MASTER

Service stock decisions for new product introductions of complex capital goods

Doumen, M.C.

Award date:
2017

Technische Universiteit
Eindhoven
University of Technology
Industrial Engineering and Innovation Sciences

Service Stock Decisions for New Product Introductions of Complex Capital Goods

Master Thesis

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If there's one thing that's certain in business, it's uncertainty.

STEPHEN COVEY

Abstract

In this research, conducted at ASML, we investigated how service stock decisions should be made for new product introductions of complex capital goods. To incorporate the demand rate uncertainty of the spare parts of new product introductions, we developed a single-location, we apply failure rates in ranges instead of point estimates. We modeled the values within the failure rate ranges by applying the Beta distribution, for which we are inspired by the field of PERT project scheduling. According to an estimate of the most likely, most optimistic and most pessimistic value of the failure rate, a failure rate range is derived. According to the failure rate range, we construct a demand process by taking the weighted average over all values within the range. This demand process is applied to the multi-item, single-location spare part inventory model by Van Houtum and Kranenburg (2015).

The model with demand rate uncertainty has been tested in a business case. In this business case the required investment for the current spare part decision-making is compared to the required investments that result from the model with demand rate uncertainty. It shows an improvement potential of 49.8% in case of high demand rate uncertainty and 60,8% in case of low demand rate uncertainty.

Keywords: Spare Parts, New Product Introduction, Product Life Cycle, Complex Capital Goods, Failure Rate Ranges, Beta Distribution, Initial Stocking, Demand Rate Uncertainty, Demand Predictability

Executive summary

In this report we present the results of our research of service stock decisions for new product introductions of complex capital goods. This research is executed within the NPL department at ASML.

Introduction

ASML faces the problem that service stock decisions for new product introductions have to be made in an early phase of the product life cycle, in order to guarantee the availability of these systems. Especially for their systems with EUV technology, making these decisions is very complicated. Since this technology is radically new and a short time to market orientation is essential, demand rates for the spare parts of these systems are very uncertain. Furthermore, these spare parts are still subject to many redesigns and therefore the risk of obsolescence is substantial.

This research area is unexplored within the literature. Research on initial spare parts stock decisions does take into account the presence of demand rate uncertainty. However, these studies do not take into account that new product introductions are concerning radically new technology or are still in the early phase of the product life cycle. Nevertheless, this issue is very relevant for ASML. Therefore we identified the following research assignment:

Develop and test a decision support tool for ASML's service stock decisions in the early phase of the PLC, while taking into account inventory cost and system availability

For this, we developed a generic model for spare part stocking under demand rate uncertainty. For the application of this model to a business case, we specified the model for ASML.

Model for spare part stocking under demand rate uncertainty

Common approaches for taking into account demand rate uncertainty of spare parts rely on empiral demand data. However, in the early phase of the product life cyle, this empirical demand data on spare parts for a new product introduction is not available. We therefore developed an alternative approach, for which we are inspired by research on project scheduling. In this field of research, it is a common approach to calculate the unknown expected project activity times by using three estimates: the most optimistic, the most pessimistic and the most likely value of the activity time. According to these values, a range of all possible project activity times is derived. We apply the same approach to spare parts demand rate uncertainty of new product introduction systems. As the spare parts demand rate is determined by a part's failure rate, we are interested in all possible failure rate values. For that reason, we introduce *failure rate ranges*. So instead of using a point estimate of the failure rate of a particular part in our stocking model, we consider all failure rate values within a range with a particular probability.

The most likely value of the failure rate is represented by the initial failure rate estimation of the spare parts. One way of obtaining the most pessimistic and most optimistic value of the failure rate, is directly from experts. Another mehtod for this is interpreting the demand predictability of the particular spare part. This is be defined as the possibility to estimate the failure rate properly. The demand predictability of spare parts for new product introductions is related to presence of information on lifetime analyses, lifetime tests and qualitative failure assessments. So spare parts without this information have a wider failure rate range than spare parts with this information.

According to the failure rate ranges, we construct a demand estimate for every spare part by taking the weighted average of all values within the ranges. This constructed demand estimate is then applied to a single-location spare part inventory model, that minimizes the costs while satisfying a target for a particular service measure.

Application of the model

We applied our spare part stocking model to spare parts for the new product introductions serviced by the local warehouse in Taiwan. First, we evaluated what investment is required according to our model, such that the current service performance of these spare parts in Taiwan is achieved. This shows an improvement potential of 49,6% in case of high demand rate uncertainty and 60,8% in case of low demand rate uncertainty.

In addition, we examined the impact of lowering demand rate uncertainty on the required investment of the stock that our model proposes. If engineers carry out extra qualitative assessments on the failures of the most expensive parts with high demand rate uncertainty, this uncertainty is reduced and an additional improvement potential is generated. For only Taiwan, a maximum improvement potential of 0.8% is realized if done for the 10 most expensive parts and 2.5% if done for the 100 most expensive parts.

Finally, we evaluated the impact of demand rate uncertainty on the type of service measure targets that is applied when making stock decisions. Stock decisions are currently made based on an aggregate fill rate target (i.e. customer service degree). However, in case of demand rate uncertainty, a target on this service measure does not consistently attain the service performance that it is supposed to achieve in terms of system availability. Service measures based on system downtime perform better in that sense.

Recommendations

Based on our research, the following recommendations are given to ASML:

Implementation of the decision-support tool: Based on the improvement potential that is generated by our model, it is recommended to ASML to use the decision-support tool that has been developed accordingly. By using this, the search for optimal basestock levels can be supported whenever a new machine needs to be serviced or a considerable amount of new demand information becomes available.

Customer service degree target: We concluded that a customer service degree target in the presence of demand rate uncertainty does not consistently attain a desired system availability. As the demand rate uncertainty increases, the difference between desired and achieved system availability increases as well. In order to consistently attain the desired system availability when making spare parts stock decisions for new product introduction systems, it is recommend to apply a target that is directly to the system's downtime. For this, our tool supports the optimization towards a target for two alternative service measures.

Extra spare part demand analyses, tests and assessments: We showed that lowering demand rate uncertainty by carrying out extra qualitative failure assessments generates a maximum improvement potential of 0.8% is realized if done for the 10 most expensive parts and 2.5% if done for the 100 most expensive parts. However, since the demand rate uncertainty reduction applies to the other local warehouses as well, this improvement potential is even larger in reality. So even though engineers within D&E are under the pressure of short time to market, it is strongly recommended to spend more time on increasing the demand predictability of expensive spare parts by carrying out extra analyses, tests and assessments.

Spare parts control characteristics: During our in-depth spare parts classification for new product introductions, we identified several relevant control characteristics, such

as part extraction time, service specialist requiremetns and demand predictability. It is argued that these charachteristics require appropriate operating policies. These control characteristics and corresponding operating policies are adopted in a decision tree. It is recommended to apply this decision tree when spare parts stock decisions need to be made, as it improves the effectiveness of the decision-making.

Preface

This thesis is the result of my graduation project for the Master Operations Management & Logistics at the University of Technology in Eindhoven, the Netherlands. It has been carried out at ASML. Completing this project has been a memorable and enlightening experience. Therefore I would like to show my gratitude to everyone who helped me along the way.

Conducting this research would not have been succesful without scientific assistance. First, I want to thank Henny van Ooijen. His supervision really fitted my style of work. Whenever I had an issue I needed help with, he was alywas available. I also really appreciated his "out of the box thinking", which played a huge role in the result of this project. I also want to thank Alp Akçay. His expertise on demand uncertainty really helped me with the challenges I had to face.

Next, I would like to express my gratitude to my three supervisors at ASML, Merel de Bruijn, Jip Bisschop and Remco van der Most. My first conversations with you really made me interested in the operational problems the NPL department face and motivated me to help solve these problems. Working with you has not only been beneficial to my project, but also very educational as a person. I am therefore certainly looking forward to continuing working together with you at NPL. I also want to thank Neda for her help the last few months of my research. I wish you the very best with your design project on the same problem. Moreover, I would like my other colleagues at ASML for their input and distractions.

I would also like to thank my family and friends for their support as well as enjoyable times I was not working on my project. This really helped me staying lively person throughout the project.

Finally I get to thank my girlfriend, Margot. Even though I could not stop talking about "spare parts" and "demand uncertainty", and you did not understand a word I was saying, your support was always unconditional.

Martijn Doumen

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Chapter 1

Introduction

1.1 Company background

ASML is a world leader in the manufacturing of chip-making equipment. They design, develop, integrate, market and service advanced lithography systems, which enable affordable microelectronics that improve the quality of life in all sorts of ways. In 1984, ASML originated as a collaboration between Philips and Advanced Semiconductor Materials International (ASMI). Throughout the years, ASML expanded, improved and excelled. Nowadays, ASML operates in 16 countries and employs more than 14.000 employees, of which more than 5000 focus on research and development. In 2015, ASML realized a turnover of about €6.3 billion.

The lithography step is one of many within the manufacturing environment of chips, but it plays a crucial role for 'chip generation' and throughput(Stein, 2012). Lithography is basically a photographic process that creates a pattern in which transistors can be built and wired together to form an integrated circuit (IC). This process has been driven by Moore's law, which implies that the number of components on chip would double every year. He later adjusted this to every two years. This is graphically represented in Figure 1.1.

As a result of the reduction of the IC pattern size, smaller chips can be created that are more powerful and therefore more valuable. Accordingly, time to market is vital, since chips of the newest generation represent an exponentially higher value than their predecessors (Stein, 2012). Hence, ASML is committed to provide customers with a superior technology that is production-ready as soon as possible. To accomplish this , ASML is introducing breakthrough technology based on Extreme Ultra Violet (EUV) light sources. This technology is radically different from the current mature volume systems based on Deep Ultra Violet (DUV) light sources and demand significantly higher investments for customers.

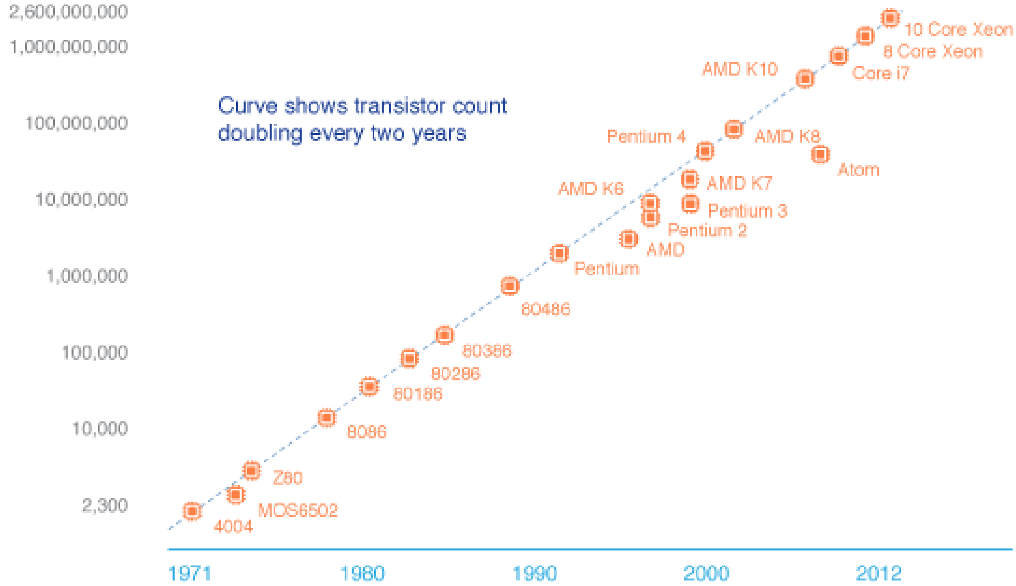

Figure 1.1: Grapical representation of Moore's law

To indicate the business environment in which our research is carried out, we show the organization chart of ASML with emphasis on its operations. This is shown in figure 1.2.

