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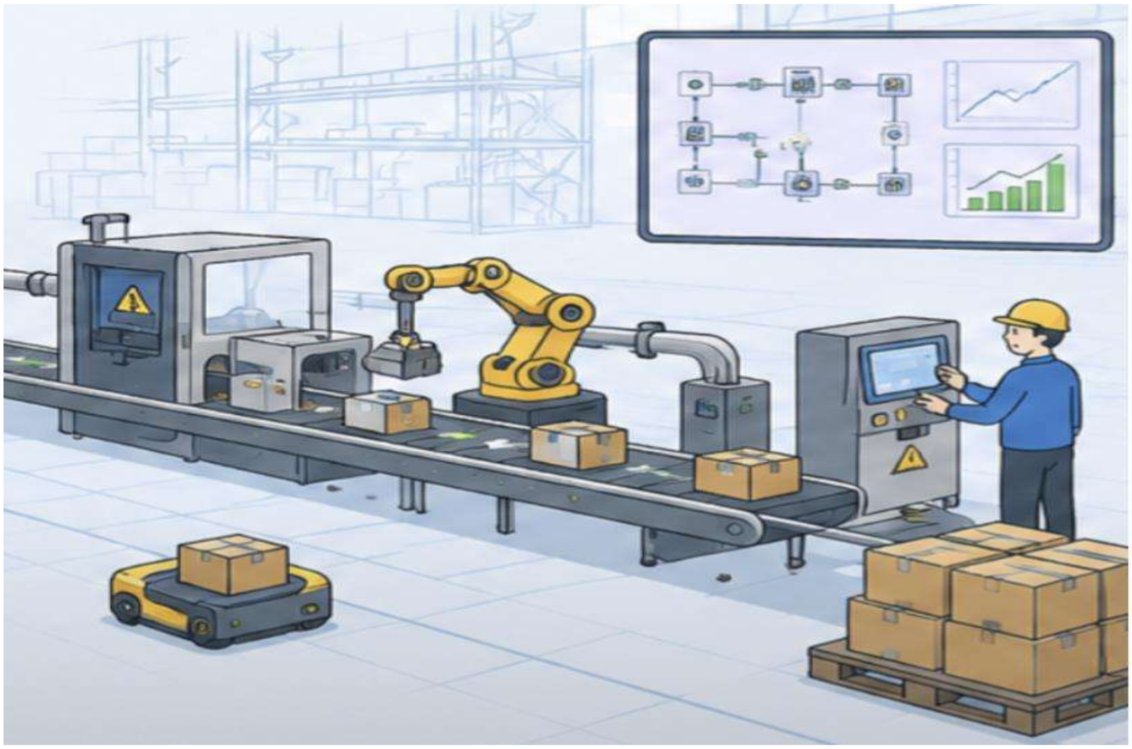

# Analyzing early-stage production through discrete event simulation: A Case study at Magna Electronics

## Developing a simulation model to analyze the performance of a production line and evaluating its ability for decision making at an early stage

Master’s thesis in Supply Chain Management

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Cover: AI and ChatGPT was used to create the illustration of an automated production line and a screen showing a simulation model and data over the production line. Note that this is not the actual production line analyzed in the project. Apart from the cover picture, no AI tools have been used when conducting this study.

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# Abstract

The highly competitive automotive industry, characterized with varying customer demands and requirements puts pressure on manufacturing organization's ability to develop flexible and efficient production systems, particularity its early stage. Magna Electronics Vårgårda production system is currently expanding and under constant development through the implementation of new production lines. Therefore, there is a need to understand how system parameters effect performance of the production line in its early stage of development. Hence, the aim of this study is to investigate and analyze the newly implemented production line CHA1 through the development of a discrete event simulation (DES) model. More specifically, understand how DES can be used as a decision-making tool, evaluate the influence of overall equipment effectiveness and direct labor cost as well as highlighting the challenges in this context. The methodology of the study is based on the first nine stages of Banks simulation framework, which were divided into three phases. Within this framework, a literature review was conducted in combination with a mixed method approach. The qualitative data collection provided in-depth understanding of the production line through the combination of interviews, observations and informal conversations. Whereas the quantitative data were collected through shop floor measurement and from the company database, essential for input modeling and the development of the DES model. The experiments conducted through the DES model and the corresponding findings showed that DES can be a useful tool to enhance decision making and evaluate performance in an early stage of production. However, the early stage contributed to several challenges regarding input data collection and a higher degree of simplifications and estimations, effecting the ability to develop a model with the highest possible accuracy.

Keywords: DES, Discrete event simulation, Early-stage production, OEE, Automotive industry

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## List of Acronyms

| | |
|---|---|
| ANOVA | Analysis of Variance |
| CT | Cycle Time |
| DES | Discrete-Event Simulation |
| DOE | Design of Experiments |
| FIFO | First in First Out |
| KPI | Key Performance Indicator |
| LIFO | Last in First Out |
| MLC | Main Line Carrier |
| OEE | Overall Equipment Effectiveness |
| VSM | Value Stream Map |

Table of contents

# List of Figures

# List of Tables

# 1. Introduction

## 1.1 Background

The automotive industry is considered one of the most complex and economically impactful industries, connecting multiple different actors to create a product built based on various sets of components. It has made the industry highly globalized, operating with complex structured supply chains and high dependent relationships between OEMs and its first-tier suppliers (Hojdik, 2021; Ahmadi et al., 2023). Actors in the industry are heavily affected by the dynamic market conditions and are required to quickly adapt to new regulations, and continuously changing customer demands to maintain competitiveness. Currently, the industry´s faces an intense transformation in demand characterized by increased quality & safety, delivery precision, technology development, customization, and cost efficiency (Gajsek et al., 2019).

Operating in a competitive environment with high varying customer demand and expectations on customization, puts pressure on the firm’s capability in developing a more efficient production (Gajsek et al., 2019). In combination, highly responsive actions are required in the sector, highlighting the importance of intelligent and autonomous attributes in addition to flexible and cost-efficient processes (Bathia & Kumar, 2022). In this context, Hinrichs et al. (2025) highlights that the ability to develop more efficient production ramp-up processes becomes increasingly important to manage higher customer demands and expectations. Therefore, it is essential for manufacturing companies to develop more efficient and rapid implementation processes of a production system, particularly to be more cost-efficient. However, according to Hinrichs et al. (2025) the challenges that arises in this context, limiting a company’s ability to achieve the required state. In fact, more than fifty percent of production ramp-up fail due to the high complexity. One of the major challenges in this context is the ability to recognize the significant factors leading to insufficient ramp-up and implementation processes. At this stage, manufacturing companies lack the ability to evaluate and understand how different process changes effect current and future production. It is further explained that quality problems not identified prior and during the start of production highly effect the efficiency and productivity in this context. Therefore, being able to control the production ramp-up phase, specifically during start of production becomes increasingly important to continue to meet customer demands and maintain competitive (Hinrichs et al. 2025).

As a result, companies view industry 4.0 as a central part of the solution for maintaining or gaining competitiveness in an intensified business environment. Industry 4.0 offers a wide range of applications that can be combined with other technologies and approaches within a manufacturing setting (Gajsek et al., 2019). More advanced manufacturing processes are developed through the integration of emerging technologies of industry 4.0, which has brought multiple advantages to manage high expectations in an efficient way (Chukwunweike et al., 2024).

A central part within the area of industry 4.0 and today's production refers to automation. It brings value to the industry by for example increase productivity, safety, consistency and quality (Chukwunweike et al., 2024; Papulová et al., 2022). At the same time, increased production costs are a representative trend of the continuous changing demands in the industry. One of the main challenges is to optimize the costs of production without compromising the fulfillment of customer demands (Matope et al., 2022). To cope with these challenges, companies recognize discrete event simulation (DES) as a tool for evaluating and understanding a production system, as well as enhance decision making (Babulak & Wang, 2010). Primarily, DES enables companies to model complex production settings and improve performance indicators without interrupting operations. However, DES can be utilized across all phases of a product-life cycle, ranging from the design of production processes to improving already existing processes.

### 1.1.1 Case company description

Magna International Group is a mobility technology company operating as one of the world's largest first-tier suppliers in the automotive industry. Magna consists of seven different divisions, representing more specific focus areas of production and development of components and systems (Magna, 2026-a). This study and research were performed at one of Magna Electronics manufacturing and assembly plant located in Vårgårda, Sweden, further referred to as Magna. The plant produces multiple different electronic components such as cameras and radar for large automakers around the world (Magna, 2026-b). They are currently undergoing a change towards a more flow oriented and automated approach in their production system. As a result of this transformation, top directives from Magna international four-year plan for the lean program Magna Factory Concept (MAFACT), have requested discrete event simulation (DES) as a part of their ongoing development process. Magna Electronics recognize the use of industry 4.0 applications as a key element of its continuous development. More specifically, the company regards the opportunity to make use of DES to enhance production efficiency at an early stage to support the transition towards a more flow-oriented production system. In addition, there is a demand for a proven method for strategic decision making in production and analyzing current implementation of their new automated production lines.

## 1.2 Purpose

The purpose of this study is to understand if DES could be used as a strategic tool at an early stage of production by analyzing different system parameter impact on the performance of a production line.

## 1.3 Problem description

CHA1 is a totally new production line with the purpose of producing three new products, Product A, Product B and Product C. Initially, Product A will be the only product produced on CHA1 up until Product B and Product C will be introduced on the line in early 2027. All products will be produced in one final assembly line, however there are plans on implementing a second line CHA2 to exclusively cover an increased demand for Product A. CHA2 is estimated to start serial production first in the summer of 2027 which makes it necessary for Magna to understand the capacity limits on CHA1. The production line is highly automated compared to other lines producing similar products at the plant, with no intended manual assembly station. In addition, the company has decided to move away from their current quality procedure used in other production lines that manufacture similar products. As a result, CHA1 is unique in its way of manufacturing these products, even if similar processes are reused in the line.

It is estimated that only one operator is needed at the line for material handling and simple maintenance in case of any issues. However, the estimated workload of the line is calculated to be below 1. Buffers with materials and components occur both in different areas connected to the production line and as an integrated part of the line. However, the WIP buffer sizes on the shop floor are not determined from mathematical optimization. In combination with a plan for increasing the production of Product A, there is a need to analyze current material flow at the line to understand what performance level that is necessary to achieve.

Increasing volumes and more demanding customer requirements have been a strong area of focus at the company and one of the reasons why the focus has moved towards a higher degree of automation. Consequently, there is a growing ambition within the company to start utilizing less traditional approaches for increasing efficiency at the production line. Therefore, the company recognizes DES as a powerful tool for enhancing decision-making and as a supporting resource for the future development of the production system. Currently, CHA1 is in an early stage of development characterized with a high degree of uncertainty and unpredictability. Hence, there is a need for understanding how decisions at this stage effect performance of the production line. More specifically, investigate the influence of how certain parameters impact the output, OEE and direct labor cost.

## 1.4 Research questions

1. *How can DES be used in early production line development environments to investigate the influence of independent production variables on Overall Equipment Effectiveness (OEE) and direct labor cost?*

2. *What challenges arise with the application of DES in early-stage production line development?*

3. *How can the development of a DES model support decision-making in early stage of an automated production line?*

## 1.5 Limitations

This study focuses only on one newly implemented production line at Magna Electronics in Vårgårda, rather than addressing the complete production system. Only the main produced Product A on the production line CHA1 was analyzed. The development and creation of the DES model was carried out using Siemens Tecnomatix Plant simulation and no other software was considered. The main objective and area of the simulation model was to analyze the different parameters' impact on the current performance, rather than replicating the production line with exact accuracy.

Moreover, the study is time-limited with a span over 20 weeks, from January to May 2026. Thus, focus was on targeted areas of the production line that can be realistically analyzed within the 20 weeks. Additionally, implementation of the result will not be realized within this time frame but rather serves as a foundation for Magna Electronics Vårgårda ongoing development.

# 2. Theoretical evidence

*This chapter cover important theoretical areas connected to the project to give a deeper understanding of discrete event simulation, the Plant Simulation software, data collection and data distributions applied in the project, KPIs and production at an early stage.*

## 2.1 Discrete event simulation

A simulation represents a reflection of activities and events in a real-world system over a period. The evaluation of the system is examined through the development of a simulation model (Banks et al., 2010). A system can be distinguished as either discrete or continuous. A continuous system can be described as a system where the state variables consistently change over time. Whereas a discrete system is characterized when the state variables change at a discrete point in time. A system is neither fully continuous nor discrete, however the dominant factor will classify the system (Banks et al., 2010).

Discrete event simulation (DES) can be explained through two main pillars: developing a model of a real-world system and utilize the model by simulating and analyzing the given system (Babulak & Wang, 2010). Accordingly, simulations are performed on the system in which outputs are analyzed to enhance decision making. The concept of DES was first developed in the late 1960s by controlling events and activities through logic and code. It was further developed into interactive simulation, enabling the user to adapt a model and directly analyze the real-world system. Since the 1980s, the development of DES has accelerated, mostly driven by large investments in advanced manufacturing technology. As a result, the industry identified DES as a tool for analyzing and streamline a system by focusing on optimizing system parameters (Babulak & Wang, 2010). Accordingly, DES can be used both as a design tool for new systems and as an analytical tool for evaluating changes to an existing system. (Banks et al., 2010).

The existing literature presents an extensive number of frameworks applicable when developing a DES model. According to Tye (1999), a substantial amount of simulation framework tends to follow a similar structure of first defining the problem and objective, secondly collecting data and lastly developing the model and execution. Two of the most common methods are Banks model (1998) together with Law and Keltons (2000) model.

### 2.1.1 Discrete event simulation in manufacturing

In the global manufacturing environment, challenges related to production planning, changes in customer demand, poor productivity and inefficient process flows are common obstacles for manufacturing companies (Huy Huynh et al., 2020). In recent years, manufacturing companies have transformed operations focusing more on automation and advanced manufacturing technologies, primarily to increase flexibility. In relation to this, DES has become a tool for companies to increase productivity and strengthen decision making. Qiao & Wang (2021) describes that DES in this context contains a wide range of applications usable in several areas. Some of the most common areas of use include production line layout simulation, material distribution simulation, production line and path simulation. Within these areas, it is argued that traditional methods are insufficient to cope with complex discrete event manufacturing systems. Hence, through modeling and evaluation, it is emphasized by Qiao & Wang (2021) that DES is a powerful tool to both identify challenges and thus streamline a production system.

Huy Huynh et al. (2020) further explains that due to the flexibility of DES, it can be used to develop manufacturing operations across the planning, implementation and operational stages. Within the different stages, DES strongly supports the development of layouts, production processes, parameter optimization and bottleneck identification.

## 2.2 Plant simulation

Plant Simulation is a simulation software developed by Siemens that allows users to create and simulate digital models representing the real world of logistic systems (Siderska, 2016). The tool is primarily used to optimize and analyze operations within production to improve manufacturing performance through discrete event simulation (Siemens, n.d). The software can be used over the entire system lifecycle, including the planning, implementation and operational stage (Bangsow, 2020). In the planning stage, the software is widely used to identify potential limitations and bottlenecks, test performance of parameters and discover hidden opportunities. During implementation, simulations are used for employee training as well as system performance evaluation in unusual conditions and environments. Whereas, in an operational context, plant simulation is utilized for enhanced efficiency and quality assurance.

Plant Simulation supports model development and simulation in both 2D and 3D environment. The software contains a substantial number of objects and tools. According to Bangsow (2020), these objects and tools are used to develop a model representing a real system with the highest possible accuracy. A model is created by placing objects such as stations, buffers, conveyors, etc., on the frame window. The objects are then connected, creating a structure that defines the path of the manufacturing unit (MU). A system is initiated with the source object which generates MUs into the system (Bangsow, 2020). Contrary, the system ends with the drain object, which defines the system's endpoint. For each object, the user defines its settings with the aim of replicating the real system with maximal accuracy (Bangsow, 2020).

Moreover, Plant simulation provides the user with several tools that can be used for optimization and evaluation of the model. Generally, the basic object settings are limited, which prevents the system to reach an acceptable level of accuracy (Bangsow, 2020). Therefore, to increase model accuracy, the Method function can be used to code logic behavior and customize objects through Plant Simulations programming language SimTalk. Another important tool for increasing accuracy is Datafit. This tool helps the modeler to determine the most appropriate distribution to capture the variations in the system (Bangsow, 2020).

Furthermore, when a model has reached the acceptable level of accuracy, the tool Experimental Manager can be used. The tool supports the modeler in both designing and performing different experiments. The experiments investigate how adjustments in input variables influence output variables in different scenarios and further provides the modeler with detailed results of the experiment (Bangsow, 2020).

## 2.3 Input data collection

According to Skoogh and Johansson (2008), the process of collecting high quality data is considered one of the fundamental and time-consuming steps in a DES project. This is further elaborated by Bengtsson et al. (2010), explaining that to achieve a legitimate simulation result, a substantial amount of the project time must be allocated towards the collection and management of data from several sources.

Input data management is described as the process of securing the quality of the data and defining the input parameters correctly into the simulation model (Skoogh & Johansson, 2008). It is explained that the method of data collection is highly dependent on the contextual condition of the investigated system. Fully automated data collection processes, where data to a greater extent is collected directly from databases or other company systems tend to reduce the lead time of the process. However, Skoogh and Johnasson (2008), explains that larger organizations often fulfill this, while smaller and medium sized organizations often lack these resources and processes.

