MASTER

A decision support system to determine the stock positions and targets in the semiconductor industry

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Master Thesis

Operations Management and Logistic

A decision support system to determine the stock positions and targets in the semiconductor industry

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Abstract

The semiconductor industry is a complex industry with various supply and demand uncertainties. Since most of the supply chains within the semiconductor industry can be described as a multi-item multi-echelon supply chain, determining the stock positions and their targets is a difficult task. ams AG acknowledges this. Furthermore, most products for ams AG are highly customized. Therefore, a product is produced for a limited number of customers. This report provides a method to determine the possible stocking points while customer lead-times differ for each order. Furthermore, the software package ChainScope is used to optimize the safety stock settings. ChainScope is based on the Synchronized Base Stock (SBS) policy. A case study is performed to compare the current (safety) stock settings to the optimized settings. The (safety) stock settings are optimized under the constraint that the desired fill rate is achieved against minimal inventory costs.

Executive Summary

Introduction

The semiconductor industry is characterized by long cycle times, short product life-cycle, proliferating product variety, yield, and customer demand uncertainty. A company operating in the semiconductor industry is ams AG. ams AG is divided into three business units, Image Sensor Solutions, Optical Sensor Solutions, and Advanced Optical Sensors. This project focuses on the Image Sensor Solutions.

Currently, a clear company strategy is missing to make two crucial decisions regarding inventory control. The first decision is determining the possible stocking points within the supply chain. Secondly, how to determine the safety stock targets for these stocking points. Due to the relatively long throughput times and the varying customer lead-times, the production of the products has to be started based on forecasted demand. However, since every order can have a different requested customer lead-time, a method is proposed to determine the customer order decoupling point. Furthermore, the demand and supply uncertainties should be considered to determine the safety stock levels. Therefore, the following assignment is defined:

Design a policy to determine the (safety) stock locations and targets considering supply and demand uncertainties to obtain the desired service levels against minimal inventory levels.

Current situation

First of all, the current situation is analyzed to identify the characteristics to develop the design. This results in the following characteristics:

- Limited number of customers for most of the products.
- The products have a serial, assembly or a divergent supply chain.
- Every order has a different customer lead-time.
- Most customer demand is stationary and follows the gamma distribution.
- Demand and throughput uncertainty are the main uncertainties obtained in the semiconductor supply chain.
- Customer demand that is not fulfilled is backordered.
- The inventory policy operating under a periodically review moment.
- The performance is measured in the confirmed line item performance and the requested line item performance.

Based on these characteristics, the design is developed.

Design

The design can be divided into three steps (Figure 0.1). The first step is determining the customer order decoupling point. Since the customer lead-time is differently for every order, a method is proposed to determine the modeled customer lead-time. Based on the minimal customer lead-time that excludes the orders that have extreme order requests, within one week, the modeled customer lead-time is determined.

The second step is determining additional stocking points. For this study, two main reasons are considered to place an additional stocking point. The first reason is a bottleneck location. Secondly, when a component is used for multiple end items in stage X, and in a stage downstream (X-1) in the supply chain, this component can only be used for fewer end items, stage X is a possible additional stocking point. The commonality in end items and customers indicates this.

The last step is to optimize the (safety) stock settings for the locations determined as stocking points in the previous steps. This is done by the software ChainScope which is based on the Synchronized Base Stock policy. Under a fill rate constraint, the optimal (safety) stock settings are calculated.

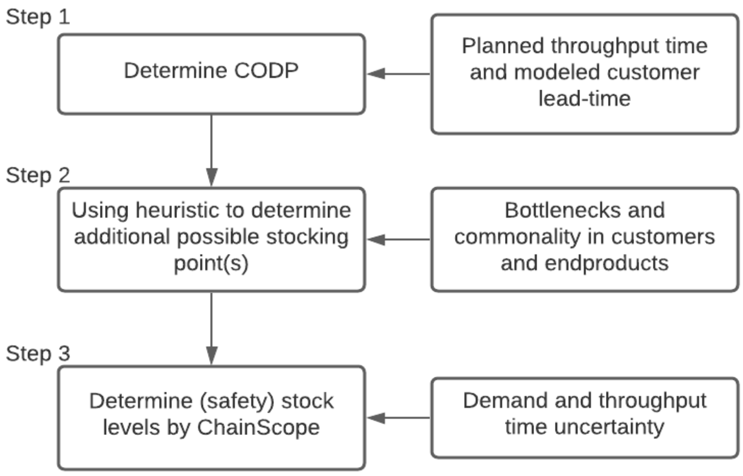

Figure 0.1: Proposed method steps

Results

A case study is performed to provide ams with insights into the proposed method. Different scenarios for the throughput time, desired fill rate, and the modeled customer lead-time are analyzed. The case study shows significant reductions in (safety) stock costs with the same or a better fill rate. These reductions are achieved by better inventory placement and by optimizing the (safety) stock settings using ChainScope.

However, this depends on the case. For some cases, an investment at a certain location is necessary to achieve the desired performance. Although, for most cases, the overall average inventory on-hand costs are significantly reduced while the performance is even better.

Recommendations

Using the proposed method to locate the possible stocking points results in a significant reduction in (safety) stock with the same or better performance in a few cases. Therefore, it is recommended to consider the customer lead-times. At this moment there is stock located at the end item for some products, while this is not necessary to achieve the same performance.

Furthermore, the (safety) stock settings are optimized by using ChainScope. The tool gives interesting insights into the (safety) stock levels needed to achieve the desired fill rate targets. Using the tool will help set targets that will cover the demand and throughput time uncertainties without holding unnecessary inventory. In the thesis, some recommendations are given on how often the parameters should be updated.

Although, the study has two major limitations. Firstly, the customer demand is based on the historical demand. It might be interesting to include the forecasted customer demand to determine the (safety) stock settings. The other limitation is that the performance in the program is measured in fill rate, while the performance measure that ams uses is RLIP. Interesting for future research would be an independent simulation model that can compare both performance measures.

Preface

This thesis marks the end of my journey for the master Operations Management and Logistics at the Eindhoven University of Technology. This project was a wonderful but remarkable journey. It was different than expected because of the COVID-19 situation. However, it was a very special and meaningful journey, which has come to an end.

First of all, I would like to thank my first supervisor, Henny van Ooijen. You helped me to slow down my thoughts and let me think multiple times. Furthermore, I am very grateful for the effort, flexibility, but also for being critical during this project. Sometimes the meetings were short and efficient when I needed a confirmation. When it was needed to have a longer meeting to discuss my thought and let me think in a different way, this was also fine. Next, I would like to thank my second supervisor Ivo Adan. You helped me with selecting the right method to solve the problem.

Next, I would thank my supervisors Edgar van Campen and Ben Wouters, for the guidance and the opportunity to conduct my project at ams AG. Edgar, despite your very busy scheme, there was always time to have a discussion. You helped me to be critical at the right moments and let me consider other directions when necessary. Ben, thank you for the pleasant meetings. They inspired me and helped me to bring this project to a higher level. Furthermore, I really liked the interest and enthusiasm for this project and the personal interest besides the project. Thank you both for being my supervisors during this project. Your contributions definitely improved this thesis and made the time at ams a learning experience.

Furthermore, I want to thank Raoul Bonnet and Evelien Klein for the bi-weekly meetings. Your feedback lets me consider different aspects which improved the insights of the project.

Lastly, I want to thank in particular my parents and my girlfriend. During this exceptional situation, working at home was the normal situation. However, this made the project at some times very tough. Thank you for always fully supporting me during this project and believing in me from the beginning of this project.

Thom van Ulden

October 2021

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Abbreviations

AOS Advanced Optical Sensors.

ATO Assemble-To-Order.

BOM Bill of Materials.

CL customer lead-time.

CLIP Confirmed Line Item Performance.

CODP Customer Order Decoupling Point.

CTO Configure-To-Order.

CV coefficient of variation.

EOL End-of-Life.

FG finished goods.

FT final tested.

FTO Finish-To-Order.

ISS Image Sensor Solutions.

LLC low level code.

MTO Make-To-Order.

MTS Make-To-Stock.

NPD New Product Development.

OSS Optical Sensor Solutions.

RLIP Requested Line Item Performance.

RM raw materials.

SBS Synchronized Base Stock.

SDS Safety-Days-of-Supply.

SS Safety Stock.

TSV Through-Silicon Via.

TT throughput time.

UT untested.

UW unsorted wafers.

WLCSP Wafer Level Chip Package.

1 Introduction

Effective supply chain management is described as: 'a mechanism that delivers products quickly with low inventories through the efficient routes, which lead to customer satisfaction and hence new competitiveness in the global market' according to Lee (2001) (p. 190). (Graves and Willems, 2003) divided the range of decisions into three categories:

1. Network design: the number, location, and size of the nodes.
2. Product design.
3. Strategic placement of safety stock. In other words, how to deal with uncertainties within the supply chain.

An exciting industry to conduct a study about these decisions is the semiconductor industry. The industry is characterized by long cycle times, short product life cycles, proliferating product variety and yield, and demand uncertainty. Therefore, the semiconductor industry is an interesting research field where demand and supply uncertainties should be considered.

This research will focus on the first and the third decisions regarding where to place inventory and how to handle the uncertainties within the supply chain. The study has been conducted at ams AG. ams AG is located all over the world. However, a design center is located in Eindhoven. Since a clear company strategy in setting the safety stock settings is missing, this study was initiated to give ams some insights on how to manage the trade-off between inventory and service levels.

As mentioned before, in this study, the placement of the inventory position is determined. Thereafter, an approach is discussed to manage the demand and throughput time uncertainties within the supply chain. The approach determines the target of the inventory position.

The rest of the thesis is structured as follows. The next sections describe the background of the company and describe the problem in more detail. Next, the research design is described. First, the available literature is reviewed. Secondly, the problem and the research goal are defined. Thirdly, the scope of the project is given. Lastly, the research plan is discussed. The third chapter is a detailed analysis of the current situation. This part analyzes the products, supply chain structures, production strategies, customer demand, forecasting error, yield, throughput time, inventory policy, performance measures, and safety stock. In chapter four, the method designed is discussed. This method is applied to the situation of ams to compare it with the current situation in a case study. Finally, a conclusion and recommendation are given to ams.

1.1 Background

In this section the background of the thesis is described. First of all, the company background discusses the general information of ams AG (section 1.2.1), the high level supply chain (section 1.2.2), the semiconductor characteristics in section 1.2.3, and their safety stock settings (section 1.2.4). Furthermore, the problem is described in section 1.3.

1.2 Company background

1.2.1 General information

ams AG designs and manufactures sensor solutions applicable to automotive, smart health sensing, mobile & wearables, and computing. In total, around 8,500 people are working at ams, distributed all over the world. The headquarters is located in Premstätten, Austria.

The 22 design centers are mainly located in Europe, 14 sales offices, and 25+ channel partners worldwide. The manufacturing takes place in Austria and Singapore, and the testing process in the Philippines.

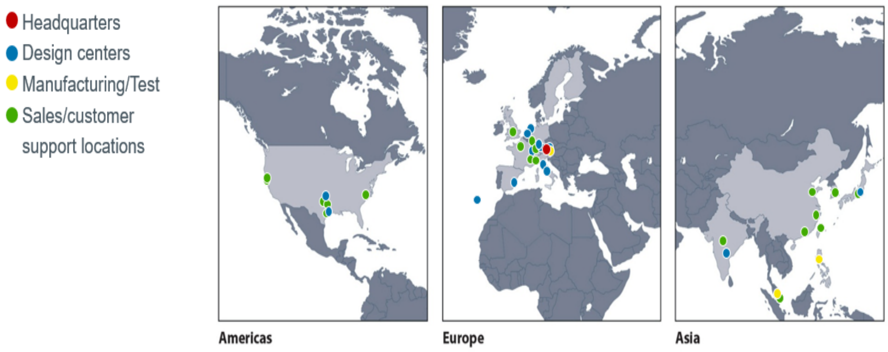


Figure 1.1: Gobal Network from ams AG

ams AG is divided into three business units: Image Sensor Solutions (ISS), Optical Sensor Solutions (OSS), and Advanced Optical Sensors (AOS). Each business unit is grouped into multiple business lines (BL). During this thesis, the ISS business unit is within the scope of the project. The other business units are out of scope.

The business unit ISS consists of five business lines. Because of confidential reasons, the five business lines are called A, B, C, D, and E.

1.2.2 Supply chain

One of the characteristics of ams is the large variety in products, which results in many different production processes within ams. In this section, a high-level supply chain is given in Figure 1.2. Later some variations on the high level supply chain will be described. A short description gives an idea of the operations in the front and back-end. The front-end operations consist of the wafer fabrication and the wafer sort. In wafer fabrication, the process consists of multiple layers. Each layer consists of multiple processing steps. These processing steps depends on the product and technology used. A characteristic is the cycle pattern, in which the same steps are repeated in the same sequence. When the wafer fabrication is finished, unsorted wafers (UW) are stocked. During the wafer sort, the dies are tested individually. The dies that do not meet the required specifications are rejected. The percentage of the dies that are not rejected is called the yield percentage. After this process, the wafers are sorted (SW). The back-end operations consist of assembly and final testing. During the assembly process, the dies are assembled in a package. In the final step, which is final testing, the untested (UT) dies are checked to guarantee that everything is working. Thereafter, the final tested (FT) dies are packed and ready to transport to the customer.

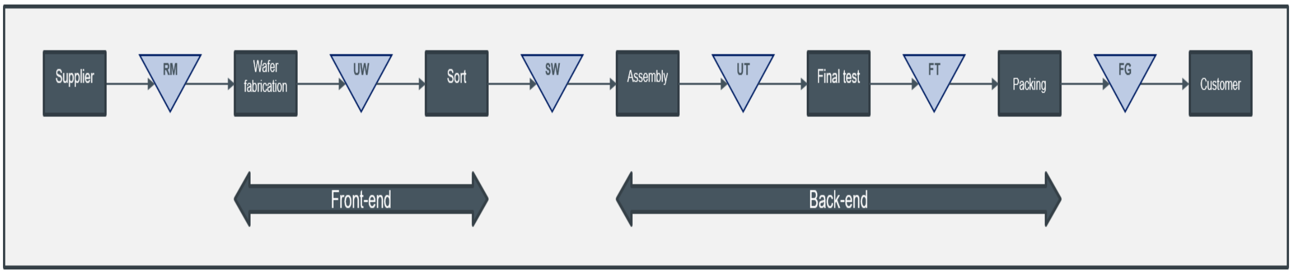


Figure 1.2: High-level supply chain

1.2.3 Characteristics

- Distributed all over the world, as mentioned above.
- Hybrid supply chain
  Some production steps are done internally, externally, or both.
- Product variety
  ams has a product portfolio for five main industries, mobile, automotive, industrial, medical, and computing. The different products within the product portfolio consist of 3D, audio, capacitive, imaging, light, position, power management, smart lighting, and temperature sensors.
- Short product life-cycle
  In the high-tech world, the life cycles of products are relatively short because of the development of new technologies. This is not the case for all products within the semiconductor industry.
- Long cycle times
  Semiconductor supply chains are typically represented by long cycle times, especially in the first process step of the front-end operations, the wafer fabrication. This process takes on average 8 - 12 weeks.
- Yield and demand uncertainty
  Yield and demand uncertainty is a well-known problem in the semiconductor supply chain that should be considered.
- Limited customers per product
  A characteristic that distinguishes ams from other semiconductor companies is the limited customers per product since most products are highly customized.

1.2.4 Safety stock

Within ams, the production engine considers the safety stock settings in two ways. The Safety-Days-of-Supply (SDS) and Safety Stock (SS). The first type, SDS, is linked to the demand and is time-based. The second type, SS, is a fixed quantity. The SS type is easier to understand. However, it needs a regular review. The SDS dynamically links the forecasted volume, which reduces the risk of obsolescence in a dynamic market.

1.3 Problem description

At this moment, there is no clear company strategy to make two crucial decisions regarding inventory control. The first decision is how to determine the possible stocking points within the supply chain. Currently, there is not a methodology that describes how to determine the Customer Order Decoupling Point (CODP) and other possible stocking points within the supply chain. The second decision is defining the desired safety stock levels at these inventory points. At this moment, there is no policy to determine these targets. Determining the targets involves multiple departments; master planners, division operations, and demand management. These departments consider different uncertainties within the supply chain and based on their experience and knowledge they determine a target for the safety stock. In other words, clear guidelines to determine (i) the position and (ii) the safety stock level are missing. Since there are no calculations to determine the safety stock, the inventory levels are probably higher than necessary, while the desired service level could still be achieved.

Overall, guidelines are missing to support the departments within ams to determine the stocking points and the safety stock targets. Therefore, this thesis proposes a design to manage the uncertainties within the semiconductor industry while lowering the inventory levels and achieving the desired service levels. This is done by determining the possible stocking points and the safety stock targets within the supply chain.

2 Research design

2.1 Literature review

Since there is not a clear strategy to determine the possible stocking points and the safety stock targets, the available methods in the literature are reviewed. First of all, the factors that are important to determine the CODP and other stocking points are discussed. Next, the different uncertainties that are relevant to set safety stock are reviewed.

2.1.1 Stocking points

Single customer order decoupling point

First, the frameworks for determining the best production strategy, based on different factors are discussed. Olhager (2003) describes the market, product, and production factors that affect the position of the customer order decoupling point. An approach is provided to choose the best production strategy based on the relative demand volatility and throughput time to delivery time ratio. There are five different strategies, Make-To-Stock (MTS), Make-To-Order (MTO), Configure-To-Order (CTO), Assemble-To-Order (ATO), and Finish-To-Order (FTO). These strategies will be explained in more detail in the next chapter. Based on the factors mentioned, the best strategy is chosen. Besides the market, product, and process-related factors, the supplier-related factors are investigated by Rafiei and Rabbani (2009). Rafiei and Rabbani proposes an analytical network process to determine the right decision based on the different factors. Later research of Rafiei and Rabbani extends his earlier study by introducing new decision criteria and family formation to decrease the complexity in decision making (Rafiei and Rabbani, 2014). Forstner and Mönch (2013) proposes a heuristic to make these decisions in the semiconductor supply chain. The order partitioning criteria of Olhager (2003) is used as a reference approach. Furthermore, a genetic algorithm is defined to support the decisions. Another study that proposes a framework to support the strategic decision is done by Sun et al. (2010). The framework first decides whether a product has a make-to-order or a make-to-stock production strategy based on the importance of on-time delivery service and the quoted lead time. For products classified between these two strategies, secondary level criteria are used. The second level criteria take into account the manufacturing variability and the aggregated demand of the final product. Based on these criteria, the strategy is chosen. However, the studies above focus on one single customer order decoupling point. Since the supply chain of ams can have multiple stocking points, studies that researched multiple (customer order) decoupling points are reviewed as well.

Multiple (customer order) decoupling points

Sun et al. (2008) describes a mathematical model that finds multi-decoupling points based on the Bill of Materials (BOM) in a supply network. The factors considered are demand variance and customer delivery time to determine the position of the decoupling points. The mathematical model minimizes the overall costs in the supply chain while the desired service level is achieved. Kim et al. (2012) proposes a strategy that suggests additional stocking points after the CODP boundary. The objective function minimizes the holding and service costs, which is a nonlinear mixed integer programming problem. The study did an experimental design in the semiconductor industry, which is comparable to the situation of ams.