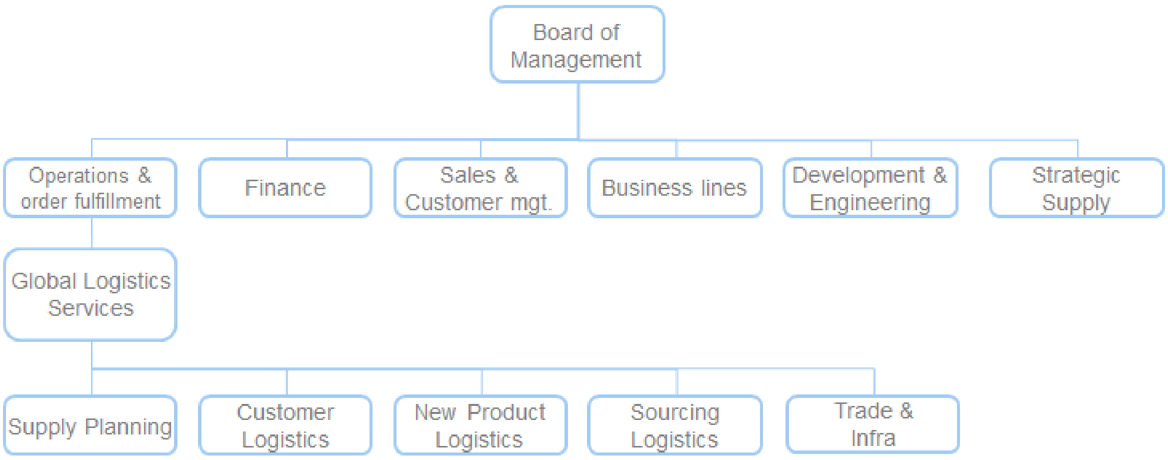

Figure 1.2: Organization chart of ASML

1.2 Service for new product introductions

The research described in this report is executed within the New Product Logistics (NPL) department. Among other responsibilities, NPL is concerned with the spare parts and tool planning for new product introductions, which mainly relate to the EUV technology. As shown in figure 1.2, NPL is part of the Global Logistics Services (GLS) department. This department within in ASML is responsible for all logistic aspects, such as supply chain planning, service planning of spare parts and sourcing.

1.2.1 System unavailability

The EUV-technology requires high investments from the customer and unavailability of these systems translates into high downtime costs. Therefore ASML's customers generally strive for high system availability, which should be attained by ASML's service. For this it manages a global customer service supply chain.

In case a system breaks down, a corrective maintenance action is required. According to a diagnosis on the system, a Service Engineer determines which spare parts and service tools are required for the repair. Subsequently, it might take some time for the requested spare parts and service tools to arrive. Thereafter, the repair is performed and the system is recovered. Figure 1.3 denotes a simplified graphical representation of ASML system unavailability and the contribution of waiting time for spare parts and service tools.

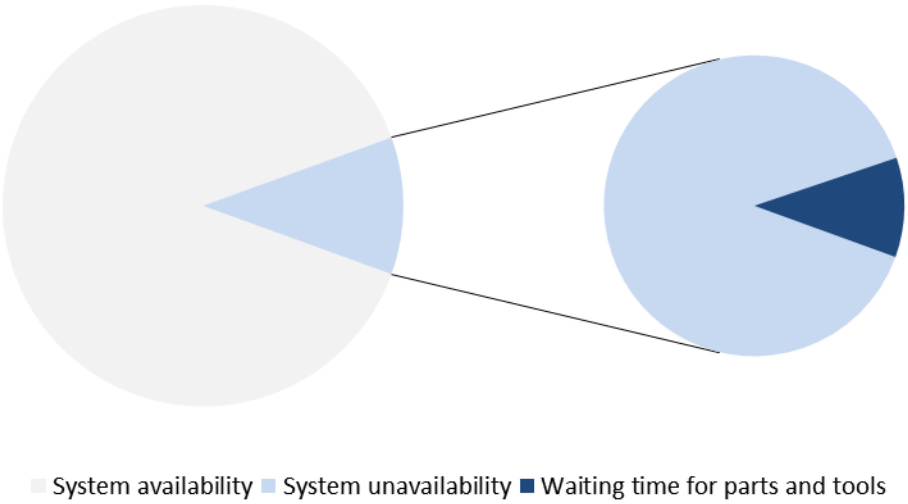

Figure 1.3: Simplified breakdown of system unavailability

The waiting time for spare parts and service tools is the aspect that is influenced by the service stocking decisions by NPL.

1.2.2 The service network

In Figure 1.4 a graphical representation is provided of the warehouses ASML operates globally to support its customer service supply chain. The red dotted circles denote the regions of local warehouses, for which the spare parts and service tool planning is executed.

Figure 1.4: Graphical representation of ASML's global service network (Van Aspert, 2013)

Most of the demand for parts and tools is satisfied from the stock in the local warehouse to which the customer is assigned to. If that local warehouse does not have the demanded item on stock, the demand is satisfied from another local warehouse in that region. Alternatively, the demand can be satisfied by the continental warehouse in that particular continent. In case all these warehouses cannot satisfy the demand, this is done by the global warehouse. Another function of the global warehouse is stock replenishment of the other warehouses.

Most of the failed parts are returned to the supplier of that part through a global warehouse. Subsequently, the supplier repairs the parts and the part is returned to the inventory pool.

1.2.3 Problem context

With effective spare parts stock decision-making, NPL aims to maximize the customer's system availability whilst incurring minimal costs. However, this also requires planning of service tools. This process and the differences from the spare part planning are elaborated in Appendix C.

For making spare parts stock decisions for a system that is a new product introduction (NPI), NPL has to answer the following questions:

1. Which spare parts need to be stocked for the new system?
2. Where should these spare parts be stocked? In a local, continental and/or global warehouse?
3. How many of these spare parts should be stocked within all the types of warehouses?

To be able to answer the first question, a spare parts assortment for the particular system needs to be available. However, since NPI's, especially for the EUV systems, are still in their development phase, these systems are subject to concurrent engineering and therefore changes continuously. Changes to parts potentially make the predecessor of that new part obsolete. This entails an obsolescence risk is present for many stock decisions of spare parts for NPI's.

In order to the second and third question properly, demand insights of the parts are vital. Especially for new systems with the EUV technology, the demand information is limited. Historical demand data for a new EUV system is absent and historical demand data for the older EUV systems is very limited due to a small installed base. In addition, the redesigns between ASML's EUV systems are substantial. This implies that there is not much commonality between the EUV system and therefore the opportunities to derive demand insights from older systems are limited. Besides historical demand data, expert knowledge is limited as well. EUV can be considered as a radically new technology, which makes it complicated for experts to give their judgement on demand insights.

Chapter 2

Research assignment

In this chapter we elaborate on the content of this research. We do this by comparing ASML's problem context and the literature with respect to spare part stock decisions of NPI's. Therefore, we provide a literature review in section 2.1. Accordingly, we formulate the research assignment and the corresponding research questions in section 2.2. In section 2.3, we discuss the scope of this research. Finally, in section 2.4, we provide the outline of this thesis.

2.1 Literature review

Since this research area is unexplored, we extensively review related research areas. In this section we discuss the parts from the literature review by Doumen (2016) that are most relevant to this research: initial spare parts stocking, spare parts demand uncertainty and inventory management of short life cycle products and spare parts.

2.1.1 Initial spare parts stocking

For new products that contain components that have never been manufactured before, the life cycle of spare parts is in its initial phase (Fortuin, 1984). Historical demand data on these parts is either very limited or cannot be obtained yet. This implies that standard forecasting methods are not applicable.Resutantly, the main challenge in this phase concerns the estimation of required stock quantities under demand uncertainty. The VARI-METRIC system (Slay, 1984), an extension of the METRIC system (Sherbrooke, 1968), provide, according to van Houtum & Zijm (2001), "a sound basis to overcome this challenge in the initial spare parts stocking for capital good. Moreover, when production processes are new and the reliability database represents primarily expert knowledge, an approximate reasoning based mode is a possibility as well. (Eisenhawer et al., 2002) This results into a spare parts prioritization model to optimize the initial spare parts stock decisions.

Besides capital goods, also initial spare parts stocking for consumer electronics have been addressed in the literature. For these products, existing inventory theory and renewal theory can be successfully applied to make service stock decisions for new spare parts. (Fortuin, 1984). In addition to capital goods and consumer electronic, initial provisioning of less specific insurance type spare parts has been concentrated on too. For the initial provisioning these spare parts, which have a probability of never being used, several models have been devised (Burton & Jaquette, 1973).

2.1.2 Spare parts demand uncertainty

Spare parts demand uncertainty is a big issue within initial spare parts stocking. It often occurs that statistical evidence on the important demand variables of particular models is lacking. As a solution, expert opinions are very suitable (Pulkkinen, 1993). The elicitation and use of expert opinion in probabilistic risk assessment has been widely addressed. For instance, Kullback Leibler information (Kullback & Leibler, 1951) can be applied to assess the probability distribution which minimizes the sum of particular "distances" between the consensus distribution and the expert's distribution (Pulkkinen, 1993).

Another quantitative method, to which expert opinion is often applied , is the Bayesian method. The Bayesian method updates the demand distribution as new demand data becomes available, which continuously improves the probability distribution, such that it can be considered as an adequate representation of the demand at any given point of time (Kamath & Pakkala, 2002). In an early stage, a prior distribution represents the unknown parameters of the demand distribution, for which expert opinion serves as the important data source (Walls & Quigley, 2001). Sherbrooke (1986) and Burton & Jaquette (1973) apply this approach for deciding on the initial spare parts stocking.

Also demand uncertainty in general inventory control has been researched. Arrow et al. (1958), amongst others, suggest that there are three streams of research, which regards the available information on the demand distribution and its parameters:

1. Unspecified parameters but known form of demand distribution function
2. Partially available information on parameters and demand distribution
3. Demand modeled by empirical distribution function of historical demand data

For the first stream of research, often the Bayesian method is applied, for stationary as well as non-stationary demand structures. Another useful contribution to this stream is the work by Akcay, Biller and Tayur (2011). By combining the ETOC concept for joint estimation optimization (Hayes, 1969) and the Johnson translation system (Johnson, 1949), they are able to quantify the inaccuracy the inventory target estimation in a repeated newsvendor setting with unknown but stationary demand parameter.

2.1.3 Inventory management of short life cycle products and spare parts

Demand of spare parts of short life cycle product shows substantial random fluctuations. As a result, traditional forecasting methods lead to overstock or understock of these spare parts (Li et al., 2013). They present an improved forecasting method based on Empirical Mode Decomposition (EMD) and Support Vector Machine (SVM), where EMD copes with nonlinear and non-stationary data and SVM is used for pattern recognition. Also installed base information proves to be a succesful information source for considering demand for short life cycle spare parts Wu et al. (2015).

It often occurs that many spare parts , when being at the end of life, are identified as a major source of costly inventory stock-outs or obsolescence (Hong, Koo, Lee, & Ahn, 2008). Moore (1971) stresses that: "the determination of economical inventory policies for past-model spare parts has achieved major problem status in various industries". To solve this problem, cumulative part demand (Moore, 1971) and renewal theory (Ritchie and Wilcox, 1997) provide a sound basis. The suppliers of spare parts often cease the production of partiuclar parts as technology advances and therefore ask the manufacturer to place a final order (van Kooten & Tan, 2008). Many studies focus on devising a method to decide upon the optimal final order (Fortuin, 1981).

2.2 Definition of Research Assignment

Based on the description of the problem context and the corresponding scientific background, we can provide a description of the research assignment. In this section, we want to elaborate what we will investigate, why this is important and how this will be handled.

2.2.1 Research Assignment

Research on initial spare parts stocking recognizes the problem of demand rate uncertainty because historical data is not available yet. However, based on the literature review by Doumen (2016), research on the initial spare parts stocking of capital goods does not take into account that NPI's are concerning radically new technology or are still in the early phase of the product life cycle (PLC). As mentioned before, the implications of this limits the demand information even more and therefore increase the demand rate uncertainty. Furthermore, due to continously changing system designs, the risk of obsolescence adds another layer of uncertainty for spare part stocking of NPI's. Similarly, research that does take this risk into account, does not recognize that systems continuously change as a result of its technology or the life cycle phase it is in.

Even though these issues are not collectively addressed in the literature, it is a very relevant issue for ASML. Because its EUV systems are very expensive, the spare parts for these system are as well. So due to existing uncertainties, stock decision-making for these spare parts is very complicated with regard to system availability and high investments. Therefore the following research assignment was formulated in the research proposal by Doumen (2016):

Develop and test a decision support tool for ASML's service stock decisions in the early phase of the PLC, while taking into account inventory cost, system availability and obsolescence risk

However, through further analysis of the problem, we realized taking into account obsoloscence risk requires a seperate research. We therefore decided to focus on the remaining NPI demand rate uncertainty. This is further elaborated in section 2.3 on scoping. Consequently, our research assignment becomes:

Develop and test a decision support tool for ASML's service stock decisions in the early phase of the PLC, while taking into account inventory cost and system availability

2.2.2 Research questions

According to the reseach assignment, the following main research question can be formulated:

How should ASML make service stock decisions in the early phase of the PLC, while taking into account inventory cost and system availability?

