected for the experimental framework. They are as described below:

- Cycle Time: It is the amount of time taken for a machine or worker to complete one process or task from start to finish.

- Productivity: It is the ratio of output to input in the production process. That is, how efficiently a company can produce products with the given amount of input.
- Throughput: It measures how many products are produced in a given amount of time, i.e the rate of production.
- OEE: Overall Equipment Effectiveness, it identifies the percentage of manufacturing time that is truly productive. The higher the OEE, the more the system is productive.

2.4 IoT Platform

An IoT platform is considered as a backbone of Industry 4.0 (Bravi and Murmura, 2021). The role of an IoT platform is to provide a set of tools and services that can be used to connect various devices over the internet (Vishwakarma et al., 2024). This is done to improve connectivity, management, and automation of an industry. IoT platform ensures there is a seamless data flow and interaction between hardware and application layer by acting as a mediator. These platforms are designed for handling large amounts of data generated by facilitating communication between various devices, and provide necessary security measures to protect the network from external threats. IoT platforms offer analytical capabilities to understand the collected data, and generate actionable insights based on collected data (Astropekakis et al., 2022).

2.4.1 Cyber Security

Smart factories are leveraging integrated information and communication technology in order to enhance their efficiency, productivity, and automation and revolutionize manufacturing processes. However, this integration also leads to cybersecurity challenges. Threats such as unauthorized access, data breaches, and malware attacks pose significant risks. To improve security (Yi and Jeong, 2022) emphasize on protection of sensitive data, intellectual properties, and improvement of critical infrastructures within the smart factories.

According to (Lin et al., 2023) to improve privacy aspects in 5G-enabled Industrial Internet of Things environments, and highlight vulnerabilities in existing execution processes a novel approach is required to secure smart factory architectures. Organizations must prioritize cybersecurity in order to safeguard their operations, maintain customers' trust, and prevent slumps in sales. As factories are evolving with industry 4.0 technologies addressing these challenges becomes paramount for sustainable and secure manufacturing.

2.4.2 PTC ThingWorx

ThingWorx is a platform provided by PTC systems, it is an Industrial Internet of Things platform that can facilitate the rapid development and deployment of smart solutions in a factory to stay connected across various industries (Thingworx, 2024). ThingWorx offers a variety of tools that can improve application development, connectivity, and data analysis in any industry. The platform is designed to accelerate digital transformation by use of advanced capabilities like machine learning, industrial connectivity , and real-time insights on operational data. To enhance the abilities of businesses, ThingWorx facilitates the integration of physical machinery with digital systems.

ThingWorx Kepware is a server solution created by the PTC system that provides industrial connectivity, ensuring secure and reliable communication between devices and applications (Kepware, 2024). Kepware has the ability to support a wide range of protocols for increasing scalability and ease of use in integrating diverse hardware devices and software applications.

3
Methodology

This chapter provides a detailed account of the methods employed throughout the project. The initial phase involved gathering information and data through a qualitative study, including a comprehensive literature review and system mapping. Following Bank's Methodology (Sokolowski and Banks, 2010), the subsequent steps included modeling a 3D representation of the drone factory, establishing a communication channel between the physical system and the digital model, validating the model against the qualitative study results, and finally, conducting what-if scenarios. The primary objective of this approach was to systematically demonstrate the benefits of bi-directional communication between the physical system and the digital model. By adhering to this structured methodology, the project aimed to ensure accuracy, reliability, and practical applicability of the findings, thereby highlighting the advantages of integrating physical and digital systems.

3.1 Preliminary Studies

The purpose of conducting the preliminar study was to gather data and information on topics such as Industry 4.0, DT, real-time data synchronization, and OPC UA. This studt aimed to identify methods, frameworks, and observations relevant to the thesis project. The information collected from the literature served as evidence to support the project's assumptions. The primary goal was to utilize this data to develop the DT model and validate the thesis objectives. Consequently, the study focused on exploring how to establish bi-directional data communication between the real system and the DT model. Additionally, the literature provided insights on the selection, calculation, and integration of Key Performance Indicators (KPIs) into the DT model.

3.1.1 Identification and Selection of KPIs

The KPIs for this thesis were identified based on its objectives. Specifically, they were derived from the contents of event logs used to determine system efficiency. Relevant research papers were reviewed, and KPIs related to production system improvements were categorized. These KPIs were organized into categories based on their applicability to manual and automatic stations. The collected data was then systematically stored in an Excel sheet.

KPIs including cycle time, productivity, and throughput were chosen to assess the efficiency of the DT model and simulate various what-if scenarios once bidirectional communication is established. For each of these KPIs, relevant elements from the event logs were carefully selected to demonstrate improvement in the DT.

3.1.2 Identification and Selection of Interface for Bi-Directional Communication

The selection of the interface for bidirectional communication between PlantSim and Kepware Server was based on specific criteria. We prioritized interfaces capable of dynamically altering attribute values in real-time while ensuring secure communication. OPC UA was chosen due to its capacity to securely connect to Kepware in real-time and directly modify attribute values. Additionally, the availability of system support and skilled professionals within the company further reinforced our decision to opt for OPC UA.

3.2 System Mapping

To create a 3D model, it is necessary to understand the key components of the physical system such as the system layout, machine/work station set-up, material flow, and other useful quantifiable attributes. The drone assembly set-up which is to be modeled is installed at SII Lab in Lindholmen, so the initial step for mapping the current system will be to visit the lab to get insight into the system layout, data being gathered and other practical knowledge through direct observation and interviews from the workers who are incharge of operating the line and data collection.

Through the interview, the information regarding the type of data being collected, what are the KPIs that are considered crucial for the thesis objective, how to read the various types of data, and how to synchronize these data types into the digital model can be gathered. It also helps in understanding the current situation where the DT hasn't been integrated yet and that will be used to run what-if scenarios in the DT being modeled to compare the results gained after integration to visualize the effect of the DT.

The next step after gathering the data and information will be the Information and Communications Technology (ICT) system mapping. An ICT system mapping is a process of identifying, analyzing and visualizing the components - the hardware, software, data and the people involved - their functions and interactions in an ICT system. An ICT system map helps to understand the structure, behavior and performance as well as identify the strengths and weaknesses of the system.