Connected to this, Skoogh & Johansson (2008) describes that ensuring the quality of the collected data is challenging during the early stage of an implementation process. In this context, the data can be divided into three distinct categories depending on the quality: A, B and C. The three categories determine the quality of the data, where A is considered high quality and C low (Skoogh & Johansson, 2008). Category A data refers to the data that is available, often through databases or other corporate business systems. Category B data is the data not available but collectable. Hence, this type of data needs to be obtained during simulation study, which often requires increases the process lead time. Additionally, data that is not collatable or available before the start of the data collection process is referred to as category C data, which often is a consequence of a newly established process (Skoogh & Johansson, 2008).

### 2.3.1 Distributions

According to Banks et al. (2010), modelling a real-world system rarely includes situations in which the system can be fully predicted. Hence, such system must be considered probabilistic, rather than deterministic. Consequently, this implies that the system contains variation. Skoogh & Johansson (2008) highlight the importance of collecting an extensive amount of data to understand the inherent variability in a real-world system. Furthermore Ullrich & Luckerath (2017) emphasize the importance of clearly formulate relationships between activities and events when developing a DES model. In this context, to create a simulation model representing the real system with the highest possible accuracy, the inherent variability must be represented through distribution.

A goodness-of-fit test is useful tool for evaluation the most suitable distribution of the input data in a DES model (Banks et al., 2010). However, in practice there is rarely one unique correct distribution representing the real system. Therefore, Banks et al. (2010) emphasize the importance of the influence of the sample size. In situations where the data availability and sample size is high, a goodness-of-fit test is expected to reject distribution to a higher extent. In contrast, if the sample size is low the test is expected to reject less distributions. Banks et al. (2010) present three different goodness-of-fit tests that can be used depending on the sample size. The Chi-square test is applicable is situations with large sample size, whereas Kologorov-Smirnov and Anderson-Darling is useful in situations where the sample size is low.

Banks et al. (2010) and Bangsow (2020) distinguish between empirical and statistical distribution. Empirical distribution includes real values collected from historical data, enabling distribution to be specified using the actual data. Whereas statistical distribution must be used when the real distribution is unknown through mathematical functions used to approximate the variability (Bangsow, 2020).

An empirical distribution is useful in situations when it's either unnecessary or impossible to assume that a random variable follows a specific parametric distribution (Banks et al., 2010). In contrast, in a situation where a random variable follows a parametric distribution, variation must be represented through statistical distribution. Fadjar et al. (2025) and Banks et al. (2010) present several useful statistical distribution types under various circumstances in discrete modeling: normal, log-normal, uniform and triangular distribution. The area of use and under which circumstances the distribution types are applicable is presented below.

#### 2.3.1.1 Normal distribution

Normal distribution is commonly used to represent the variability distributed around a mean value $\mu$, and a standard deviation $\sigma$, see equation x. Ullrich & Luckerath (2017) explains that normal distribution is commonly used in manufacturing for several purposes. However, mostly for estimation of machine processing times.

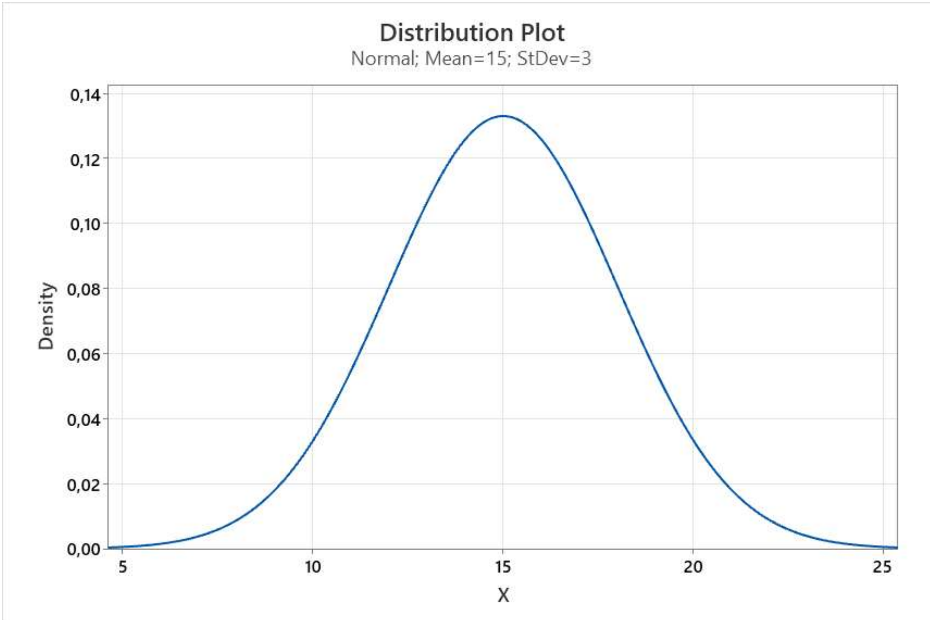


Figure 2.1: *Normal Distribution*

#### 2.3.1.2 Log-normal distribution

A stochastic variable is lognormal distributed if the variables logarithm is normal distributed (Jumiawi & El-Zaart, 2022). According to Ullrich & Luckerath (2017), the log-normal distribution is commonly used in simulation environments. Like normal distribution, lognormal distribution can be useful for approximating machine processing times.

#### 2.3.1.3 Triangular distribution

In situations where data availability is deficient, a triangular distribution can be used. In this case, insight can be obtained through interviewing process experts, providing the minimum, modal and maximum (*mode, min, max*) values of a process. A triangular distribution provides a flexible way to represent variability at different levels as well as providing the most likely estimated value of a process (Fadjar et al.,2025).

#### 2.3.1.4 Uniform distribution

If a specific value is known to be random, uniform distribution can be utilized in situations where data is limited or incomplete and no underlying distribution can be identified (Banks et al., 2010). Hence, a value is distributed between two fixed values (*min, max*) determined with the knowledge provided with the incomplete data and process experts (Ullrich & Luckerath, 2017). In this context, the distribution is not represented by a mathematical function, and the value needs to be assigned randomly. Accordingly, the individual value is distributed somewhere between the minimum and maximum value (Bangsow, 2020).

## 2.4 Design of experiments

Design of experiments (DOE) refers to a structured and systematic approach with the purpose of analyzing the relationship between a set of selected factors and their effects on the output of a system (Ranga et al., 2014). The method predefines a step-by-step process from setting the objectives to the analysis of the output data. DOE enables statistically valid and unbiased inferences to be drawn through a variation of multiple input variables and the ability to control different types of variables (Ranga et al., 2014). According to Barad (2014), DOE is equally compatible for both physical and simulation studies. It requires a suitable identification and selection of variables and level of investigation.

There are four different types of variables: Independent variables, dependent variables, nuisance variables, intermediate variables, which must be identified and classified at an early stage (Barton, 2013). Dependent and independent variables are pre-defined and selected. Dependent variables refer to the preferred parameters from the system output to analyze, while independent variables assigned with different values of a significant difference serve as a controlled factor. The varying factors indicate only a predefined number of variables chosen while there often exists several more independent variables for the user to identify. Intermediate variables are the internal system variables that influence dependent variables through the influence of the independent variable. Nuisance variables influence the dependent variable through a random variation, often representing a cause for experimental error. However, under controlled conditions, like simulation experiments, nuisance variables often don't exist (Barton, 2013).

Different design approaches could be used as a strategy to establish the number of scenarios. Full factorial design considers all possible interactions between the independent variables (x) and the obtained levels (n). $n^x$ describes the mathematical relationship for the number of experimental scenarios, assuming a fixed number of levels for each factor. With the consideration of all combinations and interaction, the system's behavior could be understood in more detail, but requires a lot of resources (Jankovic et al., 2021). Fractional factorial design tests only specific part of the combinations of a full factorial design, which allows for considerably fewer number of test runs. In a full factorial design of $n^x$, the most degree of freedom $n^x - 1$ are used for potential negligible effect of higher order interactions, which represents a large part of the experiment. To avoid wasting time and resources on potential interaction with no considerable importance to the experiment, fractions of the test are established through design generators. An identification of design generator, then allows for the determination for all existing aliases that are used to reduce the number of test runs (Gunst & Mason, 2009).

In order to correctly identify the design of a fraction, design resolutions are used as a tool to understand the quality of the design. Resolution design exists on multiple levels, which describes the confounding pattern for every interaction of the existing main effects in an experiment. Level III-V are the most relevant resolution designs to investigate, as the lower levels do not indicate any combinations or interactions of the main effects (effect of the independent variables). For example, a level II resolution equals I=AB, which corresponds to both main effects are equal, A=B. However, in level III resolution design, two-factor interactions confound the main effects. For example, I = ABC → A=BC, B=AC, and C=AB (Antony, 2023).

After the performance of an experiment, different statistical tools are applied to analyze the results. Analysis of variances (ANOVA) and regression analysis are two commonly applied approaches in this step. ANOVA investigates the root cause of any differences and effects in the response. It allows for an understanding of why certain effects occur and what caused it to exclude the potential influence of random occasions (Jankovic et al., 2021). According to Liu and Wang (2021) T-test is another statistical method to analyze the mean values of independent groups of data. The main difference compared to ANOVA is the number of groups that is analyzed. T-test investigates the meaning value of an independent group and compares it to another independent group, while an ANOVA is applied for analyzing multiple groups.

## 2.5 Production Key performance indicators (KPIs)

Analysis on the performance level of a production system is based on important strategic and measurable factors expressed as key performance indicators (KPIs). In manufacturing operation management, these indicators enable quantification of its effectiveness and efficiency, evaluation of performance, identifying areas of improvement, and understanding strategic direction and objectives (Zhu et al., 2017).

### 2.5.1 Overall Equipment Effectiveness (OEE)

Overall equipment effectiveness (OEE) calculates current productivity of the equipment based on availability, performance, and quality. The purpose is to clearly understand equipment productivity level and to give an indication of the overall performance of the production system in comparison to the optimal state. Availability, performance, and quality all refer to measurements of losses that have a negative impact on the effectiveness level in equipment (Ng Corrales et al., 2020). Losses are characterized by chronic or sporadic disturbances, each which do not bring any value to the operation. The main difference between the two is the visibility of the disturbance. Chronic occurs consequently to minor issues that are simultaneously presence and are often difficult to detect or hidden. In contrast, sporadic has a quick and major impact on the operation, creating a large difference in ratio to the baseline data which is much easier to detect (Muchiri & Pintelon, 2008).

There is a total of six major losses, two losses in each of the three aspects mentioned earlier. Availability investigates the machine’s running time, by measuring downtime losses (Muchiri & Pintelon, 2008). This loss refers to parameters affecting this aspect in terms of set-up & adjustment losses and breakdown losses in the system. Breakdown losses refer to the failures of any machine or equipment which contribute to a loss in time and number of products produced. Set-up and adjustment losses could be described as the required set-up time, testing phase of a new production and the need for minor adjustment on machine settings. The loss reflects the time of the change which production requires to stop. Performance focuses on losses in output rate of the process by measuring factors influencing the speed. It could be minor stops or a general reduction of speed that creates this type of loss. The final aspect of quality in OEE involves defects & rework and yield reduction as the two major factors to quality loss in the system. Defects and rework losses are due to equipment not processing as required to maintain the product quality and thereby cause product defects. Yield refers to the loss of quality before a system is fully stabilized, it is described as the time from a machine is required to start running to it achieve required standards (Muchiri & Pintelon, 2008).

$$OEE = \ Availability\ x\ Performance\ x\ Quality\ (1)$$

$$Availability\ rate\ (A) = \frac{Operating\ time\ (h)}{Loading\ time\ (h)}\ x\ 100$$

$$Operating\ time\ (h) = Loading\ time - Down\ time$$

$$Performance\ efficiency\ (P) = \frac{Theoretical\ cycle\ time\ (h)\ x\ actual\ ouput\ (units)}{operating\ time\ (h)}$$

$$Quality\ rate\ (Q) = \frac{Total\ production - Defect\ amount}{Total\ production\ (units)}\ x\ 100$$

In a simulation context, Bangsow (2020) introduce a simplified calculation of how the overall system availability can be calculated through the formula:

$$Availability\ = \frac{(\text{Total time}-\text{Down time})}{\text{Total time}}$$

Bokrantz et al. (2017) explains that the quality of data in a simulation environment highly effect how OEE can be applied in the model. In many cases, this challenge arises due to resolution, which implies that the level of detail in the data is low. Although OEE is a strong KPI within production environments, Bengtsson et al. (2017) emphasize the fact that it often requires modification depending on the operational context. This is further elaborated by Muthiah and Huang (2007), arguing that the original OEE calculation above (1) can be simplified as:

$$OEE = \frac{\text{Actual throughput (units)}\ from\ equipment\ in\ total\ time}{\text{Theoretical throughput (units) from eqiupment in total time}}\ (2)$$

## 2.6 Early-stage production

### 2.6.1 Bathtub curve

The bathtub curve presents the level of reliability over time, where the y-axis equals the failure rate and the x-axis equals time, see figure 2.2. As a result, the behavior of equipment, component or human populations during its lifecycle could be outlined and divided into the three phases of infant mortality, random failure, and wear-out. These phases refer to a significant change or trend in the expected failure rate during its lifetime. The infant mortality part of the curve represents a decrease in the number of failures at an early stage. It represents the general expected behavior that a failure rate is high in the beginning before decreasing to a state of stability (Ohring, 1995). From an equipment perspective, the high level of early failures is a result of defective equipment and incorrect installation, which also could be associated with a user's learning curve (Mannan, 2005).

Stability in the failure rate describes the second phase of random or intrinsic failures in the curve. During this period of the lifecycle, random failures are spread overtime to create a stable condition of failures (Ohring, 1995). According to Ohring and Kasprzak (2011), external circumstances are the reason for failure at this stage, as different screening methods are used earlier in the first stage to remove issues. In many cases regarding different equipment, an uneven load through random fluctuation causes equipment to fail (Mannan, 2005). The main reason is described as the maximum level set by the design strength is exceeded. In addition, equipment that has multiple different failure distribution in its components, often indicates a constant failure rate (Mannan, 2005). Scholars describe the low constant rate of failure as the useful period of its lifecycle or working life. After a certain time, degradation starts to impact the failure rate to increase as the last stage of its life (Ohring, 1995). The main reason could be described through the growth of minor defects over a longer period that causes the failure rate to gradually increase, which could be connected to the life of multiple mechanical components (Ohring & Kasprzak, 2011).

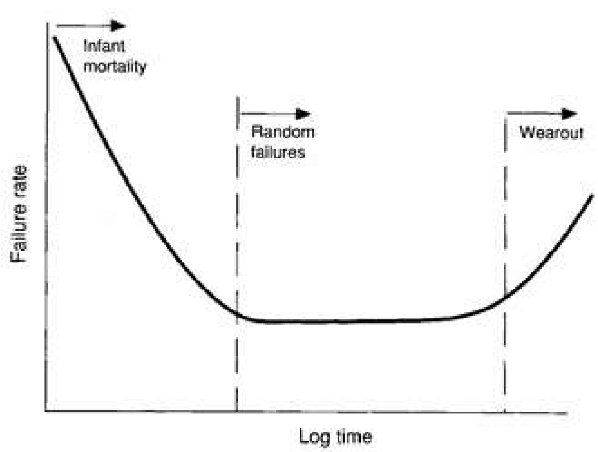

Figure 2.2: *Bathtub curve (Ohring, 1995)*

### 2.6.2 Production ramp-up

Production ramp-up defines the time of a new product launch to full scale production (Surbier et al., 2014), or from the first developed prototype until the production has reached its full capacity (Dombrowski, 2018). According to Surbier et al. (2014) cost, quality, complexity and uncertainty highlight four central reasons for its importance in new product development processes (NPD). The concept has been adapted in more detail and clearer boundaries over the years since the early NPD studies. While multiple different types of interpretation of how NPD are set-up, the general agreement is that production ramp-up refers to the last stage of the process, where an upscale of production volume occurs (Surbier et al., 2014).

Figure 2.3, visualize the ramp-up based on volume over time as a part of a product life cycle. In this case, the period is defined to start at the end of time-to-market of a product and end with the time to volume (full production). Moreover, the curve of the graph shows the overall increase in volume over time during a ramp-up phase before entering the maturity stage of stable production rate.

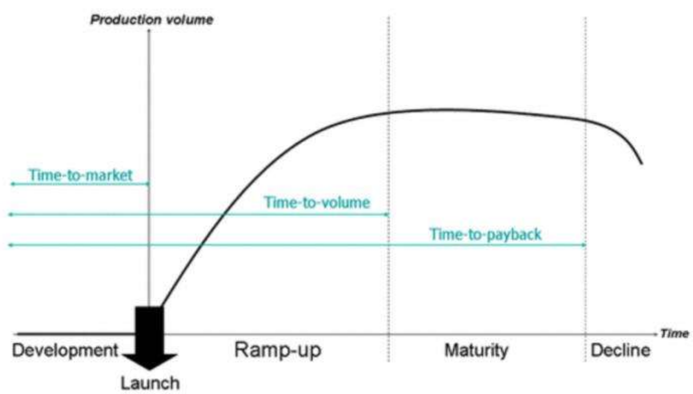


Figure 2.3: *Production volume over time for each stage of production (Surbier et al., 2014)*

Dombrowski et al. (2018) describes production ramp-up to connect pre-stages of product development processes and manufacturing operations as a transitional interface. All ramp-ups are based on specific context and condition, making each phase unique from one another. However, production ramp-up phase is characterized by a high level of uncertainty and unpredictability due to the lack of experience among responsible people in the project. During this time, multiple changes is often performed in the production line. These changes are both intentional and unintentional during this period, making complexity arise in its management and performance. Moreover, the phase operates as an integrated function with an important purpose of translating product design into value-added production process.

The global market characteristics of high customer expectations are described further as one of the main reasons for the high criticality in managing production ramp-up. Where the high degree of customization and innovation has increased product variety and shorten the product life cycles. More frequent product launches decrease the time for product development processes that is necessary to keep up with trends to stay competitive. Consequently, the majority of production ramp-ups performed do not meet the target goals (Dombrowski et al., 2018).