Six sub questions are defined to provide a detailed answer to the main research question and to complete the research assignment. The sixth one has been slightly adjusted based on the reasoning provided in the previous paragraph.

1. *What are the key factors that complicate ASML's service stock decisions for NPI's compared to these decisions for volume systems?*
2. *What parameters and variables are useful for service stock decision making in the early phase of the PLC*
3. *What are the functional requirements for a model that supports service stock decisions for NPI's of complex capital goods?*
4. *What decision model supports determining stocking quantities of spare parts for NPI's of complex capital goods?*
5. *What are the implications of the current way service stock decisions for NPI's are made at ASML?*

6. *How should ASML apply the decision support model for NPI spare parts stock, such that certain system availability can be attained while taking account the incurred cost?*

2.3 Scoping

Within the definition of the research assignment, we explained that we only focus on the demand rate uncertainty for the development of the decision support tool for NPI service stock decisions. In this section we elaborate on the aspects that are not taken into account for the development of this tool.

2.3.1 Obsolescence risk not involved in tool development

As mentioned before, obsolescence risk as a result of continuously changing system designs is not in the scope of the decision support tool that is developed. However, within the in-depth analysis of the complicating factors of service stock decisions for NPI's in Appendix C, we also address this particular problem.

2.3.2 Only spare parts involved in tool development

The performance of service, with regard to system availabilty, relies on the presence of both spare parts and service tools. However, service tool planning is substanstially different than spare part stock decision-making. We therefore only develop the decision support tool for spare part stock decisions. However, we elaborate on service tool planning within the in-depth analysis of the complicating factors of service stock decisions for NPI's in Appendix C.

2.4 Outline of Report

In this section we explain the outline of the remainder of the report. In chapter 3 we discuss the problems and implications with regard to service stock decision making of NPI spare parts. Accordingly, we describe the developed spare part stock model in chapter 4. Thereafter, in chapter 5, we carry out a case study at ASML by applying our developed model. In chapter 6, we explain how our developed model can be applied as a decision support tool in practice. Finally, the conclusion and recommendations are provided in chapter 7.

In Appendix C we provide an in-depth analysis of the problem, such that additional understanding of the problem is generated. In Appendix D, we carry out a classification of the NPI spare parts characteristics. This represents the available information for NPI spare parts. Both analyses generate valuable knowledge with regard to the development of the decision support tool.

Chapter 3

Detailed Problem Analysis

In this chapter we provide a detailed problem analysis with regard to service stock decisions for NPI's. Before the problem is described in detail, we provide some elaboration on the NPI concept for complex capital goods. This is done by explaining the relevant new product development processes in section 3.1. Accordingly, we discuss the logistical problems with regard to service for these NPI's in section 3.2.

Appendix C provides a more in-depth analysis of the problem ASML has with service stock decisions for NPI's. According to this analysis, the problem is summarized in a Cause and Effect diagram.

3.1 New Product Development Processes

Based on its product characteristics, complex capital goods often consist of costly, customized and interconnected sub-systems (Hobday, 1998). This also applies to the complex lithography systems produced by ASML. For the development of their systems, ASML assigns project teams to the different sub-systems. The relevant development processes, which these project teams are involved in, are briefly described in the next paragraphs.

3.1.1 Product Generation Process

As a result of system complexity, the new product development of capital goods, like lithography machines, requires a thorough understanding of the possibilities and limits of system architecture, the needs of highly demanding customers and the capabilities of partner (Hodbay, 1998). ASML manages these challenges with their Product Generation Process (PGP). We elaborate this PGP according to the PLC, which is graphically depicted in figure 3.1.

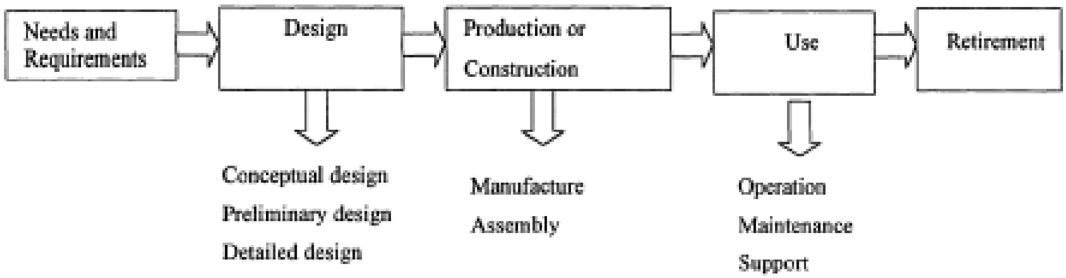

Figure 3.1: Graphical representation of the product life cycle (Dinesh Kumar et al., 2000)

This PGP consists of 14 " Key Decisions" (KD's). To illustrate this process with respect to the PLC in figure 3.1, KD1 is concerned with the Needs and Requirements and KD14 with the Use of the NPI. During KD7, the project teams construct the machine bill of materials (BOM), drive the development of the parts and tools, and devise specifications for every part and tool with regard to aspects of the machine; e.g. performance and availability. Furthermore, in preparation of system service, a part the machine BOM is translated to a service BOM. This service BOM consists of all the machine parts that might break and all the tools that are required for installation, maintenance and repair.

Besides developing radically new technology, time to market is another important aspect of the PGP as well. Time to market can be defined as the time it requires to bring a particular new product from its initial design phase to its introduction to the market. For the lithography systems, especially those with the new EUV technology, time to market is vital, since chips of the newest generation represent an exponentially higher value than their predecessors (Stein, 2012). and lead to competitive advantage. This implies that ASML primary focus is on achieving high machine performance in a short time.

3.1.2 Engineering Change Process

Innovation processes for capital goods are very user-producer driven and are required to be highly flexible (Hobday, 1998). This flexibility within ASML is managed by its Engineering Change process (EC), a cross-sectoral process during which redesigns to a particular part of the machine are evaluated, approved and executed. The EC-process and its stakeholders are graphically described in the diagram in Appendix E. As a result of this process, parts are redesigned and become more mature. However, NPI's are still in development after the first BOM identification. This entails many EC's take place on the content of the BOM.

3.2 Service for New Product Introductions

When a NPI has been installed at the customer, realizing high system availability is very important. Especially for EUV-systems, downtime can be very costly due to a high loss in opportunity costs. Within the PGP, realizing high system availability is prepared through

KD10, during which the first stock decisions are made for all the spare parts of the NPI. This step within the PGP is the responsibility of the NPL department.

For explaining service for NPI's, we first clarify on what aspects makes service stock decision-making for NPI's complex. Thereafter, we elaborate on how this complexity is dealt with when service stock decision for NPI's need to be made. Finally, we evaluate the actual service performance that is achieved as a result of the current service stock decision-making for NPI's.

3.2.1 Service stock decision complexity

The parts and sub-systems of ASML's lithography system are being designed by the Development & Engineering (D&E) department, but are mostly manufactured by external suppliers. The long supply lead time on these items requires stock decisions to be made in the early phase of PLC. Because of this, it is very plausible that a considerable amount of parts are still within their design phase. This means the service BOM is not mature yet and still subject to many redesigns in the form of EC's. An EC might entail a small redesign such that the usability remains unaffected or it might entail a big change, which makes the part obsolete. Generally, the presence of these EC's complicates the decision-making for the spare parts stock, since every decision is paired with an obsolescence risk of the particular part.

As aforementioned, another implication of making spare part stock decisions in the early phase of the PLC, is that spare part demand rate information is limited. First of all, as the decisions have to be made well in advance of the installation of the system, actual part failures have not been reported yet. Besides actual failures, numerous alternative ways exist in the literature to obtain failure insights, such as lifetime tests, lifetime analyses and FMEA (Failure mode effect analysis). However, due to ASML's short time to market orientation, there are not enough resources available to perform lifetime tests and analyses for all parts. Furthermore, the FMEA's that are carried out at ASML do not generate failure insights.

Based on the available demand information, the experts on the parts, which are the Equipment Engineers within the D&E projects are supposed to, provide an initial failure rate estimation (IFR) for every spare part. These IFR estimations represent a best guess of the number of failures per machine per year. In case there is no demand information available, the Equipment Engineer has to provide an IFR estimation for that particular part based on his expertise and "gut feeling". For this, the Equipment Engineer evaluates the product type, material and context of use. However, an extensive assessment of these characteristics is too time-consuming for the experts and therefore the resulting estimation are generally inaccurate. Appendix F shows these inaccuracies according to an analysis of the IFR's and the current failure rates of the newest DUV system and an EUV system.

3.2.2 Practice of Stock Decision-making

Even though spare parts stock decisions for NPI's are very complex, these decisions still need to be made. To reduce the obsolescence risk of the stock decisions, it is required that all spare parts are mature to the extent that these have a fixed initial design and can be ordered at the supplier. When this requirement is satisfied, stock decisions are made through a classification of the spare parts. By classifying the spare parts according to the part prices and the IFR's, stock locations within the inventory network are determined for every part. This implies deciding to stock in a local, continental and/or global warehouse. Thereafter, the stock amounts are based on a qualitative assessment of the particular part in cooperation with engineers from the Development and Engineering department (D&E). According to the procedure, the NPL department aims to reach a particular aggregate fill rate target, which is the weighted average of all part fill rates and is defined as customer service degree (CSD) within ASML.

3.2.3 Service Performance

To reach a high service performance in terms of system availability, high CSD targets are applied when making stock decisions. These CSD targets depend on the system availability that is desired by the customer. In general, the availability of a system is affected by the extent to which scheduled downtime (SD) and unscheduled downtime (USD) occur, since these activities lead to system unavailability.

As part of the causes for system unavailability, USD is the aspect that is influenced by spare parts stock decisions. This is because USD is caused by the occurence of a stockout. Currently, the USD for the new EUV systems are quite high. However, this is in contrast with the service stock decisions, since for these high CSD targets are applied. As a result of those stock decisions, only minimal amount of stockout occurs per year. This indicates that the current service stock decisions cause only a small part of the current USD of the EUV systems and that the service performance of the current service stock decisions are good in terms of system availability.

Nevertheless, this low amount of actual stockouts comes at a high cost. Satisfying high CSD targets, requires parts to be on stock in high quantities. However, based on the available demand information and the current practice of stock decision-making, inefficient stock decisions are made in terms of investment. This implies that expensive parts are stocked in relatively high quanties. So this in combination with high stock quantity requirements, leads to very high stock investments. Furhtermore, due to these inefficiencies, about half of the parts is at risk of parts being in excess or becoming obsolete in the future.

Chapter 4

Model for spare part stocking under demand rate uncertainty

In the previous chapter, we described the complexity of NPI spare part stock decisions and indicated that the risks of excess and obsolete stock in terms of investment are substantial. Therefore, in this chapter, we will focus on developing a multi-item, single-location model that supports these decisions for complex capital goods. However, as stated in the research assignment, we will not take into account obsolescence risk. This implies that we limit ourselves to taking into account only NPI spare parts demand rate uncertainty. So aspects, such as inmaturity and redesigns of spare parts, will not be involved in the model development. Nonetheless, we do consider that, as time progresses, the NPI system become more mature in terms of the PLC and the installed base of these systems increases. Accordingly, the demand rate uncertainty for NPI spare parts decreases and the demand rates become more like demand rates for volume systems.

In section 4.1 we will elaborate on important choices for the development of our model with regard to demand rate uncertainty. After we explained in what way we incorporate demand rate uncertainty, we describe the characteristics of the model conceptually in section 4.2. Accordingly, the assumptions that are made for this model are stated in section 4.3. Finally, in section 4.4, we provide the the required mathematical formulation of our model.

4.1 Model Development

Modeling a demand process with uncertainty in its parameter corresponds in the literature to a situation with unspecified parameters but known form of demand distribution function (Arrow et al., 1958)."One of the most widespread parametric approach is assuming a distribution, estimating its parameters and applying these to theoretically correct formulae" (Janssen, Strijbosch and Brekelmans, 2009). Another popular parametric approach to deal with this demand uncertainty situation is the application of a Bayesian approach (Sherbrooke, 1968, Slay, 1984). Alternative nonparametric approaches involve the bootstrap procedure (Bookbinder and Lordahl, 1989) and Kernel densities (Strijbosch and Heuts, 1992). In table 4.1, we evaluate the most common approaches from a NPI point of view.