3.3 Develop Digital Model

The 3D model of the drone assembly was modeled by following the systematic approach outlined in the Banks Methodology, utilizing 'Siemens Tecnomatix Plantsim'. This methodology consists of three main phases: preparation, model building, and analysis. During the preparation phase, tasks such as problem formulation, project planning, objective definition, and data collection were undertaken. Subsequently, in the model building phase, the translation from 2D to 3D and construction of the model took place. Finally, the analysis phase involved the development of an experimental plan, validation procedures, thorough analysis, and comprehensive documentation of the results. The procedural steps articulated in the Banks Methodology are visually represented in Figure 3.2 and will be elaborated upon in the following sections for better comprehension.

3.3.1 Preparation Phase

During the initial stage of the preparation phase, termed problem formulation, a thorough analysis of the problem at hand was conducted. This involved describing the aims and objectives of the project. Subsequently, in the second step, clear and measurable objectives were established to align with the goal of the thesis. This process also involved creating a comprehensive project plan, including the delimitations of the project, formulation of research questions, and mapping out the project timeline using tools such as Gantt charts for meticulous planning and execution.

3.3.1.1 Conceptual Model

A conceptual model is a software independent description of the real system or a model that needs to be constructed (Robinson, 2006). Two different concepts, namely AS-IS and Base scenario, were conceptualized. Using process flow charts is one of the widely used methods to map a production system hence were used to visualize the above mentioned concepts to better understand the production flow (Wang and Brooks, 2007).

The AS-IS scenario, Figure 3.1, depicts the current production process and was modeled based on the information gathered through discussions with the one incharge of the drone assembly factory at SII Lab. The AS-IS scenario model represents the assembly of two variants of the drone with an assumed failure rate, availability of 79% and MTTR of 50 mins, based on the discussion. As for the Base scenario, Figure 3.1, it follows the same production procedure of AS-IS scenario except it doesn't have a failure rate so that the throughputs of these two scenarios can be compared while simulating what-if scenarios in the later stage of the project.

A base model serves as a digital representation of an actual or conceptual system. In the case of the real system, its base model was crafted using specialized 3D modeling software. This digital rendition was constructed with reference to an earlier 2D model, integrating insights gained from the physical system to refine and enhance its accuracy.

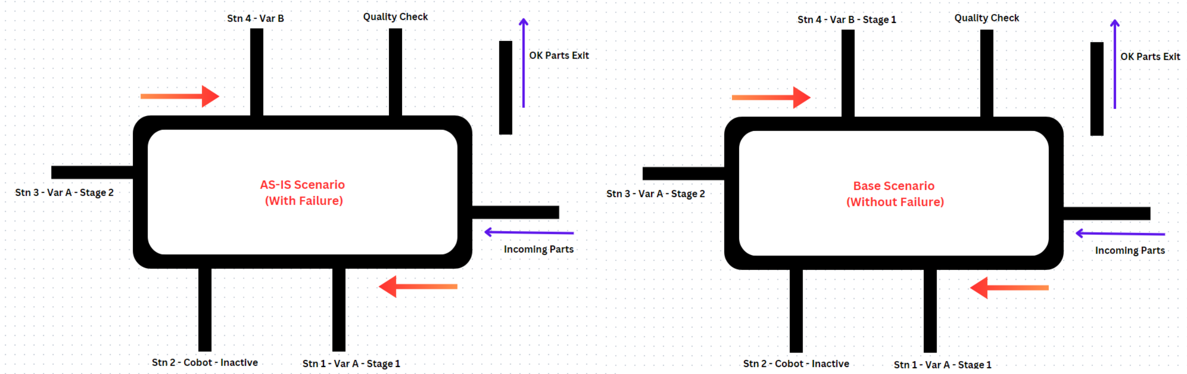

Figure 3.1: Conceptual Models for AS-IS and Base Scenario

3.3.1.2 Data Collection

The primary aim of gathering data is to acquire input information for production metrics like availability, performance, and quality. These metrics play a crucial role in computing Overall Equipment Effectiveness (OEE) for the entire production setup. Essential data points including cycle time, good count, and planned production time are necessary for deriving these metrics. Additionally, data collection serves the purpose of understanding the manufacturing process for both drone variations.

The collected data aims to comprehensively grasp the intricacies of drone manufacturing processes within the SII-Lab, functioning as both a test bed and an operational manufacturing facility. Consequently, crucial production parameters for both drone variants, including availability, setup times, scrap rate, rework rate, and Mean Time To Repair (MTTR), have been inferred. Assembly instructions for the drone variants were meticulously gathered from assembly instruction documents and videos to gain insight into the assembly process and estimate assembly durations. These timestamps were subsequently utilized in generating event logs to validate Real-Time Data Synchronization.

3.3.2 Model Building Phase

The model building phase encompasses three key stages: model translation, model verification, and model validation. Utilizing 'Siemens Tecnomatix Plant Simulation,' we created a detailed 3D representation of the drone factory physical system, subsequently transformed into a DT. The decision to employ PlantSim was driven by the existence of a pre-existing 2D model of the drone factory, serving as a foundational reference for our 3D model. The accessibility, user-friendly interface, and our familiarity with the software further supported this choice. Within this thesis, the modeling endeavor focuses on creating a DT of an assembly line within the SII-Lab, dedicated to drone production.