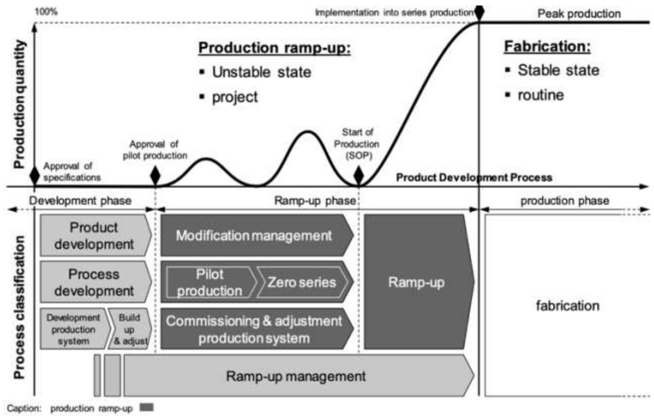


Figure 2.4: *Production ramp-up classification and quantity during implementation (Dombrowski et al., 2018)*

# 3. Methodology

*This chapter presents the methodology approach applied in this thesis step by step based on Banks (1998) simulation framework. The first part covers research design and overall project process, aiming to provide an overall understanding of the project plan. While the next steps describe in more detail how the framework from Jerry Banks (1998) and theoretical evidence were applied in the literature review, data collection, development of the simulation model, and experimental design.*

## 3.1 Research design

The study was conducted with a systematic approach, containing a prioritized sequence of steps that could be characterized into three different phases. The first phase of the design is *"Define Scope and Objectives",* which refers partially to step 1 and 2 from the framework by Banks (1998), see figure x, and is structured accordingly:

1. Understand and define the problem – *What are the reasons for the study? What are their current main issues and challenges? What parameters are important to focus on?*
2. To what extent the study will be performed – *Limitation? What are the important areas to be included? What is reasonable regarding the limited time frame?*
3. Define the objectives – *What is the purpose of the study?*

During this startup phase, multiple meetings and discussions with both our supervisor at the university and the project team at the company were performed. It was necessary to include both parts of the project to ensure that the study and the objectives were aligned with the expectations of all stakeholders. One important part of the discussion was the scope of the thesis, due to the limited time frame. In addition, informal meetings with other people at the company related to the case were held. The main purpose of this was to get a better understanding of the situation and possible challenges from multiple different perspectives, explained in more detail in chapter 3.2.

Once the problem was well formulated and the scope & objectives were clearly defined, the project took the next step into the second phase of *"Base model development":*

1. Literature review – *What does the research say about DES? What methods should be applied?*
2. Model conceptualization – *Material flow, process performance etc.*
3. Data collection – *What Quantitative & Qualitative data are necessary? How should the data be collected & presented? Sample size? Level of marginal error?*
4. Verification & Validation – *Does the model represent reality? Does the program perform correctly?*

A pre-study was applied with the primary focus on understanding important areas of the case. First, a literature review was conducted to investigate earlier research in discrete event simulation and production development at an early stage. Further literature reviews were necessary to analyze different models and methods for our research. Once a more detailed understanding of the terms and methods was in hand, the focus shifted towards the production line. The development of the simulation model followed the method developed by Jerry Banks (1998) to step 9, see figure 3.1, where this phase covers the step 3 to 7.

A mixed method approach was applied to the case to ensure covering all aspects and gaining all the necessary data to develop a foundational model that reflects reality. Qualitative data was collected continuously during the project through meetings and discussions with all stakeholders. Most of the collection occurred in the testing phase of the production line, where the qualitative data was an important part of the model conceptualization. A flow chart over the material flow of the production line and all the service points for the operators were mapped out. In addition, an already existing value stream map (VSM) and 2D CAD layout drawing was used as an additional data source.

Observations and informal conversations were further important to more closely understand the operator's pathing and working experience on the line. Quantitative data was later collected through the company's database, experts' estimations and assumptions, and manually for further verification. The layout of the base model was built simultaneously in Plant Simulation during the data collection period. Verification of the model was done through analyses of simple tests in the model structure for each process. Validation of the model was done by comparing the output of the real system with the model using the same inputs. According to Banks et al. (2010), the validation of a model is an iterative process, which was therefore performed multiple times during the process.

The third phase of the workflow was the "Experimental design" which cover step 8 & 9 of the framework Banks (1998), where the Design of Experiments (DOE) is applied.

1. Define objectives and performance measures - *What is measured?*
2. Define scenarios (independent variables) - *How many scenarios/runs? What changes between them? How many levels and factors are applied?*
3. Formulate statistical hypothesis – *what type of hypothesis?*
4. Determine simulation run parameters - *Number of replications? Run length?*
5. Statistical analysis methods

First of all, different experiments with the collected data were used to test which level of availability and OEE that is necessary to obtain to cope with peak forecasted volume.

The result is then used as baseline data for the design of experiment. In the DOE, a full factorial design with values at different levels was tested, representing a significant difference in value of identified variables compared to the baseline data. The number of scenarios tested is dependent on the number of variables and the number of levels. The first thing is to determine what type of performance measures to analyze in the experiment. In this case, the total number of units produced was directly studied in the experiment, where both OEE and direct labor cost per unit are calculated based on the result. The next step in this phase is to determine which parameters that are interesting to analyze in relation to the dependent variables. The independent variables were determined together with stakeholders at the company to find the most suitable and important parameters to analyze.

Each simulation requires 3 number of replicates over a month's time for validation, comparison, and excluding misleading data. A defined hypothesis was established before the experimental testing of the determined scenarios, which later gave an indication if the established variables have an actual impact on performance. The DOE was then connected to the simulation and present the result for the dependent variable for every scenario tested. The results are then analyzed based on statistical methods to determine any mean differences. The figure below visualizes Banks (1998) simulation framework as well as the scope of this study.

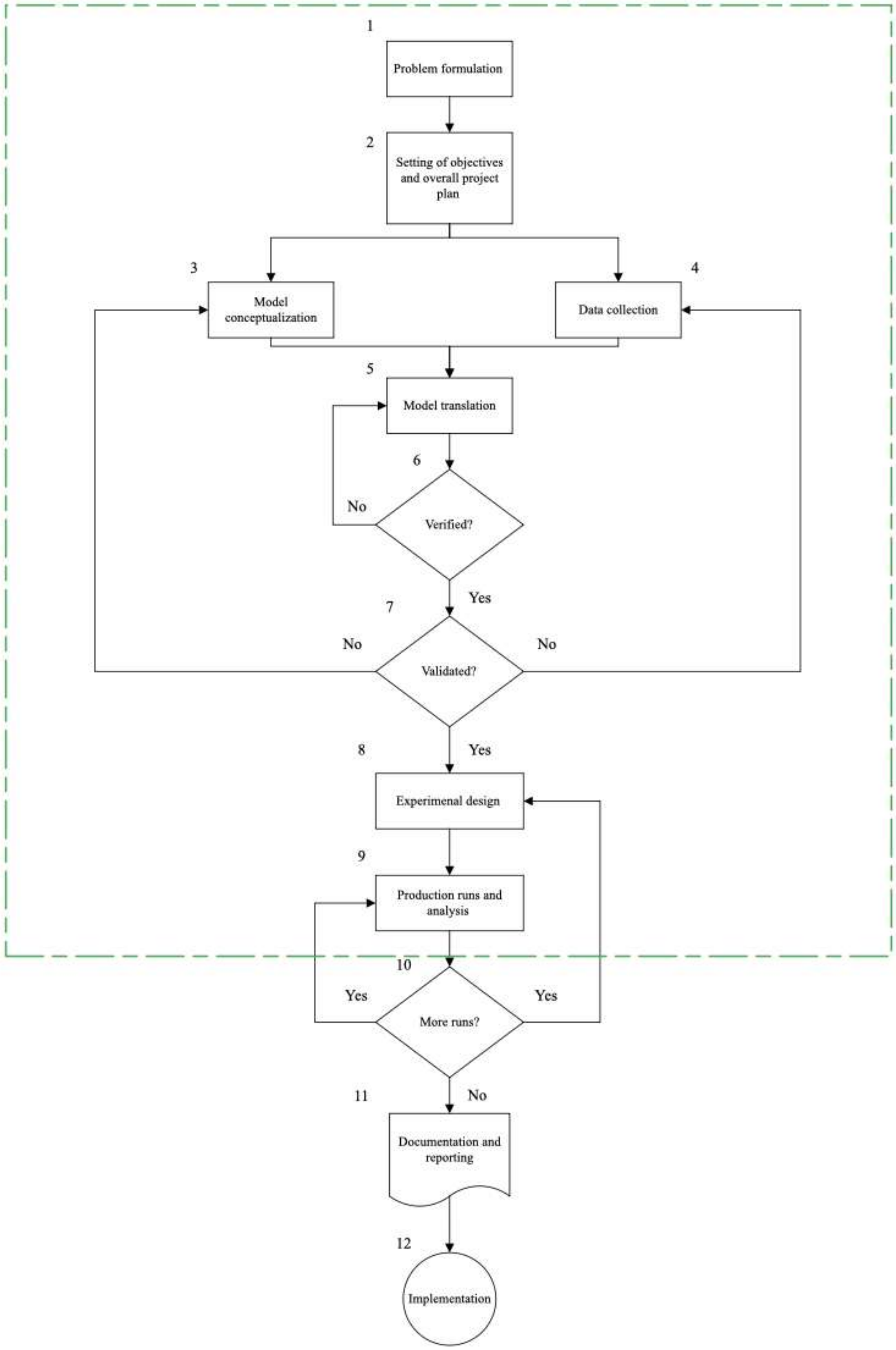


Figure 3.1: *Simulation framework (Banks, 1998)*

## 3.2 Scope and Objectives

**Step 1. Problem formulation**

The first step in the process involved stating and formulating the problem of the study. The line CHA1 has been developed over the years and was undergoing a testing stage during this period. Due to the lack of historical data and information about the performance level indicated a need for formal meetings, discussions, and additional observations with the project team, supervisor, and other representatives to clearly define the problem. A clear understanding of the problem stated the need for analyzing the OEE and direct labor cost under different scenarios in the production line.

**Step 2. Setting objectives and overall project plan.**
The objectives were set based on the problem formulation defined in collaboration with both the supervisor at the company and the supervisor at the university. It sets the standard for the overall scheduling of the project with the limited timeframe into consideration. However, because of the early stage of production at the CHA1 line, multiple things changed during the time of the project. While the primary purpose and objectives were defined to analyze the material flow of the production line was set early on, new constantly changing conditions and multiple uncertainties required a continuous discussion of what was possible or of interest to investigate for the company. OEE, and direct labor costs indicate important parameters for the overall performance level of the line, where the objectives were set to further understand the reliability, performance level and need for potential improvement based on the production volume and additional identified parameters. However, the estimated low workload for the operators at CHA1, contributed to a decision that analyzing the direct labor cost per unit would be more suitable. Different scenarios consisting of significant differences between parameters are defined in this project as an objective for the study.

### 3.2.1 literature review

The literature review was collected mainly through Google Scholar and Chalmers library to ensure credibility of the sources and research. Different keywords, presented in table 3.1, were used in search to find relevant research, articles and earlier master thesis within the same area. "Area" explains which broader area of literature the keyword covered, while the "Purpose" explains the aim of the search and use for the keyword.

Table 3.1: *Keyword, Areas and Purpose for literature review*

| Keyword | Area | Purpose |
|---|---|---|
| *"Discrete event simulation" OR "DES"* | *Simulation* | *Methodology, concept, definition* |
| *"Plant simulation"* | *Simulation* | *License, availability, capability* |
| *"Automotive industry"* | *Industry* | *History, trends, characteristics* |
| *"Automotive first-tier suppliers"* | *Industry* | *Relationship, responsibility* |
| *"Manufacturing"* | *Production* | *Overview of processes and system* |
| *"Production KPIs"* | *Production* | *Important measurements* |

| | | |
|---|---|---|
| *"Early-stage production development"* | *Production & early stage* | *Understanding of production line development* |
| *"Bathtub Curve"* | *Early stage* | *Characteristics* |
| *"Production Ramp-up"* | *Early stage* | *Characteristics* |

## 3.3 Conceptual model

**Step 3 Model Conceptualization**

A conceptual model over the production line was made through the collection of qualitative data and information from representatives. Several visits to the line with process owners, project leaders and the group responsible for taking over the line in the start of serial production, gave a detailed understanding for every process step, service points and overall material flow. With the necessary information, a representation of the material flow was made in Microsoft Visio, and each service point, material input and output in the line was pointed out on an existing drawing in PowerPoint.

## 3.4 Data collection

Qualitative and quantitative data was collected for through a mixed method approach. The following section describes the data collection process conducted to develop the simulation model.

### 3.4.1 Mixed method approach

The study utilizes a combination of both quantitative and qualitative data, which is referred to as a mixed-method approach by Taherdoost (2022). The mixed method approach aims to provide a solid understanding of the subject by covering the benefits of both quantitative and qualitative methods. Oranga (2025) emphasizes that this approach is designed to provide more comprehensive findings towards complex research questions. One of the main benefits of using this approach is the ability to identify patterns and understand the underlying mechanism of these patterns. Furthermore, there is a consensus in the literature that a mixed method research design is a powerful approach to understand an entire organizational phenomenon. Using a mixed-method approach, rather than using either method alone, will provide a more robust result and at the same time ensure the studies significance. Thus, to get an understanding of the production line CHA1 in-depth, quantitative data in combination with qualitative is required. The quantitative data provides insight into representatives' experiences, perceptions, behavior and contextual factors related to the production line. Furthermore, this method enables in-depth understanding of the production line as well as the underlying mechanisms behind them. In contrast, the quantitative method provides key statistical and numerical data which serve as a key input to the development of the simulation model. Moreover, quantitative data provide a measurable foundation to the study, contributing to identifying and evaluating performance of the production line in a systematic way.

### 3.4.2 Quantitative study

According to Skoogh & Johnasson (2008), quantitative input data is considered one of the most important fundamentals when developing a DES model. For this study, quantitative data serve a crucial purpose to develop the DES model and identify and analyze performance indicators. The quantitative data was collected from various sources and representatives across the organization. Primarily, the quantitative data is divided into two different segments: production line performance and production line functionalities. The quantitative data related to the performance of the production line was collected manually directly at the production line, targeting the cycle times for each process through shop floor measurement using a stopwatch. To complement the manual gathered data, available performance data from the company database was also collected. Moreover, the qualitative data related to the production line functionalities serves to understand how the production line operates in depth, as well as targeting operational activities not captured from the shop floor measurements. For instance, by gathering data on operators' behavior and standardized work sheets, batch size, buffer capacity, set-up times etc. This data was collected through observations and informal conversations with production line representatives such as process owners, production engineers and production technicians. In addition, quantitative data was also collected through other representatives across the organization to obtain a Value Stream Map (VSM) and CAD drawings representing the layout of the production line.

### 3.4.3 Qualitative study

In contrast to quantitative data, qualitative data aims to understand individuals' perceptions, opinions and experiences through non-numerical data. The qualitative data examines the "why" and "how", instead of "how many" and "how much" with the purpose of addressing the research question in a simple and analytical manner through interviews, observations and informal conversations.  (Oranga & Matere, 2023).

To obtain an in-depth understanding of the production line and the existing challenges, one semi-structured interview was conducted with two representatives connected to the line. The semi-structured interview provides the respondent with both flexibility and freedom, while answering a mix of closed and open-ended questions, with the purpose of obtaining deeper understanding of the respondent experiences (Kircher & Zipp, 2022). In the present study, semi-structured interviews were conducted primarily in the initial phase of the study to understand the background and existing challenges. The interviews serve as a foundation for the development of the simulation model with the aim to obtain an understanding of underlying mechanism and logical relations of the production line.

Furthermore, observations and informal conversations was conducted throughout the study as a complement to the semi-structured interviews. Davis and Brown (2024) emphasize that informal conversation can generate more natural and representative data compared to other forms. For this study, informal conversation constituted as a highly important part of the data collection process, essential for obtaining a broad understanding of the production line operational functionality. The conversations were primarily held with individuals directly connected to the production line, such as process owners, production engineers and capacity planners, as well as with supply chain planner and lean engineers, not directly connected to the day-to-day activities at the line. These conversations were conducted both directly at the production line and through scheduled meetings.

Moreover, Skoogh & Johansson (2008) highlight the significance of conducting observations to obtain a deeper insight into an investigated system. This is further elaborated by Lim (2025), describing that engaging directly with the environment and collecting observational data provides an additional in-depth insight. Hence, observational data was collected through documented field notes directly at the production line where the primary focus is to investigate production characteristics and human behavior.

The respondents for this study were carefully determined based on the research objective. Different representatives were selected with the aim to obtain abroad knowledge as well as different perspectives regarding the investigated system (Adeoye-Olatunde & Olenik, 2021). The Interview and informal conversations were primarily conducted with individuals directly connected to the production line, such as process owners, production engineers and capacity planners. However, to obtain a broader understanding and general perspective, it was also conducted with individuals indirectly associated with the production line.

The qualitative data collected through interviews, informal conversations and observations provide both extensive and profound understanding of the production line. Primarily, this data serves as foundation for understanding the production line and the development of the DES model. The interview conducted, as well as the representatives target for informal conversations are summarizing in the table below. A high presence at the line resulted in conversations with a broad variety of representatives. Therefore, table 3.2 presents the most important respondents for the data collection process.