Table 4.1: Overview of most common approaches for demand rate uncertainty

Method	Description	Advantages	Disadvantages
Bayesian inference	Demand parameter derived from prior knowledge is sequential updated as demand data becomes available	• All inferences follow a solid theoretical framework • It provides inferences that are exact • Very flexible	• Parameter uncertainty not accounted for until empirical data becomes available and inferences can be done
Distribution assumption and parameter estimation	Assuming a distribution, estimating its parameters and applying these to theoretically correct formulae	• Many different forecasting methods can be applied for parameter estimation	• Forecast methods for parameter estimation requires empirical data
Kernel Densities	Data smoothing method which makes inferences makes about a population based on finite data	• Able to estimate the unknown probability distribution of a random variable	• Requires empirical sample data for the inference of parameters
Bootstrapping	Estimates properties of a particular estimator by measuring those properties through samples of an approximating distribution	• Simple procedure for complex estimators of complex parameters • Appropriate for checking the stability of the estimation	• Requires empirical sample data for the inference of parameters

In the early phase of the PLC of capital goods, empirical demand data on all the NPI spare parts will only be available after a considerable amount of time. So even though the methods in table 4.1 hold several promising properties, these rely too heavily on empirical demand data and are therefore not applicable to our problem. This means that we need to develop an alternative approach. For this we are inspired by PERT project scheduling.

In the field of PERT project scheduling, it is a common approach to calculate the unknown expected activity times of projects by using three estimates: the most optimistic, the most pessimistic and the most likely value (Meredith and Mantel, 2008). So according to these values, a range of all possible activitiy times is derived. They emphasize that this same method can be applied to finding the expected level of resource usage, given an approximation of the three estimates. We therefore suggest that this also can be applied to NPI spare parts demand rate uncertainty. As the spare parts demand rate is determined by a part's failure rate, we are interested in all possible failure rate values. For that reason, we introduce *failure rate ranges*. So instead of using point estimate of the failure rate, we consider all failure rate values within a range with a particular possibility. Accordingly, we can take the weighted average of this failure rate range.

The possibilities of the values within the range are obtained through a probability distribution. In the literature, there are many optional distributions. However, we argue that the demand insights on NPI spare parts are insufficient to obtain many of the required parameters. Therefore the options to choose from are limited. An optional distribution could be the continuous Uniform distribution, which only requires the lower and upper bound of the failure rate range as input. Under the application of this distribution, all failure rate values within the range are equally likely, which represents complete demand rate uncertainty. Another optional distribution could be the Normal distribution. Based on the lower and upper bound of the failure rate range, the 3σ-rule can be applied to determine the required parameters μ and σ. Due to the symmertry property of this distribution, failure rate values in the middle of the range are most likely to occur. Following Meredith and Mantel (2008), the Beta distribution is a third option. Based on the most optimistic, the most pessimistic and the most likely of the failure rate, the required parameters α and β can be estimated. As shown in figure 4.1, symmetric as well as assymetric shapes of the failure rate ranges can be modeled through particular combinations of the parameters. Due to this versatility, we choose to apply the Beta distribution.

Another important aspect of the failure rate ranges is how the most likely, most optimistic and most pessimistic value of the failure rate are obtained. In the field of PERT project scheduling, it is assumed that these three values can be given fairly easily. However, due to the product complexity and time to market pressure, we argue that this is less straightforward for NPI's of capital goods. In addition, Tversky and Kahnemann (1974) argue that, due to so-called availability biases, errors in expert judgements tend to be larger for extreme values, such as most optimistic and most pessimistic values. These biases arises since people are likely to form their judgemental estimates based on readily available information. We therefore suggest an alternative method, which makes use of an initial failure rate estimation and the *demand predictability* of the spare parts. Huiskonen (2001) defines demand predictability as: "the possibilities to estimate failure patters and rates by

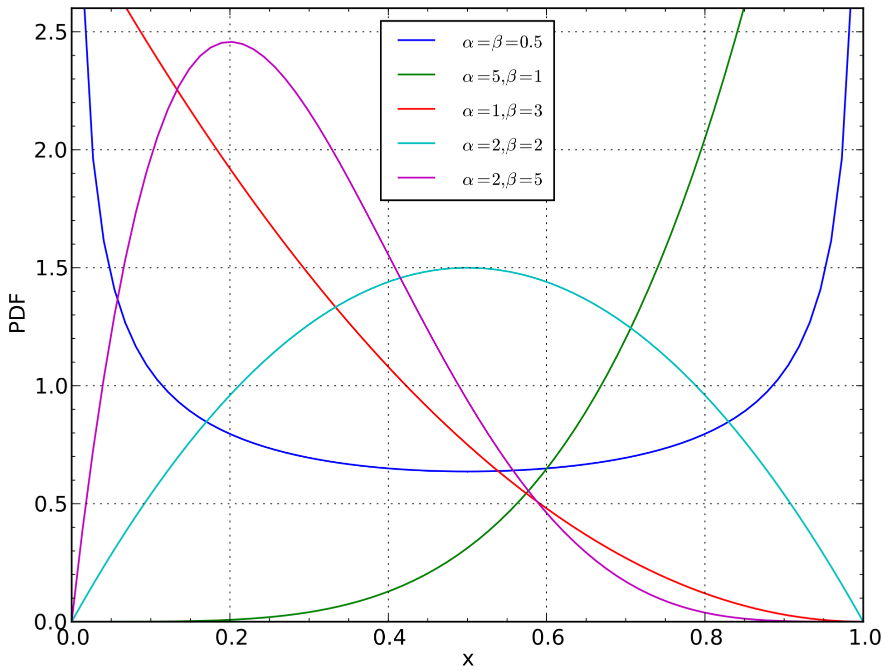

Figure 4.1: Possible Beta distribution shapes

statistical means". We claim that these possibilties are related to the presence of lifetime analyses, lifetime test, design specifications etc. In Appendix D, we classified ASML's NPI spare parts according to this criteria.

For this alternative method, we argue that the demand predictability of a particular NPI part indicates the accuracy of the initial failure rate estimation of that part. In case of a low degree of demand predictability due to the absence of analyses, test and specifications, there is high demand rate uncertainty. Accordingly, a high difference between the most optimistic and most pessimistic value is applied. As time progresses, more information becomes available and the demand predictability of NPI parts increase and therefore this difference decreases. Eventually, the demand predictability is high enough to provide a point estimate instead of a range. This method is further elaborated in paragraph 4.4.1.

4.2 Conceptual design of model

In this section we conceptually describe the model content. First elaborate on the characteristics of the spare part inventory model. Thereafter, we choose which targets we apply for optimization.

4.2.1 Spare part inventory model

Several multi-item, single-location spare part inventory models are available in the literature. We choose to develop our model using the methodology provided by Van Houtum and Kranenburg (2015). They argue that their model is appropriate to describe multiple system-oriented service measures and to show the impact of additional or alternative model assumptions. Additionally, this single-location, multi-item model suits the following warehousing situations:

- A local warehouse
- A central warehouse in a two-echelon network
- The aggregate stock in a two-echelon network with one central depot and multiple local warehouse closely located to eachother

However, the model by Van Houtum and Kranenburg (2015) does not take into account demand rate uncertainty. Therefore we extend their model by applying failure rate ranges of possible values instead of one point estimate of the failure rate. This implies that we adjust several of the formulas they have defined.

For the problem of spare part stock decisions, we will apply a basestock policy, which is justified as long as fixed ordering costs are small relative to the prices of the parts (Van Houtum and Kranenburg, 2015). Furthermore, as we are looking at spare parts for NPI's, we have to find basestock levels for first time. We refer to this as the *initial stocking problem*. With regard to this problem, the goal is to find the optimal basestock levels subject to a particular target. The optimization targets are further elaborated in paragraph 4.2.2.

In case demand cannot be satisfied directly from stock, there are two options to cope with the situation. A first option is placing a backorder. In such a situation the demanded part is fulfilled as soon a part becomes available in the repair pipeline. Another option is fulfilling the demand through an emergency shipment from another warehouse's stock in the network. As the demand is not fulfilled by the warehouse the demand initially went to, it translates to a lost sale situation. For our model we will focus on an emergency shipment situation.

The optimal solution for the initial stocking problem can be found by a Greedy algorithm. Based on this algorithm,the "biggest bang for buck" is identified every time the basestock levels of part is increased by one unit and added to a initial basestock level vector. Conclusively, after the initial failure rates are transformed into failure rate ranges, optimal basestock levels and corresponding output variables can be found for an initial stocking problem with a particular set of input parameters. A list of the input parameters and outcome variables of our model is provided in Appendix K.

4.2.2 Optimization targets

As stressed before, complex capital goods can require enormous investments and at the same time, system unavailability translates to high downtimes costs. Therefore, reaching high system availability is of utter importance. To guarantee this, original equipment manufacturers (OEM' s) agree particular targets with the customer. At the same time, the OEM aims to reach this against low investments. In this paragraph we elaborate on the relevant targets.

As shown in figure 1.3, system unavailability consists of multiple aspects, such as failure diagnosis and repair, and only partially of waiting time for spare parts. However, spare parts stock decisions only influence this particular waiting time. Since reducing system unavailability is of such importance, we will look at reducing this waiting time and thus the related system unavailability. Accordingly, we propose a *logistical system unavailability* target, the percentage of the total time a system is unavailable due to a stockout. However, to reduce this system unavailability, reaching a high fill rate is also very important. The higher the chance a part is on stock, the lower the waiting time and thus the system unavailability will be. Even though both targets are related to system availability, a logistical system unavailability target is based on time and a fill rate target is based on demand, for which the rates are uncertain. We therefore argue that these targets are not identical in case of demand rate uncertainty. Accordingly, we choose to include these targets in seperate optimization problems.

In spare parts inventory optimization, a distinction can be made between an *item approach* and a *system approach*. A system approach implies that targets are formulated at the level of capital goods instead of single items (Van Houtum and Kranenburg, 2015). They argue that this approach allows having high stock for cheap items and low stock for expensive items, while attaining the same performance in terms of service measures. This approach yields high benefits in case of high part price skewness. (Thonemann, Brown & Hausman, 2002). For complex capital goods high part price skewness applies and we therefore choose to apply a system approach. With regard to the fill rate target, we will look at the weighted average of the fill rates for all items in the system. We refer to this as the *aggregate fill rate*. So all in all, the optimization problems can be characterized as follows:

- Reaching an aggregate fill rate target while minimizing costs
- Reaching a logistical system unavailability target while minimizing costs

4.3 Overview of assumptions

In this section we explicitly mention all assumptions that are made for the development of this model. Some of these have already been mentioned in section 4.1 and 4.2. Overall, the following assumptions are made:

1. *Initial failure rate estimates and information on demand predictability are available for all SKU's in the early phase of the PLC*
   This information is required input for the computation of the failure rate ranges.

2. *The initial failure rate estimation represents a best guess for the number of failures per machine per year*
   This assumption is necessary for the application of the Beta distribution to the failure rate ranges.

3. *The demand rate is independent from previous demand.*
   Demand rates decrease when a considerable amount of the machines is down. However, when downtimes occur rarely or downtime is very short, this does not affect the demand rate significantly.

4. *Replenishment lead times for different SKU's are independent and for parts of the same SKU i.i.d. with a known intensity.*
   This assumption is justified for situations in which replenishment lead times have been agreed with the supplier.

5. *All SKU's are subject to a one-for-one replenishment strategy.*
   This assumptions holds if the fixed ordering costs are relatively small compared to the prices of the SKU's.

6. *Prices of SKU's are known.*
   The earlier in the PLC stock decisions need to be made, the more prices can be unknown. So we assume that NPI stock decisions are made during the phase of the PLC in which the prices are already known.

7. *Complex capital goods are used for production every hour of every day*
   Because complex capital goods are very expensive, it is assumed that these are used for production every possible hour.

8. *Downtime due to waiting for parts only caused in case of stockout*
   This assumption implies that no downtime is caused when the part is on stock.

4.4 Detailed design of model

In this section a detailed description of the spare part stocking model under demand rate uncertainty is provided. First, we elaborate on determining the failure rate ranges and how these affect a demand process. Thereafter, we describe the spare part stocking model in case of an emergency shipment situation.

4.4.1 Determination of failure rate ranges

Within the model development in section 4.1, we introduced the concept of failure rate ranges. We also suggested an alternative method to obtain the lower and upper bound of the range, by making use of the demand predictabilty of a part. In this section we will therefore elaborate on this method. Thereafter we illustrate how the failure rate ranges can be determined according to this method. Finally, we show how the failure rate ranges affect a demand process within a spare parts stocking model.