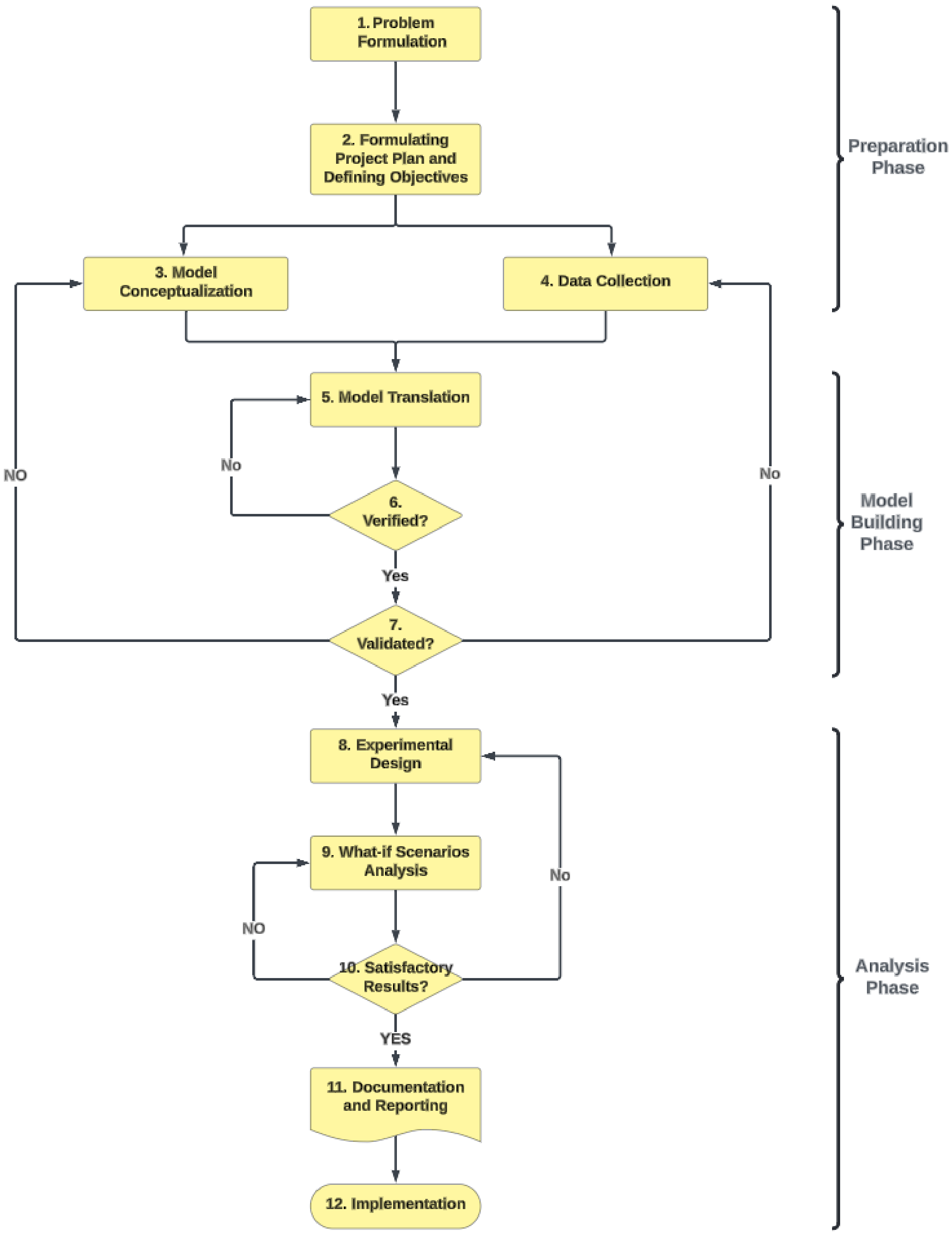

Figure 3.2: Bank's Methodology for Modeling a Digital Twin

3.3.2.1 Model Translation

Plant Simulation's object-oriented nature simplifies the structuring and management of complex systems. Leveraging object-oriented programming methodologies, users can harness features such as attributes, classes, inheritance, and derivations. Figure 3.5 presents a 3D rendition of the drone assembly line within the lab, meticulously crafted using appropriate objects in Plant Simulation.

The event controller governs simulation time, while the source initiates the process by generating Movable Units (MUs), subsequently conveyed to the next process using conveyors and connectors. MUs are temporarily stored in buffers until they proceed to the subsequent stage, with buffer capacities defined by the user. The conveyor system transports MUs between docking stations, directing pallets to assembly stations or onward to the next docking station based on production plans.

Assembly stations, integral components of Plant Simulation, facilitate the assembly of drone components on pallets. Their processing times are user-defined, derived from randomly generated event log data. Upon completion, MUs are directed to the drain, which tallies finished products—marking the throughput—before deletion, thus concluding the drone's product cycle.

Methods within the model enable the programming of custom functions, each governing specific model behaviors (as illustrated in the accompanying figure). Plant Simulation employs SimTalk, its integrated programming language, utilized within methods for coding purposes. Refer to Appendix B for the drone factory model's program details.

Bi-directional communication utilizes "Thingworx Kepware Server 6" as the OPC UA server to import data (tags) from the PLC into PlantSim, acting as the client. To effect real-time changes in the physical system, data is transmitted back to the PLC through PTC Thingworx, ensuring security. Further elaboration on the OPC UA connection's procedural intricacies between the physical system and the digital model is provided in the results section.

3.3.2.2 Communication Between Physical and Virtual System

The first step in achieving bidirectional communication is to import data from the physical system into the digital model. This initial one-way communication transforms the model into a digital shadow, which can monitor the production system in real-time. This was accomplished by setting up communication between the OPC UA interface server – here, the Thingworx Kepware server, which gathers data from the system's PLCs – and the client, PlantSim. To establish the connection, the server's IP address was provided to PlantSim's built-in OPC UA interface. Once the connection was successfully made, tags containing data from the PLCs were imported into PlantSim. These tags were then accessed using dedicated methods to serve as input for the model. This process created a digital shadow of the drone factory, allowing for real-time monitoring.

The next step in transforming the digital shadow into a DT is to establish communication from the digital model back to the physical system. Because the drone factory's PLCs are in read-only mode and cannot be directly overwritten by PlantSim, an alternative approach was necessary. With professional guidance from a PTC expert, PlantSim was connected to the Kepware OPC UA server through Thingworx IoT, which acts as a security firewall for the server. Using dedicated methods, data was written to user-created tags in Thingworx IoT. This data was then relayed to the Kepware server, which updated the drone factory's PLCs with the new information. This established a bidirectional communication loop, effectively converting the digital shadow into a DT.

3.3.2.3 Verification of Bi-Directional Communication in Digital Twin Model

In order to verify our project we have chosen to run pilot tests of our DT model connection with kepware server and ThingWorX IoT platform, in order to verify if we were able to import and export the relevant data. With the assistance of a PTC system expert we were able to verify whether our DT model can import data into PlantSim from the Kepware server and has the ability to write back to ThingWorx IoT. The following points were taken as a base for verifying our project:

- To verify whether it is possible to control real system through virtual system with the OPC UA interface.
- To verify whether the changes in real system reflect in the virtual system in PlantSim.

3.3.2.4 Verification of Digital Twin Model in Real-Time

To validate our project we have run multiple simulations on the DT model and confirmed their effectiveness in controlling the real system and vice versa. The simulations were demonstrated to our supervisors and experts in SII-Lab for their credibility and repeatability in order to get validation from them. The following points were taken as a base for validating our project:

- To check if the DT model is representative enough for this real production system.
- To check if the real system can be controlled from the DT model.