Besides determining the position of the stocking points, it is important to discuss some methods that focus on how to calculate the targets. Methods that are based on the Newsboy equation are proposed by Houtum et al. (2004) and Shang and Song (2003). The newsboy equation considers the holding costs and back-ordering costs to determine the optimal base stock level. However, these approaches are limited to a serial inventory system. Diks and de Kok (1998) discusses a method for divergent multi-echelon inventory systems. Nevertheless, no service level constraint is considered. de Kok (2018) discusses a method for general multi-item multi-echelon systems. This methodology is the Synchronized Base Stock (SBS) policy which is developed by de Kok and Visschers (1999).

2.1.2 Safety stock

Yield uncertainty

The different uncertainties that are relevant to set the safety stock are widely studied in the literature. Hung (1996) investigated the impact of yield uncertainty by using a simple variance calculation formula. This formula is equivalent to the reorder point approach. Inderfurth and Vogelgesang (2013) studied the yield uncertainty as well. However, this research took different types of yield randomness into account and combined this with stochastic demand.

Demand and throughput time uncertainty

How stochastic demand is evaluated is studied by Nakashima (2014). Nakashima (2014) proposes two options. The first option is based on historical demand data. The second option is based on the forecasting error.

More recent research showed two approaches defining the safety stock levels to obtain a particular service level (Ziarnetzky et al., 2020). The first approach is demand-driven safety stock, based on the study of Norouzi and Uzsoy (2013). This approach is only considering the demand uncertainty. Hung and Chang (1999) proposes the second approach, which is cycle-time driven. This method focuses on throughput time uncertainty.

Yield, demand, and throughput time uncertainty

Johnson (2005) studied the safety stock levels by using three different uncertainties. Firstly the demand variability. Secondly, the demand, and throughput time variability. Finally, the demand, throughput time and yield variability were considered. Research that considered a more dynamic approach is done by Bahroun and Belgacem (2019). This study used a different approach than the traditional approaches discussed above. The proposed method resulted in a better performance than the traditional approach. However, the approach used is more complex.

2.1.3 Discussion

Several approaches exist in the literature to determine the production strategy (MTO, MTS, CTO, ATO, and FTO). Different factors are studied, which contain market, product, production, and supply factors (Olhager, 2003; Rafiei and Rabbani, 2009, 2014). Sun et al. (2010) proposes an approach with two levels of criteria. However, these studies are focusing on determining one single stocking point.

Sun et al. (2008) and Kim et al. (2012) focus on how to determine multiple decoupling points. Both propose a mathematical model that minimizes the overall costs in the supply chain while achieving the desired service level. Sun et al. (2008) proposes a model that uses the BOM in the supply network to determine the decoupling points. Useful is the experimental design of the study of Kim et al. (2012), which is done in a typical semiconductor supply chain. Furthermore, multiple studies proposed a method to determine the targets for the stocking points by using the newsboy equation (Houtum et al., 2004; Shang and Song, 2003). However, these studies were limited to serial supply chains. More recent research by de Kok (2018) proposed a method to manage general and divergent supply chains.

Furthermore, in the literature, three main uncertainties are considered, yield, demand, and throughput time uncertainty. These uncertainties are widely studied in the literature. However, the majority focus on one or two aspects and do not take into account all the uncertainties. For example, Hung (1996) focuses on yield uncertainty by using a simple formula. Nakashima (2014) describes two ways of considering demand variation, based on historical demand or on the forecasting error. Ziarnetzky et al. (2020) proposes two different approaches, one that is considering demand uncertainty and the other considering throughput time uncertainty. Inderfurth and Vogelgesang (2013) and Johnson (2005) studied approaches that takes into account multiple uncertainties.

Another aspect that has barely been investigated is considering a limited (one or two) number of customers. In particular, to determine the stocking points in the supply chain to have a minimal risk while holding inventory on stock. For a company like ams AG, this aspect is very important since most products are customized.

Overall, the different uncertainties within the semiconductor industry (yield, demand, and throughput time uncertainty) are widely studied. However, these methods mainly focus on the assumption that demand is normally distributed, which is often not the case in reality. Furthermore, the research in determining multiple stocking points within the semiconductor industry is limited. In particular in a situation where the majority of the product is customized for one special customer. Therefore, by combining the existing methods and considering the characteristics of the semiconductor industry, the literature gap in the multi-echelon inventory in the semiconductor industry will be filled.

2.2 Problem definition and assignment

The main problem is a missing overall strategy on determining the possible stocking points and the safety stock levels (section 1.3). Currently, the decision-making is based on experience and knowledge, where multiple factors influence the decision. The research goal is formulated by comparing the current situation to the desired situation.

The current situation is already discussed in section 1.3. In the **desired** situation, the ideal world is described. In the ideal world, a procedure and a tool are created that supports the master planners, division operations, and demand management. The procedure and tool should support in determining the optimal stock positions and targets. First, the procedure describes how to work and which rules are followed to determine the stock positions for different products. Thereafter, a tool should optimize these positions and their targets.

This procedure and tool have the following advantages for ams:

- Determines the optimal production strategy and therefore the optimal customer order decoupling point
- Standardized way of working
- Gives better insights on how to manage the desired service levels and the inventory levels
- Optimized balance between inventory levels and service levels, which reduces the risk of inventory obsolescence and unnecessary stock
- Optimal stock positions and targets

Overall, the procedure and tool will support ams to provide better guidance on the inventory levels. Better guidance results in lower inventory while the desired service levels are still achieved. Furthermore, the tool leads to a standardized way of working and an overall policy for setting inventory levels within ams.

Based on the current and desired state and the literature review, an inventory policy is needed for the different business lines within ams. The policy should contain characteristics and uncertainties relevant to the semiconductor supply chain, especially for ams. The most important uncertainties are demand, yield, and throughput time uncertainty. This results in the following assignment:

Design a policy to determine the (safety) stock locations and targets considering supply and demand uncertainties to obtain the desired service levels against minimal inventory levels.

The policy provides ams a framework to determine the location and level of the stock in their supply chain and make the trade-off between the service and inventory levels. Furthermore, the policy considers the different uncertainties obtained in the semiconductor industry.

Sub-assignments:
Based on the research goal, the assignment is divided into sub-assignments to structure the report. The first sub-assignments will focus on defining a method, which is compared with the

current situation of ams in the last sub-assignment.

1. *What is the current performance in terms of inventory levels and service levels?*
   How is the current performance in terms of service and inventory levels to compare the developed methodology in the case study.
2. *How to combine multiple factors to determine the stocking points for different products?*
   In literature, there exist multiple factors that should be considered to determine the production strategy. Since other factors than throughput time are important as well, these factors discussed in the literature should be considered. These factors can be used to determine the production strategy for a product and therefore the CODP and other stocking points. Moreover, the characteristic that distinguishes ams from other companies, the limited number of customers per product, should be considered as well.
3. *Which factors should be considered to set the (safety) stock targets?*
   This part defines the (safety) stock formula based on the literature. The formula of the (safety) stock used in the model that is proposed should capture the demand and supply uncertainties.
4. *How to control the stock points?*
   An inventory management model is formulated to control the stock points within the supply chain of ams. In this part, the inventory policy used is defined. In this model, the stock points determined in the second step are used, and the (safety) stock formula defined in the previous sub-assignment is used, which captures the different uncertainties. An important note is that the model should be understandable for the planners.
5. *How to optimize the inventory levels and compare the performance of the model proposed and the current situation?*
   Finally, the performance of the model is compared with the current situation by using a simulation model or a software package. To compare the current situation with the model formulated in the fourth sub-assignment the inventory levels and the performance should be measured. The model designed will be used to optimize the inventory levels.

The sub-assignments will be answered by defining an decision support system that determines (a) the stock positions and (b) how to control these stock points in terms of inventory levels. Finally, this policy is analyzed to compare the performance with the current situation.

2.3 Scope

This project's scope is described by a bounded supply chain and different products from the business unit ISS classified by an ABC/XYZ analysis. The supply chain is bounded by excluding the raw materials. This analysis classifies products based on the annual sales and the demand volatility (Figure 2.2), executed by an external company. The analysis is used to classify the product customer combinations based on the demand volatility and the annual sales revenue.

The reason to use the ABC/XYZ classification is that it classifies the suitable products for safety stock.

The bounded supply chain is shown in Figure 2.1. Because of the following three reasons, the raw materials (RM) are not considered in this thesis. First, most of the products use the same raw material. Secondly, there is a relatively high safety stock for the raw materials (Appendix A). Lastly, the assumption that the suppliers deliver on-time. Therefore, from this point on, the inventory control of the raw materials is out of scope. There is assumed that the raw materials are available and delivered on time. The goods that are in the project's scope are semi-finished and finished goods (FG).

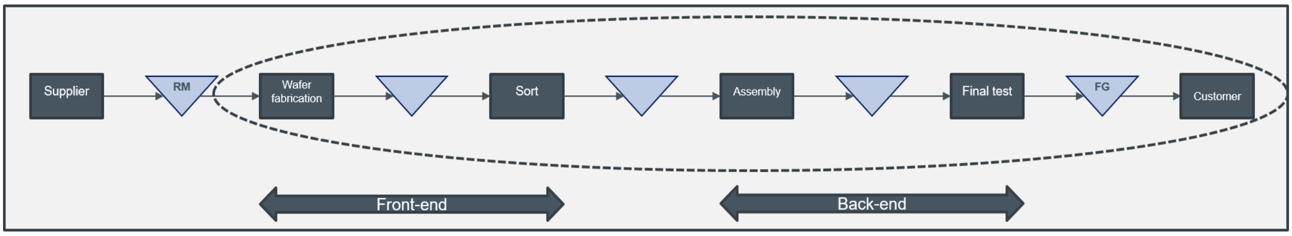


Figure 2.1: Scope high level supply chain

Within ams, the product groups classified as good candidates for safety stock are AX, AY, BX, and BY. The reason for this is that AB represents 95% of the annual sales, and X and Y are classified as stable and medium volatile demand, respectively.

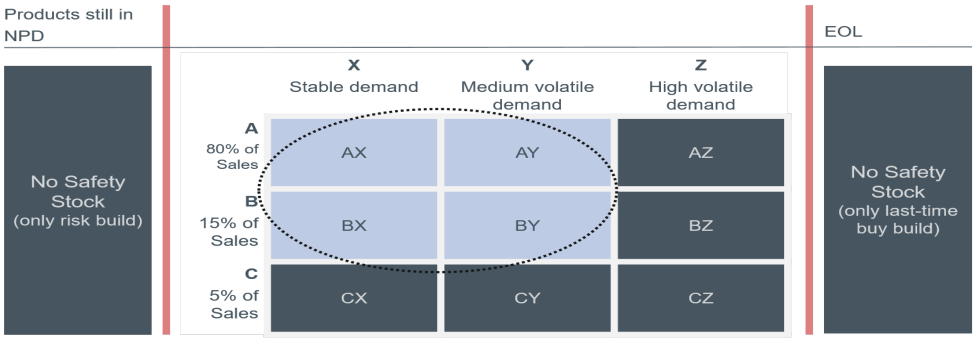


Figure 2.2: ABC/XYZ classification adapted from ams (2021)

Figure 2.2 gives a visualization of the scope of the project. Based on the classification for good candidates for safety stock, the scope of the project is chosen. Therefore, the products in the project's scope are AX, AY, BX, BY products. Products in the New Product Development (NPD), End-of-Life (EOL), AZ, BZ, CX, CY, and CZ are **not** in the project's scope. This results in 175 products from the business unit ISS in the scope of the project.

2.4 Research plan

This master thesis will consist of two parts. The first part consists of the second and third sub-assignments. The second part covers the first and last two sub-assignments. The output of the first part will be used for the second part. For the second part, the research model of Mitroff et al. (1974) is used.

For the first part, the existing literature of section 2.1 will be used. Then, to determine the production strategy, a framework will be formulated that determines the production strategy per product based on the throughput time and other important factors as well.

For the production strategies MTO and MTS, a clear distinction could be made. When this is not the case, there are multiple options (CTO, ATO, and FTO). Therefore, it will be harder to determine the correct CODP. Next, for the third sub-assignment, the different safety approaches that exist in the literature are considered.

For the second part, the research plan is based on the model of Mitroff et al. (1974). This model is divided into four phases. The problem situation, the conceptual model, the scientific model, and the solution. However, the phase that is missing, is the orientation phase, which is the literature review.

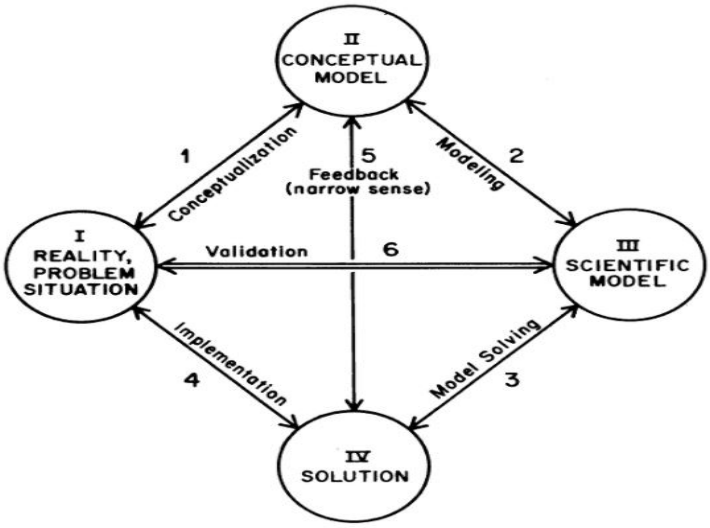


Figure 2.3: Research model from Mitroff et al. (1974)

The first phase is conceptualization. In this phase, the assumptions, input parameters, restrictions, and performance measures are defined. In fact, the second and third two sub-assignments can be seen as a part of the conceptualization phase, since the safety stock formulation and possible inventory points are defined in these two parts.

The second phase is modeling. In this phase, the model is represented formally. In other words, the model is defined in mathematical terms. The inventory model and safety stock approach that is defined in the conceptualization phase will be used.

The next phase is the model solving phase. In this phase, the model and approach will be simulated in a comparable setting to ams. Finally, the simulation or program is used to obtain the performance and compare them with the current situation.

The last phase is the implementation phase. In this phase, the model is integrated into ams. However, this is out of the scope of the master thesis. At the end of the master thesis, managerial recommendations will be given based on the results obtained from the simulation or program used.

3 Detailed analysis

After defining the problem definition, the research goal, and the assignment, the current situation at ams AG is analyzed in more detail. First, in section 3.1, the characteristic that distinguishes ams from other businesses is analyzed. Thereafter the variations on the supply chains are discussed (section 3.2). Next, the products are classified into five (MTO, CTO, ATO, FTO, MTS) different production strategies (section 3.3). Note that from this point, only the products that have a CTO, ATO, FTO, or MTS strategy are further analyzed since the other products are driven by customer orders and not by the forecast. Next, the customer demand and forecasting bias are discussed (section 3.4 and section 3.5). Subsequently, section 3.6 analyzes the yield percentage. Thereafter, the throughput times are analyzed in section 3.7. Moreover, the inventory policy of ams is discussed in section 3.8. Furthermore, section 3.9 discusses the performance measures and section 3.10 the safety stock settings. Finally, a summary (section 3.11) is given to define the characteristics and requirement(s) for the design.

3.1 Products

In the scope of the project, there are a total of 175 products. Table 3.1 gives an overview of how the 175 products are divided over the business lines.

Business line	Number of products	
	(#)	(%)
A	64	36.57%
B	47	26.86%
C	43	24.57%
D & E	21	12.00%
Total	175	100.00%

Table 3.1: Number of products per business line

In particular, there is one characteristic that distinguishes ams from other companies within the semiconductor. Due to the high customization of products, many products are produced for one customer. Therefore, for all 175 products, the number of customers per product is shown in Figure 3.1. Note that only the customers that are classified as **active** customers are taken into account. Active is defined as customers that have placed an order in the last year.

Figure 3.1 shows for the business lines C and D & E, a significant number of the products are customized for one special customer. For the business lines A and B, some products are produced for multiple customers. From Figure 3.1 can be concluded that overall, most of the products (58.9%) have only one customer, and a significant number (82.9%) of the products have only four or fewer customers.

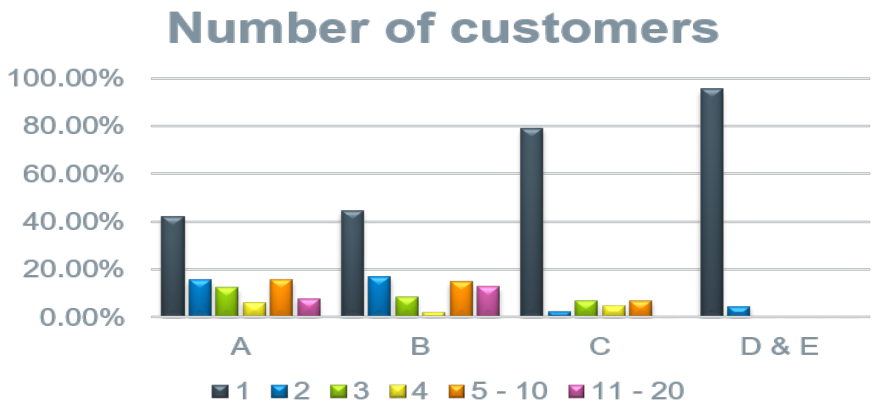


Figure 3.1: Number of customers per product

3.2 Supply chain variations

In this section, the different supply chains that are in the scope of the project are discussed. The high-level supply chain is already discussed in section 1.2.2. However, there are a few variations on this supply chain that will be discussed. Note that the supply chains discussed are still the main supply chains. Some products could have a production step less or more which is not mentioned in this section.

The first variation is the supply chain that has two additional processes, test and burn-in (Figure 3.2). The burn-in process detects early failures in the devices and is used for reliability markets like the automotive industry (A). This process is mainly used for relatively new products. When products are longer in production, these steps are no longer required. In that case, after the external assembly step, the final test is performed.

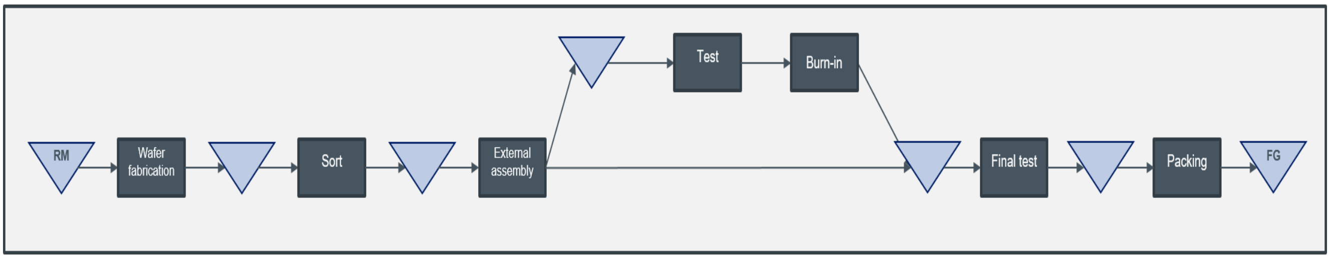


Figure 3.2: Supply chain with burn-in process

The second variation is the supply chain with the assembly structure (Figure 3.3). Multiple raw materials (RM) are used for the assembly process. The materials combined result in the final product. Products from the business line B are characterized by the assembly supply chain structure.

For special cases, the process Through-Silicon Via (TSV) is used. Figure 3.4 shows an example of this supply chain. This technique is used to create 3D integrated circuits. Another special process is the Wafer Level Chip Package (WLCSP), which is packing the wafer in extremely small packages. An external supplier performs this process. When a product has a single wafer, the TSV process is not executed. Some of the products within the business line C are classified as these special cases.

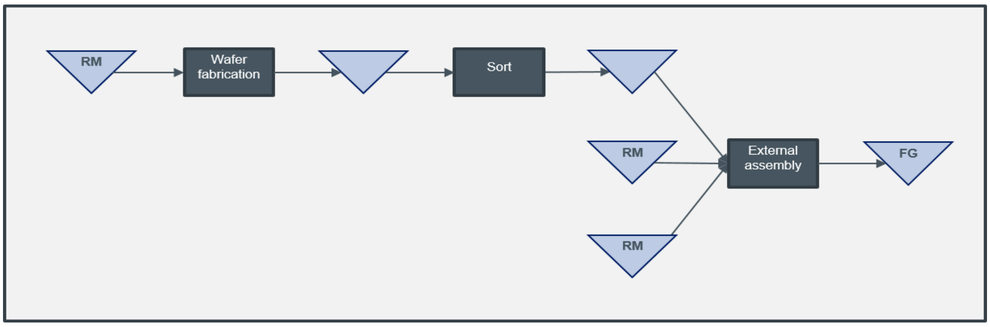


Figure 3.3: Assembly supply chain

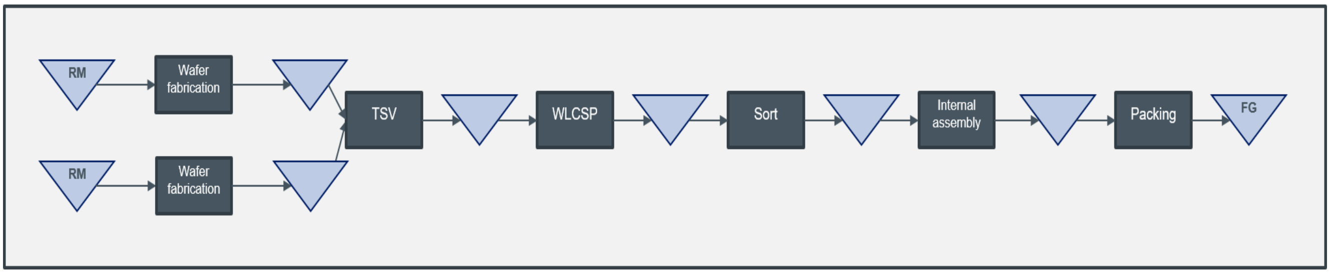


Figure 3.4: Supply chain with TSV process

An example of a short supply chain is a product that consists of the two process steps, wafer fabrication and sorting. Most of the products within the business line D consists of these two processing steps.

However, the supply chains discussed above are the supply chain for one single end product. Some components could be used for multiple end products, which is discussed further in the thesis. This results in divergent supply chains.

3.3 Production strategies

The five different production strategies used within ams are make-to-stock (MTS), make-to-order (MTO), configure-to-order (CTO), assemble-to-order (ATO), and finish-to-order (FTO). The last three strategies are used when the strategy is not a full MTS or MTO strategy, and therefore a mixture between these two strategies. For the CTO, ATO, and FTO, the first part in the supply chain is forecast-driven, from the customer-order-decoupling-point (CODP), it is order-driven. The production strategies are described as follows:

- **Make-to-stock**: All production steps start based on the demand forecast.
- **Make-to-order**: All production steps start once a customer order is received.
- **Configure-to-order**: The first production step in the front-end (wafer fabrication) is based on forecast. First, the untested wafers are stored. Wafer test and back-end operations start when a customer order is received.
- **Assemble-to-order**: The front-end production steps start based on forecast. Then, the dies that are tested and classified as good are stored. Finally, the back-end production steps start once a customer order is received.
- **Finish-to-order**: All the production steps start based on forecasted demand, except final testing. This is done once the customer order is received.

The different production strategies used within the supply are shown in Figure 3.5. The figure shows that before the CODP, the production is driven by the forecasted demand. After the CODP, the production is driven by the customer orders. Olhager (2003) defined the CODP as: 'the point in the manufacturing value chain for a product, where the product is linked to a specific customer order'.

Note that the CTO strategy is not logical since untested wafers are stored. From an inventory point of view, it is unusual to store products that have still to be sorted since it is unknown how many good dies are stored at the end. However, the reason to store untested wafers is that the wafers will be customer-specific after this step. Therefore it makes sense to apply the CTO strategy.

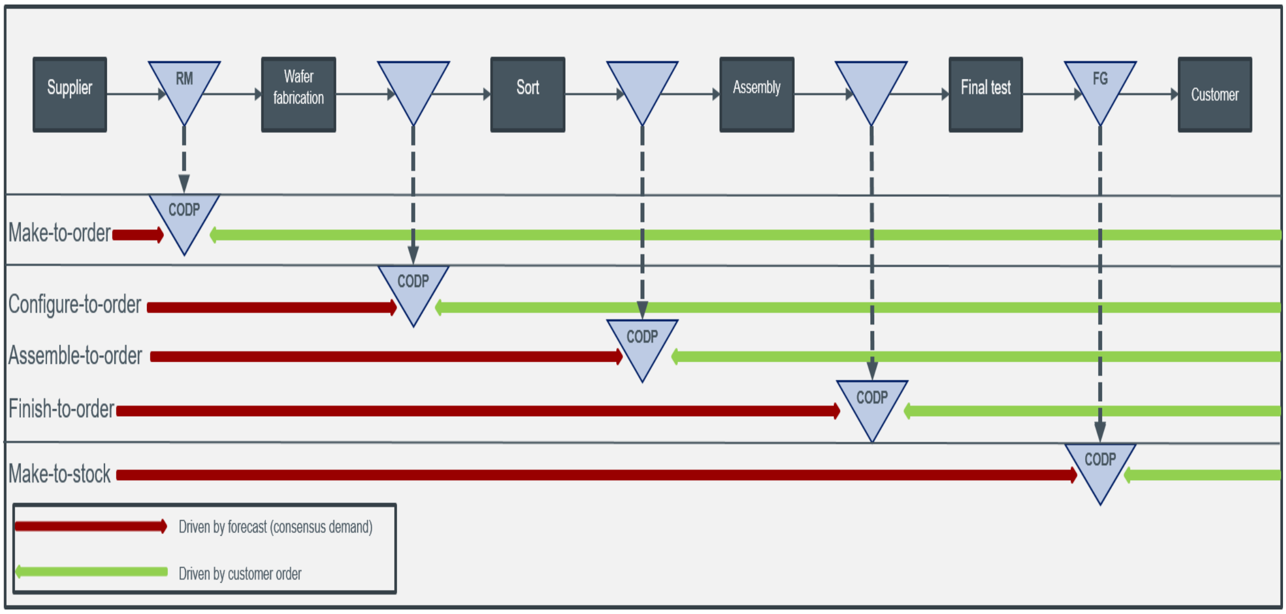


Figure 3.5: Production strategies

As mentioned in the project's scope, this project focuses on the products categorized in the business unit ISS, based on the ABC/XYZ classification (175 products). 21 products have a contractual obligation, and for these products, the CODP and safety stock target are already determined.

In this section, the production strategy is determined for the 154 products without a contractual obligation. The production strategy is determined based on the throughput time feasibility, which is formulated on the customer's request for each product. This means which strategy is applicable based on the average throughput time and the average lead-time that the customers request. In other words, where the CODP is located in the supply chain. In this thesis, it is important to determine the production strategy since there is no need for safety stock for the MTO strategy products. Using the throughput time feasibility leads to Table 3.2.

Table 3.2 shows that 51% of the products should have an MTO strategy. As mentioned before, the remainder of this thesis is focusing on the products with a **CTO, ATO, FTO** or **MTS** strategy.

Business line	Production Strategy					Total
	MTS	CTO	ATO	FTO	MTO	
A	0	20	1	0	38	**59**
B	5	21	7	5	3	**41**
C	0	7	0	0	26	**33**
D & E	2	6	0	0	13	**21**
Total	**7**	**54**	**8**	**5**	**80**	**154**

Table 3.2: Production strategies

3.4 Customer demand analysis

According to the employees, 2021 is a tough year in terms of customer demand. The reason is the extremely high demand which is one of the side effects of COVID-19. Therefore, the total demand in the business unit ISS **in units** is analyzed. Figure 3.6 shows the total customer demand per quarter over the years in units. As the figure shows, the total customer demand in units in the second quarter of 2021 is significantly higher than the years before. Based on this, the year 2021 is excluded from the data set used in the remainder of the project. Next, the coefficient of variation, average order size, and frequency, and stationarity of the customer demand are discussed.

Figure 3.6: Total customer demand in units - business unit ISS

3.4.1 Coefficient of variation

The demand distributions that are primarily applicable in the inventory control are reviewed. The first widely used distribution is the normal distribution (Teunter et al., 2010). However, the normal distribution has a disadvantage, the probability of negative demands. This is possible when large coefficients of variation occur. The coefficient of variation (CV) is a relative variability measure and is determined by dividing the standard deviation (σ) by the average (μ). The coefficient of variation is classified by Hopp and Spearman (2008). Three classes are defined, low, moderate, and high. If the CV < 0.75, it is classified as low, if $0.75 \leq$ CV < 1.33 it is moderate, if the CV ≥ 1.33 it is high.

Based on this classification, the coefficient of variation is determined based on the monthly customer demand in units. The CV is determined by dividing the standard deviation of the monthly demand in units by the average monthly demand in units. As mentioned before, the data from 2021 is excluded. Only the data from 2019 and 2020 is used to analyze the customer demand. This leads to Table 3.3, which shows that most products have a moderate or high coefficient of variation.

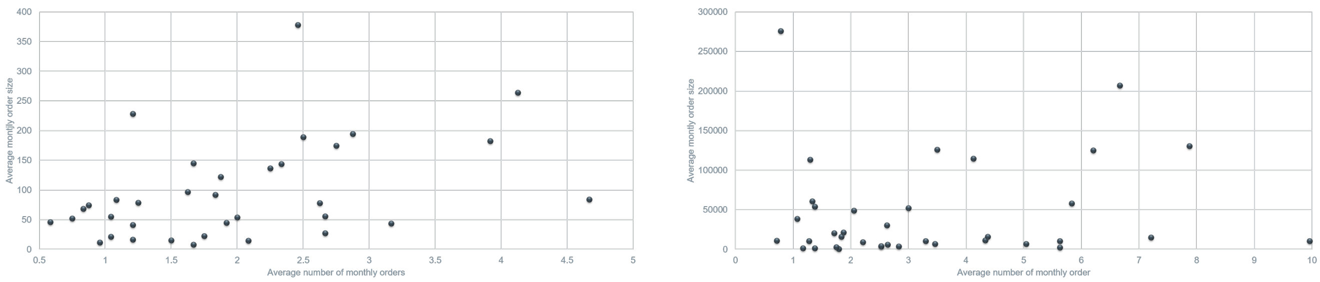
Class	CV	Number of products	
		(#)	(%)
Low	CV < 0.75	18	24.32%
Moderate	$0.75 \leq$ CV < 1.33	42	56.76%
High	CV ≥ 1.33	14	18.92%
Total		74	100.00%

Table 3.3: Coefficient of variation classification

Because most customer demand of the products have a moderate or high CV an alternative is reviewed in the literature for the normal distribution. A distribution that has non-negative values is the gamma distribution. This distribution is suggested by Aviv and Federgruen (2001) and Das (1976).

3.4.2 Average monthly order size and number of orders

Furthermore, two additional customer demand characteristics are analyzed, the average number of monthly orders and the average monthly order size. These two values are shown in the scatter plots in Figure 3.7 for every product. Since half of the products have an average order size below 400 units per month (Figure 3.7a), and the other half above 1000 units per month (Figure 3.7b), the data is separated into two figures.



(a) Average order size per month < 400 units

(b) Average order size per month > 1000 units

Figure 3.7: Average number of monthly orders versus average monthly order size

The figures show that for most products the average number of orders per month is below 4. Next, the average monthly order size is very different for all products. Half of the products have a relatively low monthly average order size (Figure 3.7a) in comparison to the other products in Figure 3.7b. This depends on the business line of the products. The products shown in Figure 3.7a are almost all products from the business line B. The majority of the products in Figure 3.7b are products from the business line A and C.

3.4.3 Stationarity

According to Pyke et al. (1998), it is important to test how the average demand is behaving over time. It impacts the number of units that have to be ordered to fulfill the expected demand. This concept is known as stationarity. Before, ams performed a statistical analysis to detect seasonality in the data. However, as mentioned before, one of the side effects of the COVID-19 situation is the high demand in the semiconductor industry. Therefore ams has decided to disable the analysis since March 2020.

Nevertheless, detecting stationarity is important. ams did not perform any tests to detect seasonality since March 2020, because these data could result in detecting false trends. Therefore, the data of 2020 is excluded. The data from 2017, 2018, and 2019 is analyzed to check whether the data is stationary or nonstationary. Since the demand of every product has to be analyzed individually, the Dickey-Fuller test (Dickey et al., 1986), which is a statistical test.

Since the data of 2020 is excluded, there was no data for 8 products that are relatively new. This results in checking the stationarity of the customer demand of 66 products. **The analysis shows that 60 products have stationary data, and for 6 products the data is nonstationary.**

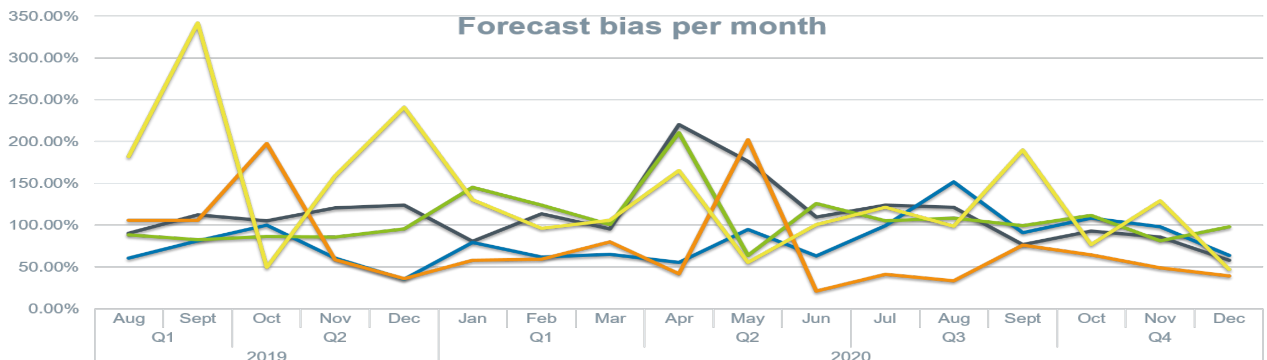
In the case of nonstationary demand, the paper of Alrefaei et al. (1999) described a method how to determine (safety) stock levels. The parameter α is introduced, which is multiplied by the random noise that is observed in the demand. By varying the parameter α between 0 and 1, the random noise can be considered. An α equal to zero means that the demand is stationary. In addition, the papers consider the forecasting error by computing the mean absolute deviation. Another technique that takes into account throughput time and demand uncertainty is a periodic dynamic reorder point control policy proposed by Babai et al. (2009). Based on the desired service level, the order quantity to fulfill the demand during one period is determined. These methods can derive relatively easily the order quantity, which considers uncertainties within the supply chain.

3.5 Forecast bias

Within ams, the forecast performance is measured in forecasting bias. The forecasting bias indicates whether there is an over- or under-forecast. In other words, an over-forecast means that the forecasted demand is higher than the actual demand, and an under-forecast means that the forecasted demand is lower than the actual demand. The forecast is essential for the products not completely produced based on customer orders (MTS, CTO, ATO, and FTO).

To visualize whether the forecast is greater or smaller than the actual demand, Figure 3.8 shows the forecast bias per month for each business line. The total amount of products they expected to sell is forecasted and compared to the actual number of products sold for each month.

Since the wafer fab process has to be started based on the forecast, the forecast five months earlier is used to calculate the forecast bias. In other words, the forecast bias of January 2020 is calculated by dividing the forecast of August 2019 by the actuals of January 2020. The five months are chosen by the company and used in their own analysis as well.



	Aug (Q1, 2019)	Sept (Q1, 2019)	Oct (Q2, 2019)	Nov (Q2, 2019)	Dec (Q2, 2019)	Jan (Q1, 2020)	Feb (Q1, 2020)	Mar (Q1, 2020)	Apr (Q2, 2020)	May (Q2, 2020)	Jun (Q2, 2020)	Jul (Q3, 2020)	Aug (Q3, 2020)	Sept (Q3, 2020)	Oct (Q4, 2020)	Nov (Q4, 2020)	Dec (Q4, 2020)
A	90.07%	112.07	104.95	120.90	123.97	80.62%	113.90	95.26%	220.61	176.42	109.65	123.83	121.59	76.49%	92.96%	85.85%	57.99%
B	60.49%	81.12%	100.02	60.32%	35.35%	79.46%	62.23%	65.07%	55.57%	94.90%	62.91%	99.12%	151.76	90.77%	108.38	97.96%	63.79%
C	88.68%	82.47%	86.61%	85.61%	95.43%	145.60	123.96	100.55	210.91	63.94%	125.85	104.97	108.61	99.69%	111.64	81.60%	98.29%
D	105.75	105.81	197.80	58.96%	36.17%	57.79%	59.21%	80.14%	42.10%	202.38	20.93%	41.06%	33.45%	76.32%	64.26%	49.14%	38.99%
E	182.09	341.64	49.83%	158.95	241.26	130.50	96.30%	106.06	165.18	55.27%	100.55	121.59	98.86%	189.70	76.83%	129.13	47.08%

Figure 3.8: Monthly forecast bias

A positive bias (>100%) means an over-forecast. A negative bias (<100%) means that the forecast was lower than the actual demand. The figure above shows that it is tough to forecast the customer demand over the months. For example, the business line B (green), in May 2020, the forecast was 63.94% of the actual demand. The next month the forecast was 125.85% of the actual demand.

3.6 Yield

One of the uncertainties of the semiconductor industry is the yield (section 2.1). The yield percentage represents the number of dies that meet the specified requirements. This percentage is based on the total number of dies on the wafer. After the sorting process, the yield percentage indicates how many good dies there are.

The standard deviation of the yield is calculated for the sorting processes. This standard deviation is based on the data from the last six months. This results in a standard deviation of the yield below 1% for 94% of the sorting processes in the project's scope. Only 6% of the processes have a standard deviation of the yield that is between the 2% and 4%.

In addition, the concept of binning is **not** used within ams. Binning is the concept of downgrading. When the specified requirements are not met for a certain product, the product is categorized as a product with a lower performance.

3.7 Throughput time

Table 3.4 shows the average and standard deviation of the throughput time (TT) of each process in the high level supply chain in **days**. The throughput time is defined as the time that is required to pass through the process from the inventory point before the process to the inventory point after the process. This includes the processing, inspection, move and queue time. For the first processing step, the wafer fabrication, the throughput times are very different per technology used. Therefore, these are grouped by the technology family. Sort is subdivided into two groups, the non-B, and the B business line(s). Test and packing does not differ in throughput time between the business lines. The assembly process used depends on the business line. Based on this, the processes are subdivided per business line. However, an important note is that especially for the assembly process, the throughput times are highly dependent on the product and technology used. This results in lower standard deviations than Table 3.4 shows.

Process	Technology Family / BL	Actual TT (days)	
		μ	σ
WaferFab	C35	70.4	19.1
	C35EE	100.1	25.0
	C80	62.8	13.0
	H18	208.5	18.1
	H18EE	237.3	47.7
	H35	80.6	19.7
	S35H	146.6	42.9
Sort	Non-B	9.5	2.8
	B	19.8	6.1

Process	BL	Actual TT (days)	
		μ	σ
Test		8.8	3.6
Assembly	B	39.6	16.2
	D	34.2	14.7
	E	31.6	13.6
	C	30.3	20.2
	A	40.3	20.2
Packing		7.7	0.9

Table 3.4: Throughput time in days

As Table 3.4 shows, there is a significant difference between the throughput times in the wafer fabrication. Especially for the S35H and H18(EE) the average throughput time and standard deviation are significantly higher than the other technologies.

3.8 Inventory policy

Two kinds of inventory policies are used within ams. An (R, s, nQ)-policy is used for the inventory position after the wafer fabrication and sorting process. For the other inventory positions, the inventory policy is described as an (R, s)-policy. It is unnecessary to define a policy for the raw materials since the raw materials are out of this project's scope.

An (R, s, nQ)-policy means that if the inventory position is below the reorder level (s) at a review moment, n times Q units are ordered to bring the inventory position back or above to the reorder level. The n is the minimum integer needed to increase the inventory level to a number of units above or equal to the reorder level (Donselaar, van and Broekmeulen, 2014). The review period (R) can be, for example, daily, weekly, or monthly.

The reorder level (s_i) at stage i consists of (i) the expected demand during the average throughput time and review period (based on the forecast) and (ii) the safety stock target (SS) at stage i. The expected demand during the average throughput time and review period is also called cycle stock. Note that for every period, the forecast will differ. Therefore, the reorder level (s_i) can change every period. No multiple integers of Q are required or the inventory positions with an (R, s)-policy. In this case, the number of units needed to bring the inventory position back to the reorder level (s_i) is ordered. For the inventory position after the wafer fabrication, Q is equal to the lot size of the wafer fab, which is 25 wafers. For the inventory position after the sorting process, the Q is equal to 1 wafer.

3.9 Performance measures

The performance within ams is measured by two Key Performance Indicators (KPIs).

- Confirmed Line Item Performance (CLIP):
  The first confirmed date versus the actual goods issue date.
- Requested Line Item Performance (RLIP):
  The last requested date versus the actual goods issue date.

The first confirmed date is defined as: the date that is first confirmed by ams to a customer request. The last requested date is defined as: the last date requested by the customer. As the customer can change their mind, the goal is to measure RLIP to the last customer request. Since the products are customized there is **not a fixed** customer lead-time (CL). All orders have different customer lead-times, even the same product that is sold to the same customers could have different customer lead-times. The RLIP is used in a dynamic market and makes the RLIP fully customer-facing.

Table 3.5 and Table 3.6 show the performance of 2020 and 2021 for the five business lines within the business unit ISS per quarter. The targets within ams are set per business unit. Therefore the targets are the same for every business line. The RLIP target of **2020** was set set to X_1%, and the target of **2021** is X_2%. For the CLIP, the target of **2020** was Y_1%, for **2021** the target is Y_2%. The targets are classified as confidential information.

Business line	RLIP 2020					RLIP 2021		
	Q1	Q2	Q3	Q4	Total	Q1	Q2	Total
A	70%	56%	74%	62%	**65%**	74%	45%	**60%**
B	69%	60%	65%	62%	**64%**	65%	37%	**51%**
C	50%	43%	44%	43%	**45%**	47%	27%	**37%**
D & E	97%	96%	89%	84%	**91%**	35%	10%	**23%**
Total	**71%**	**60%**	**59%**	**62%**	**63%**	**63%**	**36%**	**50%**

Table 3.5: RLIP 2020

Business line	CLIP 2020					CLIP 2021		
	Q1	Q2	Q3	Q4	Total	Q1	Q2	Total
A	98%	96%	92%	93%	**95%**	94%	83%	**89%**
B	95%	94%	98%	95%	**95%**	99%	94%	**96%**
C	82%	66%	78%	79%	**76%**	94%	59%	**77%**
D & E	100%	97%	96%	98%	**98%**	100%	90%	**95%**
Total	**95%**	**92%**	**93%**	**92%**	**93%**	**97%**	**88%**	**93%**

Table 3.6: CLIP 2020

Note that only the products that have a CTO, ATO, FTO, or MTS strategy are considered in the analysis above. In Appendix D the performance (RLIP and CLIP) of all the products within a business line is shown. The performance of both is comparable, as expected. Table 3.5 shows that the performance in 2021 is significantly lower than in 2020. The main reason is the high demand in the semiconductor industry, one of the side effects of the COVID-19 situation.

3.10 Safety stock settings

There exist two safety stock settings. This could be a fixed amount of safety stock (SS) or safety-days-of-supply (SDS). The SDS is linked to the demand section 1.2.4. Within ams, there is no distinction between inventory classified as safety stock or as cycle stock. Furthermore, the desired safety stock targets are not necessarily located at the stocking points. Therefore, the value of the current safety stock is calculated based on the current safety stock settings.

Business line	Safety stock percentage
A	31.6%
B	17.7%
C	17.6%
D	15.2%
E	0.4%
Total	20.1%

Table 3.7: Safety stock

Table 3.7 shows the percentage of safety stock for each business line **if** the desired safety stock target is actually located at the stocking point. This percentage represents the value in safety stock based on the total value of the on-hand inventory. Especially in the business line A, there is a relatively high percentage of safety stock. There is almost no safety stock for the business line E since these products are produced based on customer orders. In total, 20% of the inventory on-hand is safety stock within the business unit ISS. The other 80% consists of a surplus in cycle stock or finished goods that are delivered soon.

Furthermore, the safety stock settings considers the yield percentage. For example, when a safety stock of 400 units is set, and the sorting process has a yield of 50%, automatically 800 units are started in production.

3.11 Summary

This chapter discussed the important aspects that have to be considered in the design. This section gives a summary that highlights the most important findings based on the analysis.

- The project's scope consists of 175 products divided over five business lines (A, B, C, D, and E).
- The number of customers is limited. The majority (58.9%) of the products have only one customer. Especially in the business lines C, D, and E, most products are produced for

one special customer.

- Five production strategies exist within ams; MTS, CTO, ATO, FTO, and MTO. For 80 products, all production steps are started once a customer order is received (MTO). For these products, there is no need for safety stock. The other 74 products are classified as MTS, CTO, ATO, or FTO products. These products require safety stock. Therefore these products are further analyzed.
- The supply chains obtained have a **serial**, **assembly** or a **divergent** structure.
- Two commonly used distributions are considered for the customer demand, the **normal** and the **gamma** distribution. In addition, the coefficient of variation is calculated. Most of the products have a CV higher than 0.75. Furthermore, the average number of orders per month is relatively low since most products are sold to one special customer.
- The Dickey-Fuller test is used to check the data whether it is stationary or not. For the majority of the products, the data is stationary (60/66).
- Since multiple processing steps are started based on the forecast, the forecast bias is analyzed. The forecast bias is calculated by comparing the actuals with the forecast of five months earlier. The monthly forecast bias shows that it is a challenge to predict the customer demand per month.
- The yield is defined as the percentage of working dies on a wafer. The majority of the sorting processes have a standard deviation of the yield percentage below 1%.
- The throughput time of the main process steps are analyzed. In particular the wafer fab process and the external assembly have relatively high throughput times. For the wafer fab the throughput times are dependent on the technology family.
- The inventory policy of ams is described as an (R, s, nQ)-policy for the stocking points after the wafer fabrication and sorting process. For the other stocking points an (R, s)-policy is used. The reorder level (s) is calculated at every review moment since the forecast for every period can be different. The lot size for the wafer fab is 25 wafers and for the sorting process, one wafer.
- The performance is measured in two ways, the RLIP ,and the CLIP. ams set the RLIP target for 2020, and 2021 to X_1%, and X_2%, respectively. The CLIP target for 2020 was Y_1% and for 2021 it is Y_2%. For each business line the observed performance is different. Therefore, the target is not met for every business line.
- 20% of the inventory consists of safety stock. Especially the business line A has more safety stock than the other business lines.

4 Design

In this chapter, a design is developed to reach the project's goal; designing a method to determine the (customer order) decoupling points and (safety) stock targets within the semiconductor supply chain. At the same time, the desired service levels have to be reached with a minimum inventory level. In particular, the RLIP, which indicates the performance based on the lead-time that the customer requests. This chapter consists of three sections, the conceptual design, the detailed design, and the solution.

Firstly, the conceptual design is discussed. In the conceptual design, the basic idea, characteristics, and requirement of the method are explained. Furthermore, based on the available literature, some techniques that discuss similar problems are reviewed.

The second part, the detailed design, explains the conceptual design in more detail. This is based on one of the methods discussed in the conceptual design. Finally, a method is proposed to solve the detailed design.

4.1 Conceptual design

Based on the findings of the detailed analysis in section 3.11 the characteristics and requirements are defined for the design.

Characteristics

- Limited number of end customers
  Since most products are customized for one or a few customers the number of end customers is limited.
- Serial, assembly, and divergent supply chain
  For products that are fully customized, a serial or assembly supply chain is obtained. Since some components are used for multiple products, these supply chains should be seen as a divergent supply chain.
- Customer lead-time
  In the dynamic market where most of the products are customized, no fixed customer lead-times are used. Even the same products that are ordered by the same customer could have a different customer lead-time. In other words, almost every order placed has a diverse customer lead-time.
- Gamma distributed and stationary customer demand
  When high coefficients of variations are observed for customer demand that follows the normal distribution, there is a higher probability of negative demand. An alternative suggested by Aviv and Federgruen (2001); Das (1976) is the gamma distribution, which is characterized by non-negative demand. Most products have a moderate or high coefficient of variation for the customer demand, which could lead to negative customer demand. Therefore, the **gamma** distribution is used in the remaining of this thesis for the customer

demand. Furthermore, for 90.9% of the products, the data of the customer demand is stationary. Therefore the following assumption is made: all the customer demand data is **stationary**.

- Demand and throughput time uncertainty.
  The three main uncertainties observed in the semiconductor industry are demand, throughput time, and yield uncertainty. The demand and throughput time are obviously. The yield uncertainty is not considered because of two reasons. The first reason is that binning is not used within ams. Secondly, for most sorting processes (94%) the standard deviation of the yield is below 1%. Compared to the demand and throughput time uncertainty, the yield uncertainty is relatively low. Therefore, the yield uncertainty is negligible and not considered. Note that the yield percentage is constant and automatically taken into account in the orders that are produced.
- Periodical reorders
  The inventory policy is operating under a periodically review moment.
- Backorders
  Customer demand that is not immediately fulfilled is delivered later to the customer.
- Lot sizing
  For the wafer fabrication and sorting process, a lot size of 25 and one wafer is used, respectively. For the other processes no lot size restrictions are considered.

Requirement

- Service level: RLIP and CLIP
  The desired service level in terms of CLIP and RLIP should be achieved while minimal costs are obtained.

The design aims to first determine the possible stocking points within the supply chain of the semiconductor industry. After that, a decision support system is used to determine the best stocking point(s) and the (safety) stock targets. In particular, the customer lead-time is a essential aspect in determining the CODP. This policy helps manage the uncertainties and guarantees a certain service level (RLIP and CLIP) while lowering inventory costs during periodic inventory reviews. The safety stock target that is determined is a number of products that are on top of the forecasted demand. It will cover the demand and throughput time uncertainties for a certain period.

4.1.1 (Customer order) decoupling point

The first step of the design is locating the possible stocking points within the supply chain. Section 2.1.1 discussed different methodologies to determine the decoupling points within the supply chain. The most important criteria are the ratio of the delivery lead-time and throughput time Olhager (2003). Furthermore, the studies of Rafiei and Rabbani (2009) and Sun et al. (2010) consider some additional factors. These factors are categorized in the market, product, process, and supplier-related factors. However, these studies are focusing on the production strategy (MTS, ATO, FTO, and MTO), and therefore are choosing one **single** customer order decoupling point. Sun et al. (2008) and Kim et al. (2012) propose methods to determine **multiple** decoupling points, which consider different costs factors within the supply chain.

Based on above literature there is one factor that determines the CODP, **the planned throughput time versus the customer lead-time.** However, since this thesis is focusing on the semiconductor industry that produces customized products, it is important to consider the customers' requests. In addition, there are no fixed customer lead-times for the customized products, so every order could have a different customer lead-time. **The customer lead-time is defined as the difference between the booking date and the customer's request date**. Furthermore, there are multiple reasons to define additional stocking points within the supply chain. However, since the safety stock considers the demand and throughput time uncertainty, there is chosen to limit the reasons for possible stocking points to two factors. First of all the **location of the bottleneck** and secondly the **commonality** within the supply chain.

Locating the bottleneck within the supply chain is essential to maximize the output of the manufacturing system. When the process that is classified as bottleneck has a consistent supply of parts, the idle time is reduced (Roser et al., 2002), and the utilization of that process is maximized. The second reason is commonality. Commonality is used to reduce the risk of placing safety stock within the supply chain, especially in a setting where the number of customers is limited. Ma et al. (2002) states that one of the major benefits of commonality is risk-pooling. Next, based on the factors discussed in the reviewed literature (market, product, process, and supplier factors), commonality is used to determine where a possible stocking point could be placed in the supply chain. Commonality can be seen as a product-related customization opportunity and as a market-related factor (Rafiei and Rabbani, 2014).

In this thesis, we choose two kinds of commonality, commonality in **(i) customers** and **(ii) end products**. Since the number of customers per product is limited, it is important to consider the number of customers. It could be that the number of end products is the same and the number of customers is different. A higher number of customers will decrease the risk of holding inventory. This is explained by the following example. Component A is used for one end item and sold to one customer. Component B is used for one end item as well and sold to three customers. This results in the same commonality in end products and a different commonality in customers. If the customer for component A decides not to place any orders anymore, it results in no demand for component A. For component B, there is still demand if the number of customers decreases. Therefore, holding inventory for component B has less risk than holding inventory for component A. The commonality in customers and end products indicates this. Note that the order size and frequency of the customers are important as well.

The commonality in customers is defined as the number of identical and **active** (excluding EOL) customers for a component. This number is obtained by using the number of customers for the end product of that component. The commonality in end products is defined as the number of identical and **active** (excluding EOL) end products for a component.

However, two situations should be distinguished from one another. In the first situation, only one stocking points is located, which is the CODP. The second situation is characterized by multiple stocking points.

CODP

As mentioned before, the planned throughput time and the customer lead-time are chosen to determine the CODP within the supply chain. The modeled customer lead-time can be determined in multiple ways:

1. The minimal customer lead-time.
2. **The minimal customer lead-time without the extreme order requests**.
3. The average customer lead-time minus k times the standard deviation of the customer lead-time.
4. **x% percentile of the customer lead-time**.

When using the minimal customer lead-time, the extreme customer requests (within one/two days) are taken into account. However, this is not realistic. Using the minimal customer lead-time without the extreme customer requests is more reasonable. The third option considers the variation in the customer lead-times. In this situation, most of the customer orders will be fulfilled within the requested lead-time. The value of k can be defined based on the desired RLIP. However, some customers place their orders for multiple months. On the other hand, some customers would like to receive their order within a few days. These two reasons have a high effect on the average and standard deviation of the customer lead-time. Therefore another option is considered, option 4. The last option (4), determines the modeled customer lead-time by using a percentile. The following example explains this. A 10% percentile means that 10% of the data is lower or equal than the number of the 10% percentile. In other words, 10% of the requested orders have a lower or equal customer lead-time than the modeled customer lead-time. For the case study, the options that take into account the majority of the customer requests are chosen. Based on the above reasoning, options 2 and 4 are chosen to determine the modeled customer lead-time.

Location of the bottleneck

As mentioned above, locating the bottleneck within the supply chain is essential. This location determines the maximum output of the manufacturing system. Minimizing the unproductive time from a certain process can be done by locating a buffer before the bottleneck. This buffer provides the bottleneck process with a consistent supply, which results in a maximum utilization of the process.

Commonality

Commonality can be used to determine an additional stocking point or help determine a CODP with less risk. A higher commonality is reducing the risk since the specified component is used in multiple end products and has multiple customers. When one of the customers decides to decrease his demand, the inventory can still be used to fulfil the other customers' demand or for the other end items. Therefore, two options are possible, placing an additional stocking point (i) **upstream** in the supply chain or (ii) **downstream** in the supply chain.

There is a lower risk of holding inventory when the commonality is higher in a stage upstream in the supply chain. The reason is that the same component can be used for multiple end products and customers. Therefore, it is logical to place an additional stocking point more upstream in the supply chain. A stage downstream in the supply chain can result in a lower or equal commonality.

As mentioned in section 3.3, the CTO strategy means placing inventory after the wafer fabrication process. This strategy is used because for some products, after the sorting process, the dies on the wafer are customer-specific. This is the same as a decrease in commonality. However, if the component is **not** decreasing in commonality, the component can still be used for all the possible customers. In this case, it is more logical to place the inventory one stage more downstream in the supply chain. This results in two main advantages that reduce the risk of holding inventory in the semiconductor supply chain.

- Immediately feedback of the wafer fabrication process, since it is known how many good dies there are. It could be that there are some issues with a particular technology in the wafer fab. After the wafer fabrication, this feedback is received shortly after the processes by doing the sorting process directly after the wafer fabrication.
- A known number of good dies on stock. Holding inventory before the sorting process means holding the untested wafers on stock. However, from an inventory point of view it is more logical to know how many good dies there are on stock to fulfil the customer demand instead of untested wafers.

Altogether, there are two options: (i) placing an additional inventory point upstream in the supply chain if the commonality increases or (ii) placing the stock after the wafer sort process if the commonality does not decrease after this processing step.

4.1.2 (Safety) stock targets

After determining the possible stocking points within the semiconductor industry's supply chain, the next step is to choose the best stocking point(s) and set the reorder levels for a certain period. It could be possible that there is only one stocking point. The other possibility is a combination of stocking points.

For a single stock point, simple formulas are proposed to determine the safety stock, including the demand and throughput time uncertainty. These methods are based on a demand distribution. However, the majority assumes that the customer demand is following the normal distribution. There are some methods for the gamma distribution. For example, Bischak et al. (2014) defined a simple heuristic where the standard gamma distribution is used to obtain the safety factor. Furthermore, to determine the safety factor, the ratio between back-ordering costs and holding costs is used. However, an important condition for the approaches above is that the correct distribution is used. Therefore the customer demand has to be analyzed with a goodness of fit test. Furthermore, the methods discussed so far are focusing on a single stocking point. This is the case in the first situation. However, the other situation considers multiple stocking. Therefore, some papers that describe a multi-echelon problem are discussed as well.

A problem that arises when implementing a multi-item multi-echelon system is managing the inventory levels of components used for multiple end items. In this case, the customer demand pattern is different since it could be that the customer demand of the end items follows not the same distribution.

A multi-echelon inventory system is discussed by Houtum et al. (2004). To calculate the the optimal base stock level, the Newsboy equation is used. This equation considers the back ordering costs and holding costs. An advantage of this method is that it is using relatively simple calculations. In addition, back-orders are considered, which are satisfied in a first-come-first-serve order. Moreover, it assumes reorder intervals. Furthermore, it proposes a method when the demand distribution is unknown, the two moment fit (Osogami and Harchol-Balter, 2006). This method solves the problem of the different customer demand patterns. However, there are two main problems, (i) the paper is limited to a serial inventory system, (ii) it assumes constant throughput times. Note that the Newsboy equation can be used for a single stocking point situation as well.

A study that solves the problem of a serial inventory system is discussed by Diks and de Kok (1998). The study considers a divergent supply chain for which the system places the orders periodically. The goal of the research is to minimize the holding and penalty costs per period. However, problems that arise by using this method are the assumption that the final demand is normally distributed, throughput times are constant, and there is no service level constraint.

Another study that does consider a service level constraint is the study of van der Heijden (2000). This research proposes a method to control divergent networks under a periodic review. The objective is to minimize the holding costs within the supply chain while the desired fill rates are obtained. This method assumes that the demand per period is stationary in time, and demand that is not immediately fulfilled is backordered. Furthermore, lot sizing is not considered. Next, the demand distribution is unknown and the model is using the mean and standard deviation as well. Nevertheless, it assumes constant throughput times.

A more recent study of de Kok (2018) discussed a method for general multi-item multi-echelon (MIME) under a base stock policy, the Synchronized Base Stock (SBS) policy. This policy is based on two structural characteristics of a MIME system, the Bill-of-Material (BOM) and the item cumulative throughput times. The main difference between the SBS and many other planning and control concepts is the material availability check, which will be discussed in more detail in the next section. Earlier research has shown that the SBS policy is applicable in the high tech industry (de Kok et al., 2005; van Waveren, 2020; Schouten, 2018). In addition, the newsvendor problem is an applicable technique used in the SBS method. Based on these findings, there is chosen to discuss the SBS in more detail in the next section. By implementing the SBS policy for the semiconductor industry, a problem arises since fixed throughput times are assumed. This problem can be solved by assuming that the throughput times follow the normal distribution, and by considering the standard deviation.

Furthermore, two problems should be addressed, (i) how to manage extreme orders, and (ii) how to consider demand uncertainty. For the first problem two situations are assumed. In the first situation the customer demand is stable, no orders are placed that have a huge quantity size in comparison with the average order size. The second situation considers these extreme orders. The extreme orders (outliers) are defined as an order size is equal to 6 times or more the average order size. In the literature there are no strict rules to define outliers. For the first situation the methods discussed can be used. However, for the second situation two options are considered to manage the extreme demand.

1. Assume that extreme orders have a customer lead-time that is minimally equal to the planned throughput time of product. In this case the extreme orders are managed as the product is produced by the MTO strategy.

2. When these extreme orders are placed on a regular basis, the CODP can be reconsidered, or an additional stocking point can be located.

The second problem is the decision how to determine demand uncertainty. As discussed in the literature section, the demand uncertainty can be determined in two ways. The first option is based on the historical demand. The alternative is the forecasted demand. In both situations the huge orders have an impact on the standard deviation. However, since the first production step starts based on the forecast it would make sense to define the safety stock based on the forecasted demand. The safety stock would then manage the mismatch between actual demand and the forecasted demand.

4.2 Detailed design

The previous section gives a general description of how to determine the possible stocking points and how to manage the stocking targets. This section discusses how to determine the possible stocking points in more detail. Thereafter, the method is discussed to determine the target levels of a stocking point, the Synchronized Base Stock (SBS) policy (de Kok and Fransoo, 2003). The policy is based on the algorithm proposed by Diks and de Kok (1999).

4.2.1 Supply network

Before introducing the method to determine the possible stocking points, the supply network is introduced. This is described by parent-child relationships between the items. The following sets are introduced:

N: set of all items
E: set of end items, items that are not used in any other item and are delivered to the customers
E_k: end item k

I: set of intermediate items
V_i: set of successors of item i
W_i: set of predecessors of item i
a_{ij}: is introduced as the number of items i that are required to produce one item of its parent item j, which is in this thesis equal to 1 for all items.

For each item i, $i = 1, 2, .., N$ and for item j, $j = 1, 2, .., N$. For the end items, $k \in E$,

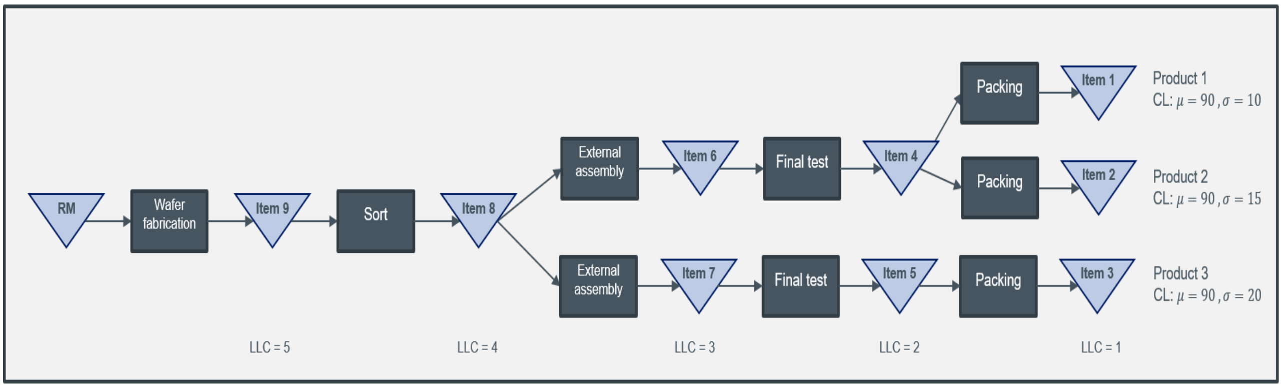


Figure 4.1: Example supply chain

Figure 4.1 shows an example of a supply chain consisting of nine items, $N = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$, and three end items, $E = \{1, 2, 3\}$. The intermediate items are $I = \{4, 5, 6, 7, 8\}$. Two end items can be produced from item 4, $V_4 = \{1, 2\}$. The items that are required to produce one unit of item 4 are indicated by $W_4 = \{6, 8, 9\}$. Furthermore, every stocking point has a low level code (LLC). For the end items, the LLC is equal to 1, for a stage upstream in the supply chain, the LLC is equal to LLC + 1.

4.2.2 (Customer) order decoupling point(s)

Since the time between the order is placed and the customer would receive the order can be different for every order, even for the same product, the modeled customer lead-time is determined. The next step is locating the CODP for each end item. Therefore the following variables are introduced:

MCL_i: modeled customer lead-time for end item i
X: desired modeled customer lead-time percentile
T_i: average throughput time of item i
T^c_{ij}: cumulative throughput time on the path from item i to item j, including i and j

Subsequently, for each end item the modeled customer lead-time (MCL_i) is determined by two options:

The first option is excluding the customer lead-times that have a value below or equal to 7 days. The second option is choosing the value based on the desired percentile X, which can be done in Microsoft Excel using the percentile function.

Next, the CODP has the following constraint, to ensure that the CODP location is not too far upstream in the supply chain to fulfil customer orders on time:

$$T^c_{ij} \leq MCL_i \tag{1}$$

Note, that when the CODP is located after the wafer fabrication step, it makes more sense to locate the CODP one stage downstream in the supply chain because of the reasons mentioned in the conceptual design (section 4.1).

To locate the other possible stocking points the commonality and utilization variables are defined:

COM_{P_i}: commonality in end products for item i
COM_{C_i}: commonality in customers for item i
U_i: utilization of process of item i

The commonality can be derived from the BOM, for example, based on Figure 4.1, $Com_{P_8} = 3$. The commonality in customers can be derived from the customer data base. Then based on these values an additional inventory point that is located more upstream than the CODP is determined by the following steps:

1. set i equal to the location of the CODP
2. if $COM_{P_{i+1}} > COM_{P_i}$ and $COM_{C_{i+1}} > COM_{C_i}$ then locate an additional inventory position on $COM_{C_{i+1}}$, if not go to step 4
3. $i = i + 1$
4. repeat step 2, 3 until the most upstream location in the supply chain is reached

In addition, processes that have a high utilization level can be defined as a bottleneck location. If the utilization level of a process is higher than a certain number, it can be seen as a bottleneck location.

4.2.3 Cost function and constraints

To define the cost function and the constraints that are relevant for a multi-item multi-echelon system the following variables are introduced:

$D_i(t)$: independent demand for item i in period t
$G_i(t)$: dependent demand for item i in period t
$y_i(t)$: quantity of item i that becomes available at the start of period t from the transformation activity generating item i
$r_i(t)$: quantity of item i released at the start of period t immediately after receipt of $y_i(t)$
$I_i(t)$: physical inventory of item i at the start of period t, immediately before receipt of $y_i(t)$
$SS_i(t)$: safety stock of item i in period t
$B_i(t)$: backlog of item i at the start of period t, immediately before receipt of $y_i(t)$
$J_i(t)$: net inventory of item i at the start of period t, immediately before receipt of $y_i(t)$

h_i: holding costs of item i per time unit t
p_i: penalty costs of end item k per time unit t
α_k: non-stock out probability at end item k
α_k^*: target non-stock out probability at end item k
β_k: fill rate at end item k (P2)
β_k^*: target fill rate at end item k

According to Pyke et al. (1998), the fill rate (P2) is defined as: 'fraction of customer demand that is met routinely; that is, without backorders or lost sales' (p. 245).

The independent demand is the demand for the end items, which is equal to the customer demand. For these end items, the demand is not known, and are based on a forecast. Therefore, the item set P is defined as:

P: set of items i with $D_i(t) > 0$ for some $t > 0$

Cost function and service level constraint
A cost function is defined which considers holding and backordering costs for all items at the end of a period t:

$$C(t) = \sum_{i=1}^{N}(h_i I_i(t) + p_i B_i(t)) \tag{2}$$

However, since multiple periods are used, the long-run average should be used. In addition to ensure a desired customer service level, a customer service level constraint is defined. The performance of the inventory system is measured by the fill rate, β. For all end items a fill rate is defined.

$$\beta_k \geq \beta_k^*, \qquad k \in P \tag{3}$$

Material release constraints
The following equations define the material release constraints. These constraints consider the availability of materials and ensure that there is not released more than physically available. The equation below means that increase in the backlog cannot exceed the exogenous demand.

$B_i(t+1) - B_i(t) \leq D_i(t), \qquad \forall i, t \geq 1$

Next, the released quantities are non-negative

$r_i(t) \geq 0, \qquad \forall i, t = 1, ..., T$

Based on the above equations, the inventory balance equation can be defined:

$I_i(t+1)$ - $B_i(t+1) = I_i(t) - B_i(t) - G_i(t) - D_i(t) - r_i(t - L_i), \qquad \forall i, t = 1, ..., T$

However, this is the case when the planned throughput time can be seen as realistic.

4.2.4 SBS policy and algorithm

The Synchronized Base Stock (SBS) policy is based on the algorithm developed by Diks and de Kok. The algorithm determines the near-optimal echelon base-stock levels and allocation fraction. In this section algorithm is shortly discussed.

First some variables are introduced:

S_i: base stock level of item i
CS_i: cycle stock of item i
q_j: allocation fraction to stockpoint j
U_i: all items on the path from the root items to item i, exclusive item i

The base stock level S_i consists of two parts, (i) the expected customer demand during the throughput time (T_i) and the review period (R), and (ii) the safety stock (SS_i). The expected customer demand during the throughput time and review period is also defined as the cycle stock (CS_i). The safety stock covers the variability in throughput time of the processes and customer demand.

The algorithm starts with determining the base stock levels of the end items (LLC = 1) by satisfying the following newsboy styled equation:

$$\alpha_k^i = \frac{\sum_{j \in U_i} h_j + p_k}{h_k + \sum_{j \in U_k} h_j + p_k} \tag{4}$$

Subsequently, the base stock levels and the allocation fractions for the next intermediate items with LLC = 2 are determined such that they satisfy Equation 4. Until the sum of the allocation fraction ($\sum_{j \in V_i} q_j$) is close to 1, the allocation fraction is adjusted. In the case that the base stock level of a stockpoint with LLC = 2 is less than the sum of the base stock levels of its successors, the base stock levels of the successors are adapted. A more detailed explanation of the algorithm can be found in Diks and de Kok (1999).

4.3 Solution

As discussed before, the first step is determining the number of stocking points. After doing this, there are two options, (i) there is one single stocking point (CODP) or (ii) there are multiple stocking points. In the case of a single stocking point, the base stock level can be calculated by using the newsboy equation (Equation 4). In the other situation, the complexity is much higher since the allocation fractions have to be calculated. Therefore, ChainScope, a software program that is based on the Synchronized Base Stock (SBS) policy will be used. The program assumes an infinite production capacity.

4.3.1 Single stocking point

For a single stocking point, the optimal base stock policy can be derived from Equation 4. Since this stocking point is the only stocking point in the supply chain, it is the stocking point that has to fulfill the customer demand for this end item. This results in the following formula that is proposed by Shang and Song (2003) as well:

$$S^* = F^{-1}(\frac{p}{h+p}) \tag{5}$$

By using Equation 5, the optimal base-stock level is calculated, where F^{-1} is the inverse cumulative distribution of the demand during the throughput time. The parameters to use F^{-1} can be derived from the historical data, which is explained in more detail in the next subsection. In the case the penalty cost p_i is unknown, it can be derived from Equation 4. Note that this method is only considering demand uncertainty. How to manage the throughput time uncertainty is covered in the next subsection.

4.3.2 Multiple stocking points - ChainScope

In the situation where multiple stocking points are determined in the supply chain, a software program that analyzes and optimizes multi-item multi-echelon systems is used. The goal of the software is to achieve the desired service levels for the end items while minimizing the inventory holding costs. In this section, the model inputs are explained. ChainScope is developed by prof. de Kok. The main advantage of SBS policies, as discussed in section 4.2, is that SBS possesses an allocation mechanism. The following section will discuss the relevant input parameters and output to use the software.

Throughput time - input

The throughput time is based on the expected throughput time, which is a fixed number. However, as discussed in section 3.7, the observed throughput time varies. Therefore, throughput time variability has to be considered. By assuming that the throughput times follows the normal distribution the following formula can be used to include the variation in the throughput time. Where, (μ_{Ti}) is the average throughput time, (σ_{Ti}), the standard deviation of the throughput time for each item i, and Z is the value from the standard normal distribution for the desired percentile X. The Z value for the desired percentile X can be looked up in Appendix F.

$$T_i = \mu_{Ti} + Z * \sigma_{Ti} \tag{6}$$

Customer demand - input

The customer demand is the independent demand D_i observed per period for the end items. The method assumes that the demand in the end items is **independent and identically distributed**. By using the two moments fit method, the parameters of the gamma distribution can be derived by using the average and standard deviation of the customer demand:

$$\mu = \frac{\alpha}{\beta}, \qquad \beta = \frac{\mu}{\alpha} \tag{7}$$

$$\sigma^2 = \frac{\alpha}{\beta^2}, \qquad \alpha = \frac{\mu^2}{\sigma^2} \tag{8}$$

BOM structure - input

Furthermore, the structure of the supply chain is based on the bill of material. This structure is based on the item-successor relations as discussed in section 4.2.

Service level - input / output

The desired service level is measured in fill rate (β_i). The fill rate is the fraction of customer demand that is fulfilled immediately without any backorders. A target fill rate (β_i^*) is given as input parameter, and ChainScope gives the calculated fill rate β_i as output.

Review period - input

Moreover, the review period (R) is the period between the release decisions for an item.

Lot size - input

First of all, the lot size variable is introduced (Q_i) as the lot size of item i. The lot size is the order batch quantity. For the stocking points after the wafer fabrication and sorting process, the released quantity (r_i) depends on the process's lot size (Q_i). The released quantity is a multiple integer of the lot size (nQ). For the wafer fabrication, the lot size is equal to 25 wafers, and for the sorting process, the lot size is equal to one wafer. The number of dies per wafer depends on the product. For the other processes, lot sizing is not considered.

Customer order lead-time - input

For each end item, the modeled customer lead-time should be determined.

Holding and penalty costs - input

The holding cost (h_i) is used as input parameter for each item in the supply chain. The penalty cost (p_i) is **not** used as input parameter in ChainScope. Based on the holding cost and the non-stock out probability, the penalty cost is determined using (Equation 4) for the end items.

Average inventory on-hand - output

The output is the average inventory on-hand that consists of the safety stock and the average cycle stock.

5 Case study

This chapter discusses the results by applying the proposed method in terms of safety stock and average inventory on hand. Ten cases are selected that differ in the supply network and the number of locations with safety stock to compare the current situation with the proposed method. First, the possible stocking points are determined. These determined stocking points are used as input in ChainScope to optimize the inventory levels. Two situations are compared. In the first situation, the current **safety stock settings** are compared with the proposed safety stock settings by ChainScope. In the second situation, the current **average inventory on-hand** is compared with the average inventory on-hand proposed by ChainScope. Distinguish these two situations is because of two reasons. First, no distinction is made between cycle stock and safety stock (section 3.10). Second, the desired safety stock targets are not necessarily located at the stocking points. Note that the scales on the vertical axis of the figures are hidden because of confidential data.

5.1 Case selection

Ten cases are selected that differ in the number of positions with safety stock, end items, and total customers. In other words, the complexity of the supply chain. In addition, the cases differ in terms of customer demand. For these cases, the current safety stock settings are compared to the calculated safety stock settings with the proposed method.

Case	Business line	Positions with safety stock	End items	Total customers
1	A	1	1	1
2	A	1	3	5
3	B	2	1	1
4	A	2	2	15
5	B	2	3	18
6	A	3	1	2
7	B	3	2	25
8	B	3	3	22
9	A	4	4	39
10	B	4	7	17

Table 5.1: Case selection

5.2 Validation

The software package ChainScope is used to measure the performance of a situation. However, ChainScope is limited in measuring in terms of performance measures. The software can measure the fill rate. As mentioned in the previous chapter, the fill rate is the fraction of customer demand immediately fulfilled. However, the performance within ams is measured in RLIP. The RLIP indicates the percentage of the orders fulfilled within the customer lead-time. Since these are two different performance measures, it is necessary to check whether these performance measures are in the same range as the observed RLIP. By using the evaluation function of ChainScope, the situations can be compared. Based on the average and standard deviation of the customer demand of the end items, the supply chain structure, and the average on-hand inventory, the situation can be evaluated. For the ten selected cases, the performance is compared with each other in Table 5.2. The average on-hand inventory of the beginning of month X and month X + 1 is used. Subsequently, the average calculated fill rate in ChainScope and the observed RLIP of these months are compared. The fill rate is measured for the location that is the CODP. For some cases, there is a slight difference in the values. However, this can be caused by the low number of orders in the period observed. The fill rate is calculated for the customer order decoupling points in the current situations.

Case/ Performance	1	2	3	4	5	6	7	8	9	10
RLIP	50.0%	80.4%	100.0%	77.0%	44.4%	81.3%	87.5%	96.4%	59.6%	74.2%
Fill rate	53.2%	79.2%	99.2%	75.7%	45.4%	80.3%	88.5%	100.0%	61.9%	76.5%

Table 5.2: RLIP - Fill rate

For the remainder of the case study, we assume that the fill rate is similar to the RLIP based on the above table. Furthermore, the values obtained for the cases with a single stocking point are validated with the output of ChainScope. For both methods, the calculated safety stock is the same. Therefore, ChainScope is used to calculate the settings for all cases.

5.3 Parameter setting

The parameters used in the software package ChainScope are introduced. Some parameters could have a relatively high impact on the results and are further investigated in the sensitivity analysis.

5.3.1 Input parameters

First of all, the supply chain structure is based on the bill of materials. For the items and end items in the supply chain, the following parameters are introduced:

Item		
Parameter	Symbol	Value
Desired percentile throughput time	X	95%
Throughput time	T_i	
Holding cost	h_i	
Review period	R_i	7
Lot size	Q_i	

End item		
Parameter	Symbol	Value
Modeled customer lead-time	MCL_j	MCL_{minj}
Average customer demand	μ_j	
Standard deviation customer demand	σ_j	
Target fill rate	β_j^*	90%

Table 5.3: Input parameters

For a few parameters, the values depend on the case. For these parameters, no value is given in Table 5.3. The throughput time is calculated by using Equation 6. For the modeled customer lead-time the minimal customer lead-time, excluding the orders with a request within one week is used. The modeled customer lead-times are based on the data from 2020. The review period is set to once a week ($R = 7$) for all processes. Furthermore, the lot size for the wafer fabrication is 25 wafers, and for the sorting process, one wafer. For the other stocking points, no lot size restrictions are considered. Next, as mentioned in section 4.1, the demand uncertainty can be determined based on the historical demand and the forecasted demand. However, the amount of available data to analyze the forecasted demand is limited. Therefore, the **historical demand** is used to determine the average and standard deviation of the customer demand. Furthermore, the values of the throughput time, review period and customer demand are expressed in **days**.

5.3.2 Output

The output that is relevant for the case study is shown in Table 5.4. For each item, the safety stock and average cycle stock are given as output. For the end items, the calculated fill rate is given.

Output	Symbol
Safety stock item i	SS_i
Average cycle stock item i	CS_i^*
Fill rate end item j	β_j

Table 5.4: Output

5.4 Results

The first step is determining the CODP and other possible stocking points. Since there are no bottleneck processes for these cases, the bottleneck criterion is not considered. The possible stocking points are used as input for the ChainScope software. The next step is calculating the (safety) stock levels for these stocking points.

5.4.1 Stocking points

In Figure 5.1 the **current** situation for each case is shown on the left-hand side. For the current situation, the yellow triangle indicates an inventory position with a safety stock setting. In the proposed situation, the yellow triangle indicates determined stocking point by using the proposed method. It could be that these determined locations will have no safety stock, which is indicated by 0% in the triangle. Note that cycle stock can still be located at other possible stocking points (blue triangles). Remember that raw materials are not taken into account. The first triangle is the inventory position after the first process step. In the proposed situation, the modeled customer lead-time (MCL) is determined by the **minimal customer lead-times without the extreme requests within one week**. The customer order decoupling points are based on the throughput time (T_i) and the MCL. For example the first case, the MCL is equal to 51 days. The throughput time of the process most downstream in the supply chain is 8 days. The process one stage upstream in the supply chain has a throughput time of 9 days and the next one 37 days. Based on this, the last two processes are executed when a customer order is received, resulting in a CODP after the first three processes. Another example is case

3. As mentioned in the design chapter, locating inventory after the sorting process is more logical if the commonality is the same. Both components are produced for the same number of customers and end items. Therefore, the CODP is located one stage more downstream in the supply chain than based on the MCL. Another additional stocking point is located for example is case 7. For both end items, the CODP is located as a finished good. However, the component used for the two end items is determined as a possible stocking point with safety stock (yellow) because of the commonality of the component.

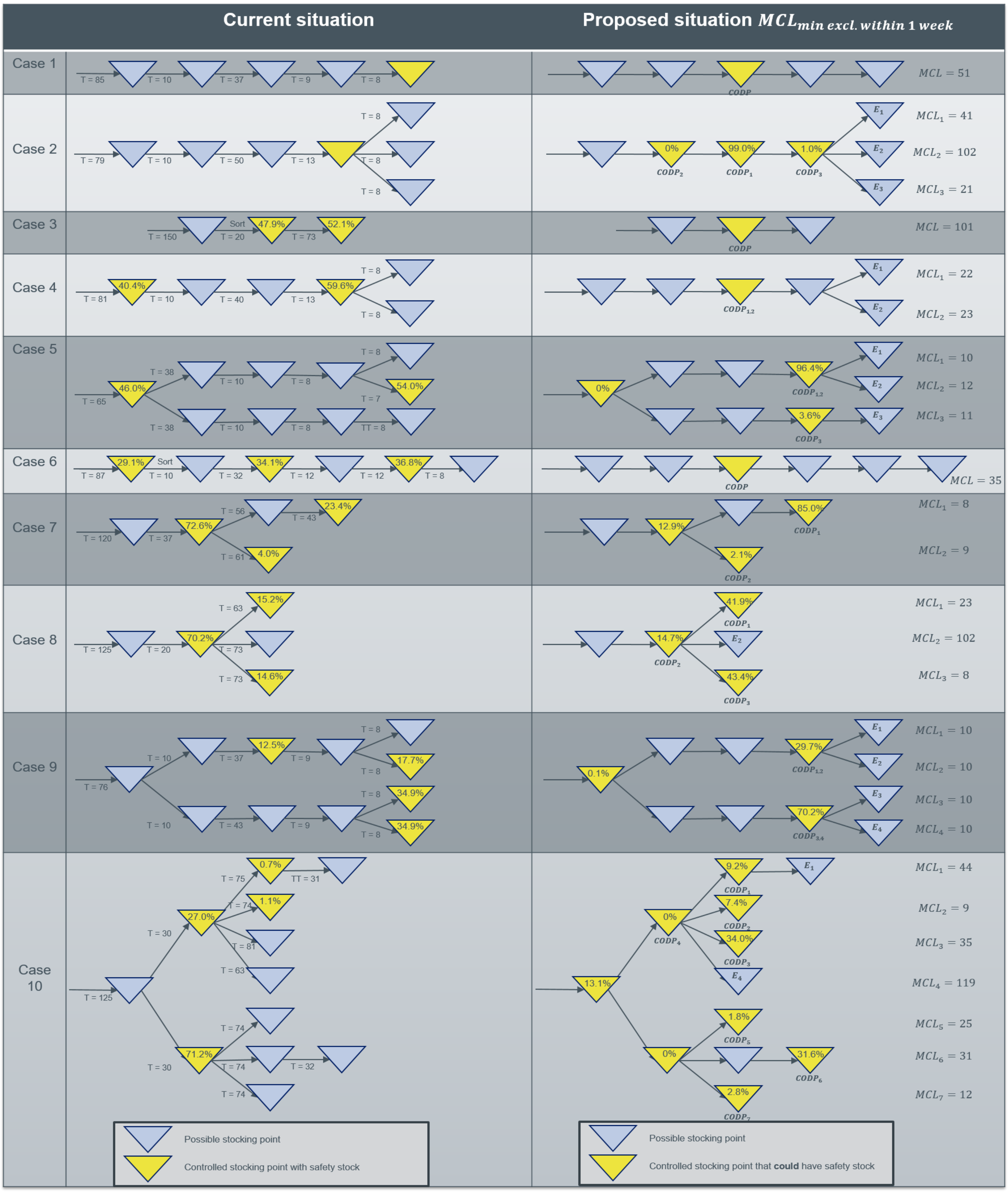


Figure 5.1: Stocking points current vs proposed situation MCL min without extreme requests

In the proposed situation, there are fewer stocking points for cases 3, 4, 6, and 9. Case 7 and 8 have the same stocking points. The cases with more stocking points than in the current situation are 2, 5, and 10. The reason for an increasing number of stocking points with safety stock are the different modeled customer lead-times for each end item. Especially in case 10, many stocking points are determined.

5.4.2 Inventory levels

After locating the possible stocking points, the stock levels are calculated. As mentioned at the beginning of this chapter, two situations are compared. Firstly, the safety stock settings. Secondly, the average inventory on-hand.

Safety stock

First of all, the current safety stock settings are used to evaluate the performance of these settings in the **proposed situation**. Table 5.5 shows the calculated fill rate achieved with the current **safety stock settings**. Note that the calculated performance in Table 5.5 is different than in Table 5.2. In Table 5.5 only the safety stock settings are considered, the cycle stock is excluded.

Case	1	2	3	4	5	6	7	8	9	10
Fill Rate	88.1%	57.0%	99.8%	93.1%	91.0%	99.5%	41.6%	54.4%	81.4%	1.9%

Table 5.5: Current calculated fill rate: proposed situation MCL min without extreme requests

For some cases, the calculated fill rate is relatively low, for example, case 2. Case 2 has a fill rate of 57.0%, while the safety stock is located at a stage that could fulfill the orders within the requested CL for the three end items. It seems that the current safety stock settings are not high enough to manage the demand uncertainty. **The percentage at the locations indicates the percentage of the total value in safety stock at that location of that supply chain**. In other words, for case 7, 72.6% of the total value in safety stock is located in the middle of the supply chain. Next, case 7 has a relatively low fill rate as well. The reason is that the majority of the safety stock (72.6%) is located upstream in the supply chain, while the CODP for end items 1 and 3 are located at the end items in the proposed situation. In other words, the safety stock should be located more downstream to achieve a better performance. This is the same for cases 8 and 10. For case 10, this results in a very low fill rate.

In Figure 5.2 the current settings are compared with the proposed situation, where the fill rate is set to the desired service level. As mentioned in the input parameter section, the fill rate target is set to 90%. In the sensitivity analysis, other fill rate targets will be analyzed. Figure 5.2 shows the total value of safety stock with the current safety stock settings in euros. Furthermore, it shows the total value of safety stock to achieve a fill rate of 90% when the MCL is determined by the minimal CL without the requests within one week.

Cases 7 and 8 show that the correct position of the safety stock is essential to achieve the desired performance. In the current situation, most of the value in safety stock (>70%) is

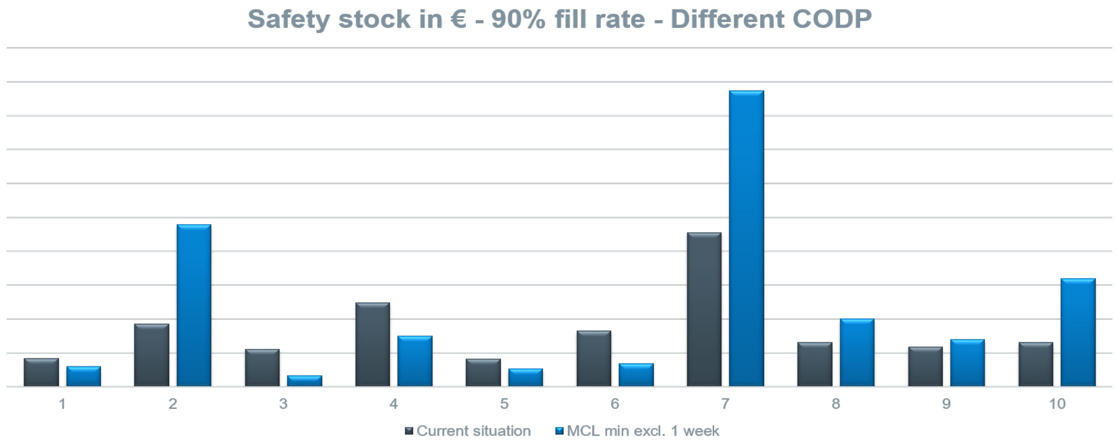


Figure 5.2: Safety stock in € - 90% fill rate

located upstream in the supply chain. Locating the safety stock at the end items, as in the proposed situation, results in a higher fill rate. For cases 2, 7, 8, 9, and 10, an investment in safety stock is needed to achieve a 90% fill rate, which is logical since the current performance is significantly lower for these cases (Table 5.5).

However, only comparing the safety stock settings does not address the total value of inventory in the supply chain. It could be that an investment in safety stock is needed, while the total average inventory on-hand decreases. Therefore, the total average inventory on-hand in the current situation and the proposed situation is compared.

Average inventory on-hand

Figure 5.3 shows the total average inventory on-hand in the current situation and in the proposed situation. The corresponding RLIP of that period is shown in Table 5.6. Note that the observed performances are different than in Table 5.2, since other data is used.

Case	1	2	3	4	5	6	7	8	9	10
RLIP	87.5%	80.8%	66.7%	70.2%	73.7%	84.2%	52.2%	67.9%	46.0%	80.3%

Table 5.6: Observed RLIP current situation - Q1 2021

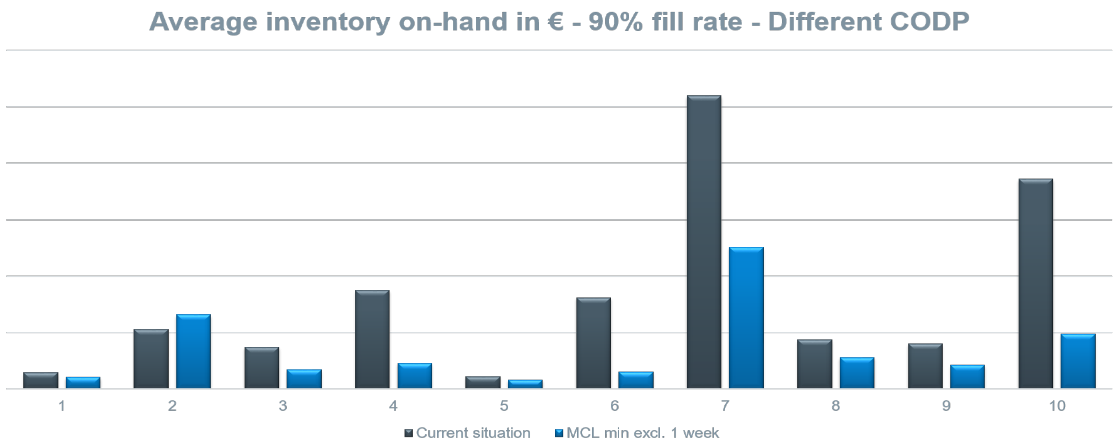


Figure 5.3: Average inventory on-hand in € - 90% fill rate

In all cases, the average on-hand inventory calculated to achieve a fill rate of 90% is lower, except in case 2. Moreover, the performance improved significantly in most cases. For case 3, 4, 6, 7, 9, and 10 the total value of the average inventory on-hand in euros is significant lower than in the current situation.

It is important be aware of the following two facts to clarify the huge differences between the average inventory on-hand. First, in the proposed situation, the historical demand is used, while in the current situation, the production is started based on the forecasted demand. As discussed in section 3.4, the demand in the second quarter of 2021 is increased significantly, which could clarify the high average inventory on-hand in the current situation. Second, it could be that some extreme orders in terms of order size are placed, which are considered in the current situation and not in the proposed situation.

Based on the ten cases, the average costs in the inventory on-hand can be reduced by 45%. This is achieved with a better performance. However, since there is a mismatch between the reality and the proposed situation, this mismatch should be taken into account. For example, by assuming that 20% of the value of the average inventory on-hand in the current situation represents the forecasted demand and extreme orders. In that case, there is still a decrease of 30% in the average inventory on-hand costs while the average fill rate increase by 26%.

5.5 Sensitivity analysis

As mentioned at the beginning of this chapter, multiple input parameters impact the (safety) stock settings. Therefore, the influence of a few input parameters is analyzed by a sensitivity analysis. First of all, the impact of the target fill rate is analyzed. Secondly, the different scenarios for the throughput time percentile are considered. Finally, three situations for the modeled customer lead-time are analyzed. The holding costs are not analyzed in the sensitivity analysis since increasing or decreasing the inventory costs for the whole supply chain does not change the stock settings. This would be interesting when for one stage the holding costs change more or less than another stage. However, this is not considered. Furthermore, the sensitivity analysis does not consider the customer demand since the impact is already analyzed using different cases with different customer demand.

5.5.1 Service level target - fill rate

The service level is calculated in fill rate. In the first situation, a 90% target fill rate is chosen. However, since the RLIP target is set per year within ams, other targets are analyzed as well. Figure 5.4 shows the costs of the current safety stock settings in comparison with other fill rate targets. The corresponding fill rates of the current situation are shown in Table 5.5.

The figure shows that a 10% difference in fill rate can significantly impact the investment in safety stock that is needed. For some cases, a relatively higher investment is needed. However, this depends on the variability in the throughput time and customer demand. For case 1 and 6, a relatively higher investment is needed to achieve a fill rate of 80% instead of 70%. This is between the 44% and 45%. For the other cases this is between 35% and 40%. The two cases

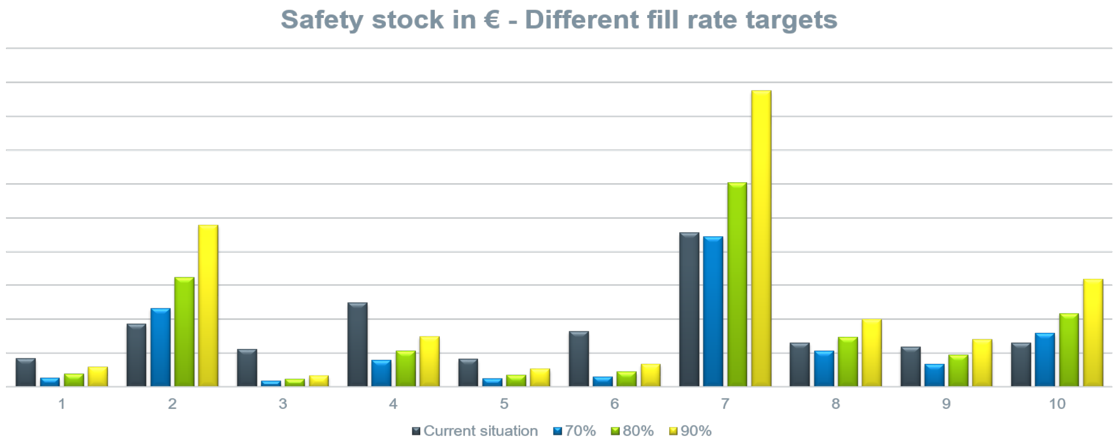


Figure 5.4: Safety stock in € - different fill rate targets

with a relatively higher investment needed to increase the fill rate from 80% to 90% are 1 and 5. An increase in value of 52.5 % is needed. Case 3 and 8, need a relatively low investment (37% - 38%). For the other cases this is between the 45% and 47% to improve the fill rate from 80% to 90%.

More interesting is the total average inventory on-hand, which is shown in Figure 5.5. For all cases all proposed scenarios are below the current average inventory on-hand, except for case 2 with a fill rate of 90%. The current observed RLIP for this case is 80.8% (Table 5.6). In the proposed situation a fill rate of 80% is achieved while the average inventory on-hand value decreased by 12%.

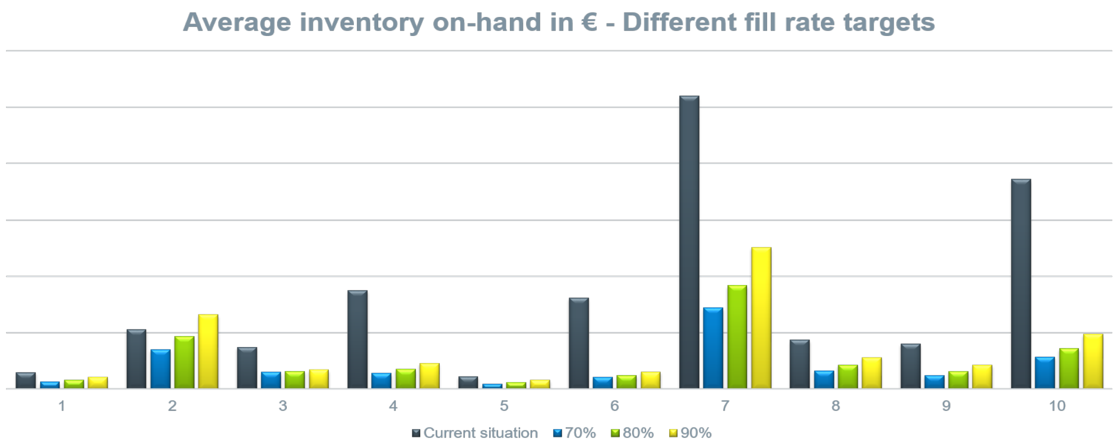


Figure 5.5: Average inventory on-hand in € - different fill rate targets

Overall, case 7 highlights the importance of locating the safety stock at the correct position. In the current situation, the fill rate is equal to 41.6%. At the same time, a fill rate of 70% can be achieved with a slightly lower safety stock level. Furthermore, the huge differences in costs for the different fill rate targets emphasize the importance of having a clear service level target.

5.5.2 Throughput time uncertainty

Since ChainScope assumes fixed throughput times, Equation 6 is used to include the variability in throughput time. Using this method results in different throughput times if the desired percentile changes. Therefore, different scenarios are chosen. For the cases above, a 95% percentile is used. The following scenarios are chosen to analyze the impact of the throughput time uncertainty: a 80%, 90%, and 98% percentile. The corresponding Z value can be found in Appendix F.

Figure 5.6 shows the value in safety stock needed to achieve a fill rate of 90%. The investment needed depends on the variability in the throughput time. For most cases, it increases in the same range. In particular, two cases (7 and 10) need a relatively higher investment. The main reason is the higher uncertainty during the assembly process for both cases. Most cases need an investment between the 12% and 15% in safety stock value to calculate the safety stock settings with a 98% percentile instead of a 80% percentile.

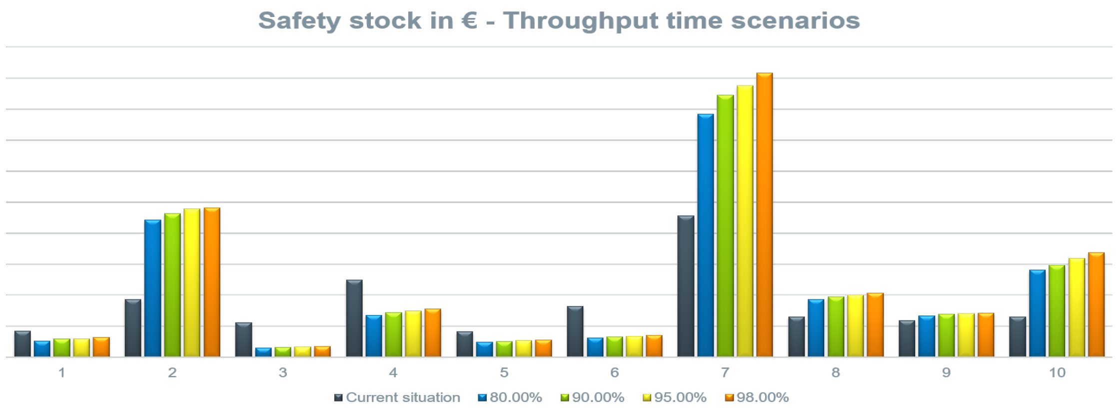


Figure 5.6: Safety stock in € - throughput time scenarios - 90% fill rate

Figure 5.7 shows the total average inventory needed for the different throughput time scenarios. Only for case 2 an investment in the total average inventory on-hand is needed. For the majority of the other cases a significant reduction in average inventory on-hand can be achieved, even with the 98% throughput time percentile scenario.

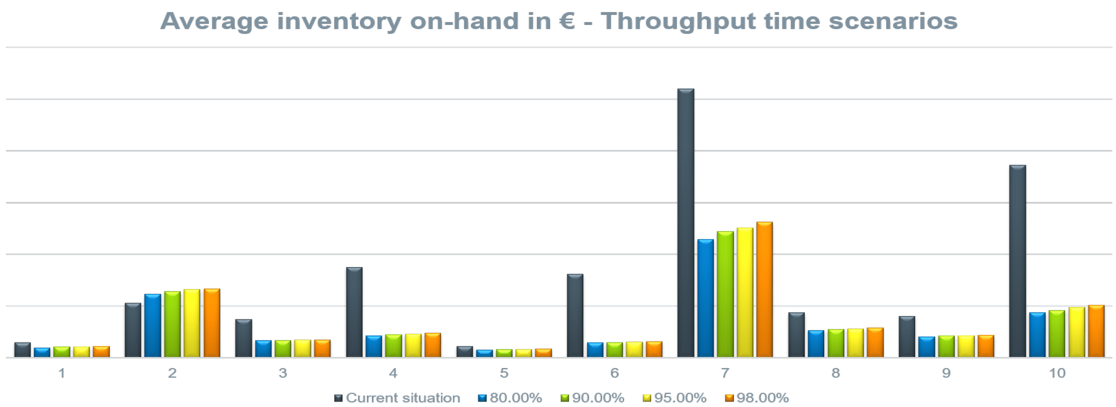


Figure 5.7: Average inventory on-hand in € - throughput time scenarios - 90% fill rate

5.5.3 Modeled customer lead-time scenarios

As described in section 4.1, there are multiple options to determine the modeled customer lead-time. In the situations above, the modeled customer lead-time is determined by using the minimal customer lead-times excluding the requests within one week (MCL_{min}). To analyze the impact of this parameter, two additional possibilities are considered. In the first one, the modeled customer lead-time is determined by a 10% percentile ($MCL_{10\%}$). In the second one, the modeled customer lead-time is determined by a 25% percentile ($MCL_{25\%}$). In other words, 10% or 25% of the orders have a lower customer lead-time than the modeled customer lead-time. This result in a CODP that can not fulfill 10% or 25% of the customer orders within the customer lead-time. Note that these settings are calculated with a target fill rate of 90%. For all cases the data of 2020 is used to determine the modeled customer lead-time.

Appendix G shows the modeled customer lead-times of each case for each scenario. For some cases, the MCL where the orders with a CL within one week are excluded has a higher MCL than the other two options. This is possible if multiple orders have a very low CL, which are included in the 10% and 25% fractile, and excluded in the other option. An example is case 4.

10% percentile

Figure 5.8 shows the new (customer order) decoupling points in the situation where the 10% fractile determines the modeled customer lead-time. Since the cases with the same stocking points as the previous setting lead to the same results, these cases are not shown in the figure (case 3, 7, 8).

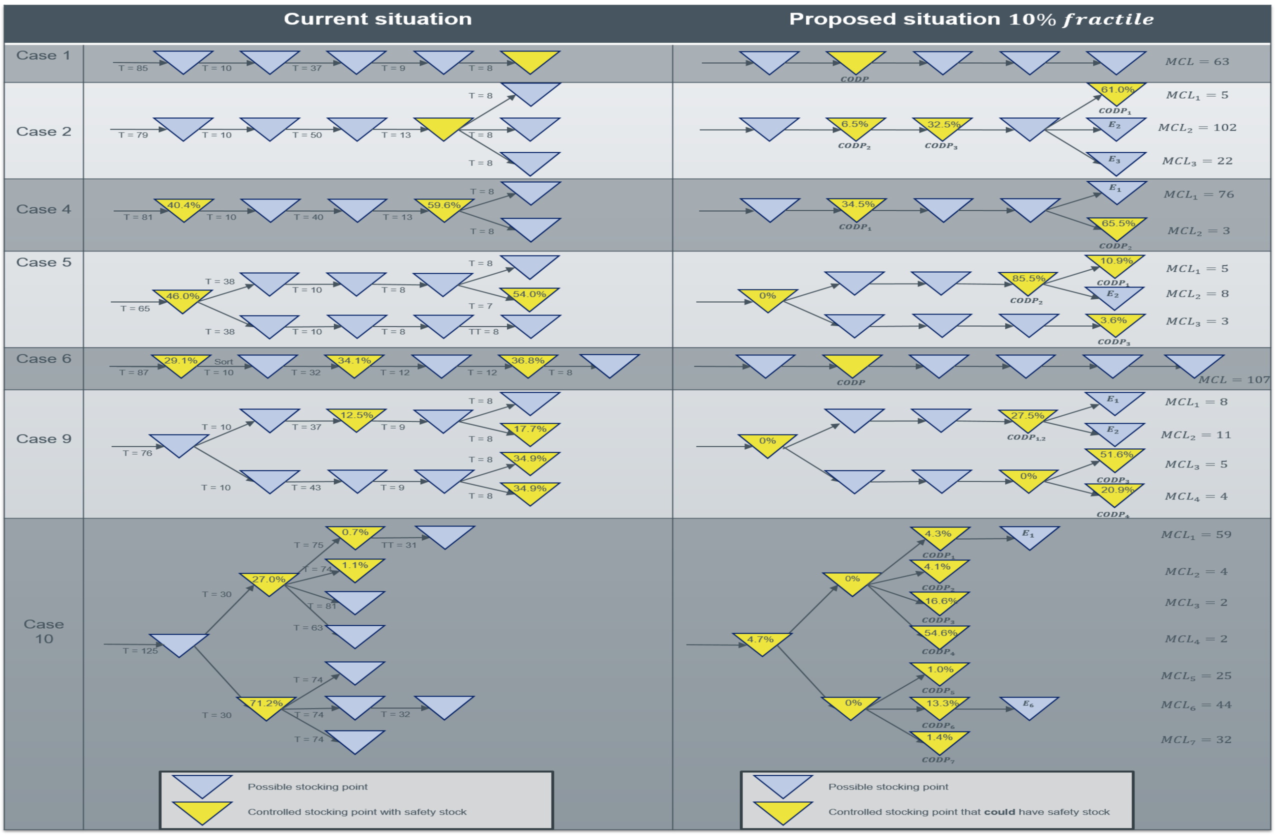


Figure 5.8: Stocking points current vs proposed situation MCL 10% fractile

25% percentile

For the situation where the modeled customer lead-time is based on the 25% fractile, the cases are shown in Figure 5.9. The cases with the same stocking points as the 10% fractile are not shown (case 4, 6, 10).

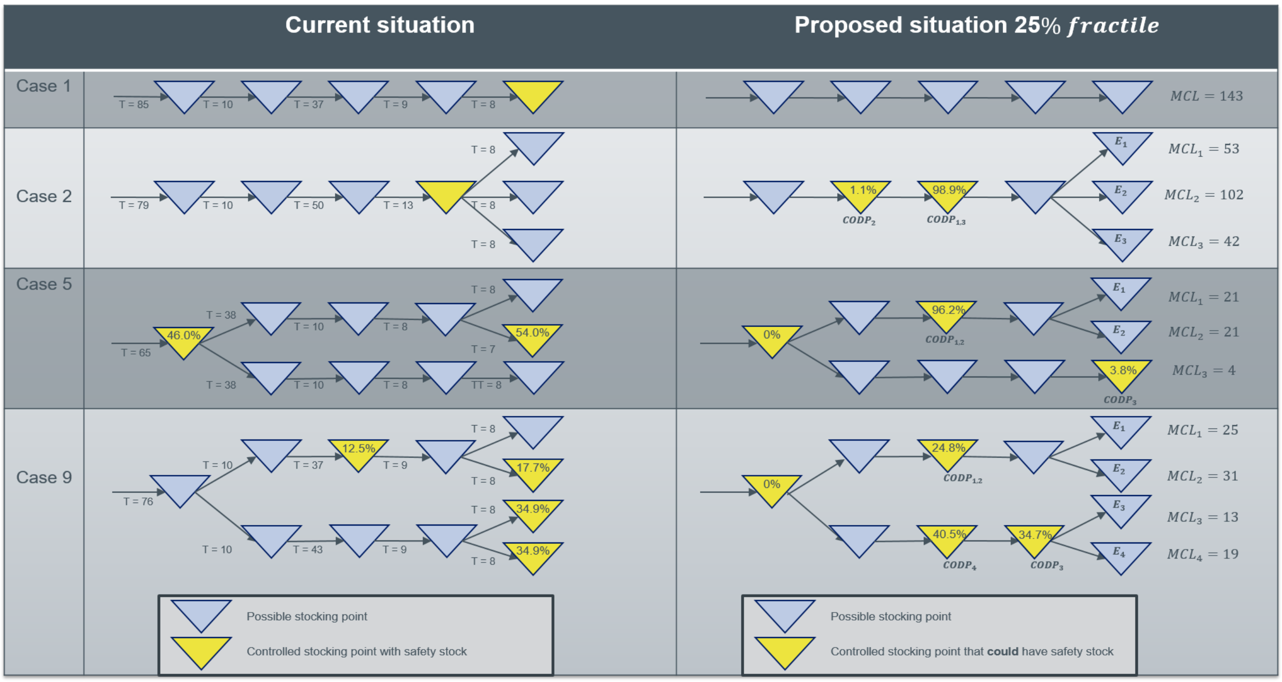


Figure 5.9: Stocking points current vs proposed situation MCL 25% fractile

Average inventory on-hand costs

The cases that are not shown in Figure 5.8 and Figure 5.9 can be noticed in Figure 5.10. For these cases, the costs are equal to the previous setting. Interesting is the differences between the modeled customer lead-times, which could lead to significant savings. For example case 1, there is only a difference of 12 days, $MCL_{min} = 51$ and $MCL_{10\%} = 63$. This results in a CODP that is one stage more upstream in the supply chain. Locating the CODP one stage more upstream results in a decrease of 58% in safety stock costs while the same fill rate is achieved. For the case that the 25% fractile determines the MCL, the product can be completely produced based on customer orders (MTO).

Another significant reduction in safety stock costs is shown for case 6. The CODP for the 10% and 25% fractile is located after the sorting process, which results in a decrease of 52.5% in safety stock costs with the same performance. As mentioned before, it is also possible that an investment is needed since the 10% or 25% has a lower MCL than the MCL_{min} situation. This results in a CODP more downstream in the supply chain, where the holding costs are higher than upstream in the supply chain. For example case 6.

In addition the average inventory on-hand for the different scenarios is shown in Figure 5.11. The figure shows, particularly for cases 2 and 10, that there is a significant difference in the average inventory on-hand for the different scenarios.

The above scenarios that determine the modeled customer lead-time differently show that it is

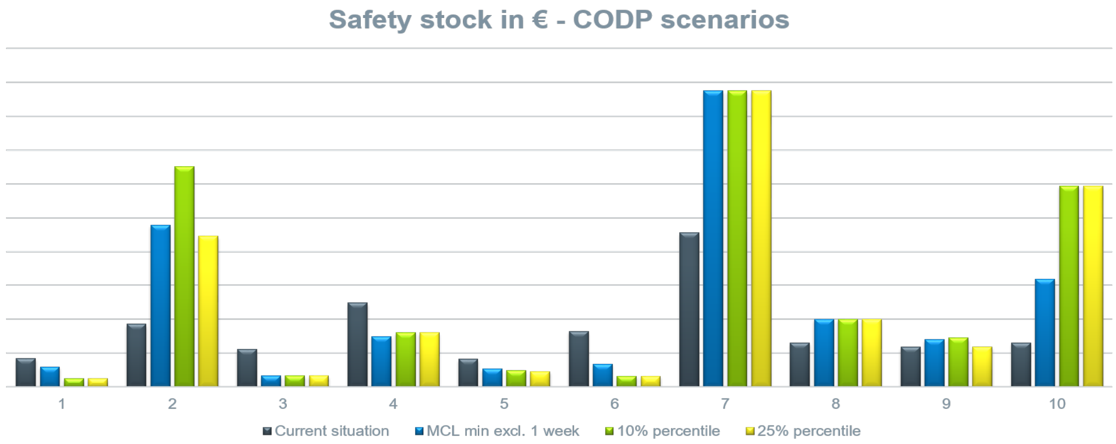


Figure 5.10: Safety stock in € - different MCL scenarios - 90% fill rate

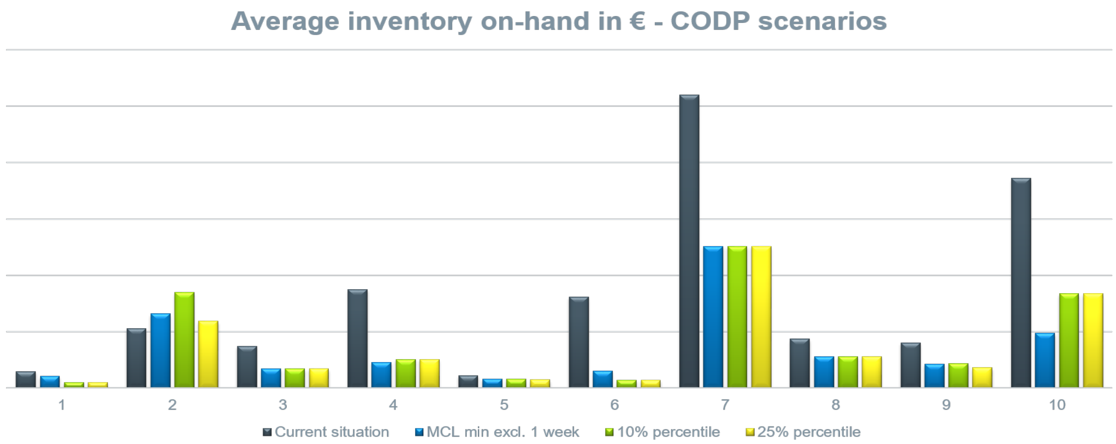


Figure 5.11: Average inventory on-hand in € - different MCL scenarios - 90% fill rate

very important to include the customer lead-time. Even by only excluding the orders with a customer lead-time within one week, the (safety) stock costs can be reduced. Furthermore, by increasing the customer lead-time minimal, the CODP can be replaced more upstream in the supply chain. This could results in significant reductions in (safety) stock costs with similar or better supply performance.

5.6 ChainScope implementation

In this section, some recommendations are given for implementing ChainScope to optimize the safety stock settings.

- Fill rate target
  As mentioned in section 3.9, the service level target is determined once a year for each business unit. Updating the fill rate targets at the same time as the target is set within ams is recommended. However, it might be better to define a service level target for each business line instead of a business unit. The reason is the relatively high difference in achieved RLIP between the business lines (section 3.9).
- Modeled customer lead-time
  As the case study has shown, the MCL is a parameter with a relatively high impact on

the performance and costs. It determines the CODP of the end items. However, there are multiple possibilities to determine the MCL. How the MCL is determined depends on the desired performance and should be chosen by ams. Therefore, it is recommended to review these locations and the data once a year, at the same time as the service level target is set.

- Customer demand data
  It is important to be aware of the extreme orders that can significant impact on the settings calculated by ChainScope, especially the safety stock levels. Furthermore, it is important to use a data set that includes the customer demand for at least one year. For products that have a stable demand pattern, this is not essential. However, for products with a low volume, a bigger data set better represents demand pattern. The customer demand data should be reviewed in the same frequency as the safety stock levels.
- Desired percentile throughput time
  The desired percentile of the throughput time can be defined for each business line or business unit. However, some products could be more important than others. Therefore, it is recommended to determine different percentiles based on the importance of the product. For example, for less important products, a 90% percentile, and for important products, a 98% percentile. These percentiles and the corresponding throughput times can be reviewed in the same frequency as the safety stock settings.
- Holding cost
  It is recommended to update the holding costs twice a year. These values will not change significantly every month.

Currently, the safety stock settings are reviewed once a quarter. Due to the relatively long throughput times for the wafer fabrication and assembly process, it takes some time to realize the safety stock targets. Therefore, it is recommended to review the safety stock settings once a quarter. This results in updating the throughput times and average and standard deviation once a quarter as well.

All the required data has to be filled in in a standard Microsoft Excel format. This could be done automatically. However, each case (supply chain) has to be imported separately in the program. Subsequently, the cases can be optimized.

6 Conclusion and recommendations

The final chapter concludes the project by providing the main conclusions in the first section. Next, the implications and recommendations for ams AG are discussed. Finally, the research limitations and directions for future research are given.

6.1 Conclusions

The main problem was that a clear company strategy is missing to determine the possible stocking points and to set appropriate inventory targets to manage the uncertainties in the supply chain. Therefore, the goal of the project was:

Design a policy to determine the (safety) stock locations and targets considering supply and demand uncertainties to obtain the desired service levels against minimal inventory levels.

To achieve the goal of the project, the assignment was divided into multiple steps. Some of these steps need to be answered first to provide a policy that achieves the research goal.

How to combine multiple factors to determine the stocking points for different products?

The first step is determining the (customer order) decoupling point(s). Based on the following two reasons it is important to consider the requests of the customers. First, most products are customized and are produced for a limited number of customers. Secondly, the requested customer lead-time is different for each order. Therefore, the CODP is determined based on the modeled customer lead-time versus the planned throughput time. The modeled customer lead-time can be determined in different ways. Other reasons to locate an additional stocking point within the supply chain are bottlenecks and commonality.

Which factors should be considered to set the (safety) stock targets?

The three main uncertainties obtained in the semiconductor industry are yield, demand, and throughput time uncertainty. Since the yield percentage is constant for the products within the project's scope, it is not considered. Therefore, the project focuses on the demand and throughput time uncertainty.

How to control the stock points?

The policy used to control the multi-item multi-echelon inventory system is the Synchronized Base Stock (SBS) policy. This policy is based on two structural characteristics: the bill of material and the item cumulative throughput times.

How to optimize the inventory levels and compare the performance of the model proposed and the current situation?

A program that is based on the SBS policy is ChainScope. This software can evaluate the current situation and optimize the (safety) stock settings while the desired service level is achieved with minimal holding costs.

After answering the steps above, the current situation is compared to the proposed policy in a case study. The following can be concluded from the case study.

It is crucial to consider the customer lead-times since for some products the (safety) stock is located at a stage while the CODP is located more upstream in the supply chain. By stocking the (safety) stock more upstream in the supply chain, significant reductions in (safety) stock costs can be achieved with similar or better performance. Even by a minimal impact on the modeled customer lead-time, it is for some cases possible, to locate the (safety) stock and the CODP a stage upstream in the supply chain. Furthermore, the safety stock settings can be reduced in some cases, with the same or better performance. However, in some cases, the CODP is located more downstream in the supply chain. For these cases, an investment is needed to achieve the desired performance. Next, the target set for the service level has a high impact on the safety stock costs.

Furthermore, comparing the average inventory on-hand of the current situation with the proposed situation in section 5.4 leads to interesting insights. Based on the ten cases, the total average inventory on-hand costs can be reduced by 45% with an average increase in fill rate of 26%. However, note that there is a mismatch between the average on-hand inventory in the current situation and the proposed situation. In reality, the reduction in average inventory on-hand will be lower. Moreover, the case study shows significant reductions in (safety) stock costs can be achieved with the same or even better performance in different scenarios. This is achieved by better placement of the safety stock and by optimizing the settings using ChainScope.

6.2 Recommendations ams AG

This thesis provides insights into the semiconductor supply chain, the CODP location's effect, and other stocking points to locate (safety) stock. Furthermore, the ChainScope software is used to determine optimal (safety) stock levels.

The main recommendation that follows from this study is the importance of where to locate the CODP and the other possible stocking points. Currently, safety stock is located at stages downstream in the supply chain, while the CODP is located more upstream in the supply chain. This results in higher safety stock costs, while the same performance can be achieved by replacing the safety stock at the CODP. In the proposed method, the CODP is based on the modeled customer lead-time. This can be determined in different ways. However, most important is determining a clear CODP.

Therefore, the new way of working must be shared and discussed with the employees making these decisions. Being aware of these concepts and understanding them will help reduce the costs in terms of safety stock while the same performance can be achieved.

Next, the importance of the target service level is highlighted. At this moment, a service level for a complete business unit is set. However, significant differences are obtained within the business unit. It might be better to set a target for each business line. This leads to a more clear understanding of what the expected performance is within each business line.

After defining the possible stocking points, ChainScope is used to optimize the (safety) stock settings for the proposed supply chains. The case study can be seen as a pilot for the business unit ISS. As in the current situation, the safety stock settings are reviewed once a quarter. This is also recommended if ChainScope will be used. The review frequencies for the input parameters are summarized in Table 6.1.

Parameter	Symbol	Update frequency
Desired percentile throughput time	X	Quarterly
Throughput time	T_i	Quarterly
Holding cost	h_i	Half-yearly
Modeled customer lead-time	MCL_j	Yearly
Average customer demand	μ_j	Quarterly
Standard deviation customer demand	σ_j	Quarterly
Target fill rate	β_j^*	Yearly

Table 6.1: Update frequency parameter settings

6.3 Limitations

The study has five limitations that should be mentioned. The first limitation is a small data set. Secondly, the limitation of the used software. Furthermore, three limitations are based on assumptions.

The first limitation is the size of the forecasting data set. Since the forecast are generated each month, there was a minimal amount of data available. Therefore, the demand input parameters are based on the historical demand. This resulted in a mismatch between the current and proposed situation.

Secondly, ChainScope measures the performance in fill rate. However, the performance measure that ams is using is the RLIP. There is validated that these performance measures are in the same range. Nevertheless, they are never exactly similar. In reality, the obtained performance could be slightly different than the calculated performance in the case study.

Furthermore, the assumption of stationary demand. For the products in the scope of the project, the customer demand data was stationary. However, this might not be the case for all products within the company.

The last limitation is the assumption of infinite production capacity. In this case, all the safety stock targets can always be produced independently of the size. However, in reality, this could be different. This could to a lower performance because of capacity issues. This is the same for the assumption of infinite raw materials.

6.4 Future research

For future research, there are many directions for this project. The first direction is considering the forecasted demand. In the study, the (safety) stock settings are based on historical demand. However, since most of the customer order decoupling points are located in the middle of the supply chain (CTO, ATO, or FTO), the production is started based on the forecasted customer demand. Therefore, it would be interesting to include the forecasted demand. This will reduce the mismatch between the current and proposed situation in terms of average inventory on-hand. This results in a more realistic comparison of the situations.

In addition, an independent simulation that can calculate the RLIP can strengthen the research findings. In that case, there can be validated whether the calculated RLIP is similar to the calculated fill rate using ChainScope.

Another direction is how the modeled customer lead-time is determined. Future research could investigate how the customer importance based on the ABC/XYZ classification could be considered. At this moment, each order has the same weight, independent of the customer classification or order size. Including this would give a more weighted modeled customer lead-time.

Furthermore, future research could investigate how this proposed approach would perform with stationary demand or in a finite production capacity setting. The last direction could be the reliability of the raw material suppliers.

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Appendix A Safety stock raw materials

Product	Safety days of supply
1	60
2	60
3	99
4	60
5	60
6	99
7	99
8	60

Table A.1: Safety stock raw materials

Appendix B One-sample Anderson-Darling test

In this master thesis the Anderson-Darling test is used to determine the distribution of the demand. The one-sample AD test statistic is calculated by the following formula:

$$AD = -n - \frac{1}{n} \sum_{(i=1)}^{n} (2i-1)(ln(x_{(i)}) + ln(1-(x_{n+1-i})))$$

The sample of size n should be order from the smallest to the largest element in the sample: $(x_{(1)}, < ... < x_{(n)})$. The underlying theoretical cumulative distribution $F(x)$ is the distribution that is compared to the sample.

Furthermore the AD-test is defined as:

- H_0: The data follow a specified distribution
- H_a: The data do not follow a specified distribution

When the observed p-value is lower than the chosen significance level, α it means that there is evidence against the H_0. In other words, the data do not follow the specified distribution.

Appendix C Customer demand analysis

To determine the specific distribution, goodness of fit techniques are used. Goodness of fit techniques are defined as: 'methods of examining how well a sample of data agrees with a given distribution as its population' (DAgostino, 1986, p.1)

The techniques that are widely used in the literature are (DAgostino, 1986):

- Chi-square test
- Kolmorogov-Smirnov (KS) test
- Anderson-Darling (AD) test

The three techniques mentioned above are reviewed in the literature. Then, the best technique is selected to fit the demand distribution.

Massey (1951) states that the KS test is superior to the Chi-square test. However, for the one-sample test, several observations are mentioned between the KS and AD test in the literature:

- The AD-test is more sensitive than the KS-test to the shape and the scale of a distribution (Anderson and Darling, 1954).
- The AD-test is applicable to small samples (Pettitt, 1976).
- The AD-test is very sensitive in detecting differences at the tail of a distribution (Engmann and Cousineau, 2011).
- The AD-test is able to detect very small differences (Engmann and Cousineau, 2011).

Therefore, based on the reviewed literature, the demand is analyzed with the AD-test for this thesis. The AD-test is explained in more detail in Appendix B. For the AD-test, the p-value is used to determine whether the demand follows a specific distribution. A significance level (α) of 0.05 is chosen because this α is mostly used in the statistics.

Furthermore, the sample size of the data of the demand is an important factor. One data point means the demand of one period. Lewis (1961) suggests using a minimal sample size of 9. However, 9 data points are relatively low. Therefore, a minimal sample size of 12 is chosen, which is equal to one year of data. By using this approach, relatively new products are excluded, which are in this case 8 products.

BL	Enough data points	Not enough data points		Total
	≥ 12	≤ 8	< 12	
A	19	0	2 (2)	19
B	34	4	0 (4)	38
C	5	1	1 (2)	6
D	1	0	0 (0)	1
E	7	0	0 (0)	10
Total	66	5	3 (8)	74

Table C.1: Data points - Demand analysis

In Table C.1 the majority of the products have more than 12 data points (89.2%). For these products the demand distribution can be fit with the AD-test. The other products that have less than 12 data points, are analyzed in more depth.

From the eight products that have less than 12 data points, all the products are relatively new. These products are sold since the beginning of 2020 and do not fit the normal or gamma distribution. Note that the demand from 2021 is not taken into account.

This results in 66 products (89.2%) for which the demand distribution can fit with the AD-test. Table C.2 shows the results of the AD-test, which is performed in Minitab, a statistical software package.

Business line	Distribution			Total
	Normal (N)	Gamma (G)	Other	
A	4	11	4	**19**
B	2	14	18	**34**
C	1	3	1	**5**
D	0	1	0	**1**
E	0	4	3	**9**
Total	**7**	**33**	**26**	**66**

Table C.2: Distribution fitting

From the 66 products, 50% follows the gamma distribution. 10.6% follows the normal distribution, and 39.1% does not fit the normal or gamma distribution. For these products, the demand is analyzed in more depth.

For the 26 products that do not fit the normal or gamma distribution, the demand is aggregated to two and three months. Table C.3 shows that for 16 products the demand does fit the normal or gamma distribution.

		Fitting									Non-fitting	Total
Period		2 months				3 months						
Number of outliers		0 outliers		1 outlier		0 outliers		1 outlier		Total		
Business line	Other	N	G	N	G	N	G	N	G			
A	4	0	1	1	0	0	0	0	1	3	1	4
B	18	3	3	0	0	4	1	1	1	13	5	18
C	1	0	0	0	0	0	0	0	0	0	1	1
D	0	0	0	0	0	0	0	0	0	0	0	0
E	3	0	0	0	0	0	0	0	0	0	3	3
Total	26	3	4	1	0	4	1	1	2	16	10	26

Table C.3: Demand analyses: others

For 10 products, it was not possible to fit one of the distributions. These products are further analyzed in Figure C.1 and are categorized into three groups (i) too few data points, (ii) too many months with no demand or strange demand, and (iii) demand that still not fits a distribution.

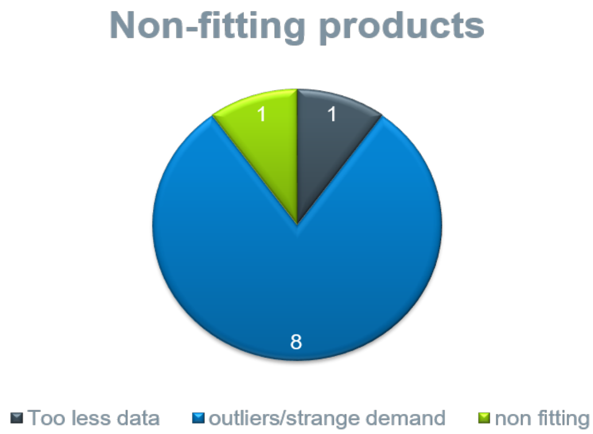

Figure C.1: Products that does not fit normal or gamma distribution

This results in a total of 56 (75.7%) products that fit the normal or gamma distribution, which Table C.4 shows. From these 56 products, 40 products fits the normal distribution and 16 fits the gamma distribution.

BL	Tested								Untested		Total
	Fit				No fit		Total		New		
	Normal	Gamma	Total (#)	Total (%)	(#)	(%)	(#)	(%)	(%)		
A	5	13	18	85.71%	1	4.76%	19	90.48%	2	9.52%	**21**
C	1	3	4	57.14%	1	14.29%	5	71.43%	2	28.57%	**7**
B	10	19	29	76.32%	5	13.16%	34	89.47%	4	10.53%	**38**
E	0	5	5	62.50%	3	37.50%	8	100.00%	0	0.00%	**8**
Total	**16**	**40**	**56**	**75.68%**	**10**	**13.51%**	**66**	**89.19%**	**8**	**10.81%**	**74**

Table C.4: Demand distributions

Appendix D RLIP & CLIP

Confidential

Appendix E Customer demand end-items case study

Case	End item	2020 week 1 - 53			2020 week 28 - 53		
		CV	Average number of monthly orders	Average monthly order size	CV	Average number of monthly orders	Average monthly order size
1	1	1.1	10	13200	1.1	5	16400
2	1	0.9	31	96323	1.4	12	46333
	2	3.5	1	1000	-	0	-
	3	0.9	32	6188	0.7	18	3333
3	1	1.4	6	80	1.4	3	80
4	1	0.4	116	13569	-	49	15184
	2	0.7	107	10855	0.7	63	10690
5	1	0.7	121	4496	0.9	53	4321
	2	1	21	71667	0.8	16	63438
	3	2.3	9	2667	1.9	5	1800
6	1	0.5	88	10391	0.4	39	8767
7	1	0.5	212	50	0.8	58	59
	2	2.6	6	10	2.4	2	21
8	1	0.8	40	223	0.7	13	248
	2	3.5	1	50	-	0	-
	3	1.1	33	170	1.5	16	124
9	1	1.1	38	11184	0.8	25	9800
	2	0.8	65	7846	1	29	9397
	3	0.7	59	1458	0.6	21	2548
	4	0.8	96	8938	0.8	51	12157
10	1	0.9	25	14	0.8	14	13
	2	0.9	22	25	0.9	10	19
	3	0.7	50	137	0.9	18	123
	4	1.2	21	929	1.7	6	667
	5	1.2	31	261	1.7	12	168
	6	1	25	88	1	10	61
	7	1	19	138	1.3	5	170

Table E.1: End-item monthly customer demand analysis

Appendix F Standard normal distribution table

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998

Appendix G Modeled customer lead-times

Case	End items	MCL excl. within 1 week	MCL 10% fractile	MCL 25% fractile
1	E_1	51	63	143
2	E_1, E_2, E_3	41, 102, 21	5, 102, 22	53, 102, 42
3	E_1	101	129	163
4	E_1, E_2	22, 23	76, 3	116, 7
5	E_1, E_2, E_3	10, 12, 11	5, 8, 3	21, 21, 4
6	E_1	35	107	146
7	E_1, E_2	8, 9	4, 3	24, 4
8	E_1, E_2, E_3	23, 102, 8	3, 102, 2	26, 102, 4
9	E_1, E_2, E_3, E_4	10, 10, 10, 10	8, 11, 5, 4	25, 31, 13, 19
10	$E_1, E_2, E_3, E_4, E_5, E_6, E_7$	44, 9, 35, 119, 25, 31, 12	59, 4, 2, 2, 25, 44, 32	75, 16, 2, 3, 37, 64, 43

Table G.1: Modeled customer lead-times - different scenarios