Table 3.2: Interviews and meetings with respondents at Magna

| Role | Method | Objective | Date/Frequency |
|---|---|---|---|
| **Senior process developer Process engineer** | Semi structured Interview | Obtain a broad understanding of the production line CHA1 | 13/03/2026 |
| **Senior process developer** | Informal conversations | Logical relationships and performance data | Weekly |
| **Process engineer** | Informal conversations | Overall production line functionalities | Weekly |

| | | | |
|---|---|---|---|
| **Production technician** | Informal conversations | Logical relationships and performance data | Weekly |
| **Capacity planner** | Informal conversations | Forecast and capacity data | Monthly |
| **AMG leader** | Informal conversations | Operator data and standardized work | Monthly |
| **NPI leader/project manager** | Informal conversations | Overall production line functionalities | Monthly |
| **Supply Chain planner** | Informal conversation | Forecast and capacity data | Two occasions |

### 3.4.4 Validity and reliability

Validity and reliability are fundamental aspects to consider for ensuring trustworthiness of the study. According to Kimberlin and Winterstien (2008), validity refers to what extent the study investigates what it is intended to measure, that is its purpose. Whereas reliability refers to the consistency and stability of the measures. In this study, the mixed method approach strengthens the validity through the combination of qualitative and quantitative methods. This approach enables the phenomena to be investigated from several perspectives, comparing and confirming the qualitative data with quantitative findings. To ensure reliability of the study the different data collection methods were performed in a systematic and structured way. The interview followed an interview guide, the purpose and content of the observations and informal conversations that was predefined and documented. The shop floor measurements were conducted using a standardized measurement approach. To minimize the risk of random variation, shop floor measurements was conducted across several occasions.

## 3.5 Model translation

Step five in Banks (1998) model, "Model translation" involves the creation of the model in the simulation software. It is further explained as the transition from the conceptual model to the operational model. As previously mentioned, this was conducted in Siemens Tecnomatix Plant Simulation, which is described as a flexible and powerful software by Bangsow (2008), supporting simulation in both 3D and 2D. Initially, representatives from Magna and the project team were hopeful that simulation could be conducted in 3D by importing CAD files into the system to provide a visual representation of the real system. However, after several meetings and informal conversations with process owners and production technician, the required 3D files could not be obtained. Therefore, in collaboration with our supervisor at the company, simulation was conducted in 2D, prioritizing functionality instead of visual representation.

In parallel to the data collecting process, together with the developed conceptual model, the operational model can be created. This involves placing all the relevant objects on a frame window in the software and defining their settings and logical relations with SimTalk in the dialog window. Together with collected CAD drawing over the layout and performance measurements data, the operational base model can be constructed in the software.

## 3.6 Verification and Validation

Verification and validation are one of the most important tasks developing a DES model (Banks et al., 2010). Verification of the DES model refers to the process of ensuring that the model is implemented correctly in the simulation software. This entails a comparison of the conceptual model and the implemented model in the simulation software, including clearly defining input parameters and logical assumptions. While verification concerns building the model correctly, validation addresses the process of developing the correct model. Hence, validation implies ensuring that the model is a truthful representation of the real system. For this study, verification is an iterative process and was conducted across all phases of the process. However, validation was conducted through an output analysis comparison as well as input from representatives connected to the production line to ensure sufficient accuracy. The early stage of production, uncertainty and low level of availability in updated performance data, required a higher acceptance on marginal error in the comparison and validation step.

## 3.7 Experimental design and production run analysis

Our experimental design follows the general steps in the design of experiments (DOE) as mentioned earlier in research design. The produced number of units/total output from the system are referred to as our dependent variable. Both OEE and direct labor cost are calculated and analyzed based on the dependent variable. In this case, direct labor cost per produced unit was analyzed. Objectives for our experiment are to test whether certain independent variables, which is presented as x-variables, influence the dependent variable. The next step is to categories all variables to detect and understand the relationships. Once all variables were defined, a full factorial/multi-level design was applied as the experimental design. It is mainly to understand the relationships in more detail, potential effects from interactions, and to identify the specific cause of an effect. Therefore, three independent variables were selected in the experiments and tested in at least 2 different levels the variables selected. These values are based on real-life situations and expertise from the company to determine a significant difference between them. It also gave us several unique runs to test and analyze, which was replicated several times each. The main reason is to ensure variability from the simulation is considered in combination of being able to estimate all responses with statistical confidence.

Relevant independent x-variables were identified in collaboration with process expert at the company. The aim is to identify variables expected to have a significant impact on the system. In addition to expertise insight, theory and empirical data, contributes to the selection of the most important variables. Once all variables are selected, a null hypothesis is formulated stating if a main effect or interaction influences the response or whether if there is no effect. With the chosen confidence interval, a P-value under 0.05 ($P > 0.05$) indicate that the investigated variables are statically significant and that the null hypothesis can be rejected. Warm-up time and simulation run time was decided in step eight of the process and the already existing random number generator in plant simulation program is used during the experiment. For the design of experiment, Minitab was used as an additional program to perform the full factorial design. Once the experiments have been conducted, the results are analyzed using a suitable statistical tool with relevant confidence interval for the hypothesis tested in this step.

# 4. Result analysis

*This chapter presents the result from jerry banks (1998) step 3 to 9 and analysis on the results from the experiments.*

## 4.1 Conceptual Model

A conceptual model over the existing system was developed through discussion with stakeholders at Magna, together with knowledge provided from the interview, observations and weekly informal conversations directly at the line. Conceptual models are traditionally developed and visualized using a structured flow chart. However, due to the high degree of complexity of the line, the decision was made to deviate from this approach to clearly visualize the layout, present the logical relationships and material flow.

To understand the logical relations and material flow in depth, a detailed insight into Product A was required. Due to the early development stage of the line, the presence of production technicians and process developers at line provided valuable understand of the product architecture. Product A consist of three primary components: a lens, a printed circuit board (PCB) and a cover. These components are highly sensitive and require right temperature, humidity and free from particles. CHA1 is the first line at the plant to transition from manual clean-room operations directly performed automated at the line. Hence, extensive amount of the line is in a closed environment to minimize the risk of damage products and to ensure the highest possible quality during production.

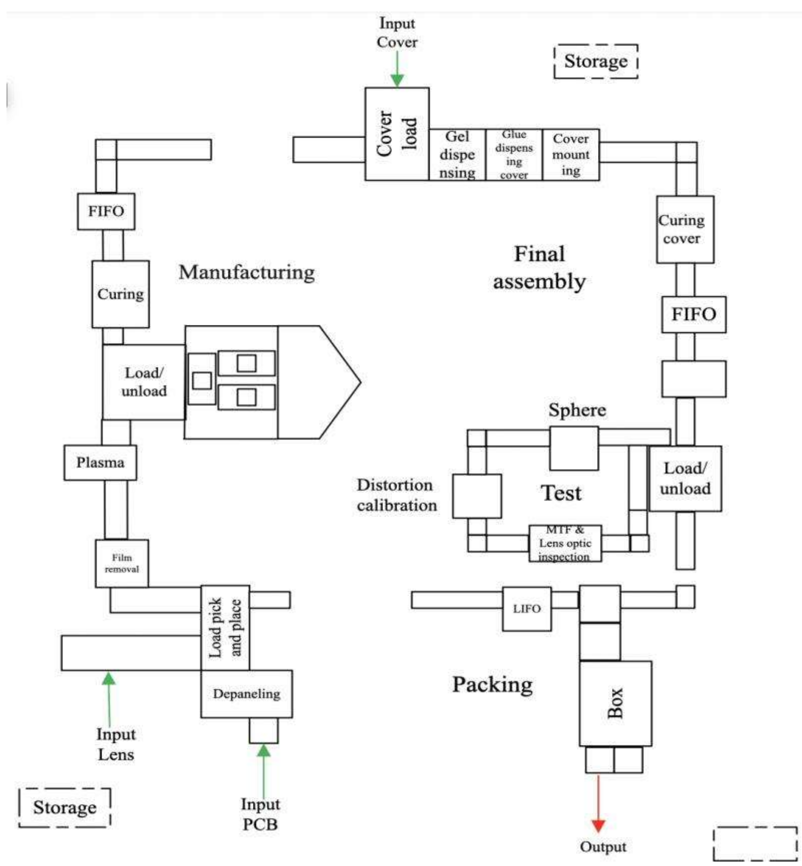


Figure 4.1: *Layout of the production line CHA1*

CHA1 is divided into three distinct segments: manufacturing, final assembly and packing, consisting of a total of 17 stations and three buffers interconnected with conveyors. As previously mentioned, CHA1 is a fully automated line with no manual stations, although semi-automation is possible in required situations. Each station in every segment serves a clear function performing a specific operational task, summarized in table 4.1.

Table 4.1: *Operational task performed by each process at CHA1*

| Process | Operational task |
|---|---|
| **Depaneling** | Milling cutter separating single unit from PCB panel |
| **Load pick and place** | System robot loading and unloading components |
| **Film Removal** | System robot that detaches film from PCB |
| **Plasma** | PCB cleaning |
| **Load/Unload Active alignment** | Load and unload components into active alignment |
| **Curing** | Temperature treatment |
| **FIFO** | Buffer (Capacity 14) |
| **Cover Load** | System robot loading covers |
| **Gel dispensing** | System robot dispensing gel to cover |
| **Glue dispensing cover** | System robot dispensing glue to cover |
| **Cover mounting** | System robot, cover assembly |
| **Curing cover** | Temperature treatment |
| **FIFO** | Buffer (Capacity 10) |
| **Load/unload** | System robot load and unload finished products |
| **Sphere** | Color test |
| **Distortion calibration** | Electrical test |
| **MTF** | Image sharpness test |
| **Lens optic inspection** | Memory test |
| **Box** | Packing |

### 4.1.1 Material Flow

The findings from the interview and observations provided key insight into the material flow and logical relations the line possesses. The interview was conducted directly at line, walking from process to process with the purpose of understanding each operational function as much as possible. The following section presents these findings and thus the material flow of CHA1 step-by step in detail. The material flow is structed around the three components delivered to the line by kanban trains at a constant interval. The kanban trains have three delivery points connected to the line and the respective components input station, see figure 4.2. The primary task of the operator is to feed the line with material according to an established standardized work guideline.

Production is initiated by the feeding of PCB panels into the depaneling station that mill single units and further advance to the station load pick and place. Thereafter, the operator feed lenses to the same station. A system robot loads eight PCB components and eight lens units onto a main line carrier (MLC) before proceeding to the next station film removal. At this stage, a protective film is detached under controlled conditions. The MLC then advances for cleaning and quality check of PCB units in the plasma station. When the MLC enters the load/unload station, all components are unloaded one-by-one by a robot, and PCB and lens units are assembly into eight components. During this process, a maximum of two particle test is conducted for each component. Approved components are loaded on the MLC for curing, while non-approved components are placed in a separate buffer for analysis. After the curing process, the MLC proceeds into a FIFO (First in First Out) buffer.

Thereafter, the MLC reaches the final assembly segment of the line. At this stage, eight covers are loaded onto the MLC. Gel and glue are applied with high precision on the covers, before assembled in the cover mounting station. Subsequently, the assembled product undergoes additional curing process before entering a second FIFO buffer. In the load/unload station, the completed products are unloaded individually from the MLC onto a single carrier for final testing. Approved products proceed to the packing area, unloaded from MLC and placed into boxes before being removed from the line by the operator. The MLC continues to a LIFO (Last in First Out) buffer before continuing back to the Load pick and place station.

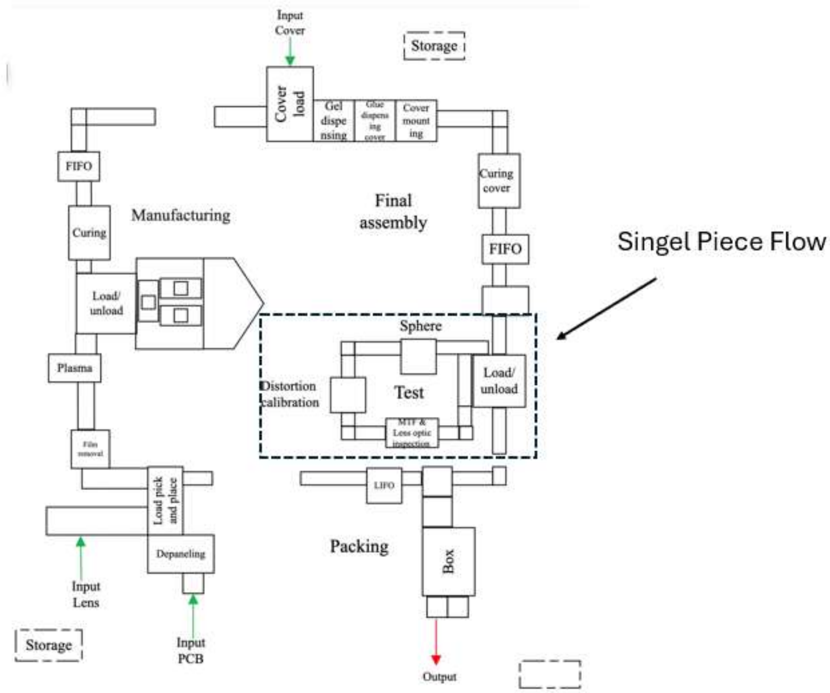


Figure 4.2: *Layout of production line CHA1 and Material in- & output*

4.1.2 Service Points

Service points for the operators were visualized and mapped out according to a standardized work chart and the estimated frequency for the operator's presence, see figure 4.3. The service points represent the position for a specific task with a high frequency between visits. It is categorized accordingly:

1. Green (High frequency): *Periodic tasks the operators perform during every shift.*
2. Blue (Medium frequency): *Periodic tasks the operators perform between each shift.*
3. Pink (Low frequency): *Periodic tasks the operators perform once a week.*

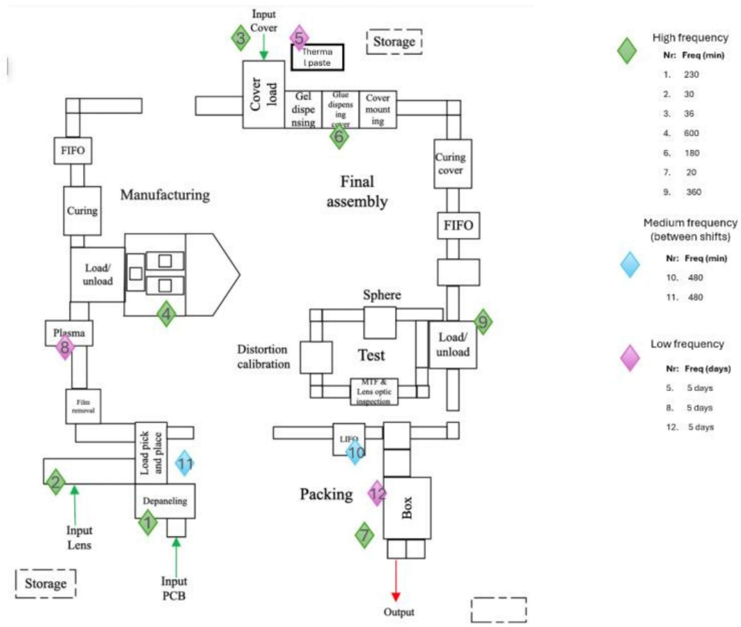


Figure 4.3*: Operators' service points and frequency for each task*

All the service points refer to the periodic work and position at the line where material is loaded or unloaded from the production line. They do not refer to all the locations an operator must visit before or after a certain task is done. For example, the input material delivered from the kanban train are placed in the two storages, see figure 4.5 for more detail on what materials and components. For the lenses, an operator goes to the storage closest to the location to pick up the components and loads it at the location of service point 2. The periodic work performed by the operators at each service point will be explained in more detail in chapter 4.2.2.

## 4.2 Data collection

The following section presents the quantitative and qualitative data collected for this study. Quantitative data serves as key input data for the DES model, which enables the model to correctly reflect the real system. Meanwhile, the qualitative data provides an overview of the current state of the production line, it's functionality and logical settings, which contributed to key insight for the development of the DES model.

### 4.2.1 Process input data

The quantitative data for CHA1 was done both manually and with already estimated and collected data through the company´s data system. Cycle times for each process was the main data point to be collected which was done manually using a stopwatch. Due to the high level of uncertainty, unpredictability and the limited time frame for data collection, a sample size of 15-30 for each process was collected. Outliers representing issues and major deviations were removed before the determination of a suitable distribution. Each deviation was carefully analyzed through observation and experts input to understand why it occurred. To understand the behavior of each process correctly and in a more realistic manner, deviations occurring from extreme circumstances due to the production line's early stage were in need to be removed. The cycle time for each process in table 4.2 is further dependent on the batch size or capacity which is being processed. A batch size of eight products moves with the MLC all the way to the test cell, see figure 4.2 and the capacity levels is shown in figure 4.5. Therefore, the data in table 4.2 is showing cycle times that was collected and used as an input data in the model and the cycle time per/product is presented in figure 4.4.

Andersson-Darling's goodness of fit test was selected for analyzing the data to understand which type of distribution would best fit the data and compare it to the different alternatives in Tecnomatix Plant Simulation. The collected data was imported directly into the program and analyzed with the object "Datafit", see Table 4.2. Each data sample results in a true or false for each selected distribution in the analysis. To find an optimal distribution, every possible distribution was included in the analysis where the ones with the result true and the lowest possible statistical value were chosen. However, certain distribution not available in the program was not selected even though they were considered suitable. Constant distribution refers to processes with a specific time setting that is required before it is released and could therefore be considered as constant. Possible variation was not possible to manual collect or study through earlier statistics, which was not tested during our time to detect the flexibility in the degree settings of the curing processes, this will automatically change dependent on the time needed which could create possible variation but was only changed under specific circumstances.