3.3.3 What-if Scenarios Experiment Design

This phase serves as the final step within the bank's methodology framework. Within this pivotal stage, various components such as the experimental plan, documentation and reporting, and the implementation process are addressed in detail. Upon the validation of the model, an experimental plan was crafted to prove the benefit of bi-directional communication.

What-if scenarios are an essential part of simulation based projects as they are hypothetical situations devised to assess the potential impact of certain events or attributes on the system (Rizzi, 2009). These scenarios help in risk identification and to make informed decisions.

For the experimental purpose, two different what-if scenarios were considered-

- **AS-IS scenario:** Simulating the system ‘with failure’ to find the current throughput.
- **Base scenario:** Simulating the system ‘without failure’ to find the throughput and use it as a standard for comparison.

Table 3.1: Throughput Analysis Table

	Conveyor Speed (m/s)				
Cycle time (sec)	**0.108**	**0.126**	**0.144**	**0.162**	**0.18**
120					
150					
180					
210					
240					

In this thesis project, we utilized controllable and easily visualizable attributes to formulate what-if scenarios for the drone assembly factory. Due to the concurrent projects at the drone factory, our selection of attributes for the what-if scenarios was limited. Consequently, ’conveyor speed’ and ’cycle time’ were chosen for simulation by varying their values.

The attributes ’conveyor speed’ and ’cycle time’ were chosen for this analysis due to their significant influence on system throughput. The main conveyor speed data was retrieved from the Programmable Logic Controller (PLC) via the Kepware server, while cycle times were determined in consultation with the person in charge of the drone factory, as all active stations were manual. The conveyor speed was varied in increments of 10%, ranging from a minimum of 60% of max speed to a maximum of 100%, that is 0.18 m/s. The cycle times were assumed to span from 120 seconds to 240 seconds, with five distinct intervals, as it is depicted in the Table 3.1. These selected conveyor speeds and cycle times were then input into the digital model in PlanSim to simulate different scenarios. Each combination of speed and time was simulated multiple times to determine the throughput for the 25 combinations. All results were compiled into a table for further analysis.

4

Results

4.1 Ecosystem Description

This DES model serves as a virtual representation of the drone factory located at the SII lab in Lindholmen. Its primary purpose is to function as a DT. Specifically, it will address the challenge of real-time data synchronization between the actual system (the drone factory) and its virtual counterpart (the DT). Additionally, this model will be utilized for conducting experiments aimed at enhancing the overall performance of the factory and validating the advantages of DTs through a proof of concept.

4.1.1 System Overview

Figure 4.1: Drone Variants A and B

Figure 4.2: Drone Assembly Factory at SII Lab

The drone factory, depicted in Figure 4.2, comprises several key components. Raw materials originate from a source and are transported to the BufferIncoming. From there, the raw materials proceed to the AssemblyStation, where they are sorted based on variant requirements and assembled onto pallets. These pallets are dispatched from the BufferContainers. Next, the pallets move to the Station, which serves as a buffer and handles preprocessing tasks. The FAConveyor receives the pallets from Station via the LoadUnloadConveyor. Depending on the specific variant, the pallets are directed to their respective assembly stations. Currently, the factory assembles two drone variants: VariantA in Assembly1 and Assembly3, and VariantB in Assembly4 while Assembly2 is inactive. After assembly at their respective stations, the drones proceed to the QualityControl station. If a product passes quality checks, it is sent for packaging. If it fails, the drone is rerouted back to the FAConveyor. Manual assembly occurs at each station except for Assembly2, which employs a cobot and is still under development. Maintenance of the assembly stations is the responsibility of a dedicated maintenance operator.

4.1.2 Events Routines and Random Variables

In this system, the primary events that occur randomly are related to failures. When a failure event happens, the operators are promptly assigned to perform maintenance on the station. In cases where multiple failures occur simultaneously, the operators prioritize maintenance tasks. Within the Discrete Event Simulation (DES) model of the drone factory, the assembly stations are assumed to have an availability rate of 79% and a Mean Time To Repair (MTTR) of 50 minutes.

4.1.3 State Variables

The state variables that capture the salient properties of this model are availability, cycle times, conveyor speed, etc. These variables reflect the current state of the system and undergo changes whenever an event occurs. The conveyor has a maximum speed of 0.18 m/s and can be varied in percentages of multiples of 10 with a lower allowable limit of 60% of maximum speed.

4.1.4 Simulation Clock and Time Progression

The drone factory operates for 8 hours per day, and time management is facilitated through the event controller. During the simulation of the model, the Next-Event Time Progression approach is employed, and the event controller is configured to bypass lengthy event intervals. Additionally, the failure time for all stations in the model is tied to the simulation time.

4.2 Data Synchronization with Digital Twin

The following section will discuss the step by step procedures we took to achieve the bi-directional communication between the physical system of the drone assembly factory and the digital model.

- The initial step in any simulation project is to understand the system being modeled and gather relevant information related to the project objectives. In this case, the focus was on the drone assembly factory at SII Lab, Lindholmen.
- After collecting the necessary data and information, a 3D model of the drone assembly factory was constructed in PlantSim. A 2D model from a previous work was used as a reference to build the 3D model and was updated to reflect the current system (Figure 4.3).
- Data from the PLC, such as attributes of assembly stations and conveyors, was collected and stored in the Thingworx Kepware server. To access and modify this data, the OPC UA communication interface in PlantSim was used, as Thingworx Kepware functions as an OPC UA server.
- The IP address of the Kepware server was entered into PlantSim's OPC UA interface to establish a connection between the PLC and the digital model while both were on the same network at SII Lab. Tags from the PLC server were then imported into PlantSim through this interface (Figure 4.4).
- Using specific functions in PlantSim, such as 'getItems' or 'getItemsValue', we accessed the data for attributes like "conveyor speed" and "conveyor on" tags from the server and visualized them in PlantSim using the 'print' function (Figure 4.5).