Bound estimation through demand predictability

Previously we proposed an alternative method for estimating the bounds of the failure rate range. We argued that the demand predictability of a particular NPI spare part is affected by the presence of particular analyses, tests and specificiations on the part. Subsequently, this indicates the inaccuracy of the initial failure rate estimation of that part. So the lower the demand predictability is, the higher the inaccuracy of the IFR estimation is and thus the wider the range will be. To numerically represent this inaccuracy, we suggest applying a *predictability variance* for every degree of demand predictability. This implies that the IFR estimation of parts with the same degree of demand predictability are subject to the same relative inaccuracy. Therefore, we propose that the predictabilty variance denotes a two-sided percentual variance instead of fixed number for every part.

Let I denote the set of SKU's containing a total number of $|I|$ SKU's. For each SKU $i \in I$, the degree of demand predictability is evaluated and a predictabiliy variance is assigned according to that particular degree. Let D denote the set of all degrees of demand predictability and $d \in D$ denote an particular degree of demand predictabiliy. Then d_i denotes the degree of demand predictability for SKU i. Furthermore, let V denote the set of the predictability variance. Then the predictability variance of SKU i that corresponds to its degree of predictabilty variance d_i is given by V_{d_i}. This is illustrated in example 2.1.

Example 2.1. Let us take a set of degrees of demand predictability $D = \{la, lt, ds, no\}$, where la = Lifetime analysis of predecessors, lt = lifetime test, ds = Design specifications and no = No demand information. Let $d_i = la$. Then V_{la} denotes the two-sided percentual predictability variance of SKU i.

Range computation

Now that we explained how the bounds of the failure rate range can be estimated, we can describe how the failure rate range itself is computed. Let λ_i denote the failure rate of SKU i, the number of failures per year. Then, $\lambda_i^{initial}$ denotes the IFR estimation of SKU i. Furthermore, let a_i the lower bound and b_i denote the upper bound of the failure rate range for SKU i. In the previous paragraph we explained that these are obtained through a particular percentual predictabiliy variance V_{d_i} with respect to the IFR estimation $\lambda_i^{initial}$. Moreover, it must be noted that a failure rate cannot be negative. Thus, $b_i = \lambda_i^{initial} + \lambda_i^{initial} \times V_{d_i}$ and $a_i = max\{\lambda_i^{initial} - \lambda_i^{initial} \times V_{d_i}, 0\}$. We illustrate this in example 2.2.

Example 2.2. Let us take an initial failure rate estimation $\lambda_i^{initial} = 0.5$. Following example 2.1, we set $V_{la} = 0.1, V_{lt} = 0.2, V_{ds} = 0.5$ and $V_{no} = 2$, where 0.2 denotes 20% predictability variance etc. Then, in case SKU i has lifetime test information available, $d_i = fa$, $V_{lt} = 0.2$ and the corresponding range is $[0.4, 0.6]$. In case SKU i has no information at all,$d_i = fa$, $V_{no} = 2$ and the corresponding range is $[0, 1.5]$.

Demand process construction

As mentioned before, we investigate failure rate ranges that follow a Beta distribution , so $Beta(\gamma, \delta)$. In this paragraph we evaluate the application of the Beta distribution. The beta distribution is characterized by the following probability density function:

$$f(x) = \begin{cases} \frac{x^{\gamma-1}(1-x)^{\delta-1}}{B(\gamma,\delta)} & 0 \leq x \leq 1 \\ 0 & \text{otherwise.} \end{cases}$$

Where, $B(\gamma, \delta)$ is denoted by $\frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$. In line with this formula, the first matter that arises, is that the Beta distribution is only defined on the interval $0 \leq x \leq 1$. However, as demonstrated in example 2.1, failure rate ranges are defined on the interval $a \leq \lambda \leq b$. For this application, Farnum and Stanton (1987), provide the following transformation:

$$x = \frac{\lambda - a}{b - a} \tag{4.1}$$

This transformation is applied for all values in the interval [a,b]. According to this transformation, x_{min} is obtained for $\lambda = a$ and x_{max} for $\lambda = b$. These values represent the most optimistic and most pessimistic value resprectively. In case $\lambda = \lambda^{initial}$, x_{mode} is obtained, which represent the most likely value. This holds because IFR estimation $\lambda^{initial}$ represents a best guess for the true value. In that case it can be identified as the mode (i.e. the most likely value) (Lichtenstein, Fischhoff and Phillips, 1980).

The second issue that arises from looking at the probability density function of the Beta distribution is the derivation of the shape parameters γ and δ. These can be found through the mean and the variance of the Beta distribution, for a given mode x_{mode} and most optimistic and most pessimistic estimates x_{min} and x_{min}. The original formulas are as follows:

$$\hat{\mu} = \frac{x_{min} + 4x_{mode} + x_{max}}{6} \tag{4.2}$$

$$\hat{\sigma}^2 = \Big(\frac{(x_{max} - x_{min})}{6}\Big)^2 \tag{4.3}$$

A considerable body of research has been done on improving the approximation of Beta distribution parameter in a PERT application. Mainly with regard to estimation of x_{min} and x_{max} being done at either 99%, 95% or 90% levels. This does not imply a confidence level, but which fractiles of the Beta distribution are used for the approximation of the mean and the variance. The original PERT formulas in equations 4.2 and 4.3 are considered to represent a 99% level. So those estimations are done on the 0.01 and 0.99 fractile of the Beta distribution. Keefer and Verdini (1993) argue that taking into account the other estimation levels potentially improves the estimation of the shape parameters γ and δ. However, the 95% and 90% level approximations require additional estimations of the 0.05, 0.1, 0.9 and 0.95 fractile. For now, we choose to limit ourselves to the 99% level because the presence of demand rate uncertainty complicates the estimations of the other fractiles.

According to the approximation of the mean and variance, Farnum and Stanton (1987) provide the following equations for the estimation of shape parameters γ and δ at the 99% level:

$$\gamma = \Big[\frac{\hat{\mu}(1-\hat{\mu})}{\hat{\sigma}^2} - 1\Big]\hat{\mu} \tag{4.4}$$

$$\delta = \Big[\frac{\hat{\mu}(1-\hat{\mu})}{\hat{\sigma}^2} - 1\Big](1-\hat{\mu}) \tag{4.5}$$

Now the issues of failure rate range following a Beta distribution have been accounted for, we apply this to the construction of demand process. Let $f_d(x, \lambda)$ denote the density function of a demand process of spares with failure rate parameter λ. Furthermore, let $f_\lambda(x)$ denote the density function of the Beta distribution of the failure rate range. Then we obtain $f_d(x, \lambda)$, with the weighted average of λ according to failure rate range distribution $f_\lambda(x)$, as follows:

$$f_d(x, \lambda) = \int_a^b f_d(x, u) f_\lambda(u) du = \int_a^b f_d(x, u) \frac{\frac{u-a}{b-a}^{\gamma-1}(1 - \frac{u-a}{b-a})^{\delta-1}}{B(\gamma, \delta)} du \tag{4.6}$$

We now provide an example of this demand process construction for SKU i if the demand process follows a Poisson distribution with mean $\lambda_i m_i t_i$. Here, t_i denotes the replenishment lead time per SKU i and m_i denotes the installed base at the customer per SKU i. First, let $f^{det}_{pois}(x, \lambda)$ denote the density function of the Poisson distribution with a deterministic failure rate. This is given by:

$$f^{det}_{pois}(x, \lambda) = \frac{(\lambda_i m_i t_i)^x}{x!} e^{-\lambda_i m_i t_i} \tag{4.7}$$

However, when λ_i is stochastic on $[a_i, b_i]$ with density function $f_\lambda(x)$, the density function of the Poisson distribution is denoted by $f^{sto}_{pois}(x, \lambda)$ and given by:

$$f^{sto}_{pois}(x,\lambda) = \int_{a_i}^{b_i} \frac{(um_i t_i)^x}{x!} e^{-um_i t_i} \frac{\frac{u-a_1}{b_i-a_i}^{\gamma-1}(1-\frac{u-a_1}{b_i-a_i})^{\delta-1}}{B(\gamma,\delta)} du \tag{4.8}$$

Now we showed how the demand process can be constructed by inserting the Beta distributed failure rate ranges, the demand process construction can be applied to a spare part stocking model.

4.4.2 Design of models for emergency shipments

In this section we look at a single-location, multi-item model, in which an emergency shipment is applied in case of stockout. First, we elaborate on the basic model for this problem, that applies to both optimization targets. Several relevant parameters within this basic depend on which probability distribution the demand process follows. We therefore provide an example of this. Thereafter, we explain the specific model for reaching an aggregate fill rate target. Finally, we do the same for a logistical system unavailability target.

Basic model

For this situation, demand will not be backordered in case of stockout, but fulfilled through an emergency shipment. This emergency shipment can be sent from either another local warehouse or a central warehouse. The average number of emergency shipment per year is equal to average number of stockouts per year.

Similar to Van Houtum and Kranenburg (2015), let **S** denote the set of basestock levels for all SKUs and S_i the basestock level per SKU i. Then let $\alpha^{det}_i(S_i)$ denote the average number of stockouts per year for SKU i with basestock level S_i in case of a determinstic demand rate. The demand rate of SKU i at a single location is obtained by multiplying the number of failures with the installed base, so $\lambda_i m_i$. To derive $\alpha^{det}_i(S_i)$, the item fill rate of SKU i is required, which is denoted by $\beta^{det}_i(S_i)$ in case of a deterministic demand rate and by $\beta^{sto}_i(S_i)$ in case of a stochastic demand rate. It represents the fraction of time at least one part is on stock for SKU i. So 1 minus the item fill rate represents the fraction of time no parts are on stock for SKU i. Multiplying this with the demand rate for SKU i, results into the average number of stockouts per year $\alpha^{det}_i(S_i)$. Hence,

$$\alpha^{det}_i(S_i) = \lambda_i m_i(1 - \beta^{det}_i(S_i)) \tag{4.9}$$

However, λ_i follows a Beta distribution. So let $\alpha^{sto}_i(S_i)$ denote the average number of stockout for SKU i with basestock level S_i in case of a stochastic demand rate. Then, by transforming equation 4.9 in a similar manner as equation 4.6, $\alpha^{sto}_i(S_i)$ is obtained as follows:

$$\alpha_i^{sto}(S_i) = \int_{a_i}^{b_i} um_i\beta_i^{sto}(S_i)f_\lambda(u)du = \int_{a_i}^{b_i} (um_i\beta_i^{sto}(S_i))\frac{\frac{u-a_i}{b_i-a_i}^{\gamma-1}(1-\frac{u-a_i}{b_i-a_i})^{\delta-1}}{B(\gamma,\delta)}du \quad (4.10)$$

It must be noted that derivation of $\beta_i^{det}(S_i)$ and $\beta_i^{sto}(S_i)$ depends on the probability distribution that is assumed for the demand process. In the case study in chapter 5, we show this derivation for a demand process that follows a Poisson distribution.

Now the average yearly number of stockouts has been derived, the total average yearly costs can be evaluated. Each time an emergency shipment has to be executed, emergency shipment cost c_i^{em} are incurred. This entails that the average yearly emergency shipment cost for SKU i is equal to $\alpha_i^{sto}(S_i)c_i^{em}$. Furthermore, as we are looking at an initial stocking problem, the purchase cost of the SKU's are relevant as well. To let these purchase costs represent yearly average costs, these costs are transformed into yearly inventory holding costs. Let c_i^h the yearly inventory holding cost per SKU i. Then, for an emergency shipment situation with a stochastic demand rate, the costs become:

$$\hat{C_i^{sto}}(S_i) = c_i^h S_i + \alpha_i^{sto}(S_i)c_i^{em} \quad (4.11)$$

The total yearly average costs for this situation are equal to $\hat{C^{sto}}(\mathbf{S}) = \sum_{i\in I}\hat{C_i^{sto}}(S_i)$. These total average yearly costs will be minimized subject to either one of the two optimization targets as identified in paragraph 4.2.2. For a situation with a stochastic demand rate, the aggregate fill rate is denoted by $\beta^{sto}(\mathbf{S})$ and the logistical system unavailability is denoted by $UA^{sto}(\mathbf{S})$. These targets will be explained seperately. Nevertheless, the optimization problem for reaching an aggregate fill rate target under demand rate uncertainty becomes:

$$\begin{aligned} \min \quad & \hat{C^{sto}}(\mathbf{S}) \\ \text{s.t.} \quad & \beta^{sto}(\mathbf{S}) \geq \beta^{obj} \\ & \qquad S_j \in \boldsymbol{S} \end{aligned} \quad (4.12)$$

For reaching a logistical system unavailability target under demand rate uncertainty, the optimization problem becomes:

$$\begin{aligned} \min \quad & \hat{C^{sto}}(\mathbf{S}) \\ \text{s.t.} \quad & UA^{sto}(\mathbf{S}) \leq UA^{obj} \\ & \qquad S_j \in \boldsymbol{S} \end{aligned} \quad (4.13)$$