Table 4.2: *Cycle Time - Data distribution for each process.*

| Process | Sample size | Mean value (Seconds) | Standard deviation | Distribution |
|---|---|---|---|---|
| **Depaneling** | 24 | 80,65 | 7,6734514 | Log-Normal |
| **Load Pick And Place** | 29 | 67 | - | Constant* |
| **Film removal** | 30 | 37,66 | 1,579889 | Normal |
| **Plasma** | 10 | 79 | 0.2 | Uniform |
| **Load/Unload** | 18 | 84,66 | 1,109583918 | Normal |
| **Curing** | 1 | 2568 | - | Constant |
| **Cover Load** | 26 | 53,34 | 1,605999 | Normal* |
| **Gel Dispensing** | 28 | 51,12 | 1,510611643 | Normal |

| | | | | |
|---|---|---|---|---|
| **Glue dispensing cover** | 24 | 60,19 | 2,024236437 | Log-Normal |
| **Cover Mounting** | 19 | 60,41 | 3,873950414 | Normal |
| **Curing Cover** | 1 | 2500 | - | Constant |
| **FT Load/Unload** | 14 | 87,75 | 7,450594821 | Normal |
| **Sphere** | 27 | 12,45 | 1,3388 | Normal |
| **Distortion calibration** | 29 | 11,89 | 0,564344949 | Log-Normal |
| **MTF** | 26 | 11,89 | 1,367 | Normal |
| **Lens optic inspection** | 27 | 12,86 | 2,089043457 | Log-Normal |
| **Box** | 1 | 9.1 | - | Constant* |

** Different distribution compared to result of the goodness of fit test and what was used in the simulation because of it either didn´t exist in the program or because of the constraints of necessary objects to create a representing and realistic working.*

Because of the multiple issues and stops at the line and the limited time frame, the last stations at the line referred to as Box were not manually collected with the required sample size and distribution. The cycle time was carefully estimated based on reasonable assumptions, experts' estimations and assumed to not being a bottleneck at the last stage of the line. Figure 4.4 presents the mean cycle time per product for each process.

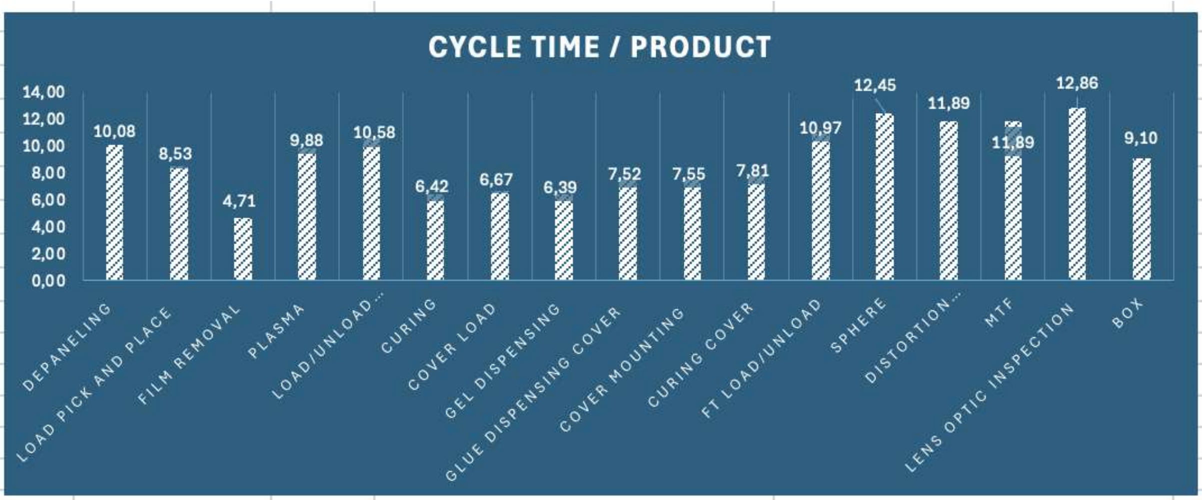


Figure 4.4*: Mean cycle time for each process per product.*

The collected data of the cycle times for each process per product indicates that the process Lens Optic Inspections is the current bottleneck (highest cycle time) of the production line. In addition, the single product flow in the test cell including Sphere, Distortion Calibration, Lens Optic Inspection and MTF, of the production line shows the highest average cycle time per process. Overall, the cycle times between processes are unevenly distributed, with a difference of up to 8,15 seconds per product between

Film removal and Lens optic inspection. This indicates an unbalanced production line where the differences in cycle time between processes are high. Both Load/unload and FT Load/unload have a significant higher standard deviation compared to the other processes at the line. FT Load/Unload gave the highest standard deviation of approximately 7,67 seconds, which creates a high degree of variation.

More important input data for the model regarding the production line was accessed from the different settings of the production lines, estimation and discussion with process experts and already collected data by the company, see table 4.3.

Table 4.3: *Input data in the Simulation model*

| Input | Value |
|---|---|
| **Batch Size** | 8 |
| **Capacity Levels** | See figure 4.5 |
| **Conveyor Speed** | 0.087 m/s |
| **Rotating conveyors** | 2sec/90° |
| **Number of Main Line Carriers** | 160 |
| **Number of Single Carriers (Test)** | 16 |
| **Storage Area** | See figure 4.5 |
| **Delivery frequency** | 30 min |
| **Quality Rate** | 97.2% |
| **Outer Dimensions** | 14x10 (m) |

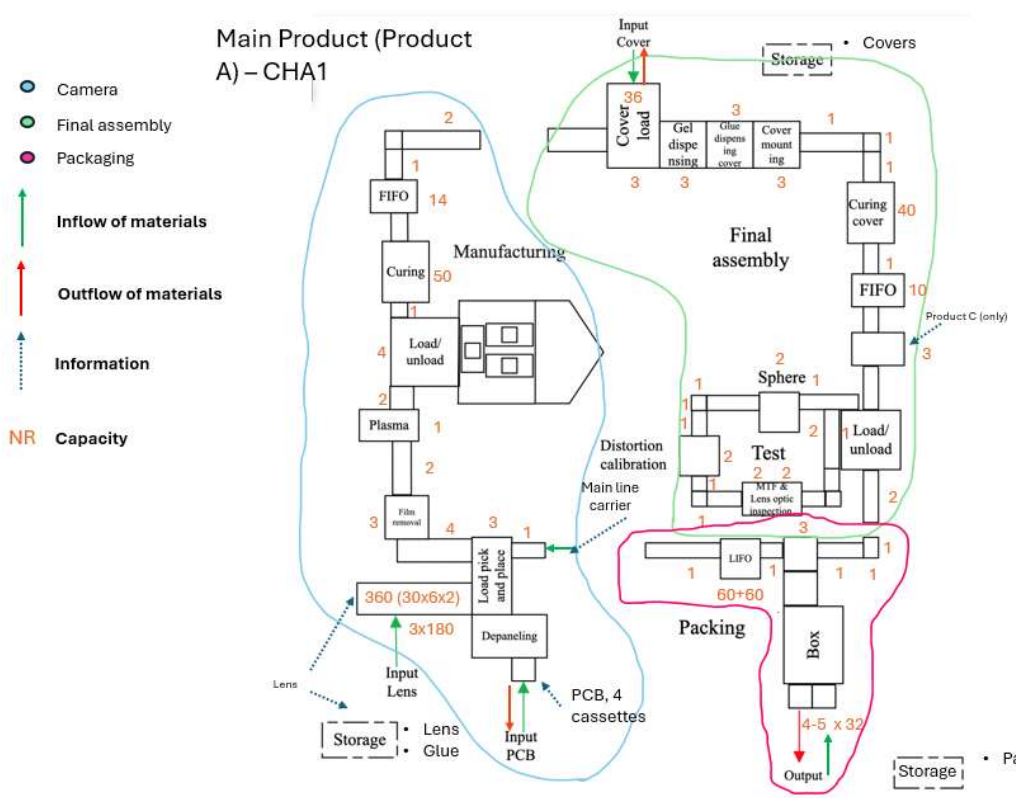

Figure 4.5: *The different segments, capacity levels, storage information (materials/components) at CHA1*

### 4.2.2 Operators and Standardized work

Data collection for the operators was gathered from the company´s own standardized work sheets calculated by experts at the company. Standardized work describes each task performed periodically by the operators with a calculated frequency based on estimations and required performance of the line. Medium frequency tasks are estimated to be performed between shifts with an estimated time of 1 minute and no effects on the performance. As the shifts involve a transfer period of 12 minutes between the operators, both tasks could be done without it affecting the performance and are considered negligible. Low frequency tasks occur every fifth day and are estimated to be done outside the shifts as a result of a 5-day working schedule. In addition, service point 9 was removed and not considered because of the high uncertainty of its application and who is supposed to have the responsibility for carrying out the work.

The column “Effects on Performance” in table 4.4 describes the loss in time that the process is in need to be stopped as a consequence of the task performed by the operator. The project and input in the model only consider the tasks which are performed during every shift, see table 4.4. In terms of service point 4, which requires a frequence of every 600 min, was instead performed at a specific time every day at 17:00 and 03:00. The main reason is the limited ability to set different times for every shift in the “shiftcalender” object in the software, which in this case refers to time that impact the performance. The calculated loss in performance was deducted from the experiments presented in chapter 4.5.

Table 4.4: *Time and effects on the performance for each task at each service point*

| Service Point | Frequency (Min) | Time worker (Min) | Effects on Performance (Min) |
|---|---|---|---|
| **1** | 230 | 3 | - |
| **2** | 30 | 3 | - |
| **3** | 36 | 2 | - |
| **4** | 600 | 25 | 20 |
| **6** | 180 | 15 | 10 |
| **7** | 20 | 1 | - |
| **9** | 360 | 5 | - |

The periodic task sequence is visualized in figure 4.6 where each square represents five minutes of time, so the sum of two tasks that is less than or equal to five minutes can be visualized as parallel performed activities. All the yellow and orange filled in boxes refers to manual performed task by the operators, where the time of each activity is presented in the column "Manual". In addition, a red line is drawn by the end of each shift.

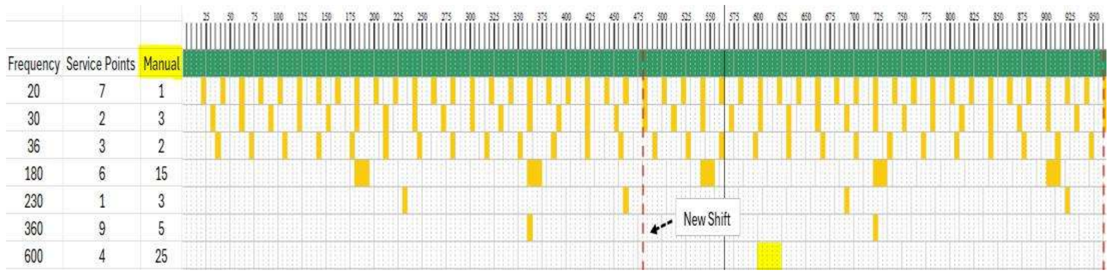

Figure 4.6: *The sequence of tasks that is performed by the operator´s over two shifts (without breaks).*

Each shift is 8 hours (480min) including two breaks, 18 minutes respectively 30 minutes, where the production line is estimated to continue working during these occasions. In more detail this means that no process is purposely stopped during the time and in case of any unplanned failures it is possible for other process maintenance technician to solve the problem. As an input in our model, the external maintenance technicians are not considered in the model because of the lack of data and the high level of uncertainty in this area. The very early stages of the line prevented clear observation and insight of the operator's behavior and operating tasks to be analyzed in a correct way. One of the main reasons was the high degree of failures and downtime that occurred frequently due to the early stage of the production line, where multiple process engineers were present to solve issues, which affected the operator's way of working compared to what is normally necessary. During this time the operators was also in a learning process. Therefore, no manual data on the operators was collected during the project and was instead purely based on data from the company´s calculated standardized work and expert estimation. Input data for shifts and the operators is presented in table 4.5.

The breaks during the shifts for the operators require some periodic tasks to be done at a different time than what is calculated to be the normal required frequency. A higher flexibility in reality makes it possible for the operators to decide whether materials are required to be filled up before a break to mitigate any risk for shortages. In terms of the simulation model, the sequence is already established, so any required task during a break was handled after the break. However, the same amount of material was produced and available for the operators to collect.

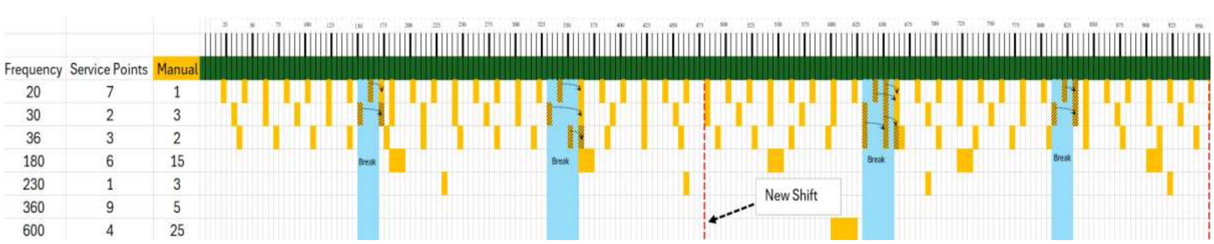

Figure 4.7: *The sequence of tasks that is performed by the operator´s over two shifts*

Table 4.5: *Operators Input data*

| Input | Value/data | Data Source |
|---|---|---|
| **Operator speed** | 1.38 m/s | Estimated |
| **Operators' capacity** | Maximum Transportation | Estimated based on data from "Standardize work" |
| **Shift calendar (night)** | 07:00-15:00, 15:00-23:00 (23:00-07:00) | Company data |
| **Breaks**<br>**(shift-1)**<br>**(shift-2)**<br>**(shift-3)** | (time)<br>(09:30-09:48, 12:00-12:30),<br>(17:30-18:00, 20:30-20:48),<br>(01:30-01:48, 04:00-04:30) | Company data |
| **Process Shifts breaks**<br>**(Glue Dispensing Cover)**<br>**(Load/Unload)** | <br>10 min every 230 min<br>20 min every 600 min | Company data "Effects on Performance" |
| **Priority Levels**<br>**Failures**<br>**Transport**<br>**Filling Material** | 0-10, (Low-High)<br>9<br>7<br>5 | Estimated |
| **Efficiency** | 100% | Estimated |

## 4.3 Model translation

The qualitative data collected from the interview, weekly informal conversations and observations formed the basis for the development of the model. The quantitative data in this step serves a crucial purpose for understand the system in-depth and thus develop the model in the correct way according to the conceptual model. This entails, modelling all the logical relations and features that the investigated system possesses. Further, the quantitative data collected through shop floor measurements and the company database serves as the input data for the model.

The development of the model in plant simulation was a step-by-step process, starting with the placement of processes followed by the development of logical relations and operators' behavior. One of the main challenges at this stage was to achieve a representation of the real system and its logical relations with the highest possible accuracy in the simulation model. While the real system consists of a total of 17 stations and three buffers, the simulation model required complementary stations and simplifications to develop certain logical relations and, particularly in situations when components leave the MLC. In this situation, the frame object was used to avoid negative effects of the layout. Moreover, during the model development phase, several limitations was identified and a number of simplifications was required. For instance, the pick and place (robot) object could not be used as intended in several situations, due to its limitations when developing some logical relationships. This situation occurred in the initial phase of the line when the system robot needed to first place eight PCB on the MLC, and then eight lenses. For this logical relation to be included in the model, a modified robot objects were developed instead. Even though the logical relation could be achieved, it was not possible to capture the variation by defining an appropriate distribution on this object. Therefore, the cycle time on this object is constant, however defined by the collected data. Similarly, a simplified version of the of the station load/unload was necessary to develop. In the real system, this station consists of one robot operating under highly complex logical behavior. Again, due to the limitations identified with the pick and place object in plant simulation, this station consists of two robots performing the required tasks instead of one.

Although assumptions and simplifications were used in several situations, it was necessary to develop the logical relations of the system and eventually a continuous flow without deadlocks occurring. Material is generated in the source object at a constant interval according to the periodic task frequency. A signal is then triggered to the operator to transport and feed the material into the line according to the standardized work guidelines. Components in the line are transported on the MLC, while system robots pick and place components to and from the MLC. In situations when a failure occurs, a signal is triggered to the operator, but with a higher priority compared to material handling and transport.

## 4.4 Verification and validation

The operational model was verified iteratively during model development. To ensure that input parameters and logical relations reflected the real system, the process of verification included systematic comparison to the conceptual model. Validation of the model was conducted through an output analysis with two process experts at the company. A comparison between real production output data and the model output was carried out, and a 5% error margin was the target. The requirement was fulfilled and the model was considered validated and in the correct condition for conducting the experiments.

## 4.5 Experiments

In our experiments we set the base settings and condition for every case according to table 4.6.

Table 4.6: *Base settings and condition for all experiments.*

| Input | Value | Reason |
|---|---|---|
| **Run Length** | 2027-04-01: 2027-05-01 (30 days) | Equals the period of time for the forecasted volume |

| | | |
|---|---|---|
| **Operating time** | 22 days | Number of working days during the period |
| **Warm-up time** | 2h | Time taken for the system to fully operate |
| **Number of shifts** | 3 | |
| **Quality Rate** | 97.2% | Historical data |

4.5.1 Experiments for determining required availability

**Case 1:** First case was to test which level of availability and number of shifts that was necessary to achieve an output level for maximum forecasted volume over a month. The maximum forecasted volume for CHA1 regarding the main Product A, was in April 2027 with a volume of 117 293 units. During this period, CHA1 is expected to produce Product B and Product C with a forecast volume of 2 947 respectively 3 131 number of units, see table 4.7. Similar cycle time and output rate is estimated for all products where the sequence of Product A-Product B-Product C-Product A is used. The changeover times are roughly estimated, see table 4.8, in combination with the forecasted volume for Product B and Product C, the required space for production could be calculated and considered for.

Table 4.7: *Forecasted volume for April 2027*

| Product A | Product B | Product C |
|---|---|---|
| 117 293 | 2 947 | 3 131 |

Table 4.8: *Changeover time matrix*

| Products | Product A | Product B | Product C |
|---|---|---|---|
| **Product A** | 0 | 1h | 1,5h |
| **Product B** | 1h | 0 | 1,2h |
| **Product C** | 1,5h | 1,2h | 0 |

The first run was to determine the maximum output with an OEE of 100 % and our data collection, simulating over 3 shifts (24h production) Monday – Friday (5-days), which gave a max output of 143 936. Each process was set to an equal availability and mean time to repair (MTTR) in this experiment for the model to put a more precise value on the overall availability and to better analyze its effect. It was important to include every process that had the possibility of failing to get a more realistic output and working environment for the operators. However, both buffers (FIFO1 & FIFO2) and both curing processes were not included as they are estimated to not contribute to any failures in more stabilized circumstances. Depending on the MTTR chosen, the simulation program automatically calculates an interval or mean time between failures (MTBF) according to the formula: MTBF/ (MTBF + MTTR).

**Theoretical max output for Product A** = 143 936 units

143 936 / (22*24) ≈ 272,6 units/h

In order to calculate the theoretical max output with the consideration of fulfill the forecasted volume for the Product B and Product C, their production time and the changeover time has to be removed from the total available production time.

**Time to produce forecasted volume for Product B:** 2 947/272,6 ≈10,8h

**Time to produce forecasted volume for Product C:** 3 131/272,6 ≈ 11,5h

**Total production time for both products:** 10,8 + 11,5 = 22,3h

**Loss due changeover time:** 1 + 1,2 + 1,5 = 3,7h

In addition, the loss in performance on the production line from periodic task performed on service point 4 is in need to be removed to get the total time loss.

**Required number of performed tasks on service point 4:** 528/10 = 52,8 times

**Actual number of performed tasks on service point 4:** 44 times

**Additional loss in time:** 52,8-44 = 8,8 → 8,8 * 0,33 ≈ 2,9h

**Required space:** 22,3+3,7+2,9= 28,9h

**Actual available time:** 528-28,9 = 499,1h

**Theoretical maximum output for Product A with regard of managing all product volumes:** 272,6 * 499,1 = 136 054,66 ≈ 136 055 units

**Minimum required OEE: (**117 293/136 055) *100 ≈ 86,2%

**Case 1 (Experiment 1):**

Table 4.9: *Settings for experiment 1*

| Input | Value |
|---|---|
| **Availability/Process** | 99% |
| **MTTR** | 1 min (Erlang ≈ 0:42.4) |
| **MTBF** | 1:38:59.99 |

All processes except Curing and Curing Cover were set to an availability of 99% and MTTR of 1 min. MTBF is automatically set by the software, and the MTTR is set with an erlang distribution of ≈ 0:42.4. Figure 4.8 shows the statistics for each process and its different operational state as a percentage of the total operating time. Green represents the working time, grey represents the waiting time for the process, yellow represents the time the process was blocked by another process, dark blue represents the time that the process was paused and red represents the downtime.

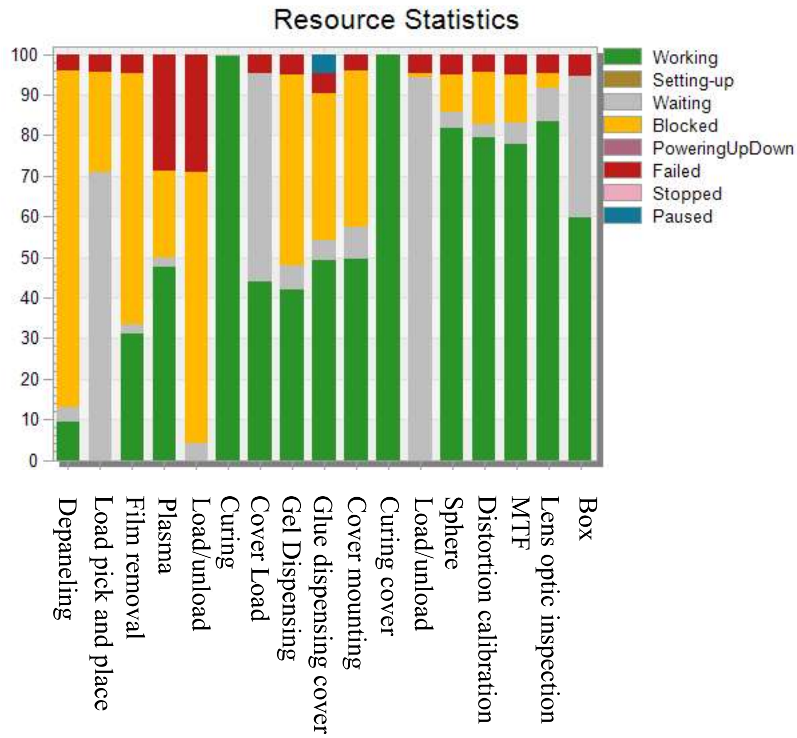


Figure 4.8: *Statistics for each process*

The statistics show that the actual downtime for each process was higher than the initial settings of the experiment. In addition, the downtime was approximately at 4 % for the majority of processes except for Plasma and Load/unload were the downtime reached closer to 30 %. The statistic result on Lens optic inspection, which according to the collected cycle time data and process experts is the main bottleneck of CHA1, shows that the process is both waiting and being blocked by the Load/unload stage of the operation. The statistics on Load pick and place and Load/unload do not show any amount of working time, the main reason is that the time and availability settings are located in different objects. This is a result of certain modification and simplification necessary to be made in order to remain a realistic behavior and at the same time keep the logic in the model, as explained earlier in chapter 4.3. Dark blue on glue dispensing cover refers to the time that periodic tasks performed by the operator affects its available working time. The result shows that around 4% is lost due to the need to change glue every third hour on the station.

Service statistics on the operators for each shift is presented in figure 4.9. Pink represents the repairing time for the operators, green represents the transporting time including the time to perform a task, orange represents the time the operators are moving towards a service point, light grey is the time waiting while no repairing or periodic tasks are in need to be performed, dark grey represents the time the operator need to wait on material. The statistic on the operators shows a clear difference in transporting time with over 12% between shift-1 and shift-3, while failures, one-route to job and waiting for materials are more similar between the shifts.

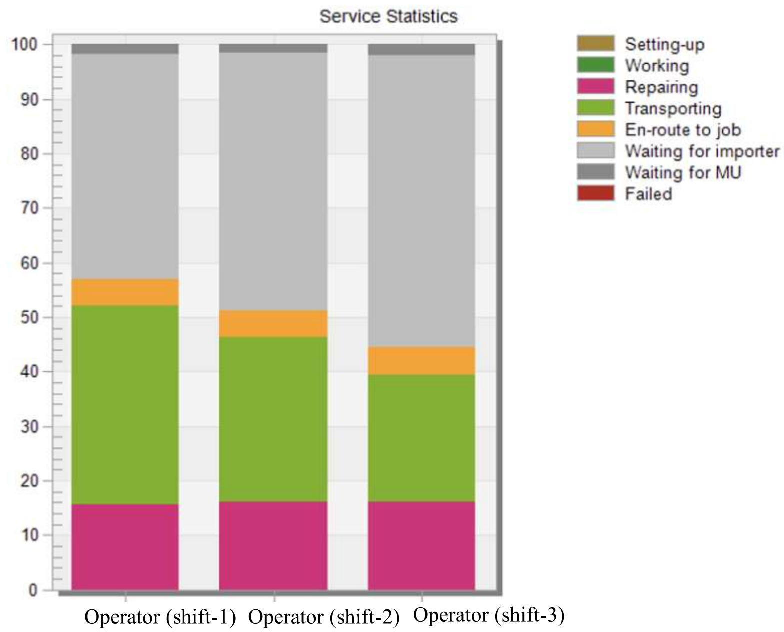


Figure 4.9: *Operators statistics*

**Results of product output:**

- Total = 124 160
- Passed = 120 539
- Reject = 3 621

120 539 number of passed products during April in 2027 is achievable with these settings and availability for each process. Equation two was used to calculate the OEE for the production line for the main product.

**Calculations:**

While the number of passed products exceeds the required number of products produced, two additional product types need to be considered. Furthermore, the loss not detected in the model from the operating task on service point 4 also needs to be considered.

**Actual output/hour:** 120 539/ (22*24) = 120 539/528 = 228,2936 ≈ 228,3 units/h

**Time to produce forecasted volume for Product B:** 2 947/228,3 ≈12,9h

**Time to produce forecasted volume for Product C:** 3 131/228,3 ≈ 13,7h

**Total production time for both products:** 12,9 + 13,7= 26,6h

**Required space:** 26,6+3,7+2,9= 33,2h

**Actual available time:** 528-33,2 = 494,8h

**Actual achievable volume of Product A in April 2027:** 228,3*494,8 ≈ 112 963 →

112 963 < 117 293

**OEE** = (112 963 /136 055) *100 ≈ 83,0% (2)

**Case 1 (Experiment 2)**

Table 4.10: *Settings for experiment 2*

| Input | Value |
|---|---|
| **Availability/Process** | 99,5% |
| **MTTR** | 1min (Erlang) |
| **MTBF** | 3:19:00 |

In experiment 2, all settings on availability are presented in table 4.10, where all processes were set to the same availability of 99,5%. The result of the resource statistics on each process from experiment 2 are visualized in figure 4.10. The statistics show that the actual availability is lower than the initial setting for each process. Both Plasma and Load/unload had considerably higher downtime than the other processes.

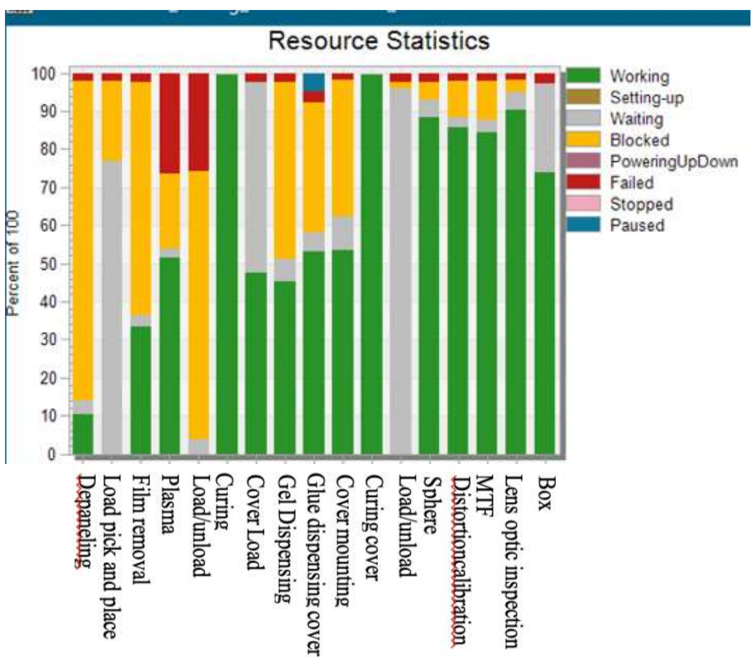


Figure 4.10: *Statistics for each process*

The results on the service statistics from experiment 2 is shown in figure 4.11. 8% of the time is spent on repairing failures on different processes which is constant between all shifts. The same goes for "En-route to job" which is approximately 4% each. The main difference is shown in the amount of time spent on transporting materials and performing periodic tasks that is up to 14% which impact the overall workload for the operators.

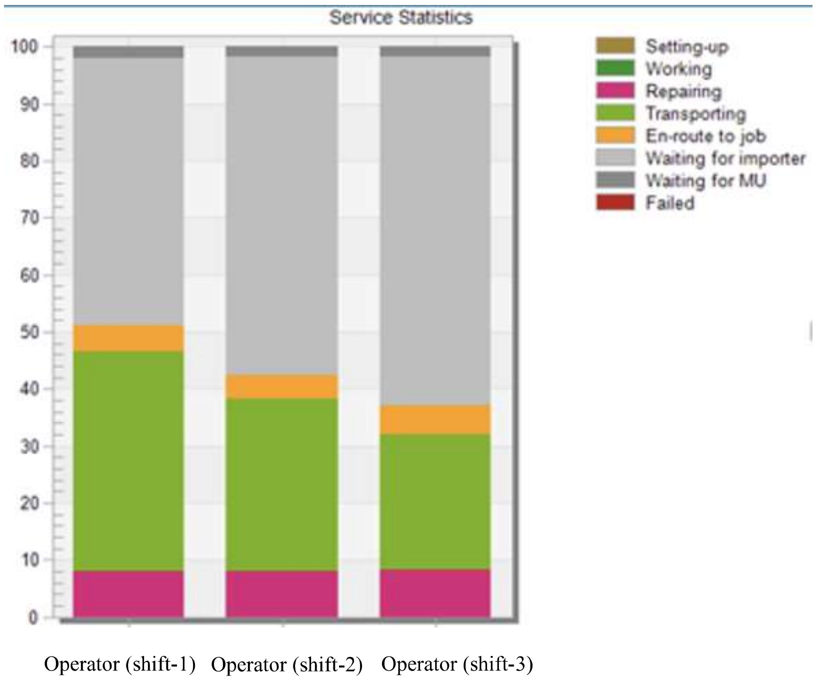

Figure 4.11: *Operators statistics*

**Results of product output:**

- Total = 134 272
- Passed = 130 328
- Reject = 3912

**Calculations:**

**Actual output/hour:** 130 328 / 528 ≈ 246,8 units/h

**Time to produce forecasted volume for Product B:** 2 947/246,8 ≈ 11,9h

**Time to produce forecasted volume for Product C:** 3 131/246,8 ≈ 12,7h

**Total production time for both products:** 11,9 + 12,7= 24,6h

**Required space:** 24,6+3,7+2,9 = 31,2h

**Actual available time:** 528-31,2 = 496,8h

**Actual achievable volume of Product A in April 2027:** 246,8 * 496,8 ≈ 122 610 units →

122 610 > 117 293

**OEE** = (122 610/136 055) * 100 ≈ 90,1% (2)

4.5.1.1 Analysis of results

Overall, the statistical result for each process and operators shows the same pattern between both experiments. Both scenarios indicate an increase in downtime per process compared to the initial settings. Interestingly, both Plasma and Load/unload have considerably higher downtime compared to the other processes even if the settings of availability, MTTR and priority for repairing a failure is the same. The bottleneck Lens optic inspection doesn´t fully operate without being starved or blocked by another process in any of cases. Which could indicate a need for additional buffer capacity connected to the process. However, the early stage of the line may also contribute to wrong identification of required improvements in system. Even if the data currently show Lens optic inspection as the main bottleneck of the line, a more stabilized state in the future might indicate on another process. Therefore, any given indications at this stage might not be the right decision for a better performance.

For the operators, the results show a low workload for the operators at the production line for all three shifts, not exceeding 60% in any of the cases. Operators spend the most time waiting during a shift which indicates on space for additional tasks that could be performed by an operator. In both experiments the operator's workload differs between the different shifts. One reason for this could be the fact that the periodic task for service point 4 that should be performed every 600 min is in fact performed after at specific times every day 17:00 and 03:00 instead of every ten hours. Which also could affect the resource statistics and the output rate. Moreover, the results regarding operator working during shift-1 could be impacted by always being the first to work after the weekends.

In terms of actual time over for additional tasks, the different shift may not have the same impact as the results shows. In addition, certain activities not included in the standardized work and periodic tasks may be present that impacts the result. On the other hand, in the simulation model the operators do not have any delays when it comes to detect any failures which may be happening in reality. Regardless of the difference between the shifts, all indicates on a workload below one. At the same time, external conditions and realistic human behavior has an impact which cannot be fully recreated in a simulation. However, there are no indications of the operators being any bottleneck on the line or contributing to any major loss that would affect the output rate of CHA1.

99,5% availability per process and a 3-shift schedule successfully achieved an output to manage peak forecast volume for CHA1. The OEE for experiment 2 was calculated to 90,1% while approximately 86% would be enough. However, due to variation affecting the output rate, the settings for availability to use as baseline data for the design of experiments are estimated with a marginal to more confident making sure it would achieve the target.

4.5.2 Design of Experiment

Three X-variables were chosen through joint discussions with experts on the firm based on multiple identified independent variables in combination of what was possible in Plant simulation. Experiment managers were used in the program to perform a multilevel and full factorial design with a confidence interval of 95%, see table 4.11. Both buffer capacity were tested at three levels while the number of operators was tested at two levels, using three observations for each scenario. The program Minitab was further used to analyze and determine the effects between each of the independent variables in relation to the output. In addition, the target volume was set to the theoretical maximum output with our base settings in the model.

Table 4.11: *Input data at each level and the tested output data.*

| Independent (Input) | Levels (data) | Dependent (Output) |
|---|---|---|
| **X1 = Buffer capacity, FIFO** | 10, 20, 30 | Number of products produced |
| **X2 = Buffer Capacity, FIFO2** | 10, 20, 30 | - |
| **X3= Number of operators** | 1 & 2 | - |

The result of the full factorial design of experiments for each experiment is shown in figure 4.13 below. The 3 levels on X1 multiplied by the 3 levels on X2 multiplied by the 2 levels on X3 multiplied by the 3 observations studied equals the number of experiments performed.

$$(3*3*2)*3 = 54$$

The result showed that the mean maximum output value was achieved from experiment 8.