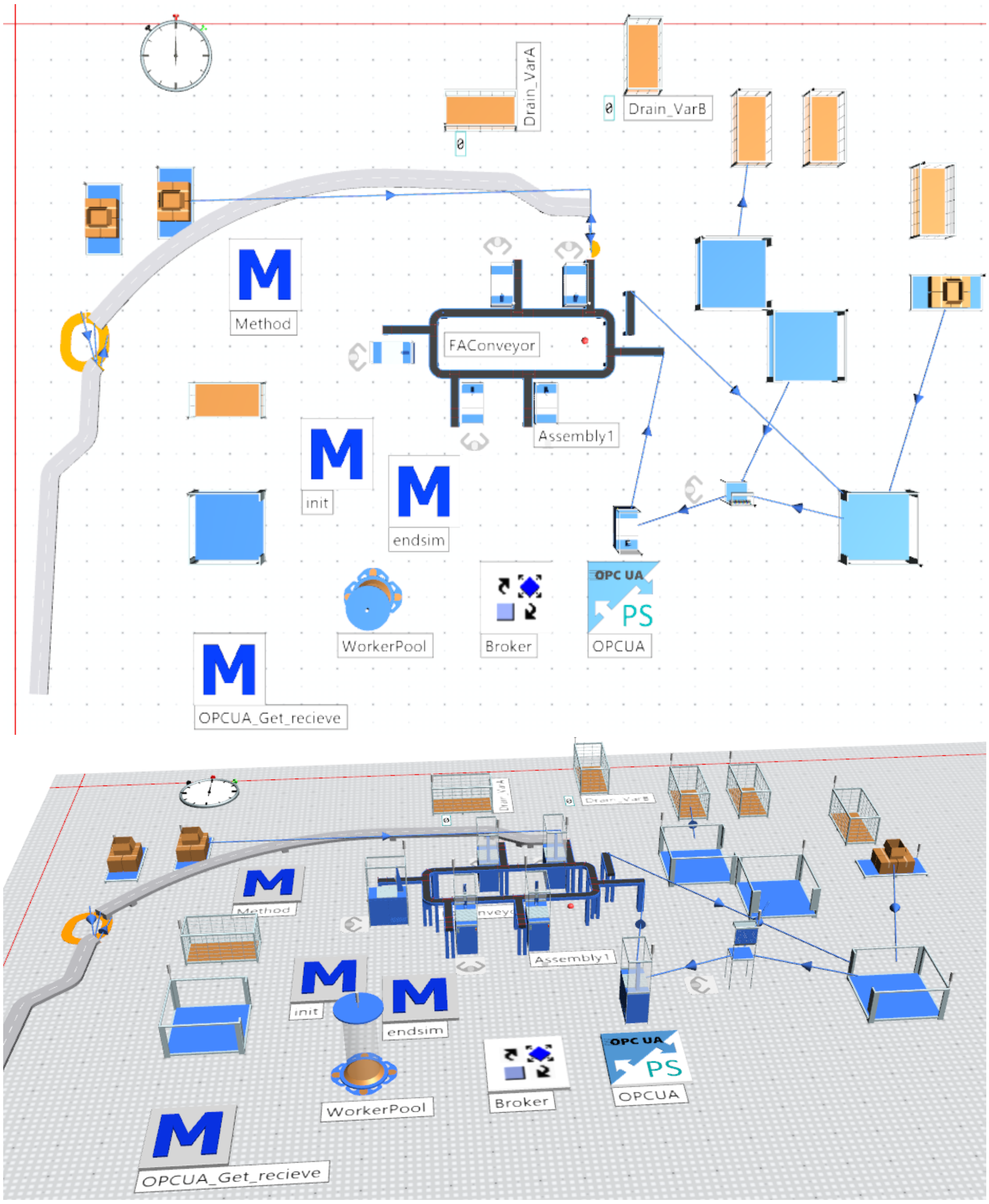

Figure 4.3: 3D Digital Model of the Drone Assembly Factory

- After accessing the data from the imported tags, we varied the desired attributes in the physical system to ensure they were updated in PlantSim in real-time. Once confirmed, a dedicated method was used to update the corresponding object's attribute in the digital model with the tag value, specifically the conveyor speed (Figure 4.6).
- Since the Kepware server operates in read-only mode, communication from the digital model to the physical system required creating user-defined tags

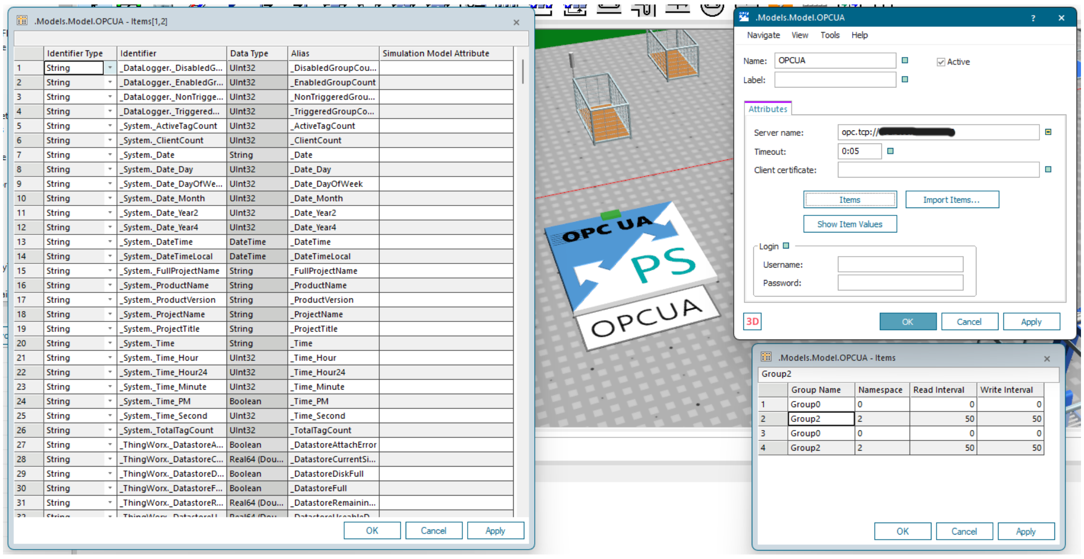

Figure 4.4: Active OPC UA connection with Imported Tags

```
print OPCUA.getItemValue("conveyor_on")
print OPCUA.getItemValue("conveyor_speed")
```

Figure 4.5: Method to Get Data from Imported Tags

for conveyor speed and ON/OFF status in the Kepware server with assistance from a PTC expert. These user-defined tags were linked to the original PLC tags via the Thingworx IoT online platform. This setup completed the bidirectional communication loop within a closed network.

- Functions like ‘SetItems’ or ‘SetItemsValue’ were used to send requests from PlantSim, to write new input data onto the user-defined tags, to Thingworx. Because the user-defined tags and PLC tags were linked through the Thingworx IoT platform, the new data was relayed to the Kepware server and updated the PLC in the physical system (Figure 4.7).

```
FAConveyor.Speed := (OPCUA.getItemValue("conveyor_speed") * 0.0018)
```

Figure 4.6: Method to Update Conveyor Speed with Imported Data

```
OPCUA.setItemValue("SpeedRequest",60)
OPCUA.setItemValue("ConveyorONRequest",false)
```

Figure 4.7: Method used to Write Back to the Server

4.3 What-if Scenarios

The what-if scenarios aimed to determine the 'throughput' of the system at various conveyor speeds and cycle times under two different conditions: the AS-IS scenario with failure (Table 4.1) and the Base scenario without failure (Table 4.2).

Each scenario involved multiple runs at different conveyor speeds and cycle times. The results were consolidated and presented in a table. The AS-IS scenario assessed the current capability of the drone factory, while the Base scenario represented an ideal condition, allowing us to compare the current situation with the potential system performance. The primary goal of this what-if scenario analysis was to prove that it is feasible to simulate and identify the optimal conveyor speed to achieve maximum throughput and then update the new attribute values back into the physical system through PlantSim, which is enabled with a bi-directional communication loop.

Table 4.1: What-if Analysis of Throughput With Failure

	Conveyor Speed (m/s)				
Cycle time (sec)	**0.108**	**0.126**	**0.144**	**0.162**	**0.18**
120	125	127	128	132	133
150	105	107	106	109	111
180	94	95	96	94	97
210	85	85	86	86	87
240	73	71	74	74	75

From the analysis of the tables and graphs, it can be inferred that there is a significant increase in throughput with a decrease in cycle time, which was an expected outcome. Although the difference in throughput may not be substantial due to the influence of other factors which we were not able to include in the what-if analysis other than failure rate as the options were limited. The study demonstrates that varying conveyor speed impacts throughput both with and without failures. The system's overall throughput includes the combined throughput of both variant A and variant B.

Table 4.2: What-if Analysis of Throughput Without Failure

	Conveyor Speed (m/s)				
Cycle time (sec)	**0.108**	**0.126**	**0.144**	**0.162**	**0.18**
120	201	204	206	209	210
150	180	183	186	188	189
180	150	153	155	155	156
210	129	131	132	132	133
240	115	115	116	116	117

At lower cycle times , changes in conveyor speed significantly affect throughput. When the cycle time was at 120 sec, from Figure 4.8 it can be noted that there was a throughput increase of 6% in the system with failure and an increase of 4% when the system was running at its ideal condition. However, as cycle time increases, throughput reaches a saturation point where further changes in conveyor speed have minimal impact. At a cycle time of 240 sec (Figure 4.9), for both the systems with and without failure the increase in throughput has dropped down to 2%.

Additionally, comparing the two scenarios shows that failure rates play a major role in determining throughput. This suggests that incorporating more influential factors would result in more accurate analyses. The results from these what-if scenarios can be used to devise a new set of parameters for the physical system, tailored to meet demand and optimize production strategy.

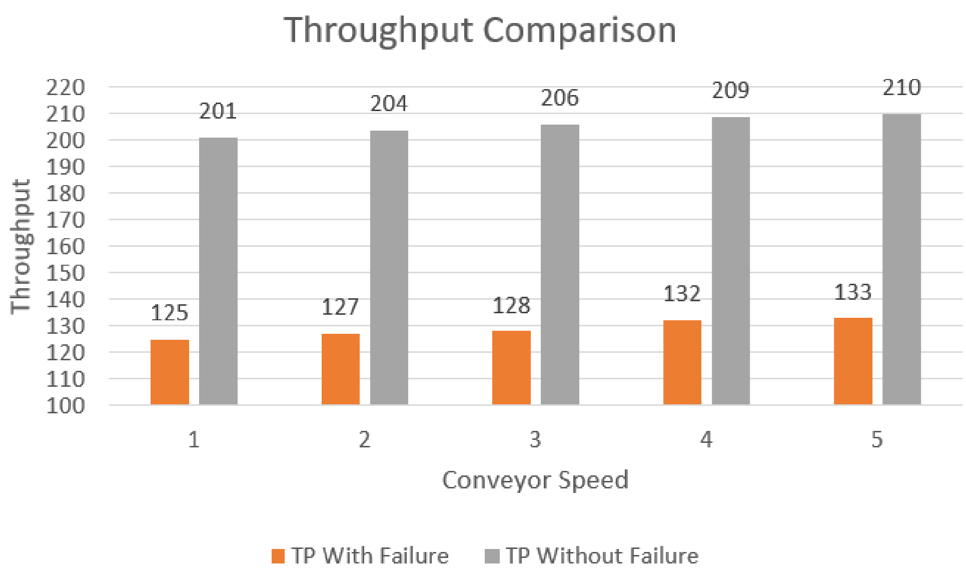

Figure 4.8: Comparison Between Throughputs at Cycle Time 120 sec

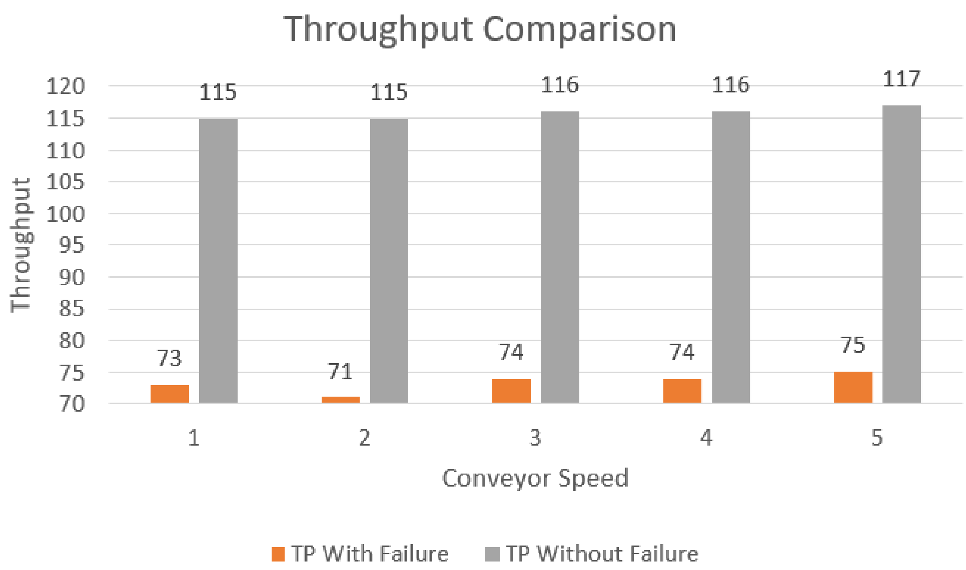

Figure 4.9: Comparison Between Throughputs at Cycle Time 240 sec

5

Discussion

5.1 Research Question 1

How can data connectivity be effectively established between a digital model and a real production system to improve data synchronization utilizing existing industrial infrastructure?

First, we developed a digital model of the actual production system at SII-Lab by referencing previous work and visiting the lab. We studied the functioning of the assembly stations, material flow, and manufacturing processes for both drone variants. Using this knowledge, we formulated a methodology to create a DT that is capable of receiving input from sensors and other data sources within the production system through a dedicated interface.

Next, after creating the digital model in PlantSim, we sought an effective communication protocol for information exchange. Considering the data types generated by the real production system, PlantSim requirements, and the existing PTC Kepware server infrastructure at SII-Lab, OPC UA communication protocol was selected.

For OPC UA in PlantSim, we required the specific IP address of the existing Kepware server at SII-Lab. Once provided, OPC UA established a connection between PlantSim and the Kepware server for data exchange, with the Kepware server acting as the OPC UA server and PlantSim as the OPC UA client. This connectivity allowed us to import data such as conveyor on/off status and conveyor speed into PlantSim. We then created methods and functions to programmatically adjust the station and conveyor attributes in PlantSim based on the data from OPC UA.

After successfully receiving data from the Kepware server, we verified data synchronization between PlantSim's DT and the real system. We toggled the conveyor in the real system using the Human-Machine Interface, generating corresponding attribute values in the server, and ensured these changes were reflected in the DT in real-time. Finally, we tested controlling the real system from the DT by modifying our methods to send data back to the OPC UA server, allowing us to turn the real system on and off from the DT model. Thus we were able to establish a stable bi-directional communication between a physical system and digital model and produce a DT with the existing infrastructure from the SII Lab.

With just a digital model, the data collected from the system have to be given as input manually to perform simulations to find optimum values of attribute and then manually update these values to the physical system to visualize it, the system might even need to be stopped to perform this. But, with the establishment of a bi-directional communication loop, it made the data synchronization simpler while providing a stable and secure connectivity with the system through the dedicated interface and IoT platform like we have demonstrated in the results section.

5.2 Research Question 2

How does bi-directional communication between a physical system and its digital twin influence the efficiency and performance of production systems?

Real-Time Monitoring and Control: Real-time monitoring and control of a physical system can be achieved by Bi-directional communication with DT. Any changes in the physical system are immediately reflected in DT, and vice versa is also possible. This enables operators and management in a company to make informed decisions and take immediate action based on the operational data that a DT provides. With this data they can manage machine's performance, effectiveness, and quality (Marah and Challenger, 2023).

Predictive Analysis and Decision-Making: DTs along with bi-directional communication enable almost all parts of a factory or a manufacturing unit to integrate and communicate with each other (Haße et al., 2022). This allows DTs to generate standardized information on machines based on the data from sensors and other software systems and helps in identifying potential issues before they occur, allowing for proactive maintenance and optimization (Hu et al., 2021).

Improved Efficiency and Performance: With bi-directional communication, DTs can be used in industrial process management and increase efficiency of the physical system (Wilhelm et al., 2021). Bi-directional data flow helps DT to monitor the manufacturing of the products, planning, execution, and prognostics of the health management (Hu et al., 2021). With these data, DTs can also improve process management by predicting and reducing risks in different sectors within the industry. It can also help in optimizing different sectors such as supply chain, etc making it more efficient and responsive to changes in demand (Haße et al., 2022).

Enhanced Collaboration and Data Sharing: Bi-directional communication aides DT in enabling enhanced collaboration and data sharing. DTs can be used as a shared data hub to establish cross company collaboration with different entities in the system such as people, machines, smart devices, etc. This collaboration can be used for improving quality of production, decision-making of the management teams, and reducing the strain on operators (Haße et al., 2022).

Competitive Edge in the Market: DTs have cloud based storage which can be used to visualize a product's lifecycle from the design stage, to manufacturing process, and till the delivery of the product to the customer and also can be used to visualize a company's assets, production systems, and manufacturing strategies (Wilhelm et al., 2021). With bi-directional communication, data related to these can be taken from the physical system and resource management systems like ERP, MRP, etc using IoT technologies. These data will be analyzed and compared with the market trends and customer demand. Based on the comparison, DT will make new decisions with the help of AI and ML, then automatically updates the physical system with the new production parameters (Hu et al., 2021).

5.3 Future works

Besides obtaining attribute values for the what-if analysis, we aimed to retrieve event logs from the ThingWorx IoT platform. These logs contain information on pallet RFID tag data, assembly station cycle times, timestamps, drone models and product numbers. Our goal was to use this data for drone traceability and to calculate the OEE of the system. We successfully imported data from ThingWorx into our computer using a REST API POST request. However, due to time constraints, we couldn't import the event logs into PlantSim.

For those continuing this project, here are the recommended steps:

1. Retrieving and Importing Event Logs into PlantSim: Utilize REST API POST or GET requests and the GitHub python-plantsim repository to import event logs into PlantSim.
2. Structuring the Event Logs: Once the event logs are imported into PlantSim, organize the data to filter out unnecessary information.
3. Traceability: With structured event logs, assign values to methods for the respective objects in PlantSim to track physical objects in the DT in real-time.
4. OEE Calculations: Use the event logs to calculate the OEE of assembly stations or the entire system. These calculations will aid in formulating maintenance strategy, identifying potential failures and optimizing the system.

6
Conclusion

This master thesis demonstrated the feasibility of connecting DT with real production systems, a lab-scale drone factory. The research findings highlight the significant benefits of bi-directional communication, which helped identify the optimal parameters for maximizing throughput and updating them in the physical system. The future applications of DT are extensive, especially in predictive maintenance. Future research should explore ways to incorporate event logs into PlantSim. This thesis makes valuable contributions to both academic and industrial fields, providing insights into the challenges and opportunities of linking DT with real systems. As this connection advances, it is poised to become a cornerstone of smart factories.

In conclusion, for a short-term strategy, depending on the company's requirements and available resources, integrating a digital shadow or digital model may be more advantageous than a DT. However, while a DT offers greater benefits compared to a digital shadow or digital model, it also entails higher complexity and cost. Therefore, based on necessity and resource availability, a company can consider implementing a DT in the long term to explore new opportunities.

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A

Appendix 1

A.1 Methods for Programming Model Building

This section provides insights on how the DES model was created on PlantSim using the in-built programming language SimTalk for modelling the production system's behaviour.

A.1.1 Code for drone processing

```
    ->time
Var Workstation, myTable : object
Var i : integer
var temp_time, temp_time1, scrapTime : time
var failure_rate : real
Var myPart, myComponentsInfo : object
Var myVariant : string

myTable :=.InputData.InputData.ProductionParameters
If @.cont.variantName = "VarA" Then
myComponentsInfo := .InputData.InputData.componentsinfoV1
myVariant := "Processing_TimeVarA"
Else
myComponentsInfo := .InputData.InputData.componentsinfoV2
myVariant := "Processing_TimeVarB"
End

If (@.cont.Scrap = true and @.cont.failedcomponent /= VOID) Then
If myComponentsInfo["Assembly_Stage", @.cont.failedcomponent.class]
 = ?.name Then
myPart := @.cont.failedcomponent.class.create(@.cont)
@.cont.failedcomponent.move(.Models.Model.Buffer_Scrap)
scrapTime := myTable["Scrap_Processing", ?]
end
end

If @.cont.variantName = "VarA" Then
```

```
temp_time := scrapTime + z_normal(5, myTable[myVariant, ?],
 myTable[myVariant, ?]*0.3, myTable[myVariant, ?]*0.3,
 myTable[myVariant, ?]*1.7)
Result := temp_time
else
Result := scrapTime + myTable[myVariant, ?]
end
```

A.1.2 Code to create parts

```
      var tempPartType, tempSum, nextCall,tempValue: real
var i, j : integer
var myPart, myTable : object

myTable := .InputData.InputData.ProductionPlan
--while true
nextCall := z_negexp(3,.InputData.InputData.interArrvialTime) --Randomize IAT
--print ""
tempPartType := z_uniform(4,0,1) --Randomize a number between 0 and 1
tempSum := 0
If .Models.Model.BufferIncoming.numMU < .Models.Model.BufferIncoming.capacity
 --Is there room for more parts?
for i := 1 to myTable.yDim
  --Go through every row in the table
tempSum := tempSum + myTable["Percentage", i]
   --Add percentage for comparison
if tempPartType < tempSum
   --Is there a match of product variant?
   myPart := .UserObjects.myPartMain.create(.Models.Model.BufferIncoming)
myPart.variantName := myTable[0,i]
    --Add variant name
---tempValue := tempValue + myTable["Scrap_rate" , i]
    ----add percentage for scrap comparison
.InputData.InputData.ProductionStages.copyRangeTo({1,myPart.variantName
 makeRGBValue(myTable["ColorR",i],myTable["ColorG",i],myTable["ColorB",i])
exitloop
end
next
End

&createParts.executeIn(nextCall) --Produce next part
--end
```

A.1.3 Code for component creation

```
       For i:= 1 To .InputData.InputData.componentsinfoV1.yDim
       --Set first production stage
tempPartType :=  .InputData.InputData.componentsinfoV1[0,i]
If @.cont.Scrap = true and scrapSet = false
tempValue := tempValue + .InputData.InputData.componentsinfoV1["Scrap",i]
If (randomValue <= tempValue) --change
partQuality := .InputData.InputData.componentsinfoV1[0,i]
End
end

If @.cont.Rework = true and scrapSet = false
tempValue := tempValue + .InputData.InputData.componentsinfoV1["Rework",i]
If (randomValue <= tempValue) --change
partQuality := .InputData.InputData.componentsinfoV1[0,i]
End
end

For j:= 1 To .InputData.InputData.componentsinfoV1["Quantity",i]
myPart := tempPartType.create(@.cont)
myPart.partWeight := .InputData.InputData.componentsinfoV1["Material weight",i]
@.cont.partWeight := @.cont.partWeight + myPart.partWeight
myPart.PartCost := .InputData.InputData.componentsinfoV1["Material cost",i]
@.cont.PartCost := @.cont.PartCost + myPart.PartCost
If @.cont.Scrap = true and scrapSet = false and partQuality = myPart.class
myPart.Scrap := true
@.cont.failedcomponent := myPart
scrapSet := true
End

If @.cont.Rework = true and scrapSet = false and partQuality = myPart.class
myPart.Rework := true
@.cont.failedcomponent := myPart
scrapSet := true
End

next

next

else
randomValue := z_uniform(33,0,1)
If (randomValue <= 0.01) --Scrap
@.cont.Scrap := true
Else
randomValue := z_uniform(33,0,1)
```

```
If (randomValue <= 0.05 and randomValue > 0.01) --Rework
@.cont.Rework := true
End
End
If @.cont.Scrap = true or @.cont.Rework = true
randomValue := z_uniform(33,0,1)
End

For i := 1 To .InputData.InputData.componentsinfoV2.yDim
tempPartType :=  .InputData.InputData.componentsinfoV2[0,i]
If @.cont.Scrap = true and scrapSet = false
tempValue := tempValue + .InputData.InputData.componentsinfoV2["Scrap",i]
If (randomValue <= tempValue) --change
partQuality := .InputData.InputData.componentsinfoV2[0,i]
End
End
If @.cont.Rework = true and scrapSet = false
tempValue := tempValue + .InputData.InputData.componentsinfoV2["Rework",i]
If (randomValue <= tempValue) --change
partQuality := .InputData.InputData.componentsinfoV2[0,i]
End
end
For j:= 1 To .InputData.InputData.componentsinfoV2["Quantity",i]
myPart := tempPartType.create(@.cont)
myPart.partWeight := .InputData.InputData.componentsinfoV2["Material weight",i]
@.cont.partWeight := @.cont.partWeight + myPart.partWeight
myPart.PartCost := .InputData.InputData.componentsinfoV2["Material cost",i]
@.cont.PartCost := @.cont.PartCost + myPart.PartCost
If @.cont.Scrap = true and scrapSet = false and partQuality = myPart.class
myPart.Scrap := true
@.cont.failedcomponent := myPart
scrapSet := true
End

If @.cont.Rework = true and scrapSet = false and partQuality = myPart.class
myPart.Rework := true
@.cont.failedcomponent := myPart
scrapSet := true

End

next
next

end
```

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