Optimization of aggregate fill rate

In this paragraph we discuss how the optimzation problem in equation 4.12 can be solved. As the term suggest, the aggregate fill rate $\beta^{sto}(\mathbf{S})$ is basically the weighted average of all item fill rates $\beta_i^{sto}(S_i)$. In case a deterministic demand rate, the weight for SKU i is computed by dividing the demand rate of SKU i by the demand rate of all SKU's. So $\frac{\lambda_i m_i}{\Lambda}$

, where $\Lambda = \sum_{i\in I} \lambda_i m_i$. However, λ_i follows a Beta distribution. So the weighted average $\bar{\lambda_i}$,according to the Beta distribution, is given by:

$$\bar{\lambda_i} = \int_{a_i}^{b_i} u \frac{\frac{u-a_i}{b_i-a_i}^{\gamma-1}(1-\frac{u-a_i}{b_i-a_i})^{\delta-1}}{B(\gamma,\delta)} du. \tag{4.14}$$

So by applying $\bar{\lambda_i}$, the aggregate fill rate $\beta(\mathbf{S})$ is computed as follows:

$$\beta^{sto}(\mathbf{S}) = \sum_{i\in I} \frac{\bar{\lambda_i} m_i}{\Lambda} \beta_i^{sto}(S_i) \tag{4.15}$$

Now we have derived $\beta^{sto}(\mathbf{S})$, we can evaluate the corresponding optimization algorithm. In our model, the item fill rates $\beta_i^{sto}(S_i)$ are maximized by increasing S_i until an aggregate fill rate target β^{obj} is satsified. This implies that the formula for $\beta_i^{sto}(S_i)$ should be increasing and concave on its whole domain as a function of S_i. In Appendix H we prove this for a Poisson distributed demand process. In addition, Van Houtum and Kranenbrug (2015) argue that $\hat{C_i^{sto}}(S_i)$ is convex on its whole domain, but might be decreasing for smaller values of S_i. This occurs when the holding cost for a part are low, but the emergency shipment costs are high. In that case it is on average cheaper to have a higher basestock level S_i. So in order to minimize $\hat{C^{sto}}(\mathbf{S})$, let $S_{i,min} := argmin\hat{C_i^{sto}}(S_i)$. Next, the increase in $\beta^{sto}(\mathbf{S})$ relative to the increase in $C^{sto}(\mathbf{S})$ is computed when S_i is increased by one unit. This implies that the increase in $\beta^{sto}(\mathbf{S})$ is divided by the increase in $C^{sto}(\mathbf{S})$. This value represents the Greedy ratio of the Greedy algortihm. For $C^{sto}(\mathbf{S})$, this increase is equal to $\Delta_i C^{sto}((S)) = \Delta C_i^{sto}(S_i) = C_i^{sto}(S_i+1) - C_i^{sto}(S_i)$. For $\beta_i^{sto}(S_i)$, this increase is equal to $\Delta\beta_i^{sto}(S_i) = \beta_i^{sto}(S_i+1) - \beta_i^{sto}(S_i)$. This entails that the greedy ratio Γ_i^{afr} for the problem of reaching an aggregate fill rate target is denoted by

$$\Gamma_i^{afr} = \frac{\lambda_i m_i \Delta\beta_i^{sto}(S_i)}{\Lambda\Delta\hat{C}_i^{sto}(S_i)}. \tag{4.16}$$

The SKU with the highest greedy ratio value Γ_i is selected, as it corresponds to the "biggest bang for buck". Accordingly, the basestock level of that particular SKU is increased by one unit. This is then changed in the solution set. This process is repeated until the aggregate fill rate target has been reached. This translates to the following optimization algorithm:

Greedy Optimization Algorithm
Step 1

1. $S_{(i,min)} := argminC_i^{sto}(S_i)$ for all $i \in I$.
2. Set $S_i = S_{(i,min)}$ for all $i \in I$, and $\mathbf{S} = (S_{1,min}, \dots, S_{|I|,min})$
3. $\boldsymbol{E} := \{\mathbf{S}\}$.
4. Compute $C^{sto}(\mathbf{S})$ and $\beta^{sto}(\mathbf{S})$

Step 2

1. $\Gamma_i^{afr} = (\bar{\lambda}_i \Delta\beta_i^{sto}(S_i))/(\Lambda\hat{C}_i^{sto}(S_i))$ for all $i \in I$.
2. $k := argmax\{\Gamma_i^{afr} : i \in I\}$
3. $\mathbf{S} := \mathbf{S} + \mathbf{e}_k$
4. $\boldsymbol{E} := \boldsymbol{E} \cup \{\mathbf{S}\}$.

Step 3

1. If $\beta^{sto}(\mathbf{S}) \geq \beta^{obj}$, then stop, else go to Step 2.

Optimization of logistical system unavailability

In this paragraph we discuss how the optimzation problem in equation 4.13 can be solved. Let $UA^{sto}(\mathbf{S})$ denote the logistical system unavailability for the set of basestock levels under demand rate uncertainty. Furthermore, let $UA_i^{sto}(S_i)$ denote the system unavailability as a result of the basestock level of SKU i. By evaluating the downtime and available time, we derive an expression for $UA_i^{sto}(S_i)$.

When a stockout occurs, downtime is caused since an emergency shipment has to be performed. Let t_i^{em} denote the emergency shipment time. Then the downtime caused by SKU i is given by $\alpha_i^{sto}(S_i)t_i^{em}$.Since we assume that an expensive capital good is available for production every hour of the day and every day of the year, the total time per system is 8760 hours. By taking this into account, the expression for $UA_i^{sto}(S_i)$ is obtained as follows:

$$UA_i^{sto}(S_i) = \frac{t_i^{em}\alpha_i^{sto}(S_i)}{m_i 8760} = \frac{t_i^{em}\int_{a_i}^{b_i} um_i\beta_i^{sto}(S_i)f_\lambda(u)du}{m_i 8760} = \frac{t_i^{em}\int_{a_i}^{b_i} u\beta_i^{sto}(S_i)f_\lambda(u)du}{8760} \quad (4.17)$$

From this it can be observed that the logistical system unavailability is not affected by the amount of machines SKU i is included. Subsequently, $UA(\mathbf{S})$ is given by:

$$UA^{sto}(\mathbf{S}) = \sum_{i \in I} UA_i^{sto}(S_i) \quad (4.18)$$

Now we have derived $UA^{sto}(\mathbf{S})$, we can evaluate the corresponding optimization algorithm. In our model, the system unavailability $UA_i^{sto}(S_i)$ is minimized by increasing S_i until a logistcal system availability target UA^{obj} is satsified. This implies that the formula for $UA_i^{sto}(S_i)$ should be decreasing and convex on its whole domain as a function of S_i. In Appendix H, we prove this for a Poisson distributed demand process. For reaching the logistical system unavailability target, we are interested in the decrease in $UA_i^{sto}(S_i)$

compared to the increase in $\hat{C}_i^{sto}(S_i)$ when S_i increases by one unit. For $UA_i^{sto}(S_i)$, this decrease is equal to $\Delta UA_i^{sto}(S_i) = UA_i^{sto}(S_i+1) - UA_i^{sto}(S_i)$. Resultantly, the corresponding greedy ratio is given by:

$$\Gamma_i^{av} = -\frac{\Delta UA_i^{sto}(S_i)}{\Lambda \hat{C}_i^{sto}(S_i)}. \tag{4.19}$$

The optimization algorithm is as follows:

Greedy Optimization Algorithm

Step 1

1. $S_{(i,min)} := argmin C_i^{sto}(S_i)$ for all $i \in I$.
2. Set $S_i = S_{(i,min)}$ for all $i \in I$, and $\mathbf{S} = (S_{1,min}, \ldots, S_{|I|,min})$
3. $\boldsymbol{E} := \{\mathbf{S}\}$.
4. Compute $C^{sto}(\mathbf{S})$ and$UA^{sto}(\mathbf{S})$

Step 2

1. $\Gamma_i^{av} = -(\Delta UA_i^{sto}(S_i))/(\Lambda \hat{C}_i^{sto}(S_i))$. for all $i \in I$.
2. $k := argmax\{\Gamma_i^{av} : i \in I\}$
3. $\mathbf{S} := \mathbf{S} + \mathbf{e}_k$
4. $\boldsymbol{E} := \boldsymbol{E} \cup \{\mathbf{S}\}$.

Step 3

1. If $UA^{sto}(\mathbf{S}) \leq UA^{obj}$, then stop, else go to Step 2.

Chapter 5

ASML Business case

In this chapter we discuss a business case in which our model for spare part stocking under demand rate uncertainty is applied to a specific situation at ASML. In section 5.1, we provide a business case introduction, in which we describe the case itself and what the objective of this business case is. We translate this objective into three business case questions. This introduction is followed by a discussion of the business case specification in section 5.2. In this section we specify the model from chapter 4 and discuss what assumptions we make. We also describe how we evaluate the failure rate ranges at ASML. Subsequently, we define the base case scenario in section 5.3 According to this, we perform the verifcation and the validation of the model in section 5.4. In section 5.5, the results are presented and discussed[1]. Finally, in section 5.6, we provide the conclusions of this business case by answering the three business case questions.

5.1 Business case introduction

As aforementioned, ASML has a two-echelon, multi-item location inventory network. In chapter 4 we presented a single-location multi-item spare part inventory model for NPI's, which suits three warehousing situations. ASML's local warehouse in Taiwan comes closest to a single-location, due to its remote location and being the only local warehouse that the corresponding customer. This customer has an installed base of in total five machines of three different EUV-systems (See figure 5.1). This entails that, due to commonality, a part can be either included in one system or in multiple systems. All together, the three types of systems contain 3772 parts that require spare parts. However, we developed a model under demand rate uncertainty that is characterizing for NPI spare parts. We will therefore evaluate the 2157 the NPI spare parts for these systems. The others are common spare parts that are included in multiple other non-EUV systems as well.

[1]The results in this chapter are adjusted, in order to secure confidentiality without limiting the scientific interpretability. Ordinary values and monetary values are scaled on a particular interval. Percentages are shown as the difference with respect to a constant (indicated by a letter) that represents the current performance.

Figure 5.1: Lithography system with EUV-technology

By applying our model for spare part stocking under demand uncertainty to a business case at ASML, our objective is to generate valuable knowledge with regard to NPI spare part stock decisions at ASML. To obtain this knowledge, we identify three business case questions:

1. *With regard to the required investment in spare parts, what is the difference between applying our model and ASML's current method for NPI spare part stock decisions?*
2. *With regard to the required investment in spare parts, what is the impact of lowering demand rate uncertainty by increasing the demand predictability of certain NPI spare parts?*
3. *In case of demand rate uncertainty, what is the effect of applying a particular optimization target when making NPI spare part stock decisions?*

To answer these questions, we need to discuss the current situation in Taiwan. In addition, this requires a specification of our model to the situation at ASML. We do this for the model in chapter 4 with a stochastic as well as a deterministic demand rate. All this is described in the next section.

5.2 Business case specifications

In this section we elaborate on how we specify our model and what assumptions we make for this, such that we can apply it to the business case at ASML. We first do this for ASML's current situation in Taiwan and thereafter for our model with and without demand rate uncertainty.

Before we start with particular business case specifications, we need to define what the required investment in spare parts is. It can be defined as the purchase/production costs of all SKU's on stock. Let $RI(\mathbf{S})$ denote the required investment. Then the required investment for spare parts of SKU i is given by $RI_i(S_i) = c_i^p S_i$, with c_i^p being the price per SKU i. Then the total required investment in spare parts can be calculated as follows:

$$RI(\mathbf{S}) = \sum_{i \in I} RI_i(S_i) = \sum_{i \in I} c_i^p(S_i) \tag{5.1}$$

Now that the required investment has been defined, we can elaborate on the business case specifications.

5.2.1 Current situation specifications

ASML's current basestock levels for the NPI spare parts in Taiwan are determined according to classification method that was mentioned in paragraph 3.2.2. According to this method, every spare part is classified according to its IFR and part price. Based on the combination of these, it is decided in what location these spare parts should be stocked in a local, continental or global warehouse within ASML's multi-location inventory network. Subsequently, the actual basestock levels are determined according to a qualitative assessment of the particular part in cooperation with D&E experts. However, these basestock levels are determined based on a multi-location network. In order to let these basestock levels correspond to a local warehouse in a single-location network, a small adjustment is made to basestock levels resulting from ASML's current stocking method. This has been done in collaboration with NPL spare parts planning experts.