**EXP-8:** X1=20, X2=10 and X3=2 → 134 365 passed units.

**Units per hour:**
134 365 / 528 ≈ 254,5 units/h

**Time to produce forecasted volume for Product B:** 2 947/254,5 ≈ 11,6h

**Time to produce forecasted volume for Product C:** 3 131/254,5 ≈ 12,3h

**Total production time for both products:** 11,6 + 12,3 = 23,9h

**Required space:** 23,9+3,7+2,9 = 30,5h

**Actual available time:** 528-30,5 = 497,5h

**Actual throughput:**
254,5 * 497,5 ≈ 126 614 units

**OEE** = (126 614 / 136 055) * 100 ≈ 93,1 %

**Impact on OEE:**
93,1 – 90,1 = 3%

4.5.2.1 Production run analysis

Each factor or independent variable and their interactions effect on the dependent variable is presented in a pareto chart, see figure 4.12. Factor A (number of operators) also referred to as X3 in the report has a major impact on the output level compared to the other two factors and all other interactions. The second most influencing factor was the capacity of FIFO2 (X2) which is visualized as factor C in figure 4.12. The third highest influence is the interaction of the two previously mentioned factors presented as AC, which has more influence than the first buffer in the production line named FIFO1 and is presented as factor B in the pareto chart. A red line was drawn at a standardized effect of 2.03 that refers to the requirement for a factor to be considered of having a statistically significant impact on the dependent variable. Therefore, only the null hypothesis for variable X3 (A) can be rejected.

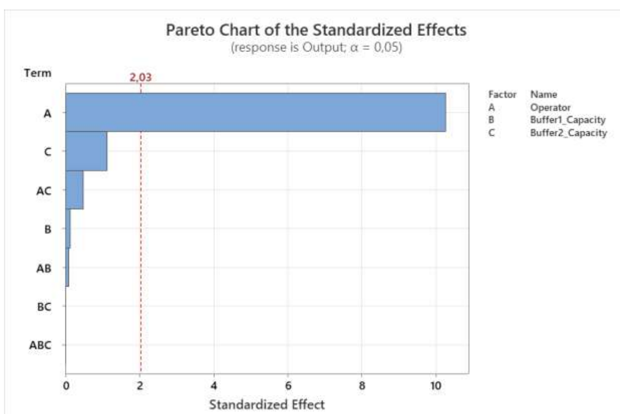

Figure 4.12: *Pareto chart over the independent variables and their interactions*

Figure 4.13 shows each run with the settings for each variable, the total output and the residual value. Output volume marked in yellow shows a significant difference in the residual value compared to other tests, which is visualized in different ways in figure 4.15.

| C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|
| StdOrder | RunOrder | PtType | Blocks | Operator | Buffer1_Capacity | Buffer2_Capacity | Output | RESI1 |
| 1 | 1 | 1 | 1 | 1 | 10 | 10 | 130886 | 653,67 |
| 2 | 2 | 1 | 1 | 1 | 10 | 20 | 130516 | -566,33 |
| 3 | 3 | 1 | 1 | 1 | 10 | 30 | 127404 | -2506,67 |
| 4 | 4 | 1 | 1 | 1 | 20 | 10 | 130080 | -512,33 |
| 5 | 5 | 1 | 1 | 1 | 20 | 20 | 129833 | -950,67 |
| 6 | 6 | 1 | 1 | 1 | 20 | 30 | 127404 | -2506,67 |
| 7 | 7 | 1 | 1 | 1 | 30 | 10 | 130267 | -474,33 |
| 8 | 8 | 1 | 1 | 1 | 30 | 20 | 130388 | -675,33 |
| 9 | 9 | 1 | 1 | 1 | 30 | 30 | 127404 | -2506,67 |
| 10 | 10 | 1 | 1 | 2 | 10 | 10 | 133088 | -715,00 |
| 11 | 11 | 1 | 1 | 2 | 10 | 20 | 133212 | -654,33 |
| 12 | 12 | 1 | 1 | 2 | 10 | 30 | 132931 | -697,00 |
| 13 | 13 | 1 | 1 | 2 | 20 | 10 | 133676 | -689,00 |
| 14 | 14 | 1 | 1 | 2 | 20 | 20 | 133554 | -469,00 |
| 15 | 15 | 1 | 1 | 2 | 20 | 30 | 132931 | -872,33 |
| 16 | 16 | 1 | 1 | 2 | 30 | 10 | 132931 | -915,33 |
| 17 | 17 | 1 | 1 | 2 | 30 | 20 | 133554 | -614,67 |
| 18 | 18 | 1 | 1 | 2 | 30 | 30 | 132931 | -872,33 |
| 19 | 19 | 1 | 1 | 1 | 10 | 10 | 127646 | -2586,33 |
| 20 | 20 | 1 | 1 | 1 | 10 | 20 | 130413 | -669,33 |
| 21 | 21 | 1 | 1 | 1 | 10 | 30 | 130972 | 1061,33 |
| 22 | 22 | 1 | 1 | 1 | 20 | 10 | 131125 | 532,67 |
| 23 | 23 | 1 | 1 | 1 | 20 | 20 | 130850 | 66,33 |
| 24 | 24 | 1 | 1 | 1 | 20 | 30 | 130972 | 1061,33 |
| 25 | 25 | 1 | 1 | 1 | 30 | 10 | 130538 | -203,33 |
| 26 | 26 | 1 | 1 | 1 | 30 | 20 | 130850 | -213,33 |
| 27 | 27 | 1 | 1 | 1 | 30 | 30 | 130972 | 1061,33 |
| 28 | 28 | 1 | 1 | 2 | 10 | 10 | 134230 | 427,00 |
| 29 | 29 | 1 | 1 | 2 | 10 | 20 | 134076 | 209,67 |
| 30 | 30 | 1 | 1 | 2 | 10 | 30 | 133610 | -18,00 |
| 31 | 31 | 1 | 1 | 2 | 20 | 10 | 134420 | 55,00 |
| 32 | 32 | 1 | 1 | 2 | 20 | 20 | 134045 | 22,00 |
| 33 | 33 | 1 | 1 | 2 | 20 | 30 | 134136 | 332,67 |
| 34 | 34 | 1 | 1 | 2 | 30 | 10 | 133518 | -328,33 |
| 35 | 35 | 1 | 1 | 2 | 30 | 20 | 134482 | 313,33 |
| 36 | 36 | 1 | 1 | 2 | 30 | 30 | 134136 | 332,67 |
| 37 | 37 | 1 | 1 | 1 | 10 | 10 | 132165 | 1932,67 |
| 38 | 38 | 1 | 1 | 1 | 10 | 20 | 132318 | 1235,67 |
| 39 | 39 | 1 | 1 | 1 | 10 | 30 | 131356 | 1445,33 |
| 40 | 40 | 1 | 1 | 1 | 20 | 10 | 130572 | -20,33 |
| 41 | 41 | 1 | 1 | 1 | 20 | 20 | 131668 | 884,33 |
| 42 | 42 | 1 | 1 | 1 | 20 | 30 | 131356 | 1445,33 |
| 43 | 43 | 1 | 1 | 1 | 30 | 10 | 131419 | 677,67 |
| 44 | 44 | 1 | 1 | 1 | 30 | 20 | 131952 | 888,67 |
| 45 | 45 | 1 | 1 | 1 | 30 | 30 | 131356 | 1445,33 |
| 46 | 46 | 1 | 1 | 2 | 10 | 10 | 134091 | 288,00 |
| 47 | 47 | 1 | 1 | 2 | 10 | 20 | 134311 | 444,67 |
| 48 | 48 | 1 | 1 | 2 | 10 | 30 | 134343 | 715,00 |
| 49 | 49 | 1 | 1 | 2 | 20 | 10 | 134999 | 634,00 |
| 50 | 50 | 1 | 1 | 2 | 20 | 20 | 134470 | 447,00 |
| 51 | 51 | 1 | 1 | 2 | 20 | 30 | 134343 | 539,67 |
| 52 | 52 | 1 | 1 | 2 | 30 | 10 | 135090 | 1243,67 |
| 53 | 53 | 1 | 1 | 2 | 30 | 20 | 134470 | 301,33 |
| 54 | 54 | 1 | 1 | 2 | 30 | 30 | 134343 | 539,67 |

Figure 4.13: *Result of the Design of experiments for each scenario.*

#### 4.5.2.2 P-Values analysis

The P-value analysis provides a comparison between all the experiment combinations to determine if the output variation is significant or not. A P-value under 0.05 ($P < 0.05$) indicates that the interaction between the experiments conducted are with 95% ($\alpha$=0.05) significant. Hence, P-values in figure 4.14 highlighted demonstrate that the observed values in output between the runs is not due to random variation.

| EXP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.109 | 0.609 | 0.106 | 0.87 | 0.117 | 0.816 | 0.082 | 0.732 | 0.101 | 0.87 | 0.106 | 0.745 | 0.098 | 0.608 | 0.093 | 0.87 | 0.106 |
| 2 | | 0.028 | 0.904 | 0.081 | 0.764 | 0.003 | 0.345 | 0.013 | 0.65 | 0.081 | 1 | 0.004 | 0.957 | 0.011 | 0.484 | 0.081 | 1 |
| 3 | | | 0.027 | 0.466 | 0.033 | 0.529 | 0.016 | 0.733 | 0.027 | 0.466 | 0.027 | 0.662 | 0.036 | 0.982 | 0.022 | 0.466 | 0.027 |
| 4 | | | | 0.079 | 0.675 | 0.002 | 0.383 | 0.012 | 0.733 | 0.079 | 0.915 | 0.003 | 0.98 | 0.01 | 0.542 | 0.079 | 0.915 |
| 5 | | | | | 0.086 | 0.646 | 0.061 | 0.573 | 0.076 | 1 | 0.077 | 0.582 | 0.069 | 0.464 | 0.07 | 1 | 0.077 |
| 6 | | | | | | 0.005 | 0.258 | 0.015 | 0.469 | 0.086 | 0.785 | 0.006 | 0.791 | 0.015 | 0.354 | 0.086 | 0.785 |
| 7 | | | | | | | 0.002 | 0.773 | 0.001 | 0.646 | 0.006 | 0.763 | 0.022 | 0.45 | 0.001 | 0.646 | 0.006 |
| 8 | | | | | | | | 0.007 | 0.508 | 0.061 | 0.391 | 0.002 | 0.535 | 0.006 | 0.711 | 0.061 | 0.391 |
| 9 | | | | | | | | | 0.013 | 0.573 | 0.013 | 0.95 | 0.023 | 0.712 | 0.01 | 0.573 | 0.013 |
| 10 | | | | | | | | | | 0.076 | 0.695 | 0.002 | 0.818 | 0.01 | 0.738 | 0.076 | 0.695 |
| 11 | | | | | | | | | | | 0.077 | 0.582 | 0.069 | 0.464 | 0.07 | 1 | 0.077 |
| 12 | | | | | | | | | | | | 0.006 | 0.959 | 0.013 | 0.538 | 0.77 | 1 |
| 13 | | | | | | | | | | | | | 0.023 | 0.61 | 0.002 | 0.582 | 0.006 |
| 14 | | | | | | | | | | | | | | 0.029 | 0.684 | 0.069 | 0.959 |
| 15 | | | | | | | | | | | | | | | 0.008 | 0.464 | 0.013 |
| 16 | | | | | | | | | | | | | | | | 0.07 | 0.538 |
| 17 | | | | | | | | | | | | | | | | | 0.077 |

Figure 4.14: *P-value comparison between all experiment runs conducted*

The result from the P-value analysis clearly shows that several observed values are statistically significant. Particularly, low $P$-value are identified between experiments 13 and 16 (0.002), seven and ten (0.001) as well as four and 13 (0.003). These values strongly indicate that deviation in output between the experiments can be explained by the factorial levels, rather than random variation. In contrast, the analysis also illustrates a substantial number of values not statistically significant ($P > 0.05$). The identified non-significant values, such as between experiment six and 12 (0.785) and three and 15 (0.982) indicate that the difference in factorial levels most likely have limited influence on the output. The observed values and experiment combinations not significant can potentially be explained by underlying parameters. For instance, that certain chosen levels of the factors might have limited effect, and that the difference between the output of the experiments cannot exclusively be explained by the chosen factors.

4.5.2.3 Residual Analysis

A residual analysis was conducted in Minitab to evaluate the model's validity. The R-sq value for the experiments was 75.32%, which indicates to what extend the variability can be explained in the model. The residual plots below present the deviation between every observed value and the values predicated by the by model, see figure 4.15. The normal distribution plot indicates that most of the observed value follow a normal distribution. However, four values show a large negative residual value, meaning that the model expect a higher value. The versus fit plot present two clear groups of values positioned around 131 000 and 134 000. The observed values appear to be distributed around zero, however with a larger variance for the observed values around 131 000. In this group, several values deviate both negatively and positively from the zero line. Apart from the outliers, the remaining values generally follows the assumptions of the model.

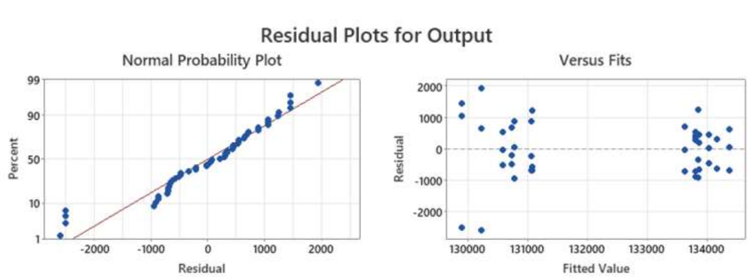


Figure 4.15: *Visualization of the residual values of each experiment*

It is evident that the residual analysis indicates that the model captures a high degree of variability in the data. However, patterns in the versus fit plot in combination with observed outliers from the normal distribution plot indicates that the results need to be analyzed with a certain attention.

4.5.2.4 Main Effect Plot

The main effect plot for output demonstrates to what extent the three independent x-variables effect the mean value of the dependent variable output. Increasing the number of operators from one to two per shift illustrate a clear impact on the dependent variable output. Specifically, two operators per shift increase the mean value output with around 3300 over the simulated period. Even though the figure presents differences between buffer capacity levels, the two variables in the study are not statistically significant, and thus no proven effect on the output can be assumed within the investigated interval.

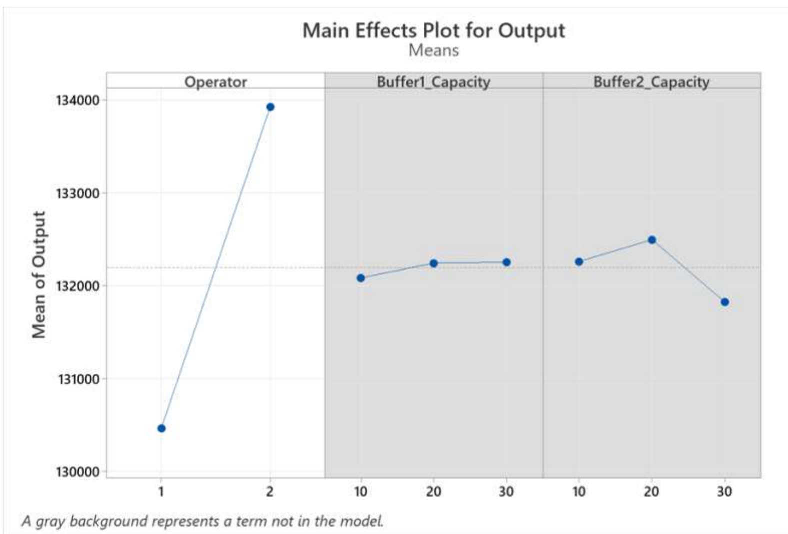


Figure 4.16: *Visualization of the effect associated with different levels of each x-variable*

4.5.2.5 Operator cost analysis

The data on operators' costs per shift are presented in table 4.12.

Table 4.12: *Costs for an operator for different shift forms.*

| Type of Shift | Monthly Cost (SEK) | Cost/hour (SEK) | Data source |
|---|---|---|---|
| Daytime | 54 827 | 313 | Company data |
| 2-shift | 58 271 | 333 | Company data |
| Night | 62 508 | 420 | Company data |

**Additional data from the experiment results and the company:**

- **Highest average output with two operators:** 134 365 units.
- **Highest average output with one operator:** 131 082 units.
- **Comparison: (**134 365/131 082) * 100 ≈ 102.5%
- **Operators' working time including transfer time between operators:** 8 hours and 12 minutes → 8.2h
- **Number of working days:** 22 days

**Calculation on direct labor costs compared to the number of units produced:**

**Cost for one operator/day:**

8.2*313 + 8.2*333 + 8.2*420 = 8 741,2 SEK

**Total cost during the experimental period:**

22*8 741,2 = 192 306,4 SEK

**Operator cost/unit:**

192 306,4/131 082 ≈ 1,467 SEK/unit

**Costs for two operators/day:**

8 741,2 * 2 = 17 482,4 SEK

**Total cost during the experimental period:**

22*17 482,4 = 384 612,8 SEK

**Operators' cost/unit:**

384 612,8/134 365 ≈ 2,862 SEK/unit

**Difference in direct labor cost/unit:**

2,862-1,467 ≈ 1,395 SEK/unit

**Saved cost/unit:**

(1,395/2,862) *100 = 48,74%

Table 4.13: *Summary of result*

| | 1 Operator/shift | 2 Operator/shift | Difference |
|---|---|---|---|
| **Highest mean output** | 131 082 | 134 365 | 102,5% |
| **Cost/Day, 3-shift (SEK)** | 8 741,2 | 17 482,4 | 200% |
| **Total Cost (SEK)** | 192 306,4 | 384 612,8 | 200% |
| **Cost/Unit (SEK)** | ≈ 1,467 | ≈ 2,862 | 195,1% |

The results show that the number of operators impacts the number of products produced with a 2.5% increase in output. Even with a considerable low workload for an operator, two people make it possible to simultaneously repair and complete tasks. The number of simultaneous machine failures between processes and periodic tasks needed to be performed changes over time, making the actual impact of an extra operator varying over time. In terms of cost, two operator doubles costs for the company, making the cost per unit to increase with approximately 1,4 SEK/unit, even though an extra operator for each shift increase the total number of products per month. This result indicates a need to make tradeoffs between the cost and the output volume.

# 5. Discussion

*In this chapter all research questions will be analyzed and discussed in order. Research question 1 in chapter 5.1, research question 2 in chapter 5.2 and research question 3 in chapter 5.3.*

## 5.1 Challenges with utilizing DES in early production environments

The study proved that utilizing DES in early-stage production environment is challenging, both in the model development phase as well as input data modelling. Several limitations between the integration of input data and model development were identified. The findings demonstrate that one of the main challenges in this context is to manage the balance between the uncertainties and complexity presented by Surbier et al (2014), with modelling logical behavior and achieving highest possible accuracy. Therefore, the DES model contains a number of assumptions, simplifications and estimations in various segments of the model. To effectively develop the logic relations in the system, the model includes more objects in comparison the real production line and its corresponding stations. Additionally, limited data on process level complicated the modelling of availability on each process in the system. Discussions with stakeholders were held regarding how to include this in the model, which was essential for operator evolution. In this case, an estimated availability rate from process experts was associated with a high degree of uncertainty, potentially effecting the results in a misleading way. Instead, the availability was determined from an output comparison testing multiple levels with the forecasted volume as the target output in the simulation model. According to Banks et al. (2010), these type of assumptions and estimations is needed to develop the model. However, it became evident that converting these assumptions and estimations into the simulation model in this context increased complexity of this task.

Moreover, evaluating OEE in early development of a production line with low data availability proved to be challenging. This is in line with Bokrantz et al. (2018) study, which demonstrates that insufficient level of detail in the data complicates OEE calculations in a simulation environment. However, Bengtsson et al. (2020) explains that OEE calculations can be modified depending on context. Due to lack of necessary data, the modified version presented by Muthiah and Huang (2007) was used. While normally applied OEE formula consists of separated factors referring to different losses in the system, the modified version of the OEE formula considers all losses as a difference between actual versus theoretical output. This makes it difficult to understand what type of loss that actually contributes to the OEE result. Consequently, a result shows the OEE level but does not contribute to any indications on areas of improvement. It is an important limitation to include, as in many cases OEE is calculated not only to give an indication on current or required performance but to analysis and understand on how to improve it. Although OEE is considered to be a strong KPI, the findings indicate that it might not be sufficient in all situations and thus adds complexity. Looking more in detail at the OEE calculations presented by Muchiri and Pintelon (2008) and Muthiah and Huang (2007), it becomes evident that this KPI is more suitable from a resource efficiency perspective. Hence, Magnas current transformation towards a more flow-efficient production system, more emphasize on throughput time might be more suitable in this context.

Another limitation is the deduction of Product B & C as a result from the lack of data on their performance. All products are assumed to have the same cycle time per product, which makes it mathematically correct but not very realistic. As the calculations assume that they are exactly the same, while in a production environment there is a likely possibility of differences in the level of performance. It became evident that the main challenges of collecting high quality data were associated with the early stage of the production line being in the infant mortality and ramp-up phase. Consequently, data collection lead time increased since category A data was difficult to collect at this stage (Skoogh & Joahnsson, 2008).

Streamline this process and decrease the lead time is essential to achieve a higher degree of accuracy. Therefore, a solid understanding of what type of data available and collatable in an early stage of the project is a key aspect. Moreover, one must recognize early how the data can be integrated and utilized to the DES models needs and conditions (Bokrantz et al., 2018). From an organizational perspective, stakeholders express that a more profound documentation and data management system of detailed production data is necessary to obtain higher quality data, which aligns with Skoogh and Johanssons (2008) research, arguing that category A data from databases or business system is condensed ideal from a simulation perspective.

## 5.2 The influence of system parameters

Even though the model consists of several uncertainties, the validation indicated that the model was in sufficient condition for executing the experiment to investigate the effect of independent variables. The experiment conducted in experiment manager and its corresponding analysis in Minitab provided noteworthy insights into how the number of operators and buffer capacity effect the investigated system. The analysis of the result presented an R-sq value of 75.32%, which indicates that a substantial amount of the variation in the dependent variable can be explained by the independent variables. Moreover, that the number of operators per shift is a statistically significant variable and the dominating factor effecting the output, while the buffer capacity did not have a significant impact on the investigated system.

Reducing the number of operators is a common strategy for decreasing labor costs and simultaneously handle the trade-off between production efficiency and costs. As mentioned earlier, due to the high degree of automation it is estimated that one operator is needed at the line. Hence, it was interesting to understanding the effect of increasing the number of operators per shift under the infant mortality phase (Ohring, 1995). Moreover, recognize this as a potential option for the development of new production lines in the future. Therefore, understanding the influence of systems parameters becomes highly important in this context.

Surbier et al (2014) emphasize the importance of managing cost, quality, complexity and uncertainty in a production line being in the ramp-up phase. In line with this, Dombrowski et al. (2018) highlight the significance of the ramp-up phase parallel to high customer expectations. Hence, the experiments conducted and the corresponding analysis demonstrate that DES can be used to evaluate how the output, and eventually OEE and direct labor cost is influenced by the number of operators. The experiments indicate that the output increases with nearly 3300 units per month when allocating two operators per shift. Eventually, this confirms that OEE can be increasing under these circumstances, which potentially could be a strategy for increasing the productivity in a highly demanding automotive market (Gajsek et al., 2019). However, the operators cost analysis presents interesting results regarding the allocation of two operators at the line. The results shows that the cost per unit increases from 1,467 SEK to 2,862 SEK when utilizing two operators pers shift, which is not ideal from a long-term perspective. Thus, it is important to understand how this decision might affect both productivity and costs. Therefore, understanding in detail how to develop a ramp-up process more rapid and efficient can be strategic tool in a highly competitive automotive market. As a result, a production line in this context characterized with high degree of uncertainty (Surbier et al., 2014) as well as high customer expectations (Dombrowski et al., 2018), the allocation of two operators can be a suitable short-term option. However, from a long-term perspective, the operator cost analysis show that this might not be a sufficient option. Accordingly, the findings demonstrate that DES can be used to evaluate how the number of operators influence both OEE and direct labor cost, as well as support companies when managing the trade-off between production efficiency and costs. Moreover, to leverage DES as strategic tool for develop a robust ramp-up phase to control higher customer expectations and uncertainties.

In contrast to the operators, the result clearly demonstrates that the effect of the chosen factorial buffer capacity levels on the investigated system is not statistically significant. This phenomenon is not unusual in this context, and several underlying factors could be potential reasons. Discussions were held with stakeholders at the company which emphasizes that the most common factor in this context is high variability in data and small sample sizes. Thus, it can be argued that small sample sizes might be an underlying factor leading to the insignificant result. A correlation between high levels of failures rates in the infant mortality phase (Ohring, 1995), as well as the ability to conduct a robust data collection process can be identified. This also confirms the statement provided by Skoogh and Johnasson (2008), emphasizing the difficulties collecting high quality data in this context. From another perceptive, the findings indicate that investigated system show robustness and stability, since the investigated factorial levels did not influence the system. Therefore, it is possible that lower buffer capacity levels could potentially be utilized in this context.

Overall, the results indicate that DES can be a useful tool for identifying and evaluate the influence of parameters of a production line in its early stage (Huy Huynh et al., 2020), however also demonstrate the challenges and uncertainties associated to the contextual conditions. Therefore, leveraging the advantages of DES in this context is highly dependent on the availability of high-quality data.

## 5.3 DES as a decision-making tool at an early stage of production

According to Banks et al. (2010), a robust data collection process is essential for developing a DES model that accurately represents the real system. At the same time, Skoogh and Johansson (2008) argue that the outcome of the data collection process is highly dependent on the contextual condition of the investigated system. The production line investigated in this study is in an early stage of implementation reflecting a production ramp-up (Dombrowski et al., 2018) and the infant mortality phase of the bathtub curve (Ohring, 1995), which created several challenges related to the development of the DES model. Hence, a significant amount of data categorized as B and C was collected and used as input for the DES model, which is not ideal according to Skoogh and Johansson (2008). Moreover, the uniqueness of the production line compared to other lines at the factory limited the possibility to look at similar lines as an alternative approach to reach higher degree of quality data. Instead, several assumptions and estimations were necessary to include in the DES model.

According to Huy Huynh (2020) discrete event simulation has the ability to optimize different parameters in manufacturing. The result from the design of experiment performed gave indications of certain effects on the output value. It showed that parameters could be tested with different value to determine the optimal solution for the dependent variables that is preferred to study. However, only one parameter showed a significant impact on the dependent variable and a R-sq value of 75% which shows a certain level of variability in the model. Nevertheless, the impact of the effects from variables itself and their interaction could be analyzed and better understood through the usage of DES. The result indicated a higher impact from the interaction between the capacity of buffer 2 and the number of operators then from the capacity of buffer 1 alone. Interactions and effects that may be very difficult to detect in reality, could be detected through DES with a higher probability. This probability may however decrease in early-stage production because of several different reasons. The main reasons lie in the lack of reliable data that is available, making it more difficult to replicate a similar behavior and logic compared to reality.

New unique manufacturing processes also complicate any comparisons and benchmarking for major uncertainties with other production lines. This provides challenges in making assumptions and estimation with a high enough confidence due uncertainty in the performance. Dombrowski et al. (2018) argues that lack of experience is one reason for creating these unpredictable conditions during this phase. It also impacts our project in terms of planning and data collection since the conditions where unstable and unpredictable. Furthermore, this led to rescheduling and changes in the project as well which potentially impacted our work with the already limited time frame.

During the project, a high degree of unpredictability and uncertainties had an impact on both structure and the planning of data collection, validation and verification methods, and input for the experiments. This is aligning with Dombrowski et al. (2018) description of the production ramp-up characteristics and its high complexity. With more than 50% failing to reach the KPI target values at an early stage, DES could be used to analyzing multiple different scenarios to determine or guide towards meeting those goals. It has the potential to more easily test and analyze several parameters at the same time to determine with more confidence their actual effects on the system. Our result shows that only one parameter had a signific impact on the output. In reality changing multiple settings and parameter simultaneously could make it difficult to understand what actually caused a change in the performance. DES could also be a tool for better understanding specific behavior, identifying issues and solving problems. However, these unpredictable and uncertain behaviors in the production line complicates the validation and the comparison to the reality.

Furthermore, to understand the possibility at an early stage like a production ramp-up of what can be achieved in terms of output level or operator´s workload can be misleading. Our result showed a different in the operator's workload between the three shifts which may be a result of certain simplification or lack of data to get e more precise workload. In contrast to the analysis of the parameters, the root cause of the variation in workload is more difficult to detect. In addition, the learning curve of the operators and process engineers' impact the results as the time to fix a machine failure decrease with experience. Machines tend to fail a lot more during an early stage which according to Mannan (2005) is connected to its quality and installation settings of the machines. The high failure rate and low production capacity formed the project to instead of using current data on availability and MTTR, it was tested to see which level was necessary to achieve future demands. However, the limitation in this context is that the variation and distribution of the availability between the different processes can't be captured. It shows some of the limitations of using a tool that heavily depends on quality data at an early stage.

More uncertainty and an uneven material flow have shown in the project to be problematic in terms of collecting data. Skoogh and Johansson (2008) describe difficulties in collecting quality data at an early stage. Even with a validated model within an approved marginal error, the small sample sizes and lack of data over time could lead to a less realistic logic and behavior of the model and potential misleading results. Data collection has also proven to be a time-consuming part of the project due to a high uncertainty in the possibility for data collection. In addition, a high amount of downtime both disrupted the process and caused major outliers in the data. The failure rate in an early stage of production according to Ohring (1995) distinguishes itself from a more mature stage. In terms of creating a realistic simulation model over time, the high difference in the amount of downtime makes it difficult to compare to a future state and will most likely not share the same behavior or result. However, DES can still be very valuable in understanding future needs and target levels in certain parameters as well as finding areas of improvement more effectively. Our results shows that the buffers capacity with the current data has no significant effect on the performance in terms of output. It also gives an indication of what output the system is currently capable of with the current cycle times. It allows to analyze with a higher flexibility and freedom with less risk-taking and financial consequences.

The potential of less financial resources is needed in comparison to reality, even if the result needs to be taken with caution. However, in an early stage, time and risk potentially increase compared to a more stable stage, where the space to take more calculated risk increases. A misleading result can instead cause a risk of higher financial consequences if it is proved to be wrong. Early-stage production may therefore need additional experiments to be tested multiple times, the result to be more carefully compared to expert analysis and combined with other decision-making tools to a greater extent. Another limitation with simulation is the need to simplify logic and process behavior of the production line, which could be necessary to a higher degree at a production ramp-up as a consequence of the low experience and lack of data. The simplification could influence the result by either overestimate or underestimate the impact a scenario or parameter has on the performance. Compared to a more stable state, these simplified solutions would be easier to avoid if the simulation software allows it. However, this limitation may be reduced in a context where similar production lines exist for benchmarking and data collection.

The result in the report shows that DES as a tool in an early stage could give guidance in the decision making at an early stage with a high enough probability and confidence level to avoid any major risk. It could also support decisions and its implementation with a more confident foundation. Our result shows that even with a low workload level on the line, adding an extra operator would increase the output. In this case, especially at an early stage with a higher level of downtime in the system, an extra operator could be a strategic decision to achieve a required volume. A DES model in general has the ability to test hypothetical solutions in a risk-free environment, which is aligned with Banks et al (2010) description of DES. This may be very important as a guideline in early-stage production with a lot of uncertainties, to more efficiently develop and achieve a stable material flow. However, with more time and knowledge, these experiments can be done to a greater extent and contribute to even clearer observations and results at an early stage.

# 6. Conclusion

DES can be used at an early stage for decision making and to analyze parameters impact on a production line. It has the potential to give guidance in decision making by more efficiently testing different scenarios and parameters to identify improvement at the current stage. It could therefore contribute to a better understanding of what performance targets that are necessary to cope with future demands and how to reach them. However, several contextual factors limit the usefulness of DES as a tool at an early stage. One of its main limitations is the reliability of the model due to the lack of historical and quality data, which makes it very difficult to capture realistic behavior and to properly validate the model.

Moreover, the findings prove that DES can be utilized in early-stage production environments to evaluate the effect of system parameters. In this context, the DES model can contribute to understand a production line more in detail and thus the influence of parameters on existing system performance. However, during these contextual conditions, several challenges arise. For instance, assumptions and simplification is required to a greater extent in the model, effecting the ability to represent the real system. In line with this, low data availability also creates uncertainties and hinders the ability to represent the real system. Overall, the study demonstrate that DES can be a useful tool already in an early stage och a production line, both as a foundation for decision making and for evaluation the existing system. However, uncertainties must be considered to a greater extent in this context.

## 7. Future research

More demanding customer requirements related to quality, efficiency and flexibility puts pressure on automotive suppliers to continuously develop to remain competitive. Hence, the ability for organizations to rapidly adapt to changing customer demands is considered to be vital in the near future. Therefore, improving and streamline the early stage of a production line processes is essential in this context. In line with this, it is expected that the use of industry 4.0 applications will increase in the years ahead to achieve this.

The study indicates that DES has the ability to evaluate the current state of a production line in the early stages, as well as support decision making in this context. However, the contextual condition also constitutes to several obstacles and challenges, limiting the ability to fully leverage DES in early-stage production. Therefore, there is a need for future research to focus on how these challenges can be managed to successfully utilize DES in this context.

A substantial amount of existing research regarding DES addresses it's application in the design phase or stable production environments, creating a research gap. Thus, increased emphasize need to be allocated towards the implementation phase to understand and leverage the advantages of DES in this context. More specifically, researchers should focus on how the challenges of collecting and integrating data in this context can be improved, since this is the main obstacle for achieving higher accuracy. Hence, the low-quality data leads to higher degree of uncertainties, thereby hinder realization of the results. Therefore, it is necessary to reduce this research gap, since there is major potential to leverage DES in the early stage of production line development.

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# A Appendix 1

**Semi-structured interview**

1. Could you briefly describe your roles at the company?
   a. How long have you worked on this line?
   b. What responsibilities do you have regarding this line?

2. Can you walk us through the complete production process step-by-step, from when material enters the line until the finished product leaves?

3. What stations are included in the line, and how does each one operate?

4. What logical relations and behavior characterize the production line?

   a. Do you expect any logistical constraints during the ramp-up phase?

5. Are there buffers or storage areas between stations? If yes, what are their capacities and how are they used?

6. What production volume is the line designed for, and what volume will be used during the initial ramp-up phase?

7. What cycle times are expected for each machine according to the design specifications or supplier information?

8. Which station is expected to be the bottleneck according to the current design?

9. How do you expect the production performance to change during the ramp-up period? For instance, in terms of slower cycles, more stops, learning effects?

10. What is the planned standardized work for the operator once production starts?
    a. Are there tasks that are expected to be difficult or time-critical for the operator?

11. Which parameters in the system are you most uncertain about right now?
12. How is the shift structured? When do breaks occur and what happens to the line during those times?

13. What data does the company collect continuously in the system?

14. How is material planned to be delivered to the line during initial production?

15. Lastly, from your perspective, how can the production ramp-up phase be improved?

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