



JÖNKÖPING UNIVERSITY
School of Engineering

Scenario-Based Simulation and Optimization of an Automated Machine Cell

MAIN AREA: Production Systems

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This thesis is conducted at the School of Engineering at Jönköping University within Production Systems. The authors are responsible for the opinions, conclusions and results herein.

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Abstract

Purpose: This thesis investigates the use of scenario-based simulation to improve the performance of an automated manufacturing cell. By virtually testing a range of layout configurations and operational scenarios, the study identifies performance trade-offs and supports data-driven decision-making for system optimization. The investigation specifically focuses on the contributions of automation to production performance, the benefits of simulation in manufacturing, and the role of scenario-based simulation in optimizing layout design.

Method: A single-case study methodology was applied, integrating both qualitative and quantitative data. Operational insights were gathered through semi-structured interviews, time studies, and direct observations. These inputs supported the development of two simulation models: a discrete-event model and a visual 3D model. Both models were validated against observed system behavior and used to test layout and process configurations across defined scenarios, measuring performance indicators such as throughput, cycle time, and resource utilization.

Findings: Automation enhanced efficiency and consistency, but challenges like complexity and skill gaps were identified. Simulation revealed material flow as the main constraint, with layout changes improving performance more than speed increases. Scenario modeling supported effective decision-making and highlighted non-obvious improvements.

Implications: The findings demonstrate that simulation is a valuable decision-support tool for evaluating automation systems. Scenario-based testing enables efficient experimentation without disrupting real operations, offering cost-effective insights for production planning and layout design. For organizations to fully benefit, investments in simulation capabilities and skill development are essential. The study contributes both practical insights for industry and methodological guidance for future research in production optimization.

Limitations: The study focused on one machine cell and tested a limited number of scenarios. It excluded broader system factors and was not validated with live data. These constraints limit generalizability and suggest the need for further research.

Keywords:

Automation, Automated manufacturing cell, Simulation, Scenario-based simulation, Discrete Event modeling, Optimization, Layout optimization, Scenario-based optimization, Manufacturing systems.

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Table of Contents

1	Introduction	11
1.1	BACKGROUND.....	11
1.2	PROBLEM STATEMENT	12
1.3	PURPOSE AND RESEARCH QUESTIONS.....	13
1.3.1	Purpose.....	13
1.3.2	Research Questions	14
1.4	SCOPE AND DELIMITATIONS.....	15
1.5	OUTLINE	16
2	Theoretical Framework	17
2.1	AUTOMATION IN MANUFACTURING	17
2.1.1	Automation Technologies and Applications.....	18
2.1.2	The Automation Pyramid.....	19
2.2	SIMULATION MODELING	20
2.2.1	Definition of Simulation Modeling	20
2.2.2	Benefits and Challenges of Simulation Modeling	21
2.2.3	Simulation Modeling Procedure.....	22
2.2.4	Simulation Modeling Methods.....	25
2.3	OPTIMIZATION IN PRODUCTION AND AUTOMATION	27
2.3.1	Definition of Optimization in Production and Automation	27
2.3.2	Benefits and Challenges of Optimization in Production and Automation	28
2.3.3	Application of Optimization in Production and Automation	29
2.3.4	Scenario-Based Optimization	30
2.4	OVERALL EQUIPMENT EFFECTIVENES (OEE)	32
3	Methodology.....	35
3.1	RESEARCH DESIGN	35
3.2	RESEARCH PROCESS	37
3.3	LITERATURE REVIEW	38
3.4	CASE STUDY	39
3.5	DATA COLLECTION	41
3.5.1	Interviews.....	41

3.5.2	Observation	43
3.5.3	Document Analysis	45
3.6	SCENARIOS FOR SIMULATION TESTING	47
3.7	DATA ANALYSIS AND QUALITY	48
3.8	VALIDITY AND RELIABILITY	49
3.9	ETHICAL CONSIDERATIONS.....	50
4	Empirical Data	51
4.1	INTERVIEWS	51
4.1.1	Participant A : Automation Manager	52
4.1.2	Participant B: Automation engineer	53
4.1.3	Participant C: Automation engineer	55
4.1.4	Participant D: Sales and Marketing manager	56
4.2	DATA COLLECTION FROM DOCUMENTS	57
4.2.1	CAD Files	57
4.2.2	Process Flow Diagrams	58
4.2.3	Video Recordings	58
5	Results	60
5.1	SIMULATION IMPLEMENTATION	60
5.1.1	System Flow and Module Overview	60
5.1.2	Time Study	65
5.1.3	Failure and Quality Evaluation	68
5.1.4	CAD and Layout Integration	70
5.1.5	Visual Simulation Modeling	70
5.1.6	Discrete Event Simulation Modeling	75
5.2	SIMULATION OUTPUT.....	78
5.2.1	Current state of the simulation	78
5.2.2	Scenario A Infeed and Outfeed Pusher Configurations	82
5.2.3	Scenario B – Robot Speed and Reachability Configurations	84
6	Analysis	86
6.1	QUALITATIVE DATA ANALYSIS	87
6.1.1	Importance of Automation	87
6.1.2	Practical Challenges in Implementing Automation	88
6.1.3	Simulation Utilization within Engineering Workflows	89
6.1.4	The Role of Optimization in System Design	89

6.1.5	Scenario-Based Exploration and Decision Support.....	90
6.2	QUANTITATIVE DATA ANALYSIS	91
6.2.1	Scenario A – Infeed and Outfeed Pusher Configuration	91
6.2.2	Scenario B – Robot Speed Configurations.....	94
6.2.3	Summary of Scenarios	96
7	Discussion	97
7.1	FOCUS ON RESEARCH QUESTIONS.....	97
7.1.1	RQ1 – What are the key contributions of automation systems on the performance of production lines?	97
7.1.2	RQ2 – What are the benefits of using simulation for enhancing the performance of automated production lines?	98
7.1.3	RQ3 – How do scenario-based simulation models support decision- making in the evaluation of production layout alternatives?	99
7.2	ACADEMIC CONTRIBUTION	101
7.3	PRACTICAL CONTRIBUTION	102
8	Conclusion	103
8.1	LIMITATION AND FUTURE STUDIES	104
8.1.1	Future studies	104
	References	106
	Appendices	1
8.2	APPENDIX A – INTERVIEW QUESTIONS (INTERVIEWS FOR ENGINEERS)	1
8.3	APPENDIX B – INTERVIEW QUESTIONS (INTERVIEWS FOR MARKETING RESPONSIBLES).....	1
8.4	APPENDIX C – ETHICAL CONSENT DOCUMENT FOR PARTICIPATION IN THE INTERVIEW.....	1

Index of Figures

Figure 1: <i>Outline of the project</i>	16
Figure 2: <i>Automation Pyramid (Körner et al., 2019)</i>	19
Figure 3: <i>Simulation Modeling Procedure (Yin & McKay, 2018)</i>	23
Figure 4: <i>Simulation Modeling Methods (Tram, 2022)</i>	25
Figure 5: <i>Systematic Optimization Model (Groten & Gallego-García, 2021)</i>	30
Figure 6: <i>Overall Equipment Effectiveness(OEE) Framework (Maideen et al., 2016)</i>	33
Figure 7: <i>System Workflow</i>	61
Figure 8: <i>CAD of Dual Gripper Tool</i>	63
Figure 9: <i>CAD is the Model Interface</i>	71
Figure 10: <i>Robot and Tool Illustration in Emulate3D</i>	72
Figure 11: <i>Tool Center Points</i>	73
Figure 12: <i>Teachpoints Configuration</i>	74
Figure 13: <i>Discrete Event Simulation Model in Arena Software</i>	75
Figure 14: <i>Press and Synchronizer Module in DES</i>	76
Figure 15: <i>Infeed Pusher Modules in DES</i>	76
Figure 16: <i>Robot Arm Module in DES</i>	77
Figure 17: <i>Outfeed Pusher Modules in DES</i>	78
Figure 18: <i>Linking Data Types to Research Questions</i>	86
Figure 19: <i>OEE Values Across 26 Different Pusher Configurations</i>	93

Index of Tables

Table 1: <i>List of the participants and interviews</i>	43
Table 2: <i>Observation Methods</i>	45
Table 3: <i>Types of Documents</i>	47
Table 4: <i>Review of Document Analysis</i>	59
Table 5: <i>Input Data for the Simulation Model</i>	65
Table 6: <i>Time-Study Output</i>	66
Table 7: <i>Data Summary for the Robotic Arm</i>	67
Table 8: <i>Failure Input for the Discrete Event Simulation</i>	69
Table 9: <i>Infeed and Outfeed Configuration Results</i>	84
Table 10: <i>Different Robot Speed Configuration Results</i>	85
Table 11: <i>Best, Current and Lowest-Performing Configurations</i>	93
Table 12: <i>Comparison of Robot Speed Configurations</i>	95
Table 13: <i>Avg. Waiting Time Comparison in Robot Speed Configurations</i>	95

List of Abbreviations

<i>CAD</i>	Computer-Aided Design
<i>DES</i>	Discrete Event Simulation
<i>OEE</i>	Overall Equipment Effectiveness
<i>PLC</i>	Programmable Logic Controller
<i>IoT</i>	Internet of Things
<i>ABS</i>	Agent Based Simulation
<i>SD</i>	System Dynamics

1 Introduction

This chapter aims to provide a comprehensive overview of the thesis project by presenting essential background information on automation systems, simulation approaches, and scenario-based optimization. It also introduces the problem statement, purpose, and research questions that will be addressed in this section.

1.1 Background

The complexity of the current manufacturing processes is primarily influenced by global competition and the increasing demand for more advanced and complex products (Kampa, 2023). To remain competitive, it is essential for companies to consistently adapt and enhance their production strategies (Balderas et al., 2021). Responding to these market needs, companies are required to completely redesign their production systems using digital technologies, such as simulation tools that enable virtual modeling and system evaluation (Li et al., 2021). This process of digital transformation not only improves industrial competitiveness but also supports data-based and optimal decision-making (Florescu & Barabas, 2020). According to Kaltum et al. (2016), digital transformation plays a significant role in enhancing operations, processes, skills, and business models to strategically benefit from digital technologies and their social impact.

Also, simulation has become an important digital tool that supports this transformation. It acts as a digital replica of an actual product, asset, process, or system and helps companies analyze, forecast, and improve performance (Melesse et al., 2021). It plays a significant role in both production and product development. For instance, simulations support sustainability by making it possible to predict potential impacts during sustainable manufacturing planning (Mani et al., 2013) and by allowing companies to test different configurations and understand their effects on system efficiency, material flow, and resource usage (Poloczek, 2025). Simulation is a key technique widely used for optimization in various areas, including scenario-based approaches to improve performance and decision-making (Salam & Khan, 2016). It is particularly useful in robotics, where it aids in the design and testing of systems (Žlajpah, 2008). One major benefit of simulation, especially in automation, is creating a digital test environment, which often costs much less than physical testing (Chang & Padir, 2020). In recent years, simulation has increasingly been used for scenario-based optimization, allowing companies to test and compare different operational setups before implementation (Negahban & Smith, 2014).

Newer simulations that are being used today involve the use of data-based models and visual computing methods. These approaches collect real-time data from actual manufacturing systems and use it in simulations to carry out detailed cost and time analyses (Ojstersek et al., 2020). In addition, simulations driven by real data help improve the flexibility of high-mix, low-volume production systems by enhancing scheduling and decision-making processes (Ojstersek et al., 2020).

Simulations used in optimizing production processes have become very demanded due to increasing demands for efficiency and competitiveness. Simulation tools are often applied across the design process, which includes steps such as identifying the problem, building the model, running simulations, optimizing solutions, and applying the results. The goal is to achieve high efficiency while reducing resource use, time, and material consumption (Monica, 2015). The combination of simulation and optimization has proven successful in evaluating and refining production strategies, logistics planning, and resource distribution. This approach has shown positive outcomes in increasing productivity and lowering operational challenges, particularly in automotive industry case studies (Monazzam et al., 2022).

1.2 Problem Statement

Automation systems are found everywhere in manufacturing, logistics, communication, and many other areas. The level of automation in these systems continues to increase, enabling more advanced tasks to be performed automatically. However, with this increased automation comes added complexity. At the same time, there are growing demands for higher safety, quality, speed, and cost efficiency in their operation (Hagebring et al., 2022).

Modern production lines consist of multiple machines working together to produce what is needed. As technology advances, these lines have been equipped with controllers and sensors to monitor plant efficiency and ensure safety. However, the increasing number of devices and variables involved has made managing and optimizing production systems increasingly complex (Longo & Fanuzzi, 2018).

Aguilar et al. (2020) highlight that manufacturers today face significant production challenges, such as bottlenecks, inefficient workstations, and inefficient layout designs. At the same time, organizations are always looking for faster production, lower operational costs, and improved system performance (Jaroslava et al., 2023). Machine process simulations allow manufacturers to test and improve product designs while reducing risks and shortening production cycles. Despite these benefits, challenges remain in effectively using simulation tools to enhance

assembly line balancing, production scheduling, and resource management in automated systems (Jian Fei et al., 2018).

To understand and overcome such challenges, this research uses different scenario-based simulations to test, evaluate and improve the performance of automated production lines. Key system metrics such as throughput, downtime, and cycle time are analyzed across different operational configurations to identify improvement opportunities.

1.3 Purpose and Research Questions

This section presents the purpose of the study and outlines the research questions that form the basis of the investigation carried out in this thesis.

1.3.1 Purpose

Modern manufacturing environments are becoming increasingly complex due to the widespread integration of automation, high product variety, and fluctuating customer demands. These dynamics often lead to critical system-level challenges such as resource inefficiencies, throughput instability, and shifting production bottlenecks (Su et al., 2022). According to Aguilar et al. (2020), companies also face persistent issues related to process-related waste and underutilized capacity, which can significantly impact overall system performance. In highly automated production lines, even small inefficiencies in layout configuration, task assignment, or flow design can accumulate over time, leading to measurable performance degradation. Traditional fixed planning methods often do not work well for managing fast-changing and connected production systems.

To manage this complexity, simulations have emerged as a practical and increasingly accepted decision-support method for evaluating and improving production workflows under variable conditions (Dombrowski & Ernst, 2013).

This study aims to investigate how scenario-based optimization can be applied through simulation to analyze the performance, such as resource utilization and throughput of an automated production cell, and to identify improvement opportunities under different layout and configuration scenarios.

By testing multiple operational scenarios, such as alternative conveyor layouts, robot task distributions, and flow strategies, the research seeks to uncover performance trade-offs related to throughput, cycle time, and resource utilization. This contributes to the growing body of research emphasizing the role of simulation as a proactive, low-risk approach to system

optimization in high-volume production settings (Okuyelu et al., 2024). Rather than relying on costly real-world experimentation, the virtual testing environment supports data-driven, early-stage design validation and continuous performance improvement.

1.3.2 Research Questions

To effectively define clear and focused research, the following questions are designed to guide the direction of the study, structure the analysis, and ensure alignment with the overall research objectives. This section presents the key research questions that form the foundation of this thesis.

RQ1. What are the key contributions of automation systems on the performance of production lines?

This question aims to explore the current benefits and challenges associated with implementing automation systems in production lines, with a focus on their impact on overall performance such as throughput, resource utilization, idle time and down time.

RQ2. What are the benefits of using simulation for enhancing the performance of automated production lines?

This question seeks to examine how simulation tools contribute to the improvement or designing of an automated production lines and what specific advantages they offer in terms of efficiency, productivity, and planning.

RQ3. How do scenario-based simulation models support decision-making in the evaluation of production layout alternatives?

This question investigates the role of scenario-based optimization techniques in combination with simulation, aiming to understand how they assist in evaluating and selecting among different production layout options.

1.4 Scope and Delimitations

The scope of this thesis is limited to simulation-based analysis and scenario testing of a single automated machine cell within the production system of a case company. The investigation focuses on identifying operational inefficiencies and evaluating different internal system configurations within a controlled virtual environment. Performance indicators such as throughput, cycle time, and machine utilization are used to assess the impact of each scenario. The study does not cover the entire production line. Instead, it aims to provide system-level insights based on selected operational scenarios within the boundaries of the defined machine cell. Broader organizational aspects such as financial analysis, customer behavior, and strategic planning are beyond the scope of this research.

Delimitations

The following delimitations define the boundaries of this study:

1. The research is limited to the analysis of a single automated machine cell and does not include other production units or systems within the factory.
2. Broader business-related aspects such as cost estimation, market performance, and strategic planning are excluded from the scope of the study.
3. The simulation model was developed with a focus on internal production logic and operational flows. It does not aim to reflect the full complexity or variability of real-world production conditions, due to the narrow focus on a single machine cell.
4. The project was conducted over a fixed academic period of 20 weeks as part of a master's program. Therefore, the results were not implemented in an actual production environment.
5. Due to limited access to real-world production data, the model and results should be considered as a decision support tool rather than a fully deployable implementation solution.

1.5 Outline

This section presents the structure of the thesis and outlines the content of each chapter. As shown in Figure 1, the thesis consists of eight main chapters, beginning with the introduction and concluding with the discussion and conclusions. Each chapter builds upon the previous one to form a coherent investigation of the research problem.

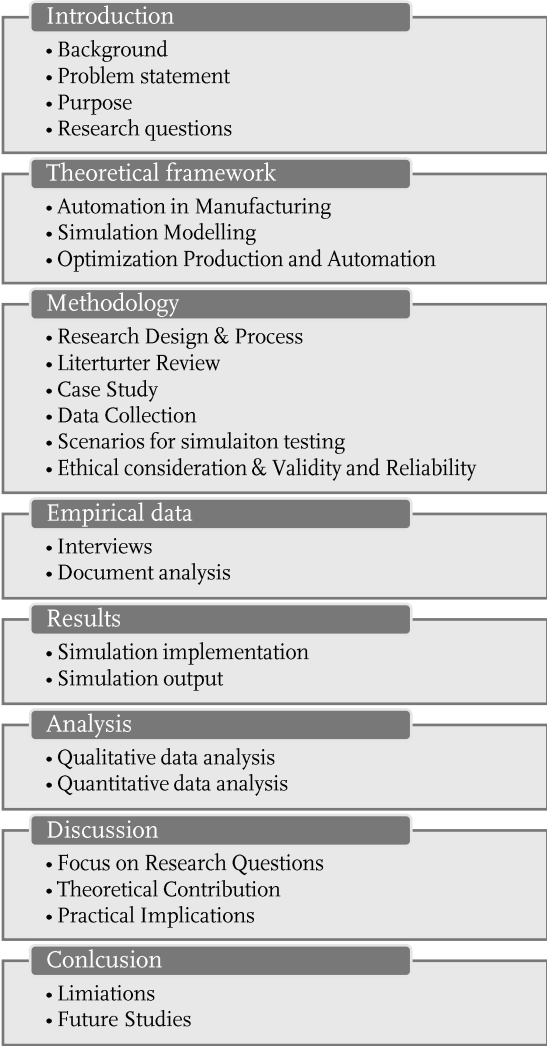


Figure 1: *Outline of the project*

2 Theoretical Framework

The second chapter provides a foundational overview of the topics explored in the thesis. These topics include automation, simulation, and optimization related to the research. It analyzes the background information that serves as the basis for the research.

2.1 Automation in Manufacturing

Manufacturing has transformed significantly over the past century, evolving from manual labor and mechanical assembly lines to highly digitized and automated production systems. It has become more demanding, and the processes are large-scale and standardized, where also digital technologies such as Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT), integrated within Industry 4.0, have added significant value and competitiveness to the market (Chukwunweike et al., 2024). As mentioned, during the Fourth Industrial Revolution, mechanical devices began to replace manual labor in production processes, leading to the increased demand for automation.

Today, automation refers to all processes that involve machines, software, and technologies originally carried out by human labor. In the 20th century, automation reached a new level, incorporating complex tasks in production, management, and services through computing and electronic technologies (Hryn et al., 2024). These tools have enhanced the development of the manufacturing sector and enhanced competitiveness by allowing various systems of production, development, and decision-making to collaborate and monitor processes using continuous and real-time data (Chukwunweike et al., 2024).

According to Alharbi (2024), relying only on manual and mechanical tasks without automation can result in lower output and decreased quality. Automating processes helps increase efficiency and enables the production of goods at a faster rate with standardized and controlled quality. Chukwunweike et al. (2024) highlight the wide range of benefits automation brings to manufacturing. It reduces manual labor, minimizes human error, enhances process consistency, and improves workplace safety. automation also handles repetitive and high-risk tasks, resulting in more efficient production and better product quality.

Automation is particularly important for small and medium-sized enterprises (SMEs). SMEs account for over 80% of manufacturing companies in Europe and employ 59% of the sector's workforce (Soldatos et al., 2018). However, limited resources and technical capacity often make

it more challenging for SMEs to adopt and implement automation technologies effectively (Soldatos et al., 2018; Li et al., 2025). According to Li et al. (2025), this shift is largely driven by growing customer expectations for more customized products, shorter delivery times, and improved quality. As a result, companies must adopt manufacturing systems that are flexible, fast, and efficient. Automated systems allow businesses to respond to market changes, adjust production volumes, and switch product lines quickly, which are capabilities that are essential in today's dynamic business environment (Chukwunweike et al., 2024).

Despite its advantages, automation also presents challenges. One such issue is redundancy, which is the duplication of processes or systems to ensure reliability. While some level of redundancy is necessary, excessive duplication can lead to inefficiencies and higher costs. Additionally, product defects caused by machine malfunction or poor material quality can increase waste and damage a company's reputation. Traditional quality control methods are often slow and may not detect issues in real time. Material strength testing and vibration analysis are also essential areas where older methods fall short in delivering timely feedback. These challenges call for more advanced, data-driven approaches to monitoring and control (Chukwunweike et al., 2024).

2.1.1 Automation Technologies and Applications

Modern manufacturing relies on a variety of automation technologies to achieve production goals. Robotics are commonly used for tasks such as assembly, welding, and material handling, especially in situations that require high precision or involve safety risks. (Chukwunweike et al., 2024). Supervisory Control and Data Acquisition (SCADA) systems provide centralized control and real-time monitoring of production lines. Artificial Intelligence (AI) and Machine Learning (ML) are being integrated into these systems to enhance process optimization, detect performance, and support predictive maintenance. These technologies enable continuous data analysis, allowing manufacturers to prevent breakdowns, minimize downtime, and improve overall system performance (Li, 2025). Programmable Logic Controllers (PLC) play a vital role in controlling machinery and processes in real time, while Computer Numerical Control (CNC) machines are used to produce complex components with high accuracy. Automated Guided Vehicles (AGVs) transport materials between different areas of a facility, reducing the need for manual handling (Chukwunweike et al., 2024).

2.1.2 The Automation Pyramid

To manage the increasing complexity of production systems, manufacturers often organize their automation using the automation pyramid, which is a hierarchical model that structures control and decision-making processes across five levels. This structure is based on the IEC 62264 standard and remains widely used in modern manufacturing (Körner et al., 2019).

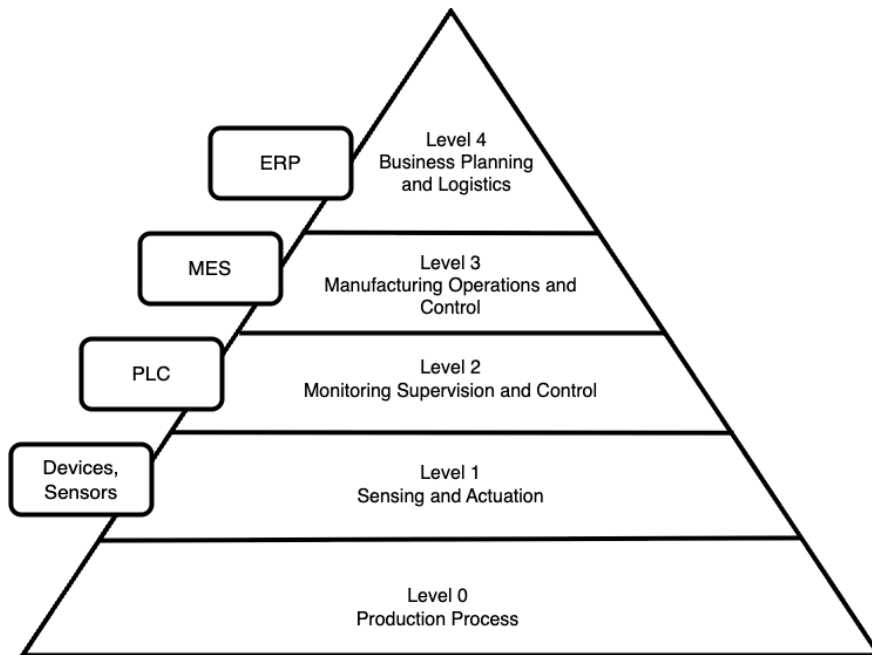


Figure 2: Automation Pyramid (Körner et al., 2019)

According to the model shown in the Figure 2:

Level 0 covers the physical production processes, such as machining or assembly.

Level 1 includes devices like sensors and actuators that control these processes in real-time, typically operating within milliseconds or seconds.

Level 2 involves control and supervision, commonly using PLCs to manage lower-level equipment and perform necessary adjustments.

Level 3 referred to as Manufacturing Operations and Control (MO&C), includes tasks such as production scheduling, order management, and workflow optimization, usually managed by Manufacturing Execution Systems (MES).

Level 4 known as Business Planning and Logistics (BPL), focuses on long-term planning and resource management, typically handled through Enterprise Resource Planning (ERP) systems.

Although modern approaches like cyber-physical systems (CPS) offer more decentralized alternatives, the automation pyramid continues to be a reliable framework for structuring industrial control systems (Körner et al., 2019).

2.2 Simulation Modeling

The continuous change in market conditions and customer requirements, as well as more complex environmental factors, force the production industry to establish quick, efficient, and effective adaptation processes (Delbrügger et al., 2019). Modern production lines consist of advanced machines supported by sensors and controllers to ensure efficiency and safety. However, the growing number of components and variables has made managing these systems increasingly complex and expensive, especially for small and medium-sized enterprises (SMEs). In that case, simulation is the key technology that enhances the product and production engineering processes (Longo & Fantuzzi, 2017).

2.2.1 Definition of Simulation Modeling

Simulation modeling is a tool that serves as a computational foundation for both real and virtual experimentation. It involves the creation of abstract models that represent complex systems, allowing researchers and practitioners to analyze and understand the dynamics of these systems under various conditions. The process of simulation modeling encompasses the formulation of models that can replicate the behavior of real-world systems, enabling the exploration of "what if" scenarios to assess potential outcomes and impacts of different variables (Sokolowski & Banks, 2009). It is a key technology for analyzing manufacturing processes, behaviors, and scenarios, enabling organizations to optimize operations and improve decision-making (Jeon & Kim, 2016). Additionally, Simulation modeling has been applied across various domains (Mielczarek & Uziółko-Mydlikowska, 2012). The areas in which simulation modeling can be applied include manufacturing, transportation, business, healthcare, social science, automation, and enterprise decision support (Sokolowski & Banks, 2009). Even though it is commonly used in various areas, engineering, production, and manufacturing are by far the most common application areas of simulation modeling (Shannon, 1992).

2.2.2 Benefits and Challenges of Simulation Modeling

Simulation modeling provides various advantages across a wide range of application domains, such as product and production development (Sokolowski & Banks, 2009). One of the most significant advantages is its ability to enable manufacturing companies to enhance or optimize production processes through precise modeling and analysis of various scenarios. This capability allows organizations to assess the impact of different production line configurations on overall system efficiency, leading to improvements such as optimized machine capacity, reduced production cycle times, increased flexibility, and enhanced operational efficiency (Poloczek & Oleksiak, 2024). Often, the economic benefits and the speed of simulating the original process far outweigh the potential drawbacks. Additionally, in some cases, real systems do not permit experimentation with multiple alternative solutions before committing to one. In such situations, it may be beneficial to develop and study a simulation model of the process (Dileepan & Etkin, 2010).

Moreover, the integration of simulation with optimization techniques, such as mathematical optimization algorithms, provides a robust framework for addressing complex industrial problems. Hybrid simulation optimization approaches enable the modeling of scheduling, capacity planning, and resource allocation issues, effectively capturing the capability nature of real systems. This flexibility allows for more accurate representations of production environments, facilitating better decision-making in manufacturing contexts (Mujica Mota et al., 2015; Parthanadee & Buddhakulsomsiri, 2012). Another major advantage is that the graphical illustration capability of simulations supports swift comprehension, efficient information exchange, and clear communication among all relevant stakeholders (Seo-young et al., 2022).

On the other hand, simulation modeling in production faces several challenges that can impact its effectiveness and efficiency (Köberlein et al., 2022). One significant challenge is the complexity, such as system complexity or data reliability, particularly in the context of production and industrial automation. As systems become increasingly complex, the models used to represent them must also evolve to capture their behavior accurately. This complexity affects various attributes of the models, including understandability, ease of use, scalability, performance, testing, and verification. Especially when integrating complex production or process flows within manufacturing systems (Ghasemi et al., 2023). That is why designing, testing, and optimizing a high-quality model needs to be conducted with considerable expertise and resources (Anurag & Iyer, 2019).

In addition, choosing the right tool plays a vital role in simulation modeling. A proposed approach involves a framework that facilitates the selection of models based on their complexity metrics and the defined system requirements, thereby addressing the need for effective complexity assessment in simulation modeling (Ghasemi et al., 2023).

Another challenge is related to model validity and accuracy, which are critical for ensuring that the models accurately represent the systems they aim to simulate. Verification and validation are essential to ensure that a simulation model accurately reflects the real system and fulfills its intended purpose; if not properly conducted, the model can produce misleading results, undermine decision-making, reduce credibility, and increase development costs (Sargent, 2014). Finally, the data availability and quality, such as limited resources about previous data or measurement uncertainty and sensor inaccuracies, can be another challenge, which can lead to not so effective outcomes across various fields in simulation modeling (Yuan et al., 2024). The models require input data that is often incomplete, poor in quality, and not easily accessible, which limits their effectiveness in projecting future modeling performance (Kephe, Ayisi, & Brilliant, 2021).

2.2.3 Simulation Modeling Procedure

As manufacturing systems grow more complex, more detailed models require longer development time. A structured approach to simulation modeling is a critical aspect of the overall success of simulation modeling (Bodner & McGinnis, 2002).

Modeling and simulation procedures provide a structured framework for guiding key activities such as defining the problem, developing a conceptual model, building the simulation model, and performing model verification and validation. Figure 3 below presents a flowchart outlining the step-by-step process of conducting simulation modeling. Each stage requires a careful and detail-oriented approach to ensure accurate results and an effective visual representation. (Yin & McKay, 2018).

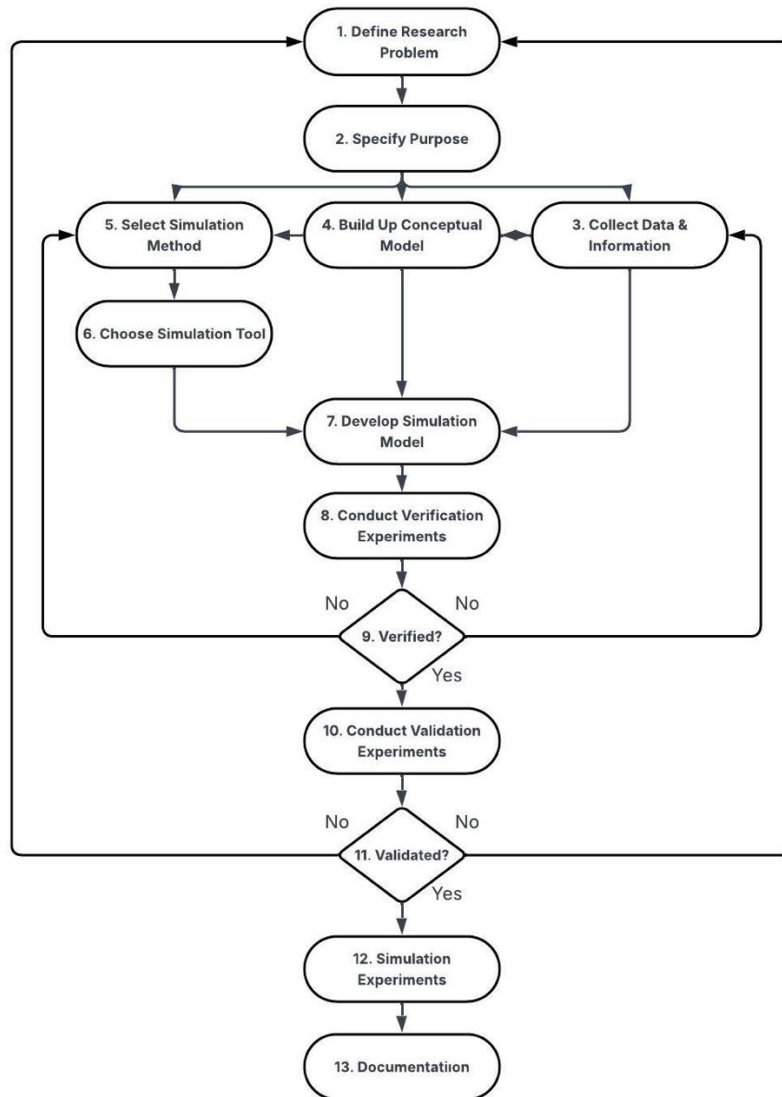


Figure 3: *Simulation Modeling Procedure (Yin & McKay, 2018)*

Yin and McKay (2018) provided and designed a thirteen-step procedure for simulation modeling. The steps are as follows:

1. Define research problem: The research interests of the researchers are discussed in detail, the main problem is clearly defined, and there is a shared understanding of what the research is expected to achieve.
2. Specify purpose: The purpose of the simulation experiments is clearly stated through a defined aim and set of objectives.
3. Collect data & information: The data required for both conceptual and simulation models is identified and collected. This process is often iterative, involving collaboration with case study owners, especially when existing data is incomplete or unavailable.

4. Build up conceptual model: A conceptual model is developed based on the research purpose and collected data to represent key relationships related to the problem.
5. Select simulation method: A suitable and feasible modeling and simulation method is chosen to represent the defined research problem.
6. Choose simulation tool: The software tool for implementing the simulation model is selected considering its availability and adaptability.
7. Develop simulation model: A computer-based simulation model is created from the conceptual model using the chosen simulation method and software tool.
8. Conduct verification experiments: Verification experiments are carried out to ensure the simulation model produces reliable and expected results for familiar scenarios, based on given inputs.
9. Verify the simulation model: Verification results are reviewed, and the model is evaluated using set criteria. Based on feedback, earlier steps may be revised to improve the model for the next phase.
10. Conduct validation experiments: Validation experiments are conducted using the updated model to ensure it accurately represents and addresses the research problem.
11. Validate the simulation model: The results of the validation experiments are evaluated using specified methods and indicators, and previous steps may be revisited if required.
12. Simulation experiments: Simulation experiments are carried out to replicate real-world scenarios. The results are analyzed, and potential management solutions are explored to address the research problem.
13. Documentation: A clear user manual is prepared to support model use, input setup, and result analysis, ensuring usability, transparency, and future adaptability.

2.2.4 Simulation Modeling Methods

Even though many modeling and simulation methods exist, some of these methods tend to be used in a specific domain (Diallo et al., 2015). With respect to simulation methods applied to modeling systems and processes, despite the wide range of simulation applications, System Dynamics (SD), Discrete Event Simulation (DES), and Agent-Based Simulation (ABS) can be considered important and suitable for widespread applications in industrial engineering and related areas (Jahangirian et al., 2010). The following Figure 4 illustrates and compares the three methods with their abstraction level (Tram, 2022):

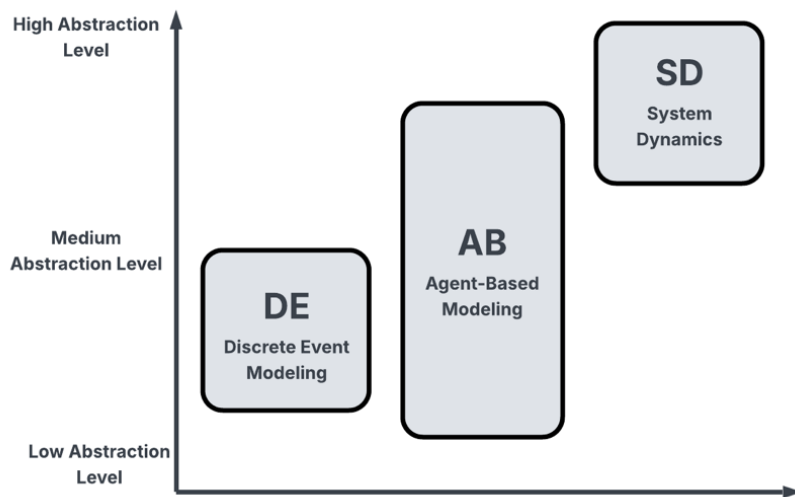


Figure 4: Simulation Modeling Methods (Tram, 2022)

System Dynamics (DS) is a method created in the 1950s and early 1960s by MIT Professor Jay Wright Forrester (Tram, 2022). System Dynamics is a methodology and computer simulation modeling technique for framing, understanding, and discussing complex issues and problems. It is widely used to analyze a range of systems in fields such as business, ecology, medicine, and social systems, as well as in engineering (Adane et al., 2019). Modeling the system is considered as a causally closed structure that defines its behavior by itself. Feedback loops, or circular causality, are the heart of System Dynamics (Tram, 2022). In this method, individual events and decisions are seen as surface-level actions that are influenced by deeper system structures and behaviors. This approach allows modelers to view the system as a continuous process, where specific events and decisions become less distinct and more part of an overall pattern. (Sterman, 2002). Consequently, System Dynamics is particularly effective in exploring complex systems where dynamic feedback and time delays significantly influence behavior.

Discrete Event Modeling (DES) was introduced in October 1961 by IBM engineer Geoffrey Gordon. The core of the discrete event modeling method is that the system is modeled as a process, which is a sequence of operations performed across entities. A process commonly includes delays, mechanical breakdowns, machine capacities, operator overwork, in-process inspections, buffer sizes, usage of resources, and waiting in queues. In a discrete event model, each operation is specified graphically as a process flowchart containing the start event and the end event, and no changes can take place in the model between any two discrete events. The dynamics of the world are continuous due to the absence of instant or major changes. Each change in the real world can be further divided into phases of the processes (Hall, 2012; Tram, 2022). As a result, DES is especially effective for analyzing systems in manufacturing, logistics, and services where process timing and resource constraints are critical.

Agent-Based Simulation (ABS) was established in 2002–2003 and was created to gain deeper insights into systems that are not well captured by traditional modeling approaches, such as system dynamics and discrete-event simulation (Harrison et al., 2007; Tram, 2022). Agent-based simulation focuses on the interactions of autonomous agents within a defined environment, allowing for the emergence of complex behaviors from simple rules. This methodology is characterized by its generative and bottom-up nature, which enables the simulation of complex systems by modeling individual entities (agents) and their interactions (Klügl & Bazzan, 2012). The ABS model is a hybrid discrete-continuous simulation model with proactive, autonomous, and intelligent entities. Proactiveness refers to the ability to take initiative. Agents can initiate actions, communicate with other agents, and make decisions on their own (Chan, Son, & Macal, 2010). ABS is particularly useful in various engineering domains, including manufacturing, logistics, and maintenance systems, as it provides insights into emergent behaviors that arise from the local interactions and decentralized decision-making of autonomous agents, such as Automated Guided Vehicles (AGVs), collaborative robots (cobots), and decentralized maintenance units (Terano et al., 2005).

2.3 Optimization in Production and Automation

In today's highly competitive and rapidly evolving industrial landscape, manufacturers are under constant pressure to increase productivity, reduce costs, shorten lead times, and meet customer demands. All while maintaining high levels of quality and sustainability (Choi et al., 2023; Utama & Abirfatin, 2023). As global supply chains become more complex and production systems more automated, the efficient utilization of available resources has become a strategic necessity rather than a technical preference (Stock & Seliger, 2016). In this context, production optimization emerges as an important enabler of operational excellence, allowing firms to systematically refine their processes to achieve maximum output with minimal input (Javaid et al., 2022).

By leveraging advanced computational techniques and mathematical algorithms, companies can identify inefficiencies, balance trade-offs between conflicting objectives, and design data-driven solutions that improve performance across the entire manufacturing value chain (Utama & Abirfatin, 2023). Whether it's minimizing energy consumption in an automated cell, reducing bottlenecks in an assembly line, or balancing cost and quality in high-mix, low-volume production, optimization supports better decision-making and long-term competitiveness (Choi et al., 2023). Thus, production optimization is not only a technical tool but a strategic capability at the core of smart manufacturing and Industry 4.0 initiatives (Stock & Seliger, 2016; Javaid et al., 2022).

2.3.1 Definition of Optimization in Production and Automation

In the context of production and automation, optimization refers to the systematic process of identifying the most effective solution from a set of feasible alternatives to achieve specific performance objectives, such as minimizing cost, maximizing throughput, or improving quality while respecting defined constraints (Stecca, Lanza, & Peters, 2019). Optimization involves transforming industrial systems into quantitative models that can be solved analytically or algorithmically to find an optimal or near-optimal outcome (Hillier & Lieberman, 2009; Stecca et al., 2019).

In manufacturing environments, optimization is applied across various domains, including production planning, scheduling, facility layout, and resource allocation. Automated systems often involve real-time decision-making based on sensor data, simulations, or digital twins to continuously adapt process parameters and maintain peak performance (Stecca et al., 2019). Ultimately, the goal is to ensure that limited resources are utilized in the most efficient and

strategic way possible, enabling companies to meet production targets, maintain high-quality standards, and stay competitive in increasingly dynamic markets.

2.3.2 Benefits and Challenges of Optimization in Production and Automation

Implementing optimization techniques in manufacturing and automation systems brings measurable improvements in productivity, efficiency, and cost-effectiveness. Research shows that optimization contributes to enhanced operational performance by enabling firms to optimize and enhance workflows, reduce cycle times, increase machine capacity, and better utilize resources such as labor, machinery, and materials (Rut & Wołczański, 2016). By systematically adjusting production parameters and minimizing idle time, organizations can significantly increase throughput and maintain stable productivity even under complex manufacturing conditions. This is particularly important in highly automated environments where real-time data and advanced algorithms make it possible to adapt quickly and maintain consistent output (Chen, 2024). Furthermore, optimization efforts often support higher product quality by reducing process variability and ensuring production runs stay within ideal parameters, thus minimizing rework and waste (Rut & Wołczański, 2016).

Another critical benefit lies in cost reduction and efficient resource allocation. Optimized production scheduling can significantly lower operational expenses by reducing bottlenecks, balancing workloads, and improving machine utilization (Rut & Wołczański, 2016). Firms that implement optimization frameworks frequently observe decreased material waste, energy usage, and downtime, all of which translate directly into financial savings. Additionally, the integration of optimization into automated systems helps organizations respond more flexibly to changes in demand and achieve better on-time delivery performance by increasing production throughput (Lalic et al., 2020).

On the other hand, the application of optimization in production faces several challenges that can significantly affect its overall effectiveness. One major challenge is the growing complexity of modern manufacturing environments, where increasing demand for customization requires highly precise and technologically advanced solutions. (Lewicki et al., 2025).

In addition, the underutilization of advanced data analysis and machine learning methods in industrial applications poses another substantial barrier (Bott et al., 2024). Furthermore, the stochastic nature of manufacturing systems complicates decision-making, as it requires balancing competing objectives, such as maximizing throughput while minimizing buffer capacity. This dynamic environment demands advanced optimization approaches that can adapt

to adjusting production volumes and changes in capacity (Barrera-Diaz et al., 2023). Lastly, the selection of inappropriate optimization methods can lead to significant inefficiencies and undesired outcomes in manufacturing processes, underlining the importance of careful method selection tailored to the specific context (Hallmann et al., 2021).

2.3.3 Application of Optimization in Production and Automation

Optimization in production covers a wide range of application areas aimed at enhancing the efficiency and effectiveness of industrial systems. The advancement of industrial development particularly within the framework of the Fourth Industrial Revolution has significantly influenced optimization strategies across key domains such as manufacturing, logistics, inventory control, and supply chain management. Moreover, the integration of advanced technologies and artificial intelligence has accelerated the evolution of these strategies, enabling more data-driven and adaptive approaches to system optimization (Sarkar & Sarkar, 2020).

Among the various optimization methodologies, the most widely recognized and applied approaches include Lean Manufacturing, Six Sigma, the Theory of Constraints (TOC), mathematical optimization algorithms, Agile Manufacturing, and Quick Response Manufacturing (QRM). These methods provide structured and systematic frameworks that can be implemented across diverse organizational contexts to improve operational performance (Groten & Gallego-García, 2021).

In this regard, Groten and Gallego-García (2021) propose a systematic optimization model consisting of six phases. An overview of the phases is presented in Figure 5. The corresponding phases are as follows:

1. Building Knowledgebase: This phase focuses on gathering knowledge related to theoretical and practical tools used in production optimization. It includes principles, guidelines, methods, techniques, and systems that form a foundation for selecting appropriate improvement strategies later in the process.

2. Current State Analysis: A detailed analysis of the existing production system is carried out by collecting data on material flows, information, energy use, equipment, workforce, and financial aspects. This step helps in identifying inefficiencies and establishing a baseline for improvement.

3. Selection of Improvement Tools: Improvement tools are selected based on their potential to enhance key performance indicators (KPIs), alignment with company strategy, investment

requirements, and operational impact. The focus is on choosing tools that are feasible and relevant to the specific context.

4. Solution Development Phase: Solutions are developed using the selected tools and supported by simulation to evaluate their effectiveness. Simulation results help predict potential outcomes and guide decision-making before implementation.

5. Implementation Phase: Selected solutions are put into practice through defined actions, training, and communication. Pilot testing is conducted before full deployment, allowing for adaptation during the rollout process.

6. Monitoring and Control Phase: The implemented solutions are monitored using key indicators to assess performance and detect deviations. This ensures control over the system and enables continuous improvement through iterative feedback.

Figure 5 below illustrates the systematic optimization model:



Figure 5: *Systematic Optimization Model (Grotten & Gallego-García, 2021)*

2.3.4 Scenario-Based Optimization

Scenario-based simulation testing is a methodological approach to evaluate how a manufacturing or automation system behaves under varying, predefined operational conditions. Rather than modifying a real production line, engineers build a virtual model and simulate different scenarios, such as layout changes, task timing variations, or machine availability, to assess their impact on system performance (Mourtzis et al., 2014). This “what-if” approach allows researchers to identify potential bottlenecks, explore improvement opportunities, and validate system robustness without incurring the costs, risks, or downtime associated with physical trials.

In modern manufacturing, particularly in automated environments, scenario-based simulation offers several critical advantages. First, it enables risk-free experimentation and early detection

of design flaws or control logic errors (Soori et al., 2023). Second, it provides a fast and cost-efficient way to evaluate multiple configurations in parallel, significantly reducing development time. Third, it supports informed decision-making by allowing stakeholders to compare scenarios based on measurable performance indicators such as throughput, utilization, and waiting times (Ruane et al., 2022). This is especially valuable when physical experimentation is constrained by production schedules or resource limitations.

Scenario-based optimization is a structured decision-support approach that combines scenario development with systematic evaluation of alternative strategies or system configurations. It is designed to aid decision-making in uncertain, variable, and incomplete information situations. Rather than relying on a single forecast or determined model, scenario-based optimization considers multiple future conditions, each representing a different set of assumptions about external and internal factors. As Miao et al. (2019) explain, this approach enables planners and decision-makers to analyze how a system or decision performs across different future environments. Each scenario incorporates a different combination of factors such as environmental, economic, or operational variables and allows for testing system responses to various possible outcomes. By evaluating these scenarios, decision-makers gain insight into which configurations or strategies are more stable and effective under different conditions. This leads to decisions that are optimized for the expected future and more robust against uncertainty.

The concept of scenario-based decision-making is further supported by Fotr et al. (2015), who emphasize that scenarios function as internally consistent representations of future developments that integrate both qualitative descriptions and quantitative data. Scenarios are not predictions but tools for structuring thinking about the future. They help organizations deal with discontinuous environments by allowing them to test the impact of uncertainty on strategic plans and investment decisions. In strategic planning contexts, the scenario approach offers a more flexible and realistic alternative to single-point forecasting by acknowledging the limits of prediction and the complexity of real-world systems. According to Fotr et al. (2015), scenario planning emerged as a method during periods of crisis, such as the oil crisis of the 1970s, when historical data alone could not account for emerging risks. This history underlines the value of scenarios in helping organizations identify critical uncertainties, define key drivers of change, and prepare for multiple potential futures. Decision-driven scenarios are closely tied to investment planning and allow decision-makers to test financial indicators such as project value or return under different environmental assumptions. In this context, scenario-based

optimization is not about finding one perfect solution but about selecting effective strategies across a wide range of possible situations, thereby reducing vulnerability and improving resilience.

Sjöstrand et al. (2020) extend this concept by applying scenario-based evaluation in risk analysis, showing how structured risk scenarios can inform economic decision-making. Their work demonstrates how predefined disruption scenarios can be used to estimate economic losses and guide the selection of risk-reduction measures. Each scenario represents a distinct challenge or failure point in a system, such as service interruptions or resource limitations. The outcomes of each scenario are assessed in terms of their likelihood and potential consequences, particularly focusing on economic costs to society. By comparing the risk-reduction benefits of different interventions across all scenarios, decision-makers can prioritize measures that deliver the greatest overall benefit while considering uncertainties in input data and event likelihoods.

Sjöstrand et al. (2020) also stress the importance of integrating both low- and high-probability events to avoid focusing too narrowly on the most likely outcomes. This is particularly relevant in systems where rare but severe disruptions could significantly impact. Their method includes a careful assessment of uncertainties through expert judgment and scenario characterization, emphasizing the need for transparency and structure in scenario-based risk assessments. In this way, scenario-based optimization allows for better prioritization, avoids sub-optimization based on isolated events, and supports more balanced and defensible decisions.

2.4 Overall Equipment Effectiveness (OEE)

Overall Equipment Effectiveness (OEE) is a widely recognized performance metric in manufacturing, where it is used to assess the utilization efficiency of equipment. It integrates three key dimensions, which are availability, performance and quality, to represent the overall operational effectiveness of a manufacturing system. By capturing losses across these dimensions, OEE helps organizations identify inefficiencies, drive continuous improvement, and enhance product quality (De Ron & Rooda, 2006).

Despite its widespread adoption and the presence of standardized calculation methods, the OEE metric is not without limitations. Scholars have pointed out concerns regarding its sensitivity to external factors unrelated to equipment functionality, such as material shortages or production planning issues, that can influence time and rate efficiency. To overcome this shortcoming, an alternative metric known as Equipment Effectiveness (E) has been introduced. This metric focuses solely on equipment-dependent conditions and offers a more accurate and focused

evaluation of equipment performance by excluding external disturbances from the analysis (de Ron & Rooda, 2005).

In industrial practice, OEE is employed as a practical method to evaluate the real-time performance of machinery within the manufacturing environment. It provides a structured approach to monitoring equipment efficiency, enabling manufacturers to identify deviations and implement targeted improvements to increase productivity. The successful implementation of OEE plays a key role in supporting operational excellence and sustaining competitiveness in the manufacturing sector (Maideen et al., 2016).

Maideen et al. (2016) proposed a structured three-phase framework for the implementation of OEE in manufacturing environments. This framework consists of Phase I: Define, Phase II: Design, and Phase III: Implementation, providing a step-by-step approach to systematically assess and improve equipment performance. The overall structure of this framework is illustrated in Figure 6.

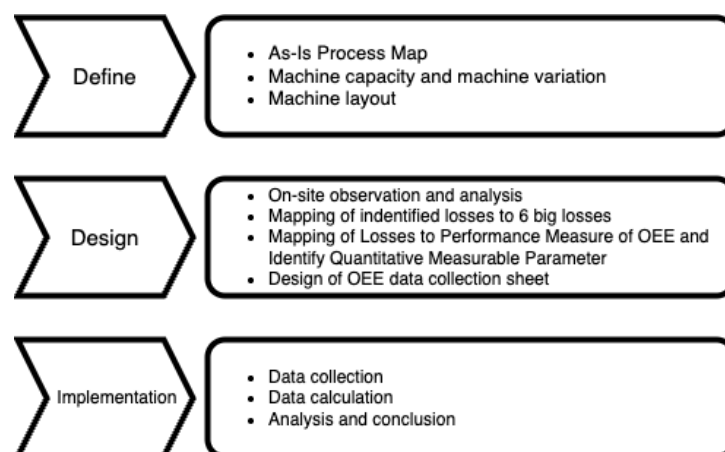


Figure 6: Overall Equipment Effectiveness(OEE) Framework (Maideen et al., 2016)

Phase I: Defining the current production conditions by first mapping the existing process flow, including inputs, outputs, and responsible personnel. It also involves identifying machine capacity and variations across different equipment types, such as differences in automation level or cycle time. Lastly, machine layout is analyzed to understand arrangements and material flow, which may impact efficiency through transfer delays or workstation idling. This initial phase helps establish a baseline and identify potential sources of production losses (Maideen et al., 2016).

Phase II: Design aims to systematically translate observed operational issues into measurable parameters within the OEE framework. This phase begins with on-site observation and analysis, where key factors such as machine breakdowns, material loading efficiency, operator presence

and skill level, and product quality are examined to determine their causes and impacts. Identified losses are then classified according to the six major loss categories defined in Total Productive Maintenance: breakdowns, setup and adjustments, small stops, reduced speed, startup rejects, and production rejects. These categories serve as a reference point for aligning each type of loss with a specific OEE component Availability (A), Performance Rate (P), or Quality Rate (Q). This structured mapping enables the definition of quantitative, measurable parameters for each loss type, which are necessary for accurate performance assessment in the next phase (Maideen et al., 2016).

The OEE value is calculated as the product of its three key components:

$$OEE = \text{Availability (A)} \times \text{Performance rate (P)} \times \text{Quality rate (Q)}$$

$$A = \left(\frac{\text{Planned Production Time} - \text{Unplanned Downtime}}{\text{Planned Production Time}} \right) \times 100$$

$$P = \left(\frac{\text{Actual Production Output}}{\text{Expected Production Output}} \right) \times 100$$

$$Q = \left(\frac{\text{Actual Production Input}}{\text{Actual Production Output}} \right) \times 100$$

Phase III: Implementation involves the execution of data collection and analysis based on the structure developed in the earlier phases. Before initiating data collection, personnel involved must be properly instructed on the procedures to ensure consistency and reliability. Although operators are familiar with the process and are ideal data collectors, their involvement may introduce bias. Therefore, assigning impartial personnel such as quality control staff or auditors is recommended. Once a data recording system is in place, automated data collection can be considered. Based on the collected data, OEE values are calculated and analyzed to draw conclusions about system performance and identify areas for improvement (Maideen et al., 2016).

3 Methodology

This chapter outlines the methodology used in the research. It begins by describing the overall research process and structure followed to achieve the study's objectives. The chapter continues with the literature review strategy that established the theoretical foundation for the research. The empirical investigation is based on a case study conducted in an industrial context, supported by observations, time studies, and interviews. Simulation modeling played a central role throughout the project, combining visual and analytical models to evaluate system behavior and test scenario-based configurations. Finally, the chapter addresses data quality, validity, reliability, and ethical considerations to ensure a structured and transparent research approach.

3.1 Research Design

A clear and structured research design is essential in guiding the development of a master's thesis, as it establishes a systematic framework for addressing the research questions. It enhances the overall quality of the study by helping researchers manage the complexity of the project and engage effectively with relevant literature and methodological approaches (Harris, 2019).

The research began with a deductive approach, where existing theories and prior knowledge formed the foundation for developing the research aim and understanding the context. In the second phase, an inductive approach was integrated to gain deeper insights from empirical data, providing a more holistic understanding of the problem and strengthening the study. According to Williamson et al. (2002), combining inductive and deductive approaches enables a comprehensive exploration and validation of theories.

This study aims to investigate how scenario-based optimization can be applied for an automated machine cell designed for handling can ends by using two different simulation tools. This process involves developing a digital model of the cell and applying different scenarios to evaluate different operational configurations. The simulations combine both visual emulation and DES, enabling a thorough analysis of system performance over time and across different physical setups under varied layout and flow conditions.

A combination of qualitative and quantitative methods was used, including semi-structured interviews, direct and indirect observations, detailed time studies, and document analysis. Each method contributed unique insights into the operation of the automated machine cell and supported the creation of a simulation model that accurately represented real-world behaviors and constraints.

This qualitative research approach supports the development of new theories through the analysis of literature, interviews, observations, and real-world data (Yin, 2018). It provides a broader understanding of the research problem, enhancing reliability by strengthening both theoretical and practical insights (Charli et al., 2022). Inductive research primarily relies on qualitative methods to identify patterns through interviews and observations, which in turn lead to the development of broader explanations and theories (Patel & Davidson, 2019). This approach is especially valuable in areas where existing theoretical frameworks are limited, as it allows patterns to emerge through repeated observations (Thomas, 2022). By focusing on real-world contexts, researchers can underline practical insights and solutions rather than relying solely on existing theory, thereby improving efficiency and effectiveness.

According to Säfsten and Gustavsson (2024), quantitative methods primarily focus on measuring quantity, size, and numerical data that represent amounts or degrees. A key advantage of quantitative methods is their ability to produce standardized data. For example, asking the same questions to all participants enables researchers to obtain comparable data across the entire sample (Roni et al., 2019). However, the use of standardized and formalized data collection methods limits flexibility, as quantitative research often requires repeated and consistent processes, whether in survey questions, production measures, or other standardized variables (Säfsten & Gustavsson, 2024).

Quantitative research is typically used either to construct theories or to test existing ones. In constructing theory, researchers collect data on observable and measurable variables to develop a theory that best explains the observed patterns (De Vaus, 2002; Roni et al., 2019). In this study, DES was applied as a quantitative method to evaluate system behavior through performance metrics such as throughput and waiting time. Overall, quantitative methods rely on numerical data to explain trends, determine relationships, and validate or challenge theoretical assumptions (Roni et al., 2019).

One of the main advantages of conducting case studies is their ability to connect theoretical knowledge with practical application. As case study findings are closely tied to real-world conditions (Säfsten & Gustavsson, 2024). Empirical data were gathered through semi-structured interviews, as well as structured and unstructured observations and document analysis. These data supported the development of the simulation model and enabled the evaluation of scenario-based system behaviors under real-world constraints.

3.2 Research Process

The study began in mid-January 2025 with an initial interview conducted with the case company's automation manager to discuss the project. During this meeting, the company introduced the project and presented the problem it wished to address through research. Following this, the authors conducted a literature review to explore research gaps and define a theoretical foundation for the study. A second meeting was held to establish a project plan and coordinate logistics such as workspace allocation and tool preparation. During this early phase, the authors focused on understanding the case company's system, simulation techniques, and machine cell structure to plan the data collection process effectively.

The company provided full access to its facility, where a test-phase machine cell was being assembled and validated. This allowed the authors to observe the machine cell at testing phase closely and collect both visual and technical data. These observations were supported by multiple informal discussions with employees and engineers. In addition, four formal interviews were conducted with experts to gather technical insights and validate design assumptions for the simulation work. Following this, a structured data collection process was carried out to prepare reliable input for the simulation phase.

The simulation phase was structured in two parts. First, a visual simulation model was built using Emulate3D. This tool was requested by the case company and helped visualize robot movements, test reachability, and understand the flow of materials in the system. This visual model was essential for analyzing the structure of the process before moving on to deeper performance testing. During this stage, the large set of Computer-Aided Design (CAD) files provided by the case company was simplified and adapted to fit simulation requirements, with support from the company's design engineers.

In the second part, a DES model was developed using Arena. This software was chosen due to the researchers' prior experience with it, which reduced the learning curve and allowed for a faster and more effective modeling process. Arena enabled the analysis of logical system behavior and performance metrics such as cycle times, robot utilization, and system throughput. During the scenario testing phase, the researchers collaborated with the automation manager and engineers to define realistic and technically relevant configurations. The scenarios were iteratively developed not only based on expert feedback, but also in response to simulation results and quantitative findings, such as identified bottlenecks and improvement opportunities. This iterative loop ensured the continuous refinement of system configurations and allowed the

research team to evaluate the effects of layout and process modifications on overall performance.

3.3 Literature Review

To contribute meaningfully to a field of study, it is essential to first understand the existing body of knowledge. This necessitates gaining a comprehensive overview of the current state of research before initiating a new study. The challenge, however, lies in determining the most effective way to achieve this. A logical starting point is to examine previously published work, which involves identifying, reading, and synthesizing relevant literature. This structured approach to reviewing and summarizing existing knowledge is known as a literature review. The term describes both the process of conducting the review and the outcome of the review itself. The connection is made between literature review, which refers to the process of gathering and analyzing sources, and literature overview, which represents the final summary and synthesis of the reviewed material (Säfsten & Gustavsson, 2024).

A literature review can serve multiple purposes depending on the stage of the research process. In the early phases, particularly before defining a research problem, conducting a preliminary literature review can be beneficial. This allows researchers to establish an understanding of state-of-the-art developments and current discussions in the field. As the study progresses, it often becomes necessary to perform more in-depth literature reviews to address specific research questions with greater precision (Säfsten & Gustavsson, 2024).

In this study, the literature review helped define the scope of simulation-based optimization in automated production systems and provided foundational concepts related to DES and scenario-based testing. It also guided the identification of relevant methodologies and performance indicators used in similar industrial settings. Academic databases such as Primo (Jönköping University's database), Google Scholar, and DIVA were utilized to conduct the literature review for this study. To refine search results and ensure relevance, Boolean operators ("AND," "OR," and "NOT") were applied. This systematic approach allowed for an efficient selection of relevant research, forming a strong theoretical foundation for the study.

To deepen the understanding of the field and ensure alignment with the research objectives, particular attention was given to refining the search logic through the use of carefully selected keyword combinations. These keywords were directly related to the study's central themes, including automation, simulation, layout optimization, discrete-event modeling, manufacturing systems, and performance improvement. For example, search queries such as "automation"

AND "automated production", "automated manufacturing cell" AND "production system", "simulation" AND "scenario-based simulation", "scenario-based optimization" AND "simulation-based improvement", ("discrete-event modeling" OR "DES") AND "cycle time", "layout optimization" AND "facility layout", "manufacturing systems" AND "industrial automation", and "optimization" AND "performance improvement" were used to identify studies that supported the development of relevant simulation and optimization approaches. Boolean operators were consistently applied to adjust the scope and relevance of the results based on the focus of each topic. In some cases, alternative phrasings like "production line optimization" in place of "manufacturing system performance" were also tested to reflect variations in terminology across the literature. Additionally, backward and forward citation searches were conducted to identify influential and frequently referenced publications. The final selection prioritized peer-reviewed journal articles and conference proceedings that offered applicable insights into simulation practices, performance measurement techniques, and improvement strategies in automated production environments. These sources together formed a strong theoretical and empirical foundation for the research.

3.4 Case Study

A case study can be defined as an intensive and systematic study of phenomena and scenarios that happen in their natural settings in which the researcher examines in-depth data relating to several variables (Gustafsson, 2017). Case studies are also used to explore complex processes within their real-life context to gain deeper insights and understanding (Hamel et al., 1993). A significant advantage of conducting case studies is the ability to bridge theoretical knowledge with practical applications. Since case study findings are closely tied to real-world conditions, they contribute to practical and actionable solutions, making them highly relevant for industrial research (Säfssten & Gustavsson, 2024).

The case company has requested to keep its name anonymous; therefore, it will be referred to as “the case company” throughout the paper. The case company is an automation company located in Jönköping, Sweden. The company designs and produces specific tools and machine cells for the area of distribution and logistics of can ends for the beverages industry. The lid of a can takes up a much smaller volume than the can itself, which makes it easier to transport lids compared with cans. This results in one factory that produces lids that can support several factories where cans are filled. The company has customers all around the world. All their work is done at their facility in Jönköping by approximately 60 employees. Their robot cells are based on a PLC control system that mainly controls different motors to transport products.

After conducting a semi-structured interview with the automation manager of the case company, relevant information was gathered. While the company offers a standardized foundation for its automation systems, each machine cell is tailored based on specific customer requirements, including the selection of control systems and mechanical configurations such as tools or robots.

Customers are offered a choice between Siemens and Allen Bradley PLCs, depending on regional compatibility or personal preference. Likewise, FANUC robots are used across all cells, but the specific robot model varies according to the payload, reach, or application requirements. These customizations also extend to the design of grippers, vision systems, and sensor integrations.

Ensuring the long-term reliability of each machine cell is considered critical, as these systems become integral components of larger production lines at customer sites. To achieve this, the company follows a comprehensive in-house validation approach before delivery.

Each machine cell is fully assembled and tested at the factory. During this phase, engineers verify that all components and subsystems, including control logic, mechanical actions, and safety protocols, meet the customer's specifications. Only after passing the internal test protocol is the robot cell disassembled, packaged, and shipped to the customer.

The machine cell is built and tested in-house at the company. In this phase, it is made sure that components and controllers are working properly and specifications are fulfilled. When the testing protocol has been approved, the robot cell is taken down and shipped to the customer, where it is installed, and the commissioning phase is carried out. The commissioning time for a normal cell is about 6 weeks, and after the shipment, an installation takes about 2 weeks. The time from production start to end of the testing protocol for a normal cell is 30 weeks. The smaller cells can have a commissioning phase as short as 2 weeks, while the largest cells can take up to 15 weeks.

3.5 Data Collection

In this study, the data collection phase played a critical role in ensuring the accuracy and validity of the simulation and optimization results. Given the complexity of automated production systems and the need for realistic input parameters, it was essential to collect both qualitative and quantitative data from multiple sources. To address this, a triangulated approach was adopted, incorporating semi-structured interviews, field observations, and document analysis.

3.5.1 Interviews

Interviews represent a qualitative research approach aimed at gathering firsthand knowledge and in-depth perspectives through dialogue. Expert interviews are particularly valuable in organizational settings, as employees often possess deep, role-specific expertise. This allows them to contribute informed, experience-based insights that enrich the understanding of internal operations and system functionality (Doody & Noonan, 2013).

Interviews are a fundamental method in qualitative research, and they can be categorized into three main types: structured, semi-structured, and unstructured interviews. Each type has distinct characteristics and applications. Structured interviews involve a predetermined set of questions that are asked in a specific order. This format allows for consistency across interviews, making it easier to compare responses. However, the structured interviews may limit the depth of information gathered, as they do not allow for follow-up questions or the exploration of unexpected topics. This method is often used when specific data points are required, but it may not capture the participant's experiences (Elhami & Khoshnevisan, 2022). Semi-structured interviews strike a balance between structure and flexibility. They consist of a mix of predetermined questions and the opportunity for the interviewer to explore topics in greater depth based on participant responses.

This approach can be particularly effective in manufacturing contexts, where understanding the complexities of processes and experiences is essential. It allows interviewers to search deeper into specific areas of interest while maintaining consistency across interviews (Wilson, 2013). Finally, unstructured interviews are the most flexible format, allowing participants to guide the conversation. This method can collect rich, detailed insights into participant experiences, as it encourages open-ended responses and the exploration of topics that may not have been anticipated by the interviewer. In manufacturing, unstructured interviews can uncover valuable information about employee perceptions, challenges, and suggestions for improvement, although they may present challenges in terms of data analysis and comparison (Gibson, 1998).

For this study, a semi-structured interview format was selected by the authors to allow for both consistency in core questions and flexibility to explore topic-specific insights depending on the interviewee's role. This format was well suited to the diverse expertise of the participants and the technical complexity of the automated system under investigation. Interviews were conducted with various participants who had relevant experience in the research field. The interviews included open-ended questions, allowing participants to speak freely while maintaining a structured format that added value to the data collection process. According to Patel and Davidson (2019), open-ended questions strike a balance between structure and spontaneity. Kapesa et al. (2023) noted that this method improves the understanding of different perspectives, attitudes, and experiences, contributing to higher-quality data during feasibility studies and process evaluations. Semi-structured interviews also uncover new aspects and theories through unexpected insights that enrich the research (Charli et al., 2022). Doody and Noonan (2013) emphasize that this data collection method is effective because it facilitates natural and open communication.

The interview participants primarily included automation manager, automation engineers, and sales and marketing manager from the case company involved in this research. Initially, an interview was conducted with the automation manager, who had direct involvement with the case being analyzed, to gain a clearer understanding of the company, the project, and its planning. In the second phase, three interviews were conducted with individuals who had hands-on experience with the project or the area being studied. The participants were contacted by the automation manager to ensure availability and to avoid disrupting their daily work activities.

Before the interviews were conducted, preparations included designing appropriate questions, selecting recording methods, and addressing ethical considerations. These steps aimed to ensure the quality and relevance of the interviews about the research problem and questions and to support the analysis in the following stages.

Interviews were requested from the automation manager, two automation engineers, and a sales and marketing manager directly involved in building the physical automation cell. Additional interviews were scheduled if further knowledge was needed or if certain requirements were not met during the initial round of interviews. After that, the interviews were analyzed, and themes were developed to ensure that the data were well connected and coded according to the needs of the research.

The list of participants and their positions are summarized in Table 1.

Participants	Position	Type of Interview	Interview Time
Participant A	Automation Manager	Semi-Structured	Approx. 60 mins
Participant B	Automation Engineer	Semi-Structured	Approx. 45 mins
Participant C	Automation Engineer	Semi-Structured	Approx. 45 mins
Participant D	Marketing and sales Manager	Semi-Structured	Approx. 60 mins

Table 1: List of the participants and interviews

3.5.2 Observation

Observation is a commonly used technique for data collection and is applied across various research methods, such as experiments, case studies, and action research. Observations can be categorized as either direct or indirect, depending on the mode of data collection. In direct observation, the researcher is physically present at the same time and space as the subject of study, gathering data through their own sensory perception. This approach is frequently employed in contexts such as monitoring production processes, project meetings, or human interactions. Indirect observation involves collecting data through measurement instruments or recording devices when physical presence is impractical, enabling the researcher to capture relevant information remotely (Säfssten & Gustavsson, 2024).

In addition to the distinction between direct and indirect approaches, observations can also be classified based on their level of structure. A structured observation is guided by a predefined schedule or protocol, specifying in advance what elements should be observed and recorded. This facilitates systematic data collection that is aligned with the study's research questions. Alternatively, unstructured observation adopts a more flexible and exploratory approach, where the observer documents findings in a narrative or note-based format without relying on predetermined criteria. The choice between structured and unstructured observation depends on the purpose of the study, the nature of the phenomenon being investigated, and the observer's expertise (Säfssten & Gustavsson, 2024). Patel and Davidson (2019) emphasized that unstructured observation can enhance the researcher's perception of the problem and offer a

more realistic view of the processes being studied. Furthermore, Hansson (2007) clarified the distinction between direct and indirect observation in industrial contexts, where indirect observation can function as a technical measurement method, whereas direct observation supports process understanding through situational engagement.

As previously mentioned, this research adopts a mixed-method approach in which observation is one of the key data collection methods. Observations were conducted both directly and indirectly across multiple settings within the case company. The initial stages of observation focused on gaining a practical understanding of the production facility through physical presence on the facility floor and analysis of recorded videos capturing the finalized machine cell in operation. This was followed by the observation of the software tools used for simulation and control logic design, which contributed to a better understanding of the types of machine cells developed by the company. Informal conversations with staff and on-site visual walkthroughs helped contextualize how automation elements such as robots, tools, and supporting systems were configured and integrated. In parallel, researchers practiced using visualization tools linked to the machine cells, making it necessary to observe the physical machine setup to comprehend the operation logic and required execution times of each task. These observations were supported by multiple technical resources provided by the case company, including CAD models, layout drawings, and video recordings of machine operation, all of which contributed to a deeper understanding of the workflow, machine capabilities, and operational timing required for simulation input development.

During the observation phase, a time study was conducted to obtain accurate measurements of the robot's operational durations. While basic speed and movement data for robotic arm were available through internal documentation, detailed cycle times, such as pick-and-place motion times, idle times, and transfer periods, were not directly accessible. Therefore, manual measurements were required to fill this gap. The initial data were collected during the internal testing phase at the company's facility, where key activities were observed and recorded on-site. To complement these findings, additional visual recordings were obtained from systems deployed in customer environments, which showed the robotic cell in real production conditions. These materials were analyzed frame by frame to identify the start and end points of operational segments, allowing for more realistic and reliable time data. Through this combined approach, valuable time-related insights were extracted to support both simulation modeling and the subsequent optimization analysis.

The integration of direct and indirect methods, along with structured and unstructured formats, including the application of time study principles, allowed the research team to collect both measurable performance data and situational insights. This triangulated approach enabled the observation process to serve as a methodological link between theoretical model design and practical system behavior, reinforcing the validity of simulation inputs and the relevance of the research outcomes.

The different types of tasks and methods are visualized to show the observations clearly in Table 2.

Task Type	Observation Type	Structure	Data Source / Area
Machine Cell Understanding	Direct and Indirect	Structured & Unstructured	Case Company Work Floor, Video Recordings, CAD Files
Simulation-Based Modeling	Indirect	Structured	Emulate3D Environment, Software Tools
Discrete Event Simulation	Indirect	Structured	Simulation Outputs (Arena), Scenario Analysis
Time Study (Robot Actions)	Direct and Indirect	Structured	On-site Observations, Video Frame Analysis
Optimization Testing	Indirect	Structured	Scenario Output Files, Performance Metrics

Table 2: *Observation Methods*

3.5.3 Document Analysis

A document study involves the utilization of secondary sources, such as various types of documents, which would be a foundation for data collection. This type of data often serves to enhance primary data and is particularly useful when the goal is to understand how others have perceived or interpreted a specific event or situation. The concept of a "document" extends far beyond just written texts. It can encompass both public and private materials, including items such as protocols, videos, photographs, newspapers, official statistics, annual and anomaly reports, as well as organizational descriptions, among many others (Säfsten & Gustavsson, 2024).

In this study, document analysis was utilized as one of the key methods of secondary data collection. This approach was particularly important to support the simulation development, as

direct and continuous access to the machine cell was limited. Various documents were obtained from the case company and systematically reviewed. These included technical documentation, CAD files, process flow charts, internal testing protocols, and video recordings of the robot cell in operation at both the testing facility and customer sites.

Furthermore, internal reports were reviewed to understand system configurations, cycle time expectations, and performance benchmarks. By combining insights from these documents, a comprehensive understanding of the production workflow was achieved. The extracted data played a critical role in model validation, ensuring that the simulated behavior closely reflected real-world operations.

The different types of internal documents reviewed, the specific data extracted from each, their intended purpose, and the corresponding application areas within the project are summarized in Table 3. This overview provides transparency regarding the sources used for data collection and clarifies how each document contributed to the development and validation of the simulation models.

Document Type	Description & Source	Data Extracted	Purpose in Study	Application Area
CAD Models	3D mechanical layouts from the case company’s mechanical design team	Technical CAD drawings, machine and tool dimensions and positions	Deeply understanding the robots and tools technical aspects and spatial constraints	Visual simulation software (Emulate3D) and movement/reachability analysis
Process Flow Diagrams	Internal documentation from automation engineer	Task sequencing, logical transitions, operation flow between processes/robot movements	Identifying key production steps and decision points	Event mapping for DES logic structuring and visual simulation (Emulate3D)

Video Recordings	2 test videos from internal trials and 5 from customer sites during live production	Robot motion cycles, pusher durations/delays and pick/place durations	Quantifying real system performance metrics, detecting timing variances	Time input calibration for DES, visual simulation (Emulate3D) and optimization
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Table 3: *Types of Documents*

3.6 Scenarios for Simulation Testing

Scenario-based simulation testing was employed in this study to systematically explore and evaluate operational performance under various system configurations. This methodological approach is commonly used to support data-informed design decisions in manufacturing systems, particularly when investigating layout changes, task allocation, or control logic variations under constrained conditions (Ruane et al., 2022). In this context, the simulation environment enabled controlled testing of potential design alternatives without disrupting real operations, allowing for flexible experimentation in a virtual setting.

The purpose of the scenarios in this thesis was to examine how adjustments to layout, material flow paths, and robot parameters affect performance indicators such as queue times and equipment utilization. Each scenario was developed iteratively based on simulation results, informal interviews with automation engineers.

Two scenario groups were defined in collaboration with automation experts at the case company:

Scenario A included adjustments to infeed and outfeed pusher configurations, focusing on Pusher numbers, waiting times, and robot utilization. Several configurations were created and simulated to identify the most efficient setup. According to the customer needs, automation engineers would design the machine with either a higher number of infeed pushers or a higher number of outfeed pushers, depending on whether it needs to synchronize with the preceding press unit or the subsequent downstream process following the machine cell used in this simulation.

Scenario B explores different robot configurations such as speed and reachability. The need for this scenario was derived from operational observations indicating opportunities for increased throughput via improved robot performance.

The simulation model was built to incorporate realistic system constraints. Each scenario variant was implemented in the simulation environment and assessed using standardized performance indicators. Scenario development and refinement were carried out through continuous feedback loops with production engineers to ensure that all configurations were technically feasible and practically relevant. As Ruane et al. (2022) emphasize, integrating domain expertise throughout the simulation process enhances the reliability and validity of scenario-based evaluations in industrial contexts.

The study included only two simulation scenarios on purpose. This decision was made carefully to ensure both research accuracy and industrial relevance. After talking in detail with the automation engineers and manager at the case company, it was agreed that the simulation should focus on two main scenario types. These were chosen because they reflect realistic production conditions and can actually be applied in the company's operations.

3.7 Data Analysis and Quality

Data analysis is a fundamental phase of the research process. The selection of analytical methods is closely linked to the study's objectives and the nature of the data collected, whether qualitative or quantitative. In this study, both types were utilized, and tailored strategies were implemented to ensure meaningful and context-relevant interpretations (Säfsten & Gustavsson, 2024).

Thematic analysis was applied to the interview transcripts to identify patterns and themes. Thematic analysis is a method used in qualitative research to find and understand common themes or patterns in data, especially from interviews. It helps make sense of participants' views, thoughts, and experiences by organizing the information in a clear and structured way (Scharp & Sanders, 2019). On the other hand, time study data was examined using basic statistical methods and scenario simulation results were evaluated through comparative output analysis, providing insights into the system's behavior under different configuration scenarios.

Regardless of the data type, all collected information was processed, organized, and interpreted carefully. Semi-structured interviews were audio-recorded with prior consent and transcribed in line with ethical protocols. Observational notes, time study records, and scenario outcomes were systematically documented and stored in structured Excel files to ensure traceability and

transparency. Furthermore, consistent procedures were followed across all data collection efforts, including structured and unstructured observations and document analysis. This ensured that the analysis was grounded in operational realities and that the data could be handled effectively throughout the research process.

3.8 Validity and Reliability

To ensure the integrity of the research findings, data quality assessments were conducted based on three main criteria: credibility, reliability, and internal and external validity.

Credibility was strengthened by using multiple data collection techniques, such as semi-structured interviews, direct and indirect observations, and document analysis, all chosen for their relevance to the case company's machinery and automation environment (Säfsten & Gustavsson, 2024). These diverse sources allowed triangulation, enhancing the trustworthiness of the study. Interviews were conducted with consent, audio-recorded, and transcribed, while all observational and simulation data were logged systematically.

Reliability was addressed by standardizing the data collection processes and applying consistent methodologies throughout the study. Each research method followed a documented structure to ensure repeatability. This standardized approach enables other researchers to replicate the procedures and validate the findings under similar conditions (Yin, 2018).

Internal validity was supported through the application of logical reasoning and established analytical techniques. By ensuring that each method accurately measured what it was intended to measure, the study preserved its internal coherence. For example, time studies and scenario simulations were designed to reflect real-world production behaviors.

External validity, referring to the generalizability of findings, was improved through detailed documentation of the research context and methodology. The case selected was representative of a typical automated warehouse environment, allowing the findings to be applied to similar industrial settings. Theoretical sampling further ensured that the conclusions drawn are relevant beyond the specific context examined (Yin, 2018).

3.9 Ethical Considerations

Ethical considerations play an important role in research by ensuring that the study is carried out with honesty and credibility. Research ethics refer to the principles and values that help maintain the quality, trustworthiness, and societal value of the research while also protecting the people involved. This means being accurate, objective, and open in every step of data collection and analysis (Säfsten & Gustavsson, 2024). In this study, ethics were especially important for building trust and keeping the research process transparent.

Several ethical aspects were carefully planned and implemented in collaboration with the company supervisors and university representatives. These included the protection of personal data, assurance of confidentiality and anonymity, and the process of obtaining informed consent. Special attention was given to these principles during the integration of company-specific information into the simulation software, as well as throughout the interviews and observations conducted as part of the study. The company name, employee names, and any other identifiable organizational details were fully anonymized in all parts of the research to protect internal confidentiality.

Before conducting interviews, participants were provided with clear and detailed information regarding the aim of the study, their role in the research, the methods to be used, and how their input would be treated. Written or verbal informed consent was obtained in each case, and participants were explicitly informed of their right to withdraw from the study at any time without any consequences. All names were excluded from the data set, and individuals were referred to only by their job titles to ensure anonymity.

The research purpose and structure were fully explained to all participants to maintain transparency and ensure that expectations were clear. In addition, participants were kept informed about the progress of the research and its outcomes to avoid any potential misunderstandings, bias, or misinterpretation of the data. By adhering to these ethical principles, the credibility and integrity of the study were continuously supported throughout the research process.

4 Empirical Data

This chapter presents the empirical foundation of the study, which was essential for understanding the operational context, identifying key system challenges, and informing the development of the simulation models. The collected data supported not only the technical aspects of modeling and performance analysis, but also contributed to a deeper understanding of the research problem and refinement of the research questions. Two sources of data were used: interviews and internal technical documentation. The interviews provided practical insights into automation workflows, organizational practices, and perceived inefficiencies. In addition, the technical documents, including CAD files, process flow diagrams, and video recordings, enabled a detailed examination of the machine cell's physical and logical structure. These empirical inputs formed the basis for scenario development, performance evaluation, and interpretation of simulation results in the later chapters.

4.1 Interviews

A semi-structured interview was conducted with the automation manager during the early stages of the research to initiate the qualitative data collection process. The interview helped to gain a deeper understanding of the case company's operations, production strategies, and customization approaches that are not publicly available on their website or in official documents. This conversation provided valuable context for how machine cells are configured, tested, and delivered based on customer-specific requirements. It also showed the internal decision-making processes, the degree of flexibility offered to customers, and the importance of system reliability.

The aim of what is to be found from the qualitative data is the interviewees' perception of automation, the use of simulation, and the application of optimization. The goal is to understand the different perspectives from different angles since different interviewees with different backgrounds will be interviewed for this type of data. The researchers aim to understand how effective automated systems have changed the production line and what additional benefits simulation has brought to the process.

The researchers have conducted interviews with an automation manager, two automation engineers, and a sales and marketing manager who mainly manages the selling part and making contracts with clients but also has a mechanical degree, and the participant was part of the designing engineers in the past before shifting to only focus on marketing. The interviews will follow the three main theories, automation, simulation, and optimization, to provide a clear way

of analyzing the data in the next section. All three interviews with the automation manager and the automation engineers had the same set of questions; only the marketing and sales manager had more questions focused on sales and marketing, but the questions kept the main topics in focus.

4.1.1 Participant A : Automation Manager

The participant began the interview by introducing himself and describing his role as automation manager in the company, where he is responsible for managing all control systems and automation design, as well as participating in the implementation phase of machines. When asked about the role of automation, he emphasized its growing importance, stating that "it is the evolving of the manufacturing section."

The interviewee further explained that, in many cases, their machines are sold to customers who are either building new manufacturing plants or updating existing layouts. In such cases, clients often prefer fully automated solutions. However, when selling to companies that maintain their current facilities, partial manual processes are sometimes preferred. This is typically due to limitations such as restricted physical space or the need for extensive employee training, which can make full automation less practical.

When asked about challenges in the current automation market, the participant pointed out several key issues. One major challenge is the increasing demand for faster processes and the difficulty of developing more user-friendly machines. He noted that both untrained operators and, in some cases, companies themselves lack the necessary knowledge to implement advanced automated systems. This knowledge gap makes it difficult to meet growing customer expectations. He also highlighted that companies seek to reduce labor. While manual processes may require up to 20 operators, automation can significantly lower this number.

Another challenge mentioned was the risk of cyberattacks, which are a growing concern in automated environments. The participant explained that such threats often prevent companies from fully integrating data collection systems, forcing them to rely on physical or isolated data sources due to security risks.

Regarding simulation, the participant stated that while simulation is not yet used extensively at the company, it plays a small role primarily in programming robots and ensuring reachability. They rely mostly on 2D and 3D static drawings for client demonstrations, without dynamic or interactive simulation. He noted the difficulty of building a simulation model that fits all clients due to differences in layout and operational requirements. However, the company is exploring

the possibility of hiring a dedicated simulation expert to support internal development and design. Currently, most process control is implemented through PLCs, supported by mathematical calculations. The participant explained that, although they are exploring the use of simulation for layout and process design, every configuration needs to be tested and calculated to ensure it meets efficiency and reliability standards. The participant acknowledged that a standard simulation model could be useful for internal benchmarking and optimization.

When asked about optimization, the interviewee noted that while the company is interested in exploring such techniques, their standard machine configurations already provide consistent performance in terms of output size, cycle time, and maintenance. This consistency simplifies sales and manufacturing. Optimization, according to the participant, may be more useful in future product development but would depend heavily on specific customer needs and machine usage patterns.

The participant also identified a major constraint, which was the short lead times for machine production. Because the delivery timelines are tight, there's little room for testing new configurations or experimenting with optimization strategies that could introduce delays. Lastly, the participant emphasized that the automation department is actively researching new solutions, but most work remains theoretical rather than practical. The interviewee noted that simulation could help reduce costs by eliminating unnecessary components (e.g., reducing the number of pushers while maintaining production capacity). However, the interviewee acknowledged that implementing advanced optimization techniques for each unique case would require significant time and financial investment, limiting its current feasibility.

4.1.2 Participant B: Automation engineer

The participant began by explaining his role as an automation engineer, having worked at the company for eight years. Most of his responsibilities focus on the development of machinery within the company. The interviewee emphasized that automation significantly improves the speed and efficiency of production processes. In the interviewee's view, manual operations have become an inefficient method for managing manufacturing tasks. The interviewee added that, due to the fast-changing demands of the market and customers, companies must increasingly adopt automation to remain competitive. This shift has also led to a decrease in the number of operators needed in production lines. According to the participant, the company places considerable focus on the design of the machine before mechanical development begins. In this workflow, the automation team collaborates closely with the mechanical department, unlike in other organizations where these functions are often separated. The interviewee reflected that

this integrated structure adds value by aligning process logic with hardware development from the outset.

When discussing challenges, the participant noted that the demand for machine development is continuous due to evolving customer requirements. While the machines currently produced by the company are advanced and have served the market well for years, the interviewee acknowledged that newer machines (e.g., presses, tools) from competitors are now capable of producing faster. As a result, the interviewee stressed the importance of continuous development to avoid losing market position. The machines produced internally are typically configured to meet a fixed output level, so there is less emphasis on efficiency parameters if customer demand is met.

The participant also reflected on the potential benefits of simulation. The participant noted that simulation could reduce the time needed for design, testing, and implementation. However, at present, the company uses simulation only for robot programming, specifically to validate reachability and speed. The interviewee explained that the idea of broader simulation use is under discussion within the company. One challenge that was pointed out was the significant time investment required to develop an accurate and reliable simulation model. To make full use of simulation, the company would need to hire a dedicated employee with expertise in the relevant software. The interviewee added that once the simulation modules are standardized, they will become easier to maintain and reuse in future projects.

Regarding optimization, the participant stated that the company currently does not apply any optimization methods, neither software-based nor mathematical. Instead, they rely on manual calculations to estimate throughput, cycle time, and production rate. Nevertheless, the participant recognized that implementing optimization tools could provide a competitive advantage. Such tools could help improve process efficiency, such as minimizing unnecessary robot movements or increasing robot availability. A key barrier, however, is time. The company operates under tight delivery schedules, which leaves little room for experimentation or the application of new optimization methods.

The interviewee emphasized that improvements should not only focus on machine performance but also on workflow and strategic planning. For example, the primary operational goal is to ensure that all end caps are delivered to the next process in the required quality. To achieve this, the company uses recorded video footage to identify and resolve issues in the production process. The interviewee also noted that customers continually demand higher machine speeds, and optimization could provide a mathematical basis for meeting those expectations reliably.

One specific improvement mentioned was enabling the robot to determine how many stacks of product to move between processes. Currently, this decision is managed using sensors and timers, but this method has led to malfunctions in some cases.

4.1.3 Participant C: Automation engineer

The participant is an automation engineer whose responsibilities include robot programming, onsite installation at the company and customer locations, as well as pre-studies for future projects. The interviewee is primarily responsible for improving robot functionality and validating reachability and cycle time in new systems.

When asked about the role of automation, it was noted that more companies are moving toward automated systems to achieve faster production, higher efficiency, and more ergonomic working conditions for operators. Given the production rate and customer demands, it was explained that maintaining the required output using manual processes would be highly challenging and would require a large number of operators. It was clarified that the company's focus is not on producing the product (e.g., can ends), but rather on developing machines that support processes such as distribution, packaging, and transfer. One of the key challenges in automation, it was added, is that customers are consistently requesting higher production rates and faster machine cycles, which makes it difficult for the company to rely on selling standardized machines.

It was explained that the participant is responsible for creating initial simulations to reflect customer requirements and evaluate how effectively the proposed machine can perform. These simulations are focused on robot reachability and cycle time. It was added that many of the machines sold by the company are already tested and standardized to a certain degree, which often eliminates the need for full-scale simulation. However, in more complex or tailored cases, simulations are used to propose higher-level solutions.

Regarding simulation accuracy, it was stated that the results are highly reliable, primarily because simulations are limited to reachability and cycle time checks. It was emphasized that simulation has saved the company significant time during development by reducing the number of physical tests or scenarios that need to be validated. It was also mentioned that no optimization techniques have been used, either in simulation or in general company operations. Nevertheless, it was expressed that incorporating advanced optimization techniques would be highly beneficial. In this view, optimization could help improve machine performance and potentially reduce energy consumption, an area that has not yet been a focus within the

company. At present, OEE is the only method used to assess machine efficiency and product throughput.

4.1.4 Participant D: Sales and Marketing manager

The participant currently works as the Marketing and Sales Manager, with responsibilities both in commercial and technical domains. A background in mechanical engineering was noted, and the participant was in the role of a mechanical engineer when starting at the company. In that capacity, involvement included machine development, designing solutions, and participation in development projects before a transition into sales and marketing occurred. Due to extensive experience within the company, close collaboration is maintained with both the automation and mechanical departments. In the current role, responsibility is held for preparing quotations, cost estimates, and managing client interactions. It was explained that the sales process typically occurs in two phases: first, a meeting involving the client and engineers to propose solutions, and second, the finalization of deals and contracts.

When asked about automation, it was stated that the company specializes in offering automated solutions for the can-ends market. It was emphasized that demand for automation is growing within the industry as it increases operational efficiency and reduces ergonomic risks for operators. Product quality and consistency were also highlighted as central to client expectations. It was explained that the company takes full responsibility for delivering complete process solutions, including layout planning, drawings, and machine systems, rather than simply providing machines. Although some clients still request systems involving more manual labor, this typically depends on their production volume and specific operational needs. It was noted that cost and machine capability are the primary factors influencing customer decision-making. While competitors may offer machines at a lower cost, these often fail to deliver the promised production output. Machines offered by the company come at a higher price but consistently meet or exceed performance expectations.

Regarding the use of simulation in the sales process, it was expressed that although simulation offers clear benefits in terms of visualization and product validation, its role in sales remains somewhat limited. It was explained that simulations must be both reliable and adaptable to client-specific requirements. Features such as machine motion, 3D visuals, and system layouts can support the sales process by helping customers better understand proposed solutions; however, the development of such simulations is both costly and time-consuming. Therefore, it was suggested that simulation is better suited to the engineering and design phases than sales presentations. Nonetheless, it was acknowledged that simulation adds value by validating

machine capabilities and providing performance assurances. It was also noted that energy consumption is becoming increasingly important for clients, and simulation could play a role in analyzing and optimizing energy usage.

It was mentioned that no personal experience with optimization techniques exists, though their potential benefits in improving certain machine components for enhanced speed and efficiency were recognized. However, from a sales perspective, it was observed that customers rarely focus on the internal details of optimization. Instead, customer priorities center on the machine's overall output and the company's ability to meet performance guarantees. It was explained that since the machines sold by the company are already tested and validated, customers are generally satisfied with performance assurances based on prior results. When a specific production output is requested by a customer, an evaluation is conducted to determine whether the existing machine configuration can meet the requirement. If not, design improvements are made to achieve the necessary performance.

4.2 Data Collection from Documents

To accurately develop and validate the simulation model, a document analysis was performed based on multiple data sources provided by the case company. Since direct access to the live production environment was limited, secondary documentation was critically important for extracting structural, functional, and operational information. Different types of documents, including CAD models, process flow diagrams and video recordings were carefully reviewed and analyzed. Each document type played a specific role in either constructing the simulation environment or defining and validating the model parameters to reflect real-world system behavior. The following sections describe the document analysis process in detail.

4.2.1 CAD Files

A total of 1034 CAD files were collected from the mechanical design engineers and systematically analyzed to support the development of the simulation environment and to gain a detailed understanding of the robot and the tool's specific operational mechanisms.

Each component within the CAD assemblies was individually evaluated to determine whether it held functional significance specifically for the simulation environment. Components that did not impact simulation behavior, such as internal fasteners, bolts, wiring elements, and purely decorative features, were merged into their parent assemblies to preserve the overall visual integrity while optimizing model performance.

Components critical to simulating operational logic, such as grippers, magnetic holders, and mechanical actuators, were maintained as independent functional entities. These parts were mapped into the visual simulation tool to ensure that their motion sequences and interactive behaviors were accurately represented during simulation runs.

4.2.2 Process Flow Diagrams

The process flow diagrams were provided directly by the automation manager and served as a fundamental reference for understanding the overall production logic. These diagrams were systematically analyzed to extract task dependencies, event sequences, and operational logic essential for the construction of the simulation model.

Each module including the press, synchronizers, infeed pushers, robotic arm, buffer trays, and outfeed pushers was described verbally during discussions with the automation manager. Detailed notes were taken to capture module-specific functions, transition rules, and operational expectations. Following the document analysis, every module was physically observed and validated on the test machine located at the case company's facility. This hands-on verification ensured that the documented process flow accurately reflected real-world system behavior and allowed for the correction of any discrepancies between the written diagrams and actual operations.

Critical event rules such as the distribution of stacks by synchronizers, robotic arm decision logic based on outfeed availability, and buffer tray changeover mechanisms were identified, formalized, and implemented as discrete events within the DES environment. In addition to the DES model, the extracted operational logic and workflow structure were also incorporated into the visual simulation environment using Emulate3D. This dual-model approach ensured that both analytical and visual aspects of the production system were accurately represented and validated.

4.2.3 Video Recordings

A total of seven video recordings were utilized to support the analysis and development of the simulation model. These videos consisted of recordings made by the researchers during internal testing of the robotic cell at the case company, as well as footage obtained from customer production facilities operating under real-world conditions.

The videos served a dual purpose: to observe and document the overall process flow within the automated system and more importantly to compensate for the lack of time-based motion data regarding the robotic arm. Although detailed information on speed, acceleration, movement

types, and material handling was available through documentation and discussions, explicit motion durations were not recorded. Therefore, video analysis was critical for extracting empirical timing information required for accurate simulation modeling. Detailed Time Study conducted to have the most realistic simulation possible for the future steps. Detailed Time Study can be found in Section 5.1.2.

The motion duration data extracted from the videos were validated and verified directly by the automation engineers and the automation manager. Only after this validation process were the finalized time values incorporated into both the DES and the Emulate3D visual simulation environment, resulting in a simulation model that closely mirrors the real-world system behavior with high accuracy and technical credibility.

Table 4 summarizes the document types reviewed in this study, including their sources, the quantity of data collected, and their specific purposes within the simulation modeling and verification phases.

Document Type	Source	Amount/Quantity	Purpose in Simulation
CAD Files	Case Company (Mechanical Engineers)	1034 CAD files	Geometrical modeling of the production cell, simplification of robot and tool structures, and gaining a detailed technical understanding of individual robotic components.
Process Flow Diagrams	Automation Manager	1 main flow diagram	Extraction of workflow logic, definition of each module’s operational responsibilities, and gathering of technical parameters necessary for accurate system modeling.
Video Recordings	Researchers (Internal Testing) + Customer Sites	7 videos (2 internal, 5 customer)	Extraction of robotic motion timing data (pick-up, drop-off, buffer transfer) and detailed observation of real-world production systems at customer facilities for workflow analysis.

Table 4: Review of Document Analysis

5 Results

This chapter presents the key findings from the simulation work conducted for the automated machine cell. It includes results from both the visual model developed in Emulate3D and the discrete event simulation created in Arena. The simulations were based on observational data and time studies, while some internal documents were excluded due to ethical considerations. The results are structured under two main sections: simulation implementation and simulation output. The implementation part covers system setup, time measurements, and layout modeling. The output section presents the current system performance and compares it with alternative layout and speed configurations using performance indicators such as throughput, cycle time, and OEE.

5.1 Simulation Implementation

To construct a realistic and reliable simulation model of the automated machine cell, a multi-layered approach was employed combining with flow charts, time study, visual simulation integration, and DES modeling. The development process aimed to create a digital representation that accurately replicates the behavior of the physical system under various operational conditions. Emulate3D was used to build the 3D visual simulation model for layout planning and motion verification, while Arena software was employed to implement DES logic for performance evaluation and scenario analysis.

5.1.1 System Flow and Module Overview

Through a comprehensive combination of observations, document analysis, and detailed discussions with automation engineers and the automation manager, a complete understanding of the system's operational process flow was established. The objective of this section is to describe the clear movement of products through the various modules that constitute the automated cell.

The system initiates from the press operation, where can ends are produced, and follows a structured path through synchronizers, infeed pushers, a robotic arm, buffer trays, and outfeed pushers before reaching the subsequent processing stages. Although some components, such as the press and synchronizer modules, are not directly part of the simulation scope, they play a critical role in influencing the system's operational flow and were thus included to provide complete contextual understanding.

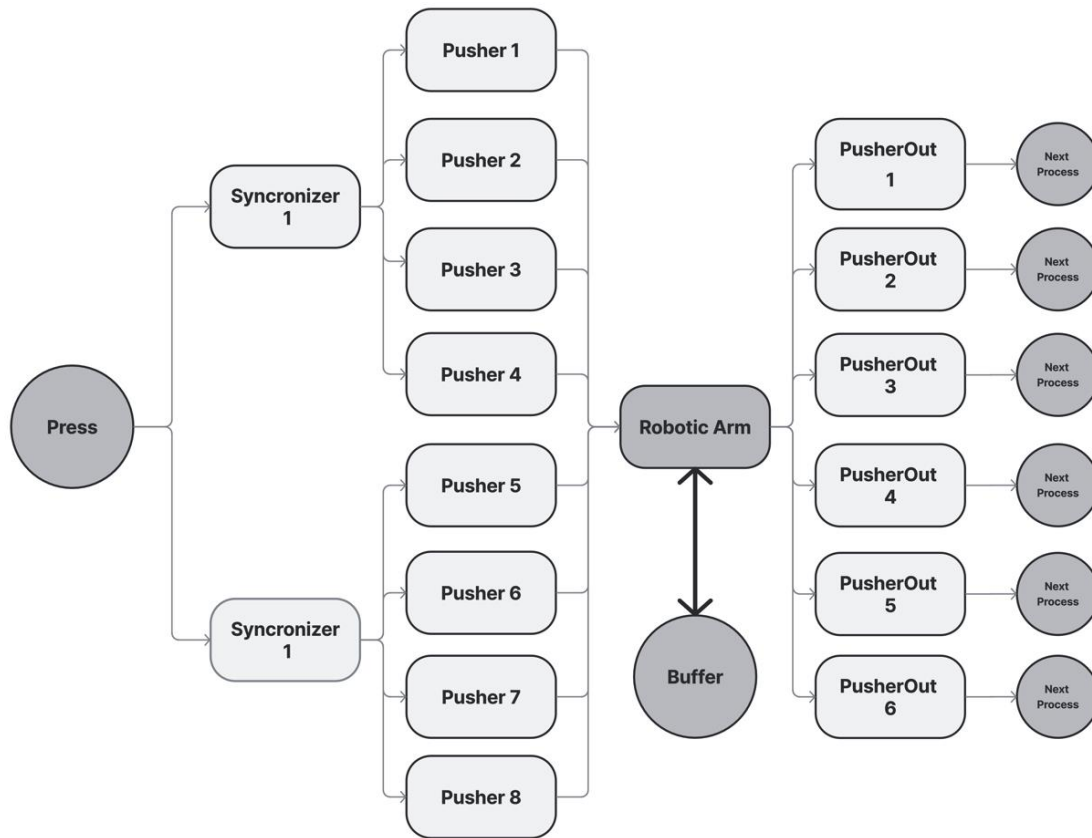


Figure 7: *System Workflow*

The following sections provide a detailed explanation of each process shown in the workflow diagram in Figure 7, focusing on their operational roles and interactions within the system:

Press: Although the press is not directly part of the simulation model developed in this study, it represents the starting point of the production flow and plays an important role in understanding the overall system behavior. The press is responsible for producing can ends, which are used as the primary input for the following automated processes.

The press cycle produces approximately 12,600 can ends per minute. After production, the can ends are transferred downstream toward the synchronizers for further handling. Understanding the press's capacity and output speed was necessary to align the material flow within the simulation and ensure consistency across the workflow analysis.

Synchronizers: The synchronizers are responsible for the initial distribution of the produced can ends into the infeed pushers equally. In the system, there are two synchronizers operating in parallel, each managing the flow of products to different sets of pushers. Each synchronizer receives approximately 6,300 can ends per minute from the press operation. Their main task is to divide the incoming flow and distribute it to the pushers in groups of 1,000 can ends.

In the current setup, Synchronizer 1 feeds the first four pushers, while Synchronizer 2 feeds the remaining four. However, the number and distribution configuration of the synchronizers can be adapted depending on customer requirements or production volume demands. Although the synchronizers are not directly included within the simulation model, their role is essential for maintaining a continuous and balanced material flow between the press operation and the downstream pusher conveyors.

Infeed Pushers: After the can ends are divided by the synchronizers, they are transferred to the infeed pushers. In the current system configuration, eight infeed pushers are installed to receive and transport the incoming products toward the robotic arm handling area. Unlike traditional conveyor belts, the infeed pushers operate through a linear pushing mechanism that moves the can ends along a specially designed guideway. A physical pusher unit, positioned behind the product stacks, pushes them forward at controlled intervals without allowing queuing on the pusher itself. This ensures synchronized and orderly movement throughout the process.

Each infeed pusher operates with a fixed cycle time of ≈ 4 seconds for each travel, maintaining a steady flow rate that matches the system's throughput requirements, and the return motion of the internal pushing mechanism takes approximately the same amount of time, ensuring a consistent cycle for repeated operations.

The pusher mechanism offers significant advantages, including the ability to manage high-speed transfers independently of conveyor speed constraints, thus improving line balancing and optimizing floor space utilization. Additionally, the number, dimensions, and configuration of the infeed pushers can be customized based on specific customer requirements.

Robotic Arm: The robotic arm is responsible for transferring the can ends from the infeed pushers to the outfeed pushers under normal operating conditions. However, in cases where the outfeed pushers are busy or in maintenance the robotic arm redirects the can ends from the infeed pushers to the buffer trays.

The robot is equipped with a specially designed dual holding unit tool, which allows it to handle two stacks of products simultaneously. Each side of the tool operates independently, enabling the robot to pick up two separate stacks of can ends in a single movement cycle and place them accurately onto the corresponding outfeed pusher lines. The tool incorporates magnetic and mechanical gripping systems tailored to the material and handling requirements of the products, ensuring fast, reliable, and damage-free transfers. Figure 8 provides a visual representation of

the dual gripper tool as implemented in the simulation environment, highlighting its symmetrical layout and independent actuation design.

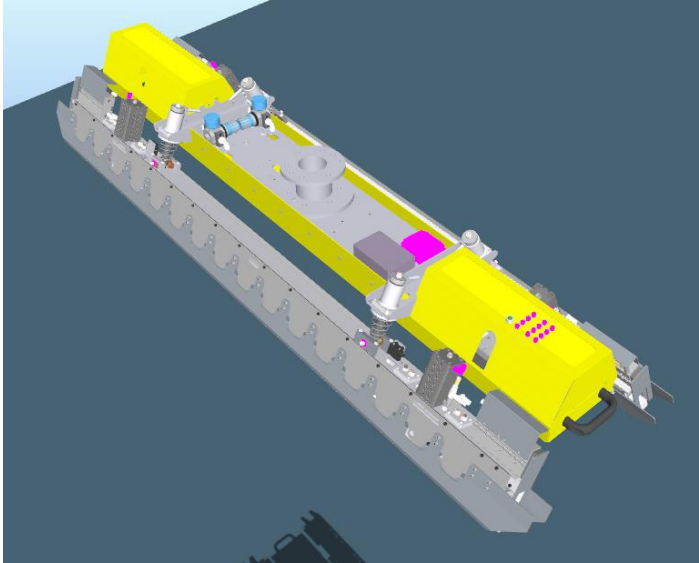


Figure 8: CAD of Dual Gripper Tool

This dual carrying capability significantly reduces the robot’s cycle time and increases the overall system throughput.

Due to the absence of precise motion duration data in the company's internal documentation, a detailed time study was conducted. Speed, acceleration, and material handling characteristics were initially obtained from the company's engineers and automation manager, while movement durations were later measured through structured observations and validated collaboratively.

The Robotic Arm plays a critical role in synchronizing the material flow between the infeed pushers, buffer trays, and outfeed pushers, ensuring a smooth, flexible, and efficient production process.

Buffer: The buffer, also referred to as the tray system, serves as a temporary storage and transfer platform for the can ends, when outfeed pushers is not possible due to system constraints. Such constraints typically occur when the outfeed pushers are fully occupied, undergoing maintenance, or when downstream production processes are temporarily delayed. In these situations, the robotic arm redirects the flow of products into the buffer trays to maintain continuous operation.

The buffer system uses custom-manufactured trays made from lightweight, durable, and dust-resistant sheet metal. Each tray is engineered with designated compartments to securely hold

individual can ends, minimizing the risk of movement or damage during transportation. A single buffer unit incorporates a vertical stacking mechanism capable of holding up to seven trays simultaneously, allowing for high-density storage without compromising accessibility.

Outfeed Pushers: The outfeed pushers are responsible for transferring the can ends received directly from the robotic arm to the subsequent processing stations. They operate based on the same linear pushing mechanism as the infeed pushers, moving products forward at fixed intervals without allowing queuing on the pusher surface.

Each outfeed pusher operates with a fixed cycle time of ≈ 4 seconds each travel, identical to the infeed pushers, ensuring synchronized and efficient material flow across the system. The return motion of the pusher mechanism also takes approximately 4 seconds, resulting in a complete cycle duration that remains consistent across operations. In the current system configuration, six outfeed pushers are installed. The number, dimensions, and configuration of the outfeed pushers can be customized according to customer requirements or future production demands.

The operational data determined through document analysis, field observations, and time studies have been compiled and are presented in Table 5 as the primary input parameters for the simulation model.

Module/Operation	Key Data
Press	-12,600 can ends per minute
Synchronizers	-6,300 can ends per minute per synchronizer -1,000 can ends per stack
Infeed Pushers	-8 infeed pushers - ≈ 4 seconds travel time - ≈ 4 seconds return time
Robotic Arm	-2 stacks per cycle -timing analyzed in Time Study section
Buffer (Tray System)	-Buffer movements for Robotic Arm analyzed in Time Study section

Outfeed Pushers	-6 outfeed pushers - \approx 4 seconds travel time - \approx 4 seconds return time
------------------------	--

Table 5: *Input Data for the Simulation Model*

5.1.2 Time Study

The internal documentation provided by the case company was first analyzed to gather technical information relevant to the robot's configuration. While data regarding the robot's speed, acceleration rates, and material handling capabilities were available through document analysis, no specific information related to motion durations or operational cycle times could be identified. Due to the absence of such critical time-based parameters, it was necessary to conduct a dedicated time study. The time study was designed to empirically capture realistic duration values for key robotic operations, thereby enabling the development of a simulation model that accurately reflects the system's dynamic behavior under real-world conditions.

The time study was exclusively designed for the robotic arm and covered the following five main actions observed in the cell:

- Move to Pick-Up
- Move to Drop-Off
- Tool Movement (including pick-up, drop-off, and handling of a second part)
- Move to Buffer
- Move from Buffer to Infeed

Each action was measured 15 times using a stopwatch to ensure statistical consistency and account for process variability from the video recordings. To achieve high precision, the videos were reviewed at 0.10x playback speed, enabling frame-by-frame identification of motion start and end points. This slow-motion method allowed the researchers to capture subtle movement transitions and inflection points with high accuracy. As a result, the durations extracted from the footage were considered highly reliable and realistic representations of the robot's performance under standardized conditions. This observation methodology enhanced the overall confidence in the measured durations and the quality of data used in simulation modeling. After the measurements were completed, the resulting values were reviewed and validated collaboratively with automation engineers and the automation manager at the case

company. The complete data set including all 15 measurements for each action is presented in the Table 6 below:

Iteration Number:	Move To Pick-Up (Seconds)	Move To Drop-Off (Seconds)	Tool Movement (Pick/Drop-Off) (Seconds)	Move To Buffer (Seconds)	Move From Buffer to Infeed (Seconds)
1	1.87	2.12	0.84	2.20	1.80
2	2.24	1.80	0.92	1.76	1.99
3	1.88	2.16	0.76	2.28	1.82
4	2.12	1.70	0.87	1.69	2.13
5	1.72	1.88	1.12	2.24	1.92
6	2.24	2.04	0.96	2.01	1.98
7	1.80	2.16	0.88	1.96	1.62
8	1.76	1.80	0.92	2.12	2.37
9	2.28	2.12	1.26	2.07	1.84
10	1.72	1.84	0.78	1.80	1.92
11	1.96	2.34	0.97	2.32	2.13
12	2.28	1.92	0.88	1.96	1.77
13	1.76	2.04	0.92	2.27	1.34
14	1.88	1.84	1.12	1.92	1.98
15	2.24	2.20	0.77	1.80	2.07
Average	1.98	1.99	0.91	2.03	1.91
Min	1.72	1.70	0.76	1.69	1.34
Max	2.28	2.34	1.26	2.32	2.37

Table 6: *Time-Study Output*

Following the data collection, the average, minimum, and maximum durations were calculated and are presented below in a simplified summary table. These statistical values were used as input parameters for the DES model and visual simulation tool (Emulate3D) to replicate robot behavior in the most realistic and accurate way possible, as presented in Table 7.

Operation	Average (s)	Minimum (s)	Maximum (s)
Move To Pick-Up	1.98	1.72	2.28
Move to Drop-Off	1.99	1.70	2.34
Tool Movement (Pick/Drop)	0.91	0.76	1.26
Move To Buffer	2.03	1.69	2.32
Move from Buffer to Infeed	1.91	1.34	2.37

Table 7: Data Summary for the Robotic Arm

The time study data was applied across the two simulation environments. In Emulate3D, the detailed motion steps were directly assigned to the robotic arm using individual path segments for each operation. This allowed the software to visually and dynamically simulate real-time robot movements between pick-up, drop-off, and buffer locations.

However, in the DES model, the robot is represented by a single process module that simulates the entire pick-and-place operation. Therefore, to accurately represent the total duration, the time values for Move to Pick-Up, Move to Drop-Off, and Tool Movement (Pick/Drop) were combined. Only the tool movement was doubled to replicate the actual movement, once for the pick cycle and once for the drop cycle. As a result, a triangular distribution of TRIA(4.94, 5.79, 7.14) seconds was used in the DES model to reflect the total handling time per cycle.

This approach was necessary due to the varying distances between the infeed and outfeed pusher units. Since these physical variations influence movement times, the aggregated time input ensures that the simulation remains adaptable to different layout configurations.

5.1.3 Failure and Quality Evaluation

To better simulate real-world production conditions, this section includes failure scenarios and system stoppages based on real-life experience shared by the automation manager. These values are not valid for every product manufactured by the case company and should be interpreted as indicative. They may vary depending on factors such as the maintenance status of the pusher mechanisms, their specific versions, downstream processes, the condition of the robot, and calibration settings. All provided figures are approximate and based on practical insights.

According to the automation manager, infeed pusher units typically experience stoppages approximately every four hours, each lasting around six minutes. In the simulation, these failures were modeled using a TRIA(3,4,5) distribution for the interval between events and TRIA(5,6,7) for the duration. One of the most common causes of these interruptions is Can Stack jams, which occur due to factors such as insufficient lubrication, lack of regular maintenance, and the use of older mechanical versions. In addition to these issues, other stoppages may also occur because of routine maintenance activities or cleaning procedures.

Outfeed pusher failures occur less frequently than those at the infeed side. The automation manager indicated that these stoppages usually happen every nine hours and last about six minutes. These are primarily linked to downstream process delays and Can Stack jams within the outfeed units. Like the infeed side, contributing factors include inadequate lubrication, lack of maintenance, and the presence of older mechanical versions. Additionally, other stoppages may result from routine cleaning procedures or maintenance work performed on the downstream equipment. In the simulation, these failures were implemented using a TRIA (8,9,10) distribution for the time between events and TRIA (5,6,7) for the duration.

Regarding the robot and tool, the automation manager stated that no production-related stoppages have been reported. It was explained that the robotic system and tool operate reliably under normal conditions and only require scheduled maintenance approximately once per month. Since such maintenance activities are infrequent and do not interfere with daily operations, robot-related failures were not included in the simulation model.

The failure rates and durations used in the simulation model are summarized in Table 8 below.

Pusher Name	Type	Up Time	Up Time Units	Down Time	Down Time Units
Pusher 1	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher 2	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher 3	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher 4	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher 5	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher 6	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher 7	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher 8	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher 9	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher 10	Time	TRIA(3,4,5)	Hours	TRIA(5,6,7)	Minutes
Pusher Out 1	Time	TRIA(8,9,10)	Hours	TRIA(5,6,7)	Minutes
Pusher Out 2	Time	TRIA(8,9,10)	Hours	TRIA(5,6,7)	Minutes
Pusher Out 3	Time	TRIA(8,9,10)	Hours	TRIA(5,6,7)	Minutes
Pusher Out 4	Time	TRIA(8,9,10)	Hours	TRIA(5,6,7)	Minutes
Pusher Out 5	Time	TRIA(8,9,10)	Hours	TRIA(5,6,7)	Minutes
Pusher Out 6	Time	TRIA(8,9,10)	Hours	TRIA(5,6,7)	Minutes
Pusher Out 7	Time	TRIA(8,9,10)	Hours	TRIA(5,6,7)	Minutes
Pusher Out 8	Time	TRIA(8,9,10)	Hours	TRIA(5,6,7)	Minutes

Table 8: Failure Input for the Discrete Event Simulation

In terms of product quality, information gathered through informal discussions with the automation manager indicated that approximately one out of every 1,000 products become defective due to handling issues caused by the tool mounted on the robotic arm. Specifically, the defect typically occurs when a product is unintentionally dropped during the pick-and-place process. Although such incidents are rare, they have been acknowledged as a recurring risk

under certain conditions. Based on this insight, the quality rate used in the simulation model was set to 99.9 percent to reflect realistic system behavior.

$$\text{Quality Rate} = 99.9\%$$

5.1.4 CAD and Layout Integration

To construct an accurate virtual model, the case company provided a set of technical CAD drawings representing the physical layout of the machine cell. These drawings included component dimensions, physical boundaries, and machine placement data. The CAD files were initially reviewed and simplified to remove unnecessary design details that could slow down the simulation software, such as bolts, engravings, or decorative geometry.

The cleaned models were imported into Emulate3D, where the relationships between modules such as the press, synchronizers, infeed and outfeed pushers, robotic arm, and buffer system were verified against the actual physical setup observed during on-site visits. Manual adjustments were made to align CAD-based positions with real-world distances and operational clearances, ensuring that robot reaches, material travel paths, and spatial constraints reflected actual production conditions. Additionally, the CAD layout served as a reference for the logical flow design used in the Arena DES model. Although the Arena model does not use visual representations, the structure and flow logic of the simulation, particularly for travel delays, entity routes, and buffer logic, were grounded in the spatial configuration provided by the CAD drawings.

This integration of CAD data helped ensure consistency between the physical factory layout and the virtual simulation environments, improving the reliability of layout-based scenario testing and supporting more realistic performance evaluations. How technical layouts were translated into CAD files and integrated into Emulate3D.

5.1.5 Visual Simulation Modeling

For the visual functional simulation, Emulate3D software was utilized to replicate a single automated production cell from the case company's operations. The primary objective of this simulation was to validate the layout and analyze the robot's behavior, with particular attention to reachability, task feasibility, and motion cycle durations across different configuration scenarios. Rather than targeting full virtual commissioning or PLC integration, the simulation served as a tool to support early-stage validation of design logic and to collect time-based performance data for scenario development.

Emulate3D, developed by Rockwell Automation, is widely used in logistics and material handling applications, particularly in systems involving conveyors, palletizing, and robotic operations. Although PLC connectivity was not implemented in this project, the software supports broad integration across various industrial brands and communication protocols, making it suitable for future use cases. A key feature utilized in this study was the “CAD is the Model” function, which enabled the direct import and automatic conversion of CAD files into functional simulation elements.

As illustrated in Figure 9, the “CAD is the Model” interface in Emulate3D allows users to import CAD geometries directly into the simulation environment.

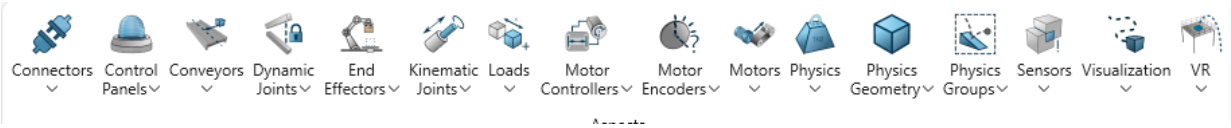


Figure 9: *CAD is the Model Interface*

While this function provided a structural foundation for building the model, it did not generate ready-to-use components. All simulation relevant properties, such as kinematic behavior, physical constraints, motion control, and interaction logic, had to be defined and configured manually by the researchers. This ensured that the simulated system not only matched the geometry of the real cell but also replicated its functional behavior under operational conditions.

To ensure a realistic and functional digital representation, all critical simulation functionalities, such as Physics, Physics Geometry, Kinematic Joints, Motors, End Effectors, and Connectors, were applied in the model. Physics was used to simulate real-world physical interactions, including mass, and frictional forces affecting moving components. Physics Geometry defined the collision boundaries and contact surfaces, allowing objects to interact accurately based on their physical shapes. Kinematic Joints enabled rotational and linear motion between connected bodies, replicating the degrees of freedom observed in the actual robotic arm.

Motors controlled the speed and movement of mechanical parts such as joints and axes, ensuring the robot followed its intended motion paths. End Effectors represented the gripping mechanism of the robot, responsible for executing the pick-and-place tasks within the cell. Finally, Connectors established logical and mechanical relationships between components, enabling coordinated behavior and communication across the simulation structure.

The simulation was built using Emulate3D’s internal logic-based scripting system, which enabled early-stage prototyping and flexible control logic adjustments without relying on

external PLC hardware. The software’s add-in support for CAD platforms such as SolidWorks further enhanced interoperability during model development by enabling seamless geometry transfer into the simulation environment.

To ensure accuracy, all major physical components in the model were based directly on the real machine cell. The robot used in the simulation was the same model as the one implemented in the actual production environment. The tool mounted on the robot was also modeled with identical dimensions, ensuring that gripping behavior and spatial interaction mirrored real-world performance. Figure 10 presents a simulation view of the robot with the mounted tool, as modeled based on CAD data from the case company. The geometry was manually integrated into the simulation environment to ensure accuracy.

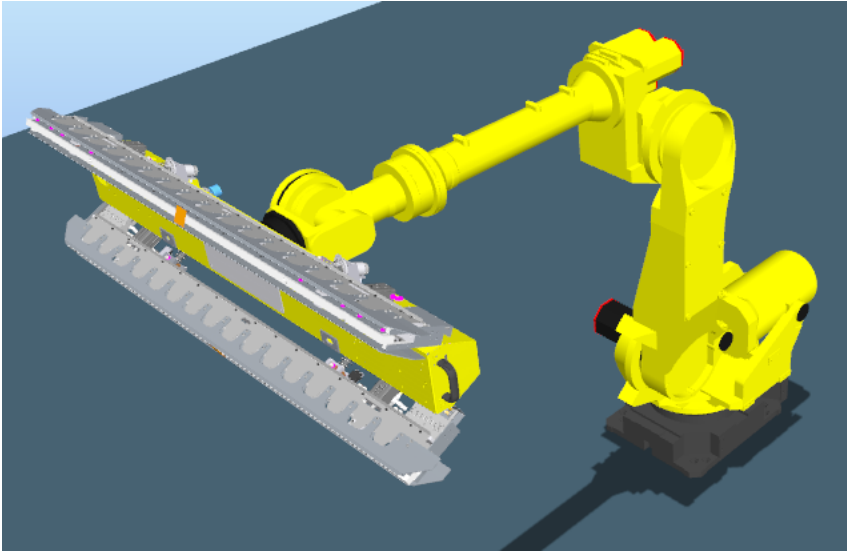


Figure 10: *Robot and Tool Illustration in Emulate3D*

Furthermore, the conveyors and buffer units in the simulation were constructed using the same width, height, and length measurements as the actual equipment used by the case company. These details were confirmed through CAD documentation and physical observations at the facility, allowing the simulation to represent real spatial conditions with high precision.

Although a range of standard components were available within the software library, including conveyors, sensors, and signal triggers, further configuration was necessary to replicate the dynamic behavior of the actual system. Logic was implemented through node-based scripting to define sequencing, event conditions, and interactions between modules. While Emulate3D provides a large catalog of industrial robots from manufacturers such as Fanuc, ABB, and KUKA, these models are not directly functional for simulation purposes

upon insertion. Therefore, the researchers manually configured essential parameters such as Kinematic Joints, Motor speeds, physical material characteristics, and Tool Center Point (TCP) positions to enable accurate motion behavior.

Figure 11 shows the manually defined Tool Center Points (TCPs) used in the simulation based on the actual geometry of the tool provided by the case company. For clarity, the active TCPs are indicated in red.

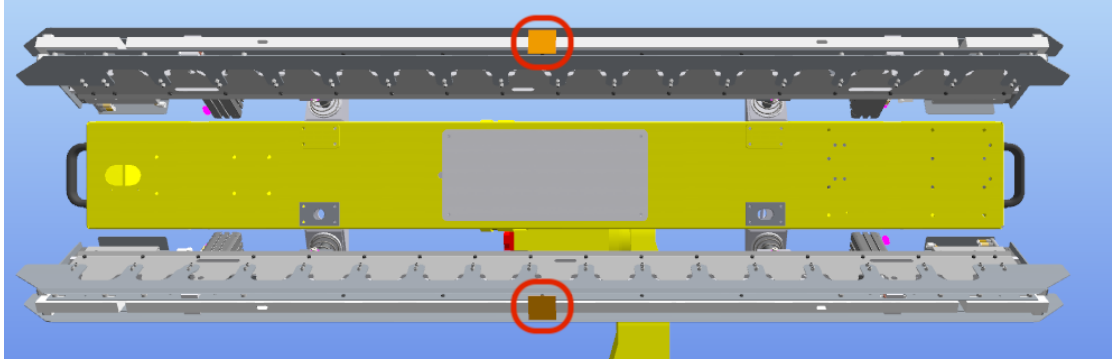


Figure 11: *Tool Center Points*

The manual definition of TCPs was essential for aligning the robot’s interaction logic with its physical tool geometry. Accurate positioning ensured that pick-and-place operations in the simulation corresponded precisely to the behavior expected in the real cell. Combined with calibrated motion paths and kinematic constraints, this alignment allowed for a realistic representation of robotic interaction within the system.

A custom script was also developed to define the robot-mounted tool, making sure that its geometry and TCP were properly aligned with the actions required in the simulation. Important motion parameters like speed, orientation, and task sequence were manually set to reflect the timing observed during time studies. One of the challenges during this phase was importing and aligning the CAD files of the robot and the tool. This process often required several manual adjustments to get things working correctly. Combined with the unique scripting logic of Emulate3D, these technical details made the learning process more demanding.

Robot movements were programmed using teach points, which are specific positions in space that the robot is instructed to move through during its cycle. In this project, a high number of teach points were created to ensure that the robot followed smooth, accurate, and realistic motion paths. These points were used not only for basic pick-and-place movements but also for intermediate transitions, alignment maneuvers, and navigation between areas such as buffer and outfeed. By carefully adjusting the location and sequence of each teach point, the researchers

ensured that the simulated motion closely resembled the robot's expected performance in the actual production cell.

Figure 12 illustrates the teach point configuration within the simulation environment, highlighting the robot's programmed motion path between different stations of the production cell.

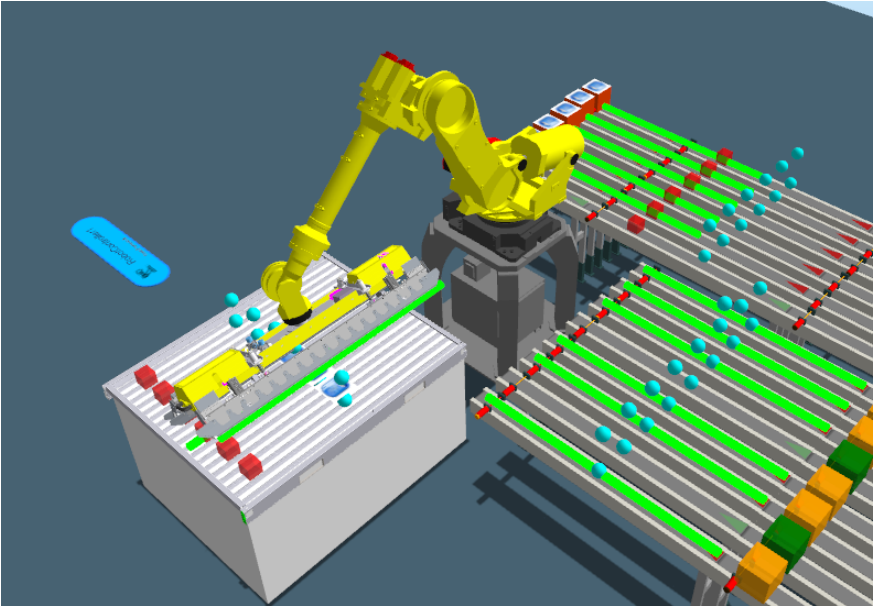


Figure 12: *Teachpoints Configuration*

Once the core model was operational, different robot setups and layout scenarios were tested. These included using various robot models, changing cell layouts, trying single-part and dual-part handling, and exploring different ways of redirecting parts to the outfeed. Each test was used to check whether the setup worked logically and whether the motion timing matched real-life expectations. During these tests, time-based data was collected from the simulation environment to support later stages of quantitative evaluation. This included measuring task durations, cycle times, and delays through built-in timers and manually defined observation points. The collected data served as the foundation for the DES and was also used to compare the efficiency of different configuration scenarios. After the model was finalized, it was shared with the automation and design teams at the case company. Their response was very positive, and the model increased interest in using simulation as a decision-making tool for future projects as well.

5.1.6 Discrete Event Simulation Modeling

In parallel with the visual simulation, a DES model was developed using Arena Simulation Software to capture the logic and dynamics of the automated machine cell under realistic operating conditions. The model structure was based on time parameters obtained through structured observations and detailed video analysis. Key inputs included robot cycle times, conveyor sequencing, buffer logic, and idle-state durations.

The simulation logic was constructed using standard Arena modules for entity creation, decision-making, processing, queuing, and transport. Time-based data were manually integrated into the model using a combination of fixed values and probability distributions derived from field measurements. Control rules such as pusher availability checks, path selection, and resource allocation were embedded within the logic flow to simulate realistic system behavior. Model validation was carried out in collaboration with the case company’s automation engineer and was further supported by internal process documentation. This ensured a high degree of alignment between the simulation model and the actual system dynamics.

Figure 13 presents the overall process structure and logic flow of the Arena-based DES model used for scenario analysis.

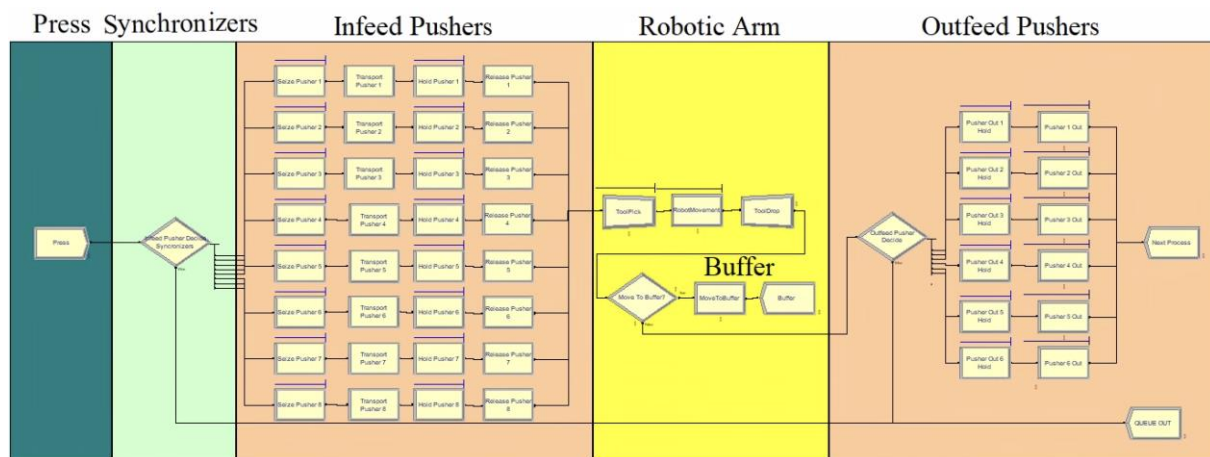


Figure 13: Discrete Event Simulation Model in Arena Software

The Arena simulation model begins with the Press module, implemented using a Create module. This module generates entities at fixed intervals to reflect the constant production speed of can stacks in the actual system. Following this, a Decide module functions as a logical synchronizer. While the real system uses two physical synchronizers, Arena enables the use of a single decision logic to evenly distribute can stacks across the eight infeed pushers. The Press and Synchronizer logics are illustrated in Figure 14.

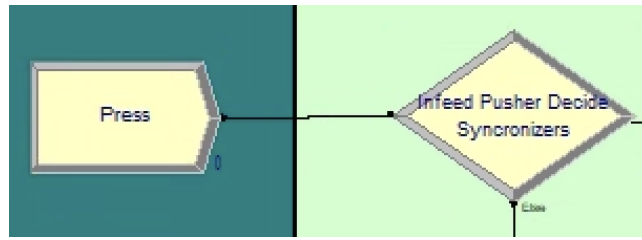


Figure 14: *Press and Synchronizer Module in DES*

As it is shown in the Figure 15, the Infeed Pushers are modeled using Seize–Delay–Hold–Release modules sequence. First, the Seize module allocates the can stack to a specific pusher. Then, a Delay module introduces the constant pushing time observed in the real system. The Hold module ensures that the can stack remains on the pusher until the robot becomes available, preventing any queuing or overlap. Once the robot is ready, the Release module passes the stack to the next stage.

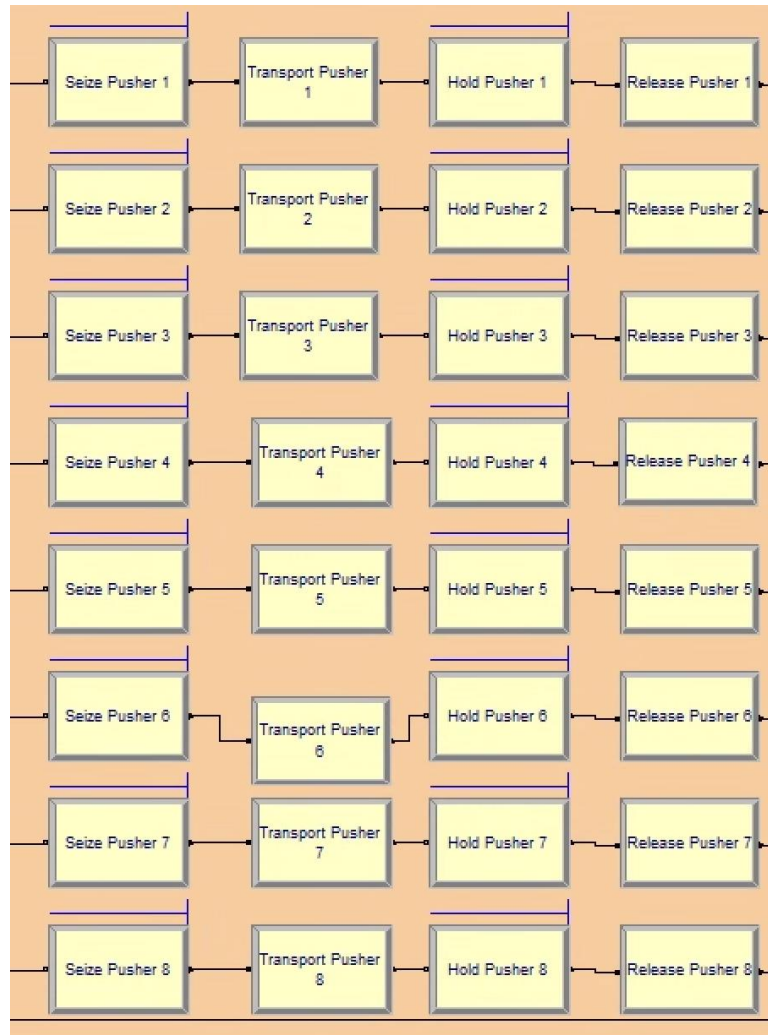


Figure 15: *Infeed Pusher Modules in DES*

The ToolPick module is implemented as a Batch module, combining two entities to simulate the robot’s dual-handling capacity. After batching, the grouped entities enter the RobotMovement section, modeled with another Seize–Delay–Release sequence. The movement durations, including pick-up and drop-off times, are based on the time study results. Next, the ToolDrop module is designed as a Separate module. This step splits the previously batched can stacks into two separate entities so that each unit can be tracked and analyzed independently in the simulation output. A Decide module then evaluates the availability of Outfeed Pushers. If no outfeed is currently available, the system uses a Decide module to route the entity to a Delay module named MoveToBuffer, which then directs it to the Buffer. The Delay module is implemented to simulate the additional time required due to the buffer’s relatively greater distance compared to the outfeed pushers. Figure 16 illustrates how each motion of the robotic arm is simulated in the model, including pick-up, transfer, and drop-off sequences.

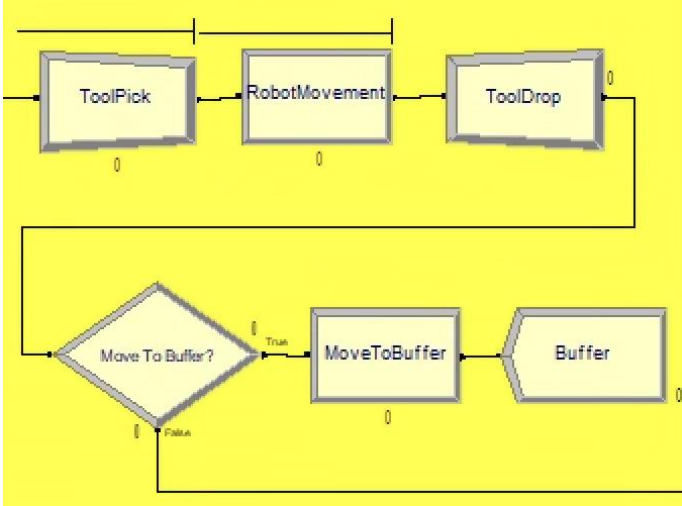


Figure 16: Robot Arm Module in DES

If space is available at the outfeed pushers, a Decide module evaluates the availability and evenly distributes the entities across the Pusher Out modules. Each outfeed pusher is modeled using the same Seize–Delay–Release logic as applied in the infeed zone. A Hold module is placed before each Pusher Out to prevent queuing and maintain correct pusher dynamics. Finally, entities pass through a Next Process module and are removed from the system via a Dispose module. Figure 17 illustrates the complete outfeed control logic, including the Decide, Hold, and Pusher Out modules.

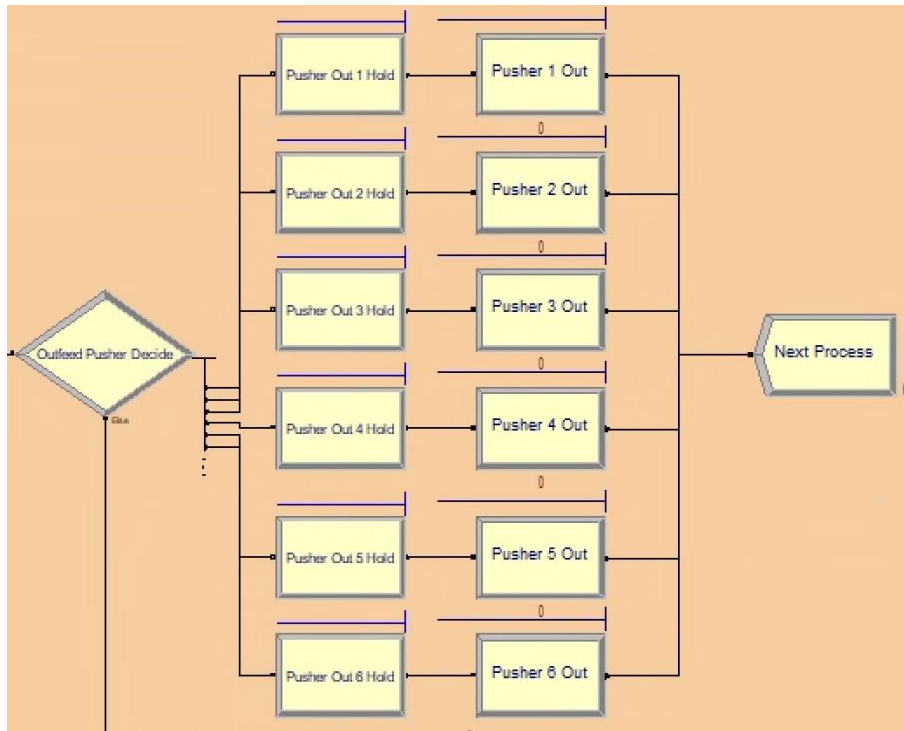


Figure 17: *Outfeed Pusher Modules in DES*

5.2 Simulation Output

This section presents the results obtained from the DES conducted across both scenarios: the infeed and outfeed pusher configurations, as well as the robot configuration. Each simulation scenario was replicated ten times, with each replication representing a 24-hour production period. The results aim to provide a comprehensive comparison of system performance under the different configurations evaluated.

5.2.1 Current state of the simulation

This section presents the results of the DES developed to replicate the operational behavior of the case company's automated machine cell. The simulation model was designed to reflect real production performance and to generate baseline values for key performance indicators, including throughput, robot utilization, waiting time, and OEE. Several important assumptions and constraints were considered during the development and execution of the model, as outlined below.

The simulation was created using the student edition of Arena software, which limits the system to processing a maximum of 150 entities at any one time. To work within this constraint, the total production volume of 12,600 can ends were represented as stacks, with

each stack containing 1,000 can ends. As a result, the simulation was set to process 12.6 stacks per minute, which is equivalent to one stack entering the system every 4.76 seconds.

$$\text{Stacks per minute} = \frac{12,600 \text{ cans}}{1000 \text{ cans /stack}} = 12.6 \text{ stacks}$$

$$\text{Time per stack (seconds)} = \frac{60 \text{ seconds}}{12.6 \text{ stacks}} = 4.7619 \text{ seconds}$$

The simulation was run for 10 replications, each covering 24 hours of production (or 86,400 seconds). Based on the defined production rate, this should result in approximately 18,144 stacks produced. However, the actual simulation output was 18,140 stacks. The minor shortfall of four stacks is attributed to items still in progress within the system at the end of the simulation, which had not yet reached the final disposal stage. These small losses reflect normal system behavior and are discussed further in the analysis of system availability and downtime.

$$\text{Expected output} = \frac{86400 \text{ seconds}}{4.7619 \text{ seconds per stack}} = 18,144 \text{ stacks}$$

To accurately assess system performance, the robot’s handling speed was carefully configured. The robot module in the simulation software was programmed to pick up two stacks at a time and transfer them to the outfeed pushers. Based on an analysis of the robot’s motion, its cycle time was modeled using a triangular distribution with a minimum of 4.94 seconds, a most likely value (mode) of 5.79 seconds, and a maximum of 7.14 seconds. The simulation recorded 9,070 robot pick-and-place cycles. Since each cycle handles two stacks, this aligns exactly with the 18,140 stacks processed.

$$\text{Mean cycle time} = \frac{\text{Min} + \text{Mode} + \text{Max}}{3} = \frac{4.94 + 5.79 + 7.14}{3} = 5.9567 \text{ seconds}$$

However, Arena treats each batch of two stacks as a single unit when calculating resource usage. This could lead to an underestimation of robot utilization if not corrected. To address this, the average of the triangular distribution was calculated and applied to all 9,070 robot cycles to obtain a more accurate estimate of active robot time. This adjustment resulted in a corrected robot utilization rate of approximately 62.5%. This means the robot was actively working for more than half the total simulation time, with the rest of the time spent waiting or idle.

$$\text{Utilization} = \frac{\text{Total operation time}}{\text{Total simulation time}} \times 100$$

$$\text{Utilization} = \frac{9,070 \times 5.9567}{86,400} \times 100 = 62.50\%$$

To evaluate system efficiency and identify potential bottlenecks, the average waiting time experienced by stacks was analyzed. This was done by collecting delay times from key modules in the model, specifically the Hold, Seize, and Release modules that represent areas where stacks wait due to limited resource availability.

The simulation generated a report that included the following values:

- Total output: 18,140 entities
- Value-added time (time without waiting): 21.9548 seconds
- Waiting time: 8.6604 seconds
- Total time per entity: 30.6152 seconds

OEE Calculation for Current State

Finally, the OEE value was calculated using the availability, performance, and quality metrics derived from the simulation results and company-provided data. The following formula was applied to consolidate these three components into a single measure of overall system efficiency:

$$\text{OEE} = \text{Availability} \times \text{Performance} \times \text{Quality}$$

This result serves as a baseline benchmark for evaluating all future scenario tests. It confirms that the existing layout and operation of the machine cell is already performing at a high level of efficiency, though moderate improvements may still be possible through layout optimization or operational tuning, as explored in the following sections.

Availability

Availability represents the proportion of planned production time during which the system is actively engaged in processing activities. In standard OEE calculations, it is typically determined as the ratio between actual operating time and planned production time (Ylipää et al., 2017).

In this study, due to the unavailability of total machine-level downtime logs in the Arena simulation environment, availability was calculated according to the logs of entities. Specifically, average waiting time per entity was used to represent downtime. As planned production time could not be directly obtained, total time per entity was used.

While this approach adapts the OEE formulation to the constraints of simulation modeling, it retains the conceptual integrity of the availability calculation by comparing effective processing time to total time in the system.

The calculation was carried out using the following formula:

$$Availability = \frac{\text{Total time} - \text{Waiting time}}{\text{Total time}} \times 100$$

In this case, the average total time per entity was 30.6152 seconds and the average waiting time per entity was 8.6604 seconds. These values were applied to the formula as follows:

$$Availability = \frac{30.6152 - 8.6604}{30.6152} \times 100 = 71.71\%$$

Performance

Performance refers to the degree to which a production system operates at its intended speed under actual working conditions. It is used to measure how efficiently the system performs in terms of output quantity, without considering downtime or quality losses. This indicator helps evaluate whether the system is running at its designed processing capacity when it is in operation.

In this study, performance indicates the ratio between the number of units actually produced and the number of units that were expected to be produced during the simulation period. The actual production output was obtained directly from the simulation results. The expected production output was determined based on the system's ideal operating rate and simulation time, as previously described in Section 5.2.1, where the expected throughput capacity was defined.

Performance was calculated using the following formula:

$$Performance = \left(\frac{\text{Actual Production Output}}{\text{Expected Production Output}} \right) \times 100$$

The actual number of produced units was 18,140, and the expected output was 18,144. These values were applied to the formula as follows:

$$Performance = \frac{18,140}{18,144} \times 100 = 99.98\%$$

This result indicates that the system operated very close to its ideal output rate, with a negligible deviation from the expected production efficiency.

Quality

Quality refers to the proportion of units produced that meet the required specifications without defects. It indicates the output quality level and reflects the number of conforming products relative to the total production.

As previously mentioned, the quality value in this study was defined based on information provided by the automation manager at the case company. According to internal feedback, approximately one defective unit is observed in every 1,000 units produced. Based on this information, the quality rate was set as:

$$\text{Quality Rate} = 99.9\%$$

Overall OEE Result

The OEE for the current system configuration was calculated using the standard formula:

$$OEE = \text{Availability (A)} \times \text{Performance rate (P)} \times \text{Quality rate (Q)}$$

The individual values used in the calculation were derived from simulation results and company-provided input:

- Availability (A) = 71.71%
- Performance (P) = 99.98%
- Quality (Q) = 99.9%

These values were applied to the formula as follows:

$$OEE = 71.71\% \times 99.98\% \times 99.9\% = 71.62\%$$

This value represents the overall effectiveness of the current state of the production system.

5.2.2 Scenario A Infeed and Outfeed Pusher Configurations

This section presents the simulation results and OEE values for various scenarios in which the number of infeed and outfeed pushers was adjusted to assess how these changes influence system performance. Based on insights gathered from interviews and on-site observations, it was noted that some machine cells operate with a higher number of infeed pushers and fewer outfeed pushers, while others are configured in the opposite way. To explore the impact of these different setups, a total of 26 simulation scenarios were tested, each varying the number of infeed and outfeed pushers.

The aim was to evaluate how these variations affect key performance indicators and the overall efficiency of the automated system. The number of infeed pushers was limited to 10 due to the physical constraints of the robotic arm's reachability, which limited further expansion. The outcomes of these scenarios provide a comparative understanding of how different configurations can be optimized to enhance production flow.

Table 9 shows all 26 different infeed and outfeed configurations and their Availability, Performance, Quality, and OEE results.

Infeed and Outfeed Numbers	Availability (A)	Performance (P)	Quality (Q)	OEE (OEE = A x P x Q)
10 Infeed - 6 Outfeed	72,53%	99,98%	99,90%	72,44%
9 Infeed-6 Outfeed	72,39%	99,98%	99,90%	72,30%
8 Infeed - 6 Outfeed (Current)	71,71%	99,98%	99,90%	71,62%
7 Infeed - 6 Outfeed	71,56%	99,97%	99,90%	71,47%
8 Infeed - 8 Outfeed	71,33%	99,98%	99,90%	71,24%
8 Infeed - 7 Outfeed	71,25%	99,98%	99,90%	71,17%
7 Infeed - 7 Outfeed	70,87%	99,97%	99,90%	70,78%
10 Infeed - 8 Outfeed	70,77%	99,98%	99,90%	70,69%
8 Infeed - 5 Outfeed	70,57%	99,97%	99,90%	70,48%
9 Infeed - 8 Outfeed	70,57%	99,97%	99,90%	70,48%
7 Infeed - 5 Outfeed	70,44%	99,97%	99,90%	70,35%
10 Infeed - 7 Outfeed	70,44%	99,98%	99,90%	70,35%
9 Infeed - 7 Outfeed	70,13%	99,97%	99,90%	70,04%
10 Infeed - 5 Outfeed	70,02%	99,97%	99,90%	69,93%
6 Infeed - 6 Outfeed	69,75%	99,98%	99,90%	69,66%
7 Infeed - 8 Outfeed	69,57%	99,98%	99,90%	69,49%
9 Infeed - 5 Outfeed	69,48%	99,97%	99,90%	69,39%

8 Infeed - 4 Outfeed	68,89%	99,97%	99,90%	68,80%
7 Infeed - 4 Outfeed	68,51%	99,97%	99,90%	68,42%
6 Infeed - 8 Outfeed	68,12%	99,97%	99,90%	68,03%
6 Infeed - 7 Outfeed	67,71%	99,97%	99,90%	67,62%
5 Infeed - 6 Outfeed	67,69%	99,97%	99,90%	67,60%
6 Infeed - 5 Outfeed	67,18%	99,98%	99,90%	67,10%
5 Infeed - 5 Outfeed	67,02%	99,97%	99,90%	66,94%
6 Infeed - 4 Outfeed	66,82%	99,97%	99,90%	66,74%
5 Infeed - 4 Outfeed	65,16%	99,97%	99,90%	65,08%

Table 9: *Infeed and Outfeed Configuration Results*

5.2.3 Scenario B – Robot Speed and Reachability Configurations

This section presents the results of simulation scenarios in which the robot's speed configuration was modified to evaluate its impact on system performance and OEE. These configurations were implemented within the DES model. Based on findings from interviews and on-site observations, it was noted that the case company is actively exploring opportunities to improve the performance of its machine cell. One potential area of improvement is increasing the speed of the robotic arm, which has occasionally been identified as a bottleneck in the production process.

As established in the previous section, the robot in the current simulation model operates with a utilization rate of 62.5%. This indicates that the robot has additional capacity and could potentially perform more tasks within the same time frame. To assess this further, the authors designed two alternative simulation scenarios by modifying the robot's speed, aiming to understand how these changes would affect overall system efficiency and OEE.

In the current state, the robot's pick-and-place cycle time is modeled using a triangular distribution with the following parameters: minimum = 4.94 seconds, mode = 5.79 seconds, and maximum = 7.14 seconds. Two new speed configurations were tested:

1. A 10% increase in speed, which results in a faster cycle time with a triangular distribution of (4.44, 5.21, 6.42) seconds.
2. A 10% decrease in speed, representing a slower cycle time with a triangular distribution of (5.43, 6.36, 7.85) seconds.

The goal of these scenarios was to determine how small changes in the robot's speed would influence key performance indicators such as throughput, waiting time, and OEE. These simulations help provide insight into the robot’s role in the overall process performance and inform whether investing in faster robot configurations would yield significant operational benefits. Regarding reachability, the authors will include the discussion of the results in the analysis section.

The results of these simulations are summarized in Table 10 below, which compares the different speed configurations and their corresponding effects on OEE and system performance.

Robot	Total Time	Value-Added Time	Availability (A)	Number Out	Expected Number Out	Performance (P)	Quality (Q)	OEE	Utilization
Slower Robot	31,6568	22,5443	71,21%	18 139	18 144	99,97%	99,90%	71,12%	68,7%
Current State	30.6152	21.9548	71.71%	18,140	18,144	99.98%	99.9%	71.62%	62.50%
Faster Robot	29,8956	21,3548	71,43%	18 140	18 144	99,98%	99,90%	71,34%	56,2%

Table 10: *Different Robot Speed Configuration Results*

6 Analysis

This section presents the analysis of the collected data, including both qualitative and quantitative components. The analysis is grounded in the theoretical framework and aims to provide a structured understanding to answer the research questions. The qualitative analysis is primarily based on interview transcripts and internal document reviews, while the quantitative analysis draws on simulation results generated from different scenario configurations. To clarify how each type of data contributes to answering the research questions, Figure 18 illustrates the relationship between the analysis components and the research focus areas.

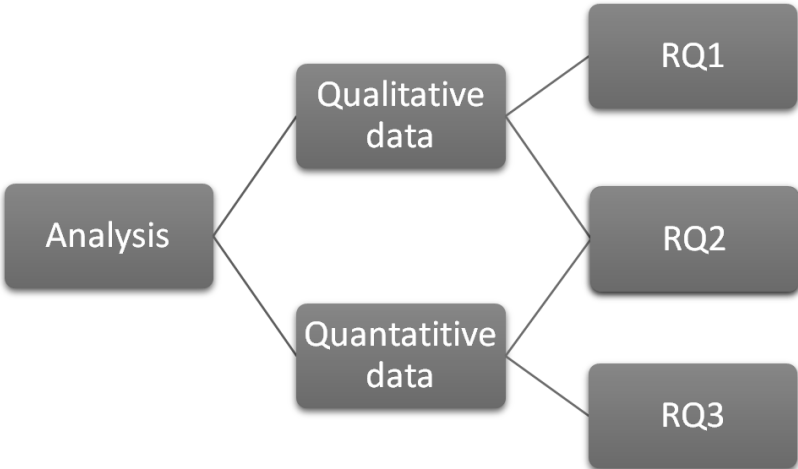


Figure 18: *Linking Data Types to Research Questions*

As shown in the figure, RQ1 and RQ2 are addressed through qualitative data, which includes insights derived from interviews with automation professionals and document analysis related to system structure and operational constraints. In contrast, RQ3 and RQ2 are supported by quantitative data obtained from simulation outputs. This includes performance metrics such as throughput, waiting time, and OEE across different layout and robot speed scenarios.

6.1 Qualitative Data Analysis

The qualitative analysis presented in this section is based on a thematic evaluation of semi-structured interviews conducted with interview participants at the case company. The interviews were transcribed and analyzed to identify recurring patterns and underlying perspectives relevant to the research questions. Thematic analysis was selected as the primary method due to its flexibility and suitability for capturing both explicit and implicit meanings in participant narratives.

To ensure clarity and analytical depth, the qualitative findings were categorized into five core themes:

1. Importance of Automation
2. Practical Challenges in Implementing Automation
3. Simulation Utilization within Engineering Workflows
4. The Role of Optimization in System Design
5. Scenario-Based Exploration and Decision Support

Each theme shows participant views and links them to concepts from the theoretical framework. The thematic structure enables a comparison between theoretical expectations and real-world engineering practice.

6.1.1 *Importance of Automation*

All participants emphasized the important role of automation in improving production efficiency and output. Participant A mentioned that automation helps reduce the need for many operators and allows for consistent production at higher speeds. Participant B also highlighted that manual processes are no longer efficient in modern manufacturing, and automation is necessary to stay competitive and meet changing demands. Participant C pointed out that automation is critical for meeting production needs and avoiding the need for a large workforce. Participant D, from a sales perspective, confirmed the growing demand for automated systems and said automation helps improve throughput, quality, and workplace safety.

These views support what is stated in the literature. Research shows that automation reduces manual labor, lowers the chance of human error, and ensures steady, high-speed production with good quality (Chukwunweike et al., 2024). Studies have shown that manual processes tend to have lower output and quality, while automated systems help maintain high-quality standards more easily (Alharbi, 2024). Participant D's point about improved workplace safety

is also backed by research that connects automation with reduced injuries and better working conditions (Chukwunweike et al., 2024). The interviews clearly show that automation improves efficiency, productivity, and consistency, in line with findings in other studies. They also suggest that while automation has many advantages, there are still some practical challenges that must be managed.

6.1.2 Practical Challenges in Implementing Automation

Even though automation offers many benefits, the participants also mentioned several real-world challenges when putting automated systems into practice. Participant A talked about issues like the complexity of the systems, lack of skilled workers, cybersecurity risks, layout constraints, and pressure from tight project timelines. Participant A explained that short deadlines limit the ability to test and improve new configurations. Participant B agreed and noted that projects often need to be delivered on time without room for experimentation. Participant C added that customer demands for faster production make it difficult to rely on standard machine designs, pushing engineers to create customized solutions. These responses show that achieving the full benefits of automation requires overcoming design, resource, and integration challenges.

These challenges are widely reported in research as well. As manufacturing systems become more complex, managing them becomes more difficult (Longo & Fanuzzi, 2018). Studies also mention problems like bottlenecks and inefficient layouts that reduce the effectiveness of automation (Aguilar et al., 2020). The issue of finding qualified staff, mentioned by Participant B, is also a known problem in the industry. Many companies, especially smaller ones, lack the experts needed to design and manage automated systems properly. Participant A's note about the need for a dedicated simulation expert also matches what is said in the literature. These constraints such as limited time, budget, and technical skills, make it harder to use advanced tools effectively. Overall, while automation can improve performance, real-world limitations like complexity, cost, and workforce challenges must be addressed first (Longo & Fanuzzi, 2018; Ghasemi et al., 2023).

6.1.3 Simulation Utilization within Engineering Workflows

All participants said that simulation tools are currently used only in specific parts of the engineering process. Instead of using simulations to evaluate entire systems, the company mainly uses them for tasks like checking robot reach. Participant C said he uses simulations to make sure designs meet customer needs for reach and cycle time, which has helped reduce the number of physical tests. However, Participant A and Participant B said that the company does not use simulation to model entire systems or test different layouts. They mentioned that making detailed simulation models takes a lot of time and requires special skills. Participant B noted that having a simulation engineer would help create standard models that could be reused in future projects. Without such support, the engineering team relies on manual calculations to estimate performance. Participant D added that while simulations can help show solutions to clients, they are usually too time-consuming and costly to use in the sales process. All participants agreed that simulation has potential, but it is not yet used as a regular tool for decision-making.

In the literature, simulation is seen as a valuable tool that supports better decisions and helps predict how systems will behave under different conditions (Dombrowski & Ernst, 2013; Soori et al., 2023). It is especially useful in complex environments like robotics, where physical testing is costly and risky (Žlajpah, 2008; Chang & Padir, 2020). Simulations let engineers try out different setups without changing the real system. In theory, they help improve the layout, throughput, and other performance measures. However, just like in the case of a company, many firms use simulations only for small tasks and not for ongoing optimization. This is often due to the same reasons mentioned by the participants: limited data, time, and expertise. While the benefits are well known, entirely using simulation in engineering workflows still requires extra effort and resources.

6.1.4 The Role of Optimization in System Design

Participants reported that optimization techniques, such as mathematical models or software-based tools, are not currently used in the company. Participant B said they do not use any formal optimization methods and instead rely on manual calculations. Participant C also noted that no optimization tools are used, although he believes they could help improve machine performance. Participant D, who works in sales, mentioned that customers are mainly concerned with output and do not ask about how optimized the internal system is. Participant A explained that the company focuses on standard setups that already meet performance goals,

and due to time limits, there is little room to explore optimization strategies. Most design work relies on proven setups and small improvements rather than formal optimization.

Despite not using optimization tools, participants agreed that they could be helpful. Participant B said such tools could reduce robot movement and improve availability. He gave an example of how better logic could replace basic timers, which sometimes lead to system errors. Participant C thought optimization could reduce energy use while increasing production. Participant D said that even though customers don't demand optimization, it could make the machines more efficient. Still, introducing optimization would require changes such as new software, time for analysis, and hiring skilled staff.

The literature supports this view. Optimization is a major part of improving production systems and is often used to refine layouts, balance resources, and reduce waste (Monica, 2015). Combining simulation and optimization has been effective in other industries, like automotive, where it helps increase productivity (Monazzam et al., 2022). However, many companies, especially smaller ones, do not use optimization due to practical barriers (Bott et al., 2024). The case company is a good example of this. Engineers understand what optimization can offer but still uses the standard solutions due to time and cost constraints. This matches research findings that suggest companies need to invest in skills and time to take full advantage of optimization (Monica, 2015; Monazzam et al., 2022).

6.1.5 Scenario-Based Exploration and Decision Support

Participants recognized that scenario-based simulation could be useful for decision-making but said it is not used regularly. Participant A and Participant B mentioned that they would like to test multiple layouts or configurations, but time and resource limitations prevent them from doing so. Instead, the case company usually applies known solutions and only changes designs when needed. Participant D said that if a customer asks for higher output than usual, the company will adjust the design accordingly. Participant C said they sometimes simulate special cases to check if the system can meet specific customer needs, but these are exceptions. There is no standard practice for comparing multiple scenarios before making design decisions. Participant B said that creating reusable simulation modules could help, but that is not currently possible. Participant D added that while showing different scenarios could be helpful for customers, the time required to build them is often not practical.

Research shows that scenario-based simulation is a powerful way to test how systems respond to different changes (Dombrowski & Ernst, 2013; Miao et al., 2019). It helps find design

problems early and supports better decisions by showing what works best under different conditions (Fotr et al., 2015; Soori et al., 2023). This kind of simulation is especially useful when there is uncertainty or when trying to balance different goals. The case study in this thesis itself shows the benefits of testing different setups, such as changing robot speeds or material flow paths. These tests help find better ways to improve performance. The company could use similar methods to improve design decisions. While participants agree with the idea of using scenarios, they do not yet use them regularly because of time and resource limits. The gap between theory and practice is clear, and moving to a more proactive scenario-based approach could help the company make better, more informed design choices (Dombrowski & Ernst, 2013).

6.2 Quantitative Data Analysis

This section presents a detailed quantitative analysis based on the simulation results obtained from the DES model developed in Arena. The aim is to evaluate and compare the performance of different system configurations using key operational metrics such as throughput, resource utilization, OEE, and waiting time. While Emulate3D was used in the project for visualizing the machine cell and testing physical reachability and flow validation, all quantitative data used in this analysis were extracted from the DES environment.

The simulation scenarios were designed to test and compare a wide range of possible configurations under realistic constraints and assumptions. The data collected from each scenario allowed the researchers to evaluate trade-offs and highlight the influence of design parameters on production performance. Two primary scenario groups were tested during the simulation phase: Scenario A, which investigated variations in infeed and outfeed pusher configurations, and Scenario B, which analyzed how changes in robot operating speed affected system behavior.

6.2.1 Scenario A – Infeed and Outfeed Pusher Configuration

Scenario A focused on the impact of adjusting the number of infeed and outfeed pushers in the automated production cell. In total, 26 different configurations were simulated to test different effects on the performance of the machine. The current state configuration, representing the system currently in use at the case company, consisted of 8 infeed pushers and 6 outfeed pushers. This configuration served as the reference point for comparison with different scenarios.

Under the current state setup, the system achieved an OEE of approximately 71.62%, with throughput reaching 18,140 units, which corresponds to 99.98% production performance rate. The Performance component of OEE remained extremely high in all scenarios, indicating that the production system was consistently meeting its output targets. Most of the performance loss in the current state and other scenarios was caused by the system standing idle. This means that even though the machines and robot were available, they were not actively working during significant portions of the production time. This lack of activity is reflected in the Availability score of the OEE.

The optimal configuration in Scenario A was the one with 10 infeed pushers and 6 outfeed pushers, which achieved an OEE of approximately 72.44%. A similar layout with 9 infeed and 6 outfeed pushers also performed well, with an OEE of 72.30%. These results indicate that increasing the number of infeed pushers, without increasing the outfeed pushers, can slightly improve system efficiency by ensuring more consistent material flow into the cell.

On the other hand, configurations that provided fewer infeed pushers or that caused an imbalance in the system due to too many outfeed pushers led to a noticeable decline in OEE. For instance, a configuration with only 5 infeed and 4 outfeed pushers had the lowest OEE, around 65.08%, due to longer waiting times and underused system resources. While the throughput remained high across all scenarios (generally performance exceeding 99.97%).

To provide a full picture of performance across all tested layouts, a bar chart visualizing the OEE values of all 26 configurations was created. The configurations were carefully selected based on practical limits. Specifically, the number of infeed pushers was limited at 10 and outfeed pushers at 8 because of the robot's maximum reach within the cell. These limits were confirmed through discussions with the automation manager at the case company and reflect the real working range of the robot. The goal was to ensure all pushers were located where the robot could operate safely and effectively, without reaching too far or risking movement issues. The results are presented in Figure 19 below.

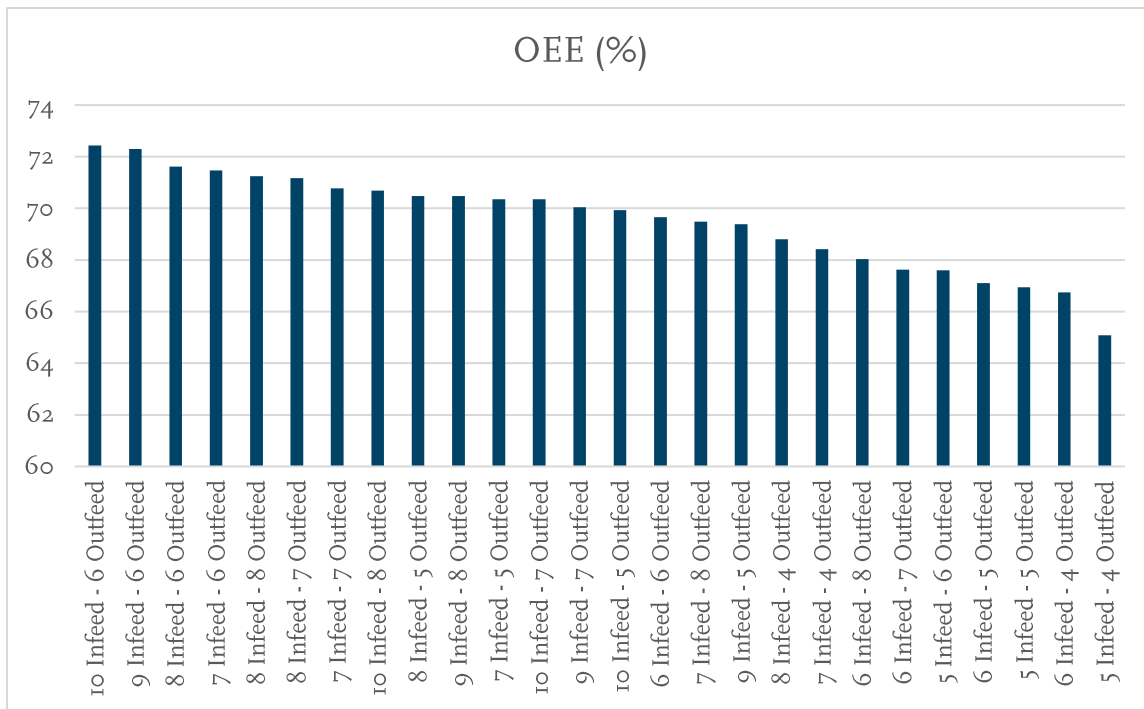


Figure 19: OEE Values Across 26 Different Pusher Configurations

Figure 19 clearly shows that only a few configurations, especially those with 9 or 10 infeed pushers, reached OEE values above 72%, while most were under 70%. Although the differences might seem small at first, even a 1% improvement in OEE can bring significant financial benefits for high-volume manufacturers, since it increases output without more labor or equipment (Matics, 2024). This reinforces the importance of carefully configured layout design and validates the simulation approach as an effective tool for performance-driven decision-making.

To give a clearer look at the best, current, and lowest-performing setups, Table 11 lists their OEE values. It breaks down the results into Availability, Performance, Quality, and total OEE. The details are presented in Table 11 below.

Infeed and Outfeed Numbers	Availability (A)	Performance (P)	Quality (Q)	OEE (OEE = A x P x Q)
10 Infeed - 6 Outfeed	72,53%	99,98%	99,90%	72,44%
8 Infeed - 6 Outfeed (Current)	71,71%	99,98%	99,90%	71,62%
5 Infeed - 4 Outfeed	65,16%	99,97%	99,90%	65,08%

Table 11: Best, Current and Lowest-Performing Configurations

These results show that most differences in OEE were caused by changes in Availability. Quality and Performance stayed almost the same across all configurations. This means layout changes did not affect performance values much. However, better layout design, especially more infeed pushers, reduced idle time and made better use of system resources.

From a design and planning perspective, this analysis shows that simple layout changes can improve efficiency in automated systems. Using simulation-based testing during layout planning helps make smart decisions without changing the physical setup.

6.2.2 Scenario B – Robot Speed Configurations

Scenario B explored how variations in robot operating speed influence the overall performance of the automated production cell. Two alternative speed settings were tested against the current robot speed: one with the robot operating 10% slower and another with the robot operating 10% faster. To ensure that the analysis remained focused on robot behavior, all other system components and layout configurations were kept constant across simulations.

The simulation results revealed that changes in robot speed had minimal influence on total system throughput. All three configurations resulted in approximately 18,140 processed units, maintaining a consistent performance rate between 99.97% and 99.98%. This indicates that the robot, under current operational constraints, does not serve as a system bottleneck. In other words, the robot's speed does not dictate the pace of the overall system.

Under the current state configuration, where the robot operated at current speed, the system achieved an OEE of 71.62%, with the robot's utilization measured at approximately 62.5%. As shown in Table 13, when the robot speed was decreased by 10%, its utilization increased to 68.7%, indicating that the robot spent more time picking and dropping activities. However, the OEE slightly declined to 71.12%, primarily due to increased waiting times in downstream processes. In contrast, when the robot speed was increased by 10%, utilization dropped to 56.2% as the robot completed its tasks faster but remained idle longer, waiting for subsequent operations to catch up. Despite this reduction in utilization, OEE rose slightly to 71.34%, suggesting that the efficiency gain from faster task execution was marginal.

Table 12 presents a side-by-side comparison of robot speed settings, showing how slight variations in robot speed influence OEE, average waiting time per entity and robot utilization across the three configurations.

Configuration	Robot Speed	OEE (%)	Robot Utilization (%)	Avg. Waiting Time per Entity (s)
Faster Robot	+10%	71.34%	56.2%	8.54
Current State	-	71.62%	62.5%	8.66
Slower Robot	-10%	71.12%	68.7%	9.11

Table 12: Comparison of Robot Speed Configurations

To investigate this further, while the robot’s speed changes affected its own utilization, they had almost no measurable effect on the system’s output. To better understand this, entity-level time data was examined to calculate the average waiting time experienced by individual products in the system. This was done by subtracting value-added time from the total time spent in the system. The results showed that the average waiting time only decreased by approximately 0.12 seconds when comparing the faster robot scenario to the current state.

Table 13 highlights the minimal changes in average waiting time per entity under each speed configuration, illustrating how robot speed had almost no significant impact on system-level waiting time.

Configuration	Robot Speed	Avg. Waiting Time (s)	Difference vs. Current State (s)	Cumulative Change over 18,000 Units (min)
Faster Robot	+10%	8.54	-0.12	-36.0
Current State	-	8.66	-	-
Slower Robot	-10%	9.11	+0.45	+135.0

Table 13: Avg. Waiting Time Comparison in Robot Speed Configurations

Although the observed differences in entity-level average waiting time may appear small on a per-entity basis, they become more substantial when scaled across the total batch. When the robot was operated 10% faster, the average waiting time per entity decreased by approximately 0.12 seconds compared to the current state, resulting in a cumulative saving of nearly 36 minutes over 18,000 processed entities. Operating the robot 10% slower increased the average waiting time per unit by 0.45 seconds, leading to an additional 2.25 hours of accumulated waiting time. While these variations did not lead to measurable improvements in throughput or resource utilization because they did not address any specific system constraint, their operational implications should not be overlooked. In high-volume manufacturing environments, even small changes in cycle-related waiting time can compound into noticeable

inefficiencies over multiple shifts, potentially affecting labor utilization, shift balancing, or equipment energy consumption.

6.2.3 Summary of Scenarios

The results from both scenario groups provide a strong basis for evaluating layout and process design decisions in the automated machine cell. The simulations clearly show that while the current system is already performing near optimal levels in terms of throughput, modest improvements in OEE and efficiency can be achieved through strategic configuration adjustments, particularly in the material handling components.

In Scenario A, the most effective configurations were those that increased infeed capacity while maintaining a moderate number of outfeed pushers. This helped ensure that the robot received material consistently, reducing idle time and increasing utilization. In contrast, simply adding more outfeed capacity did not provide additional benefits and in some cases even caused minor performance losses.

In Scenario B, changing the robot's speed had a small effect on total output, suggesting that capacity enhancements should be directed at upstream or downstream processes rather than the robot itself. The robot had sufficient idle time in the current configuration to accommodate faster operation without improving overall system performance. This has also made a possibility for the case company in future development project to add use a robot with more reachability that might help increase flexibility in new layout design.

These findings demonstrate the value of simulation-driven optimization in automated manufacturing. By virtually testing various system configurations, the study was able to identify performance bottlenecks and determine which changes had the most significant impact on overall effectiveness. The combination of visual modeling in Emulate3D and quantitative modeling in Arena allowed for both qualitative insights and data-driven conclusions, supporting more informed decision-making in layout design and process improvement.

7 Discussion

This chapter presents a comprehensive discussion of the study's key findings in relation to the defined research questions and theoretical framework. By integrating insights from qualitative interviews, direct observations, and simulation-based analysis, the authors aim to reflect critically on how the objectives of the study were addressed. The section begins by revisiting the research questions and analyzing them with the empirical and simulation data. Furthermore, the academic and practical contributions of the study are outlined, emphasizing its relevance to both scholarly literature and real-world manufacturing practices. This discussion aims to bridge the gap between theoretical knowledge and practical application.

7.1 Focus on Research Questions

7.1.1 *RQ1 – What are the key contributions of automation systems on the performance of production lines?*

The first research question addressed how automation systems contribute to production line performance. Both previous research and the findings from the case study mentioned that automation provides considerable benefits in terms of efficiency and productivity. Participants emphasized that modern manufacturing depends on automation to achieve high throughput, maintain consistency, and remain competitive. For instance, the automation manager noted that automating the production cell "significantly reduces the number of operators needed and allows us to maintain consistent output, even at higher speeds," highlighting the benefits of labor reduction and steady production levels. This is consistent with existing literature showing that automation reduces reliance on manual labor, minimizes errors, and delivers stable, high-speed output with controlled quality (Chukwunweike et al., 2024).

Additionally, participants noted that automation leads to improved ergonomics and operator safety, such as reduced repetitive injuries, which aligns with previous studies that link automation to better workplace conditions. In summary, the study confirms that automation contributes to enhanced operational efficiency, higher output quality and consistency, and the ability to respond to dynamic customer requirements, supporting conclusions in recent research on manufacturing performance (Alharbi, 2024).

However, the findings also show that achieving these benefits is not straightforward. Interviews revealed several implementation challenges, including system complexity, skills shortages, cybersecurity concerns, layout constraints, and tight project timelines. These issues can reduce the practical effectiveness of automation, despite its potential. As systems grow more advanced,

they become more difficult to design, operate, and integrate, often requiring customized solutions for each client. The case also showed that both engineers and customers sometimes lack the technical expertise to fully implement and utilize complex automated systems. This skills gap has also been noted in the literature, particularly among smaller manufacturers (Longo & Fantuzzi, 2017).

One engineer mentioned that to fully benefit from simulation tools in automation design, a dedicated specialist would be needed, an investment the company had not made (Participant B). These insights are consistent with research emphasizing that trained personnel and technical capabilities are essential to realizing the full potential of automation.

7.1.2 RQ2 – What are the benefits of using simulation for enhancing the performance of automated production lines?

The second research question is how simulation can enhance performance in automated production lines. The findings show that simulation is an effective tool for system optimization, allowing engineers to test various scenarios without disrupting real operations. This is consistent with literature describing simulation to analyze system behavior and evaluate different strategies in a controlled, virtual environment (Poloczek & Oleksiak, 2024). Theoretical studies suggest that simulation can improve equipment capacity, shorten cycle times, and detect inefficiencies before physical changes are made (Miao et al., 2019).

The case study provided practical evidence of these benefits. By running different configurations in a DES model, the researchers identified actual performance-improving adjustments. The experiments revealed that the system's throughput was already close to its theoretical maximum (~99.98%). For example, increasing the number of infeed pushers up to a point reduced the robot's idle time and slightly raised OEE from approximately 71.6% to 72.4%, whereas increasing the robot's speed by 10% had almost no effect on throughput. This simulation-based comparison showed that material flow, not robot speed, was the key performance constraint.

These findings confirm the value of simulation in guiding improvement efforts. Rather than relying on assumptions or theory alone, the simulation enabled data-driven analysis of proposed changes, showing which strategies (e.g., more infeed pushers) would be effective. This supports RQ2 by demonstrating that simulation can improve automated line performance by identifying hidden bottlenecks and testing solutions virtually (Ruane et al., 2022).

At the case company, simulation is mainly used for visualizations and layout verification, not for comprehensive performance enhancement (Participant B). Although participants recognized the value of simulation, they mentioned challenges such as the time and expertise required to develop accurate models, and the need for reliable data. In practice, the company used simulation tools primarily for specific checks, such as robot reach or generating animations for customers, not for in-depth throughput analysis or ongoing process improvement. This limited use contrasts with the broader advantages discussed in literature (Sargent, 2014).

The case study addressed this gap by combining a 3D visual model with a quantitative DES to evaluate system performance across various scenarios. The success of this approach indicates that with proper investment in simulation capabilities and data quality, companies can gain substantial performance improvements. In summary, the answer to RQ2 confirms that simulation offers measurable benefits for automated systems, as evidenced by improved OEE and better system insights. Leveraging these benefits requires organizational commitment to make simulation a standard part of engineering work.

7.1.3 RQ3 – How do scenario-based simulation models support decision-making in the evaluation of production layout alternatives?

The third research question examined how scenario-based simulation models support decision-making in layout design. This study's method where configuring layout and operational parameters in simulation proved effective for decision support. Both qualitative and quantitative results indicate that scenario-based simulation allows engineers to make better-informed layout decisions. In early design phases, engineers created multiple layout alternatives and evaluated them by comparing performance indicators like throughput, cycle time, and robot idle time (Participant C).

This approach enhances a flexible strategy and helps avoid early design decisions. The project extended this by testing a broader set of layout options. The main advantage of this method is that it provides both measurable performance data and visual outputs that facilitate communication with stakeholders. In interviews, participants noted that simulations of alternative layouts helped both internal teams and clients understand and evaluate different options, leading to more collaborative decision-making (Ruane et al., 2022).

The study also showed that scenario-based simulation acts as a practical optimization method in industry. Rather than applying complex algorithms, the researchers simulated a manageable number of configurations and chose the best one. This form of "soft" optimization is not

guaranteed to find the absolute best solution but is suitable for environments with time and resource constraints. It also allows for expert input and practical trade-offs like ease of maintenance or cost considerations (Fotr et al., 2015).

The scenario testing process in this case led to a slightly more effective layout with balanced operations with OEE value. Adjustments such as adding infeed pushers and reconfiguring robot speed improved system performance. In answering RQ3, the study shows that scenario-based simulation supports effective decision-making. It enables comparison of options, reveals performance differences, and helps engineers base decisions on data rather than assumptions. The simulation process also integrates expert experience and real-world constraints, making it highly practical.

In line with previous research, the approach allowed the team to identify design trade-offs and achieve a solution aligned with performance goals (Stecca, Lanza, & Peters, 2019). Still, the study acknowledges the limitations of this method. Participants noted that only a limited number of scenarios could be explored due to time constraints. This means some potentially better configurations may have been overlooked. This is a common issue in industry, where time and modeling effort limit the number of options evaluated (Ghasemi et al., 2023).

Despite these limitations, the method proved its value by increasing the transparency and reliability of the decision-making process. Compared to decisions based on experience alone, scenario simulation made the reasons behind layout changes clear and supported by performance data.

In conclusion, regarding RQ3, scenario-based simulation is an effective tool for evaluating layout alternatives in automated manufacturing. It enhances the decision-making process by showing the impacts of each choice and enabling iterative improvements, while being realistic for practical use compared to complex mathematical optimization methods.

7.2 Academic Contribution

This research contributes to the automation and simulation literature by demonstrating how a scenario-based optimization approach can be systematically integrated with discrete-event simulation (DES) in a manufacturing setting. Prior work in manufacturing simulation has often used models for design validation or limited “what-if” checks (Negahban & Smith, 2014), but rarely applied them across a broad range of operational scenarios. By contrast, this thesis shows how varying parameters such as layout configurations, and robot speed configurations can be tested in a virtual model to reveal their impact on key performance metrics. In doing so, it extends existing theoretical understanding of automated systems under uncertainty.

The findings aligns with established modeling principles: for example, Sokolowski and Banks (2009) emphasize that scenario exploration deepens insight into system behavior, and this study confirms that insight by mapping out how throughput, utilization, waiting times, and OEE respond to different operational conditions. Salam and Khan’s (2016) view of simulation as a decision-support tool, the thesis showed relationships among performance indicators in an automated line, showing how upstream changes affects downstream outcomes.

Methodologically, the study advances how simulation models are constructed and used for scenario testing. A detailed DES model of the machine cell was developed and configured using empirical time-study and throughput data, following best practices in model validation (Ruane et al., 2022; Sokolowski & Banks, 2009). Importantly, the thesis formalizes a repeatable structured procedure for defining and evaluating alternative production scenarios within the simulation environment.

The integration of layout and visualization adds another methodological layer. The research connects a logical DES model with CAD-based visual references of the cell, ensuring that constraints and robot reachabilities are captured in the analysis. This hybrid use of visual and data-driven simulation is consistent with recent advances in visualization-enhanced modeling (Chai et al., 2018) and with integrated modeling approaches in automated settings (Cao et al., 2020). As a result, the model not only computes numeric outputs but also aligns with the physical layout for validation and communication of results.

The model is thoroughly validated using multiple performance measures (throughput, utilization, waiting time, OEE) and cross-checked against observed data, which strengthens the methodological contribution. This follows the validation practices supported by Ruane et al. (2022), who emphasize the importance of matching model outputs to real system performance.

In this sense, the contribution is not a new technology, but an improved implementation of known techniques: a configured, scenario-based DES that can be adapted to other automated systems.

7.3 Practical Contribution

The practical contributions of this study are seen most clearly in how the case company's automated cell can be improved through targeted simulation experiments. By constructing a detailed model of the production line and running multiple "what-if" scenarios, the research provided concrete evidence of performance gains from a simulation-driven approach. For example, simulated adjustments to layout configuration and robot speed configuration in the model resulted in higher OEE and decreased waiting times relative to the current layout. These results highlight that even layout or parameter changes identified via simulation can result significant gains in efficiency and productivity. In practical terms, this means the case company can implement simple modifications that can improve the performance.

Equally important, the scenario-based simulation served as a safe decision-support tool for the company. Engineers or experts could conduct rapid, cost-effective virtual experiments instead of altering the real production line. This trial-and-error approach, which would be expensive or disruptive on the physical shop floor, could be carried out rapidly and without risk in the simulation environment. As a result, the company gained actionable insights: for instance, identifying that configuring the layout significantly improved OEE, all before making any real-world changes. This kind of insight is exactly what the study's scenario models were designed to provide.

By systematically evaluating alternative layouts, the company could plan for higher throughput and better resource utilization. The simulations also highlighted how to improve OEE: for example, testing different scenarios suggested changes that would enhance machine availability and performance. These findings translated directly into practical recommendations, such as configuring specific workstations, which can be implemented because their benefits were already "validated virtually" in the model. Beyond this specific case company, the thesis emphasizes that any automated production environment can adopt a similar scenario-based simulation approach to guide decisions. Building a tailored 3D simulation model and DES for testing key scenarios gives organizations a deep understanding of system behavior under varying conditions.

8 Conclusion

This thesis has explored the application of scenario-based simulation as a decision-support tool for optimizing the performance of an automated machine cell for beverage industry. Through a comprehensive integration of theoretical frameworks, empirical data collection, and simulation modeling, the study has demonstrated how DES and visual modeling can be leveraged to evaluate system performance.

Combining qualitative insights from semi-structured interviews and observations with quantitative data derived from time studies and simulation outputs. This mixed-methods approach enabled an extensive understanding of both the technical and organizational dimensions of automation, simulation, and scenario-based optimization. The findings confirmed that while automation significantly enhances production efficiency, consistency, and safety, its full potential is often constrained by system complexity, skill gaps, and limited integration of advanced decision-support tools.

The simulation phase, structured around two scenario groups layout configurations (Scenario A) and robot speed variations (Scenario B) revealed critical insights into system dynamics. Scenario A demonstrated that increasing the number of infeed pushers improved decreased waiting time resulting in a measurable increase in OEE. In contrast, Scenario B showed that modifying robot speed had negligible impact on average waiting time per entity or OEE, indicating that the robot was not the system's primary constraint.

A key contribution of this study lies in its methodological. The mixed modeling approach combining a CAD-integrated visual simulation in Emulate3D with a logic-driven DES model in Arena ensured both realistic layout and analytical depth. This approach aligns with contemporary research advocating for simulation as a low-risk, high-impact tool for early-stage design validation and continuous improvement (Sokolowski & Banks, 2009; Maideen et al., 2016).

In conclusion, this thesis shows that scenario-based simulation is a practical and flexible method for improving automated production systems. It allows companies to test different layout and operational options using data, helping them make better decisions that improve performance and reduce risks. The study offers value to both academic research and industrial practice by supporting the development of more efficient, reliable, and well-planned manufacturing systems.

8.1 Limitation and Future studies

After conducting the study, the authors have faced several limitations:

This study has several limitations that should be acknowledged. Firstly, the research focused exclusively on a single machine cell within a larger production line. While this allowed for a detailed and manageable analysis, it limited the scope of the study. Investigating the full production line would have introduced more variability and operational parameters, potentially leading to more accurate results and a broader understanding of system behavior under different conditions.

Secondly, the implementation of the simulation results in a real-world setting was not possible due to time constraints. As the project was conducted within a fixed 20-week period typical for a master's thesis, there was insufficient time to carry out real-life testing. Additionally, access to the actual machine cell at the company was limited, further restricting the ability to validate simulation outcomes in practice.

Finally, the researcher had limited prior experience in simulation modeling, particularly in discrete-event and visual simulation environments. This lack of familiarity required additional time for self-training and learning the necessary tools and techniques before developing a functional simulation model. As a result, the learning curve added pressure to the project timeline and may have influenced the depth and complexity of the simulation work.

8.1.1 Future studies

This study has several limitations that point to potential directions for future research. First, expanding the scope to cover larger parts of the production process, or even entire production lines, could offer a more complete picture of how the system performs. This might include linking multiple production cells, scheduling tasks, considering supply chain effects, and analyzing costs.

Second, implementing simulation results in a real production environment would help verify their accuracy and usefulness. By measuring actual performance after making the suggested changes, researchers could compare the results with the simulation and identify practical challenges not captured in the model.

Third, future research could explore using advanced optimization methods, such as advanced mathematical algorithms or other optimization techniques, to find better-performing system

setups. This would allow for a wider range of options and support more informed decision-making.

Finally, it is important to make simulation a regular part of engineering work. Creating real-time tools or digital twins could help with ongoing monitoring and improvement. To make this possible, companies would need to invest in training, resources, and organizational support.

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Appendices

8.2 Appendix A – Interview Questions (Interviews for Engineers)

The following questions were used in semi-structured interviews conducted with automation engineers and the automation manager at the case company. The aim was to explore their perspectives on automation systems, simulation practices, data usage, and optimization opportunities.

1. Introduction & Background

These questions aimed to understand the participants' roles and responsibilities within the organization.

1. Can you briefly introduce yourself and describe your role within the organization?

2. Current Production System & Automation Processes

These questions focused on the structure and performance of the existing production and automation systems.

2. What is your general opinion on automation in production environments?
3. Can you describe your current production system and the role automation plays within it?
4. What challenges do you face with your existing automation processes?
5. How do you measure or evaluate the performance and efficiency of your automated systems?

3. Use of Simulation Tools

These questions aimed to explore the current use of simulation technologies within the organization.

6. Do you use simulation tools to represent or analyze your production processes? If yes, which tools (e.g., RoboGuide) are currently used?
 - If yes:
7. What is the main function or application of simulation in your department?
8. How accurately do your simulation models reflect the actual production processes?
 - If no:
9. How do you currently analyze or measure production performance in the absence of simulation

4. Optimization

These questions addressed awareness of and attitudes toward optimization techniques in general, including both qualitative and quantitative approaches.

10. Although structured optimization methods are not currently used, how familiar are you with such approaches?
11. What potential benefits do you think could be achieved by applying optimization techniques in your production system?
12. What challenges do you anticipate in integrating optimization approaches into your current setup?

5. Data Collection & Performance Metrics

These questions explored how data is collected and used to monitor production performance.

13. What types of data do you currently collect during production (e.g., cycle times, machine utilization, throughput, downtime)?
14. Which performance metrics are most critical for your operations, and how would you prioritize them in an optimization process?

6. Integration of Simulation and Optimization

These questions aimed to understand expectations regarding the potential integration of simulation and optimization.

15. How do you expect production efficiency (e.g., machine capacity utilization, waste reduction) to improve by combining simulation models with optimization techniques?
16. What production bottlenecks do you think could be resolved through optimization methods?
17. Which performance metrics (e.g., cycle times, throughput, downtime) do you think could benefit the most from optimization, and how would you prioritize these improvements?

8.3 Appendix B – Interview Questions (Interviews for Marketing Responsibles)

The following questions were used in semi-structured interviews conducted with marketing and customer communication professionals at the case company. The aim was to explore their insights regarding customer demands, product presentation strategies, simulation-based communication, and perceived value of optimization in production and delivery processes.

1. Introduction & Background

These questions aimed to understand the participants' roles and their connection to customer needs and product presentation.

1. Can you briefly introduce yourself and describe your role within the organization?
2. How does your role relate to customer communication, product delivery, or sales presentations?

2. Customer Expectations & Product Communication

These questions explored how customer needs are identified and communicated, and how product functionalities are conveyed.

3. How are customer requirements typically gathered and integrated into product or system design?
4. What are the most common questions or concerns customers have regarding production or delivery capabilities?
5. How do you currently present automation-related features or technical system capabilities to customers?
6. Do customers usually request customization or specific production functionalities? If yes, how do you address them?

3. Use of Visual Tools and Simulations

These questions examined the role of visual representation in customer-facing communication.

7. Do you use visual materials or simulations (e.g., 3D animations, videos) to support customer understanding?
 - If yes:
8. What tools do you typically use for visualizing production or automation systems in customer presentations?

9. How do these visual tools influence customer understanding or decision-making?

- If no:

10. What alternative methods do you use to help customers visualize system capabilities?

4. Optimization Awareness

These questions focused on participants' perceptions of production efficiency and process improvements from a customer perspective.

11. How important is production efficiency or delivery time in your customers' purchasing decisions?

12. Are you familiar with optimization efforts or improvements made within the production process?

13. What benefits do you think could be communicated to customers if optimization improves delivery, lead time, or flexibility?

5. Integration of Simulation and Optimization in Communication

These questions aimed to understand the potential of simulation and optimization as a communication and marketing tool.

14. Do you think combining simulation models with optimization results could improve customer communication (e.g., clearer lead time expectations, production flexibility)?

15. How could these tools be used more effectively to communicate system capabilities or process improvements to customers?

16. Would visualizing different production scenarios or configurations help customers make better-informed decisions? Why or why not?

8.4 Appendix C – Ethical Consent Document for Participation in the Interview

This interview is being conducted as part of a thesis study titled “Scenario-Based Simulation and Optimization of an Automated Machine Cell,” which is intended to explore scenario-based simulation for optimizing automated manufacturing systems. During the interview, a series of questions will be asked regarding professional experiences, details about the company, and specific inquiries related to the thesis topic. The purpose of the interview is to gather valuable insights that are expected to contribute to the research analysis and the eventual thesis findings.

It is assured that all information provided during the interview will be treated with the utmost confidentiality. In the final thesis report, the participant’s name will not be disclosed; only the position held within the company will be referenced. Any personal or company-related data is to be anonymized to ensure that privacy is maintained.

It should be noted that the entire interview will be audio-recorded for documentation and analysis purposes only. The recorded material will be securely stored and will be used solely for research purposes. Access to the recordings will be restricted to the research team, and they will be disposed of in accordance with data protection guidelines once the study has been completed.

Participation in this interview is entirely voluntary. The right to refuse to answer any questions is guaranteed, and it is emphasized that the interview may be discontinued at any point without any repercussions. Autonomy is fully respected, and the decision to contribute to this research is entirely left to the participant.

By signing this consent document, it is acknowledged that the information provided above has been read and understood. Voluntary consent to participate in the interview, to have the session recorded, and to the use of the provided information in an anonymized form for academic research and thesis preparation is hereby given. Should any questions regarding rights or the interview process arise, they should be raised before proceeding.

Participant Information and Consent

It is assured that the participant’s name will remain confidential, and in all published documents the identity will be represented solely by the position held within the organization. The contribution to this study is appreciated, and it is anticipated that the research findings will be both accurate and relevant.

If the terms outlined above are accepted, the document is to be signed and dated below.

Signature: _____

Name (for verification purposes only): _____

Company Position: _____

Date: _____