As mentioned in paragraph 3.2.2, ASML defines a CSD target to reach the desired service performance at a particular customer. In our model, this CSD is defined as the aggregate fill rate $\beta(\mathbf{S})$. According to this CSD, a downtime waiting for parts value (DTWP) is derived that indicates the service perfomance with regard to the system availability. Based on our notation in chapter 4, the formula for DTWP can be defined as:

$$DTWP = \frac{(1 - \beta(\mathbf{S}))\Lambda t^{em} + \beta(\mathbf{S})\Lambda t^{norm}}{m8760}$$

Here t^{norm} denotes the shipment time when the part is deliverd from the stock in the local warehouse. This equation shows that the DTWP measure not only considers the downtime due to waiting for parts in case of a stockout, but also when the part can be delivered from stock. In that way, it differs from the logistical system unavailability target $UA(\mathbf{S})$ in our model. Even though currently just the aggregate fill rate is applied at ASML, we decide to take into account and evaluate all three service measures, since our last business case question regards the effect of applying a particular optimization target.

Let vector $\mathbf{S}^{tw} = (S_1^{tw} \dots S_{|I|}^{tw})$ denote the currently proposed basestock levels for all spare parts in Taiwan for the NPI systems. Accordingly, the total stock is computed by $\sum_{I \in i} \mathbf{S}^{tw}$ and the required investment by $RI(\mathbf{S}^{tw})$. Furthermore, let $\beta^c(\mathbf{S}^{tw})$ denote the current aggregate fill rate (CSD), $DTWP^c(\mathbf{S}^{tw})$ the current DTWP, $UA^c(\mathbf{S}^{tw})$ current logistical system unavailability and Λ^c the current expected yearly demand of all SKU's. By setting $t^{norm} = 0$ in the formula for DTWP, $UA^c(\mathbf{S}^{tw})$ can be computed. All these values are shown in table 5.1. [2]

Table 5.1: Service performance of current basestock levels for all spare parts in Taiwan (adjusted)

$\sum \mathbf{S}^{tw}$	$RI(\mathbf{S}^{tw})$	$\beta^c(\mathbf{S}^{tw})$	$DTWP^c(\mathbf{S}^{tw})$	$UA^c(\mathbf{S}^{tw})$	Λ^c
100.0	€100,000	A	B	C	34.4

Furthermore, we define $I^{NPI} \subseteq I$ as the set of NPI spare parts. Then the vector of basestock levels for these NPI spare parts $\mathbf{S}^{tw,NPI}$ is defined as $\mathbf{S}^{tw,NPI} := \{\mathbf{S} = S_i, \forall_i \in I^{NPI}\}$. However, for these basestock levels $\mathbf{S}^{tw,NPI}$, no separate service measures are monitored in terms of $\beta^c(\mathbf{S}^{tw,NPI})$ and $DTWP^c(\mathbf{S}^{tw,NPI})$. We therefore can computed the total stock and the required investments for these spare parts. These values are shown in table 5.2

Table 5.2: Total stock and required investment of NPI spare parts in Taiwan (adjusted)

$\sum \mathbf{S}^{tw,NPI}$	$RI(\mathbf{S}^{tw,NPI})$
52.2	€53,292

Next, we elaborate on the ASML specific spare part stocking model.

5.2.2 ASML specific spare part stocking model

In this paragraph, we specify the model from chapter 4 with respect to ASML. We do this for stochastic as well as deterministic demand rates, such that the difference between demand rate uncertainty and no demand rate uncertainty can be evaluated. In order to do this, we need to make an assumption about the distribution of the demand process. We assume that this demand process is modeled by a Poisson process. Based on Van Aspert (2015), the demand process within ASML multi-location spare part planning model for volume systems is also modeled by a Poisson process. With regard to the Poisson process assumption, Van Houtum and Kranenburg (2015) state that "the Poisson process is

[2] In this chapter, values that represent a number of parts are scaled on the interval 0-100, where $\sum \mathbf{S}^{tw}$ denotes 100 (See table 5.1). Monetary values are scaled on the interval €0- €100,000, where $RI(\mathbf{S}^{tw})$ denotes €100.000 (See table 5.1). Percentages are shown as the difference with respect to a constant (indicated by a letter) that represents the current performance, where the letter A denotes $\beta^c(\mathbf{S}^{tw})$,the letter B denotes $DTWP^c(\mathbf{S}^{tw})$ and the letter C $UA^c(\mathbf{S}^{tw})$ (See table 5.1).

justified either when lifetimes of components are exponential or when lifetimes are generally distributed and installed base served by the warehouse is sufficiently large". This entails that, in case of volume systems, this assumption holds because of an overall large installed base. However, for our application, the assumption only holds if the lifetimes are expontially distributed or an installed base is considered to be sufficiently large. Since the installed base for NPI's is small, we therefore assume the lifetimes are expontially distributed.

Since we decided to also evaluate a DTWP target, we need to define the equations for obtaining this target. We will do this for the deterministic as well as the stochastic demand rate model. Furthermore, the corresponding optimization algorithm is shown in Appendix I.

Deterministic demand rate model

Because no demand uncertainty is involved in this situation, the failure rates do not have to be transformed into failure rate ranges. This entails that we have to slightly adjust the spare part stocking model as described in chapter 4 for the aggregate fill rate and logistical system unavailability targets.

When looking at the aggregate fill rate target, the "weight" for SKU i can be obtained via the original failure rate λ_i instead of the average failure rate $\bar{\lambda}_i$. So the aggregate fill rate is given by:

$$\beta^{det}(\mathbf{S}) = \sum_{i \in I} \frac{\lambda_i m_i}{\Lambda} \beta_i^{det}(S_i) \tag{5.2}$$

Furthermore, since we assumed a Poisson distribution demand process, we now can derive $\beta_i^{det}(S_i)$. According to van Houtum and Kranenburg (2015), a single-location warehousing situation with emergency shipments and Poisson distributed demand can be modeled by an *Erlang loss system* (a M/G/c/c queuing system). This implies that the item fill rate $\beta_i^{det}(S_i)$ can be derived through the Erlang Loss probability, which denotes the blocking probability. Then the item fill rate is equal to 1 minus the Erlang loss probability. Hence,

$$\beta_i^{det}(S_i) = 1 - \frac{\frac{1}{S!}\rho_i^{S_i}}{\sum_{j=0}^{S_i} \frac{1}{j!}\rho_i^j} \tag{5.3}$$

where $\rho_i := \lambda_i m_i t_i$. According to equation 4.9, the formula for the average amount of stockouts per SKU i $\alpha_i^{det}(S_i)$ now becomes:

$$\alpha_i^{det}(S_i) = \lambda_i m_i \frac{\frac{1}{S!}(\lambda_i m_i t_i)^{S_i}}{\sum_{j=0}^{S_i} \frac{1}{j!}(\lambda_i m_i t_i)^j} \tag{5.4}$$

Then the average yearly cost per SKU i becomes $\hat{C_i^{det}}(S_i) = c_i^h S_i + \alpha_i^{det}(S_i)c_i^{em}$ and the total average yearly cost become $\hat{C^{det}}(\mathbf{S}) = \sum_{i \in I} \hat{C_i^{det}}(S_i)$. Moreover, according to $\alpha_i^{det}(S_i)$, we can obtain the system unavailability as a result of basestock levels of SKU i as follows:

$$UA_i^{det}(S_i) = \frac{t_i^{em}\alpha_i^{det}(S_i)}{m_i 8760} = \frac{t_i^{em}\lambda_i m_i \frac{\frac{1}{S!}(\lambda_i m_i t_i)^{S_i}}{\sum_{j=0}^{S_i}\frac{1}{j!}(\lambda_i m_i t_i)^j}}{m_i 8760} = \frac{t_i^{em}\lambda_i \frac{\frac{1}{S!}(\lambda_i m_i t_i)^{S_i}}{\sum_{j=0}^{S_i}\frac{1}{j!}(\lambda_i m_i t_i)^j}}{8760} \tag{5.5}$$

Then $UA^{det}(\mathbf{S}) = \sum_{i \in I} UA_i^{det}(S_i)$. Finally, we need to define the DTWP for a deterministic demand rate. Let $DTWP_i^{det}$ denote the DTWP for a deterministic demand rate for SKU i. From the equation in paragraph 5.2.1, $DTWP_i^{det}$ is obtained as follows:

$$DTWP_i^{det} = \frac{(1-\beta_i^{det}(S_i))\lambda_i m_i t_i^{em} + \beta_i^{det}(S_i)\lambda_i m_i t_i^{norm}}{m_i 8760} \tag{5.6}$$

Then $DTWP^{det}(\mathbf{S}) = \sum_{i \in I} DTWP_i^{det}(S_i)$. Now that all parameters for our model with a deterministic demand rate have been defined, the optimization problems for the different optimization targets can be described. The optimization problem for reaching an aggregate fill rate target becomes.

$$\begin{array}{ll} \min & \hat{C^{det}}(\mathbf{S}) \\ \text{s.t.} & \beta^{det}(\mathbf{S}) \geq \beta^{obj} \\ & \qquad S_j \in \boldsymbol{S} \end{array} \tag{5.7}$$

For reaching a logistical system unavailability target with a deterministic demand rate, the optimization problem becomes:

$$\begin{array}{ll} \min & \hat{C^{det}}(\mathbf{S}) \\ \text{s.t.} & UA^{det}(\mathbf{S}) \leq UA^{obj} \\ & \qquad S_j \in \boldsymbol{S} \end{array} \tag{5.8}$$

Finally, for reaching a DTWP target with a deterministic demand rate, the optimization problem becomes:

$$\begin{array}{ll} \min & \hat{C^{det}}(\mathbf{S}) \\ \text{s.t.} & DTWP^{det}(\mathbf{S}) \leq DTWP^{obj} \\ & \qquad S_j \in \boldsymbol{S} \end{array} \tag{5.9}$$

Solving the optimization problems in equation 5.7 and 5.8 is done according to the corresponding optimization algorithms in paragraph 4.4.2. Solving the optimization problem in equation 5.9 is done based on the algorithm in Appendix I. For this, the parameters defined for a stochastic demand rate situation have to be replaced with the parameters for a deterministic demand rate situation, e.g. $\beta_i^{sto}(S_i)$ becomes $\beta_i^{det}(S_i)$.

In equation 5.7 we maximize the item fill rate $\beta_i^{det}(S_i)$ by increasing S_i until target β^{obj} is reached. This implies that the formula for $\beta_i^{det}(S_i)$ should be increasing and concave on its whole domain as a function of S_i. As a function of the number of servers, the Erlang loss probabilty is decreasing and strictly convex (Karush, 1957). Accordingly, it can be derived that $\beta_i^{det}(S_i)$ is increasing and concave on its whole domain. Similarly, in equation 5.8 and 5.9 we minimize $UA_i^{det}(S_i)$ and $DTWP_i^{det}(S_i)$ until targets UA^{obj} and $DTWP^{obj}$ are reached respectively. This implies that the formulas for $UA_i^{det}(S_i)$ and $DTWP_i^{det}(S_i)$ should be decreasing and convex on its whole domain as a function of S_i. Based on the Erlang loss probability, it can be derived that this the case. Although, it must be noted that for $DTWP_i^{det}(S_i)$, this only holds if $t_i^{em} \geq t_i^{norm}$.

Stochastic demand rate

Before specifying our model to ASML, we need to determine how to estimate the bounds of the failure rate ranges. As discussed in section 4.1, this can be done directly by experts, Equipment Engineers in case of ASML, or through the demand predicatibility of the parts. For this situation, we argue that the bound estimation through demand predictability of the parts is more accurate, since ASML's product complexity and time to market pressure negatively influences the accuracy of expert judgement. In Appendix D we provide an in-depth spare parts classification with regard to ASML. Accordingly, we identified the following degrees of demand predictability at ASML:

- Lifetime analysis through Weibull analysis (LA)
- Failure rate analysis through Crow-AMSAA analysis (FA)
- Design verification through lifetime test (LT)
- Design specifications (DS)
- "Gut feeling" of Equipment Engineer (GF)

Accordingly, we take the set of degrees of demand predictability $D = \{la, fa, lt, ds, gf\}$, where la denotes lifetime analysis etc. For this set D, we have to identify corresponding values for V_d. We do this be interpreting the characteristics of the degrees of demand predictability d. The quantitative tests and analyses that are performed at ASML always yield certain statistical confidence levels when completed. These confidence levels provide us with a solid indication of the value of corresponding predictability variance. We therefore claim that we can assign a fixed value to the predictability variances V_{la}, V_{fa} and V_{lt}. However, it must be noted that confidence level of the Crow-AMSAA analysis depends on the cumulative machine years the analysis is based on (i.e. the machine age). Basically, the longer the time period the analysis is based on, the higher the confidence level. We therefore evaluated this aspect. However, this evaluation showed that the impact was neglible. With respect to the qualitative assessments by experts, design specifications ds and gut feeling gf, we cannot assign a fixed value for the predictability variances, since the quality of the assessment depends on expertise and devoted time. We will therefore evaluate different values for V_{ds} and V_{gf}.

Another remark we make, with regard to predictability variance, is based on the analysis between the IFR's and current failure rates (CFR's) of ASML's newest DUV system and an EUV system in Appendix F. One of the observations that can be made, according to this analysis, is that the predictability variance depends on the value of the IFR estimation. It indicates that IFR's of a low degree, for example 10^{-5}, have a relatively higher prediction error than IFR's of a higher degree. Therefore we decided to evaluate predictability variance percentage values that depend on the degree of IFR estimation instead of constant percentage values for the predictability variances V_d as defined in chapter 4. We do this for the demand predictability of the qualitative assessments by experts, design specifications ds and gut feeling gf. So, for these degrees of demand predictability, we assign a higher predictability variance for IFR's of degree 10^{-5} than for IFR's of degree 10^{-4} etc. Let DI denote all the degrees of IFR's. Then the IFR-dependent predictability variance is denoted by $V_{d,di}$.

Now that we clarified how failure rate ranges can be determined at ASML, we need to specify our model in chapter 4. The ASML specific model is closely related to our model as described in chapter 4. However, we do need to derive item fill rate $\beta_i^{sto}(S_i)$ for Poisson distributed demand. Similar to $\beta_i^{det}(S_i)$ in equation 5.2, this can be accomplished according to the Erlang loss probability. Since λ_i follows a Beta distribution, $\beta_i^{sto}(S_i)$ is obtained as follows:

$$\beta_i^{sto}(S_i) = \int_{a_i}^{b_i} 1 - \frac{\frac{1}{S_i!}(um_i t_i)^{S_i}}{\sum_{j=0}^{S_i} \frac{1}{j!}(um_i t_i)^j} f_\lambda(u) du = \int_{a_i}^{b_i} \left(1 - \frac{\frac{1}{S_i!}(um_i t_i)^{S_i}}{\sum_{j=0}^{S_i} \frac{1}{j!}(um_i t_i)^j}\right) \frac{\frac{u-a_i}{b_i-a_i}^{\gamma-1}(1-\frac{u-a_i}{b_i-a_i})^{\delta-1}}{B(\gamma,\delta)} du \tag{5.10}$$

Similarly, the average yearly number of stockouts $\alpha_i^{sto}(S_i)$ becomes:

$$\alpha_i^{sto}(S_i) = \int_{a_i}^{b_i} um_i \frac{\frac{1}{S_i!}(um_i t_i)^{S_i}}{\sum_{j=0}^{S_i} \frac{1}{j!}(um_i t_i)^j} f_\lambda(u) du = \int_{a_i}^{b_i} \left(um_i \frac{\frac{1}{S_i!}(um_i t_i)^{S_i}}{\sum_{j=0}^{S_i} \frac{1}{j!}(um_i t_i)^j}\right) \frac{\frac{u-a_i}{b_i-a_i}^{\gamma-1}(1-\frac{u-a_i}{b_i-a_i})^{\delta-1}}{B(\gamma,\delta)} du \tag{5.11}$$

By combining equation 4.17 and 5.11 , the system unavailability $UA_i^{sto}(S_i)$ is given by:

$$UA_i^{sto}(S_i) = \frac{1}{8760} t_i^{em} \int_{a_i}^{b_i} u \frac{\frac{1}{S_i!}(um_i t_i)^{S_i}}{\sum_{j=0}^{S_i} \frac{1}{j!}(um_i t_i)^j} \frac{\frac{u-a_i}{b_i-a_i}^{\gamma-1}(1-\frac{u-a_i}{b_i-a_i})^{\delta-1}}{B(\gamma,\delta)} du \tag{5.12}$$

Finally, we define the DTWP for a stochastic demand rate, which is denoted by $DTWP_i^{sto}$. By the combining the formula in paragraph 5.2.1 and β_i^{sto}, $DTWP_i^{sto}$ can be obtained as follows:

$$DTWP_i^{sto} = \frac{1}{8760}\int_{a_i}^{b_i}\left(ut_i^{em}\frac{\frac{1}{S_i!}(um_it_i)^{S_i}}{\sum_{j=0}^{S_i}\frac{1}{j!}(um_it_i)^j}+ut_i^{norm}\left(1-\frac{\frac{1}{S_i!}(um_it_i)^{S_i}}{\sum_{j=0}^{S_i}\frac{1}{j!}(um_it_i)^j}\right)\right)\frac{\frac{u-a_i}{b_i-a_i}^{\gamma-1}(1-\frac{u-a_i}{b_i-a_i})^{\delta-1}}{B(\gamma,\delta)}du \tag{5.13}$$

Then $DTWP^{sto}(\mathbf{S}) = \sum_{i\in I} DTWP_i^{sto}(S_i)$. The optimization problem for reaching this DTWP target is given by:

$$\begin{aligned} \min \quad & \hat{C^{sto}}(\mathbf{S}) \\ \text{s.t.} \quad & DTWP^{sto}(\mathbf{S}) \leq DTWP^{obj} \\ & \qquad\qquad\qquad S_j \in \boldsymbol{S} \end{aligned} \tag{5.14}$$

Equation 5.10 and 5.12 can now be applied to the optimization problems in equation 4.12 and 4.13, and solved through the corresponding optimization algorithms in paragraph 4.4.2. Equation 5.13 can be applied to equation 5.14 and solved through the optimization algorithm in Appendix I. Furthermore, for the same reason as for our model with a deterministic demand rate, we need to proof that $\beta_i^{sto}(S_i)$ is increasing and concave on its whole domain and $\alpha_i^{sto}(S_i)$, $UA_i^{sto}(S_i)$ and $DTWP_i^{sto}(S_i)$ are decreasing and convex on their whole domain. We provide this proof in Appendix H.

5.3 Base case scenario

Before we discuss the verification and validation of our model in terms of the situation at ASML, we provide the setting of the input parameters that correspond to those for current situation in Taiwan . The replenishment lead times are given in week days. The emergency and normal shipment times are given in hours. In table 5.3 an overview of the input parameters is provided.

Table 5.3: Input parameters for base case scenario

t(days)	t^{em}(hrs)	t^{norm}(hrs)	c^{em}(€)
14	48	1	900

Besides the values in table 5.3, also the settings for predictability variance $V_{d,di}$ need to be determined. For the predictability variance, we look at a low, medium and high uncertainty setting for the demand predictabilities of design specfication and gut feeling.

These settings are denoted by $V_{d,di}^{low}$, $V_{d,di}^{medium}$ and $V_{d,di}^{high}$. The values we set for these parameters are shown in Appendix G. Here, the low uncertainty setting is very optimistic and represents the demand rate uncertainty for the newest DUV volume system. The high uncertainty setting is very pessimistic and represents the demand rate uncertainty for an EUV system. These are derived from the analysis in Appendix F. We argue that the degree of demand rate uncertainty for the systems in Taiwan is somewhere in between these degrees.

5.4 Verification and validation

The purpose of verification is to check whether our model performs as expected. To check this, we apply extreme values to certain input parameters. The approach and results of this verification are showed in Appendix J. This verification shows that setting the predictability variance $V_{d_i} = 0$ for all $i \in I$ is the same as applying the deterministic demand rate model from paragraph 5.2.2. Therefore we will refer to the deterministic demand rate model by $V_d = 0$ in the remainder of this business case.

For the validation of our model, we insert the basestock levels $\mathbf{S}^{tw,NPI}$ into our model with a deterministic demand rate and into our model with a stochastic demand rate with the three different predictability variance settings. We then compare the results with the service measures in table 5.1. For the sake of interpretation of the results, we also compute the expected yearly number of stockouts $\alpha^{sto}(\mathbf{S}^{tw,NPI})$ and the expected yearly demand Λ.

Table 5.4: Outcome variables for current basestock levels in Taiwan (adjusted)

V	$\beta^{sto}(\mathbf{S}^{tw,NPI})$	$DTWP^{sto}(\mathbf{S}^{tw,NPI})$	$UA^{sto}(\mathbf{S}^{tw,NPI})$	$\alpha^{sto}(\mathbf{S}^{tw,NPI})$	Λ
$V_d = 0$	A -3.3%	B +7.5	C +7.3%	2.0	24.1
$V_{d,ifr}^{low}$	A -3.4%	B +8.0%	C +7.6%	2.1	24.3
$V_{d,ifr}^{medium}$	A -3.5%	B +10.6%	C +10.0%	2.5	26.7
$V_{d,ifr}^{high}$	A -3.5%	B +15.3%	C +14.3%	3.1	30.4

Table 5.4 shows that, when the basestock levels $\mathbf{S}^{tw,NPI}$ are inserted into our model, the aggregate fill rate $\beta^{sto}(\mathbf{S}^{tw,NPI})$ is considerably lower that the current aggregate fill rate in Taiwan $\beta^{c}(\mathbf{S}^{tw})$ for all spare parts. Accordingly, the logistical system unavailability $UA^{sto}(\mathbf{S}^{tw,NPI})$ and DTWP $DTWP^{sto}(\mathbf{S}^{tw,NPI})$ are higher. In collaboration with spare part planning experts within the NPL department, it can be evaluated what the reasons are for this difference. The first reason is that the current performance, in terms of the service measures in table 5.1, are derived from ASML's multi-location inventory planning tool.

The calculations in that model differ from the calculations made by our single-location model. However, a more influencing aspect is that we limit ourselves to only evaluating the NPI spare parts of the EUV systems in this business case and not consider the common spare parts for these systems. These common spare parts are included in many other systems and are therefore stocked in higher quantities than NPI spare parts. As a result, these common spare parts have higher item fill rates, which compensates the lower item fill rates of NPI spare parts with respect to the aggregate fill rate.

Table 5.4 also shows that the difference between the service measures for the basestock levels $\mathbf{S}^{tw,NPI}$ and $\mathbf{S}^{tw}$ increases as the demand rate uncertainty increases. This can be explained by looking at the total yearly demand Λ and the expected number of stockouts $\alpha(\mathbf{S})$. The aggregate fill rate represents the percentage of the demand cannot be satisfied directly from stock. However, table 5.4 also shows that the yearly average demand Λ is higher for higher demand rate uncertainty. As a result, less demand can be satisfied from stock with the same aggregate fill rate. So, the expected number of stockouts $\alpha(\mathbf{S})$ increases and the logistical system unavailability $UA^{sto}(\mathbf{S}^{tw,NPI})$ and DTWP $DTWP^{sto}(\mathbf{S}^{tw,NPI})$, but the aggregate fill rate $\beta^{sto}(\mathbf{S}^{tw,NPI})$ stays roughly the same. We elaborate further on this observation when we answer the third business case question in paragraph 5.5.1.

5.5 Results

In the introduction of this business case, we idenitfied three business case questions that need to be answered in order to generate valuable knowldge with regard to NPI spare part stock decisions at ASML. We start with providing and interpreting the results that are required to answer the business case questions. Thereafter, we carry out a scenario analysis, such that we can evaluate the impact of target setting. Finally, we carry out a sensitivity analysis, which provides an understanding of the effect of the input paramaters.

5.5.1 Business case questions

During the validation of our model, several aspects emerged that indicate that the application of our model to this business case slightly differs from the reality at ASML. Therefore we will refer to *improvement potential*, when comparing our model and the current situation is terms of required investment $RI(\mathbf{S})$.

Question 1

In order to answer the first business case question, we need to compare the required investment in spare part for the current basestock levels in taiwan $\mathbf{S}^{tw,NPI}$ and the required investment for the basestock levels that are generated by our model. To properly make this comparison, we evaluate what investments in spare parts are required for our model to attain the same service performance as the current basestock levels $\mathbf{S}^{tw,NPI}$. Since the current basestock levels have been determined according to an aggregate fill rate target, we will evaluate this service performance in terms of aggregate fill rate as well. This implies that, for the optimization problem for the aggregate fill rate in equation 4.12, we set the target β^{obj} equal to $\beta^{sto}(\mathbf{S}^{tw,NPI})$. This is done for every predictability variance setting, for which the corresponding value can be found in table 5.4.

In table 5.5 we show the required investments and saving indications for the basestock levels generated by our model when attaining the same aggregate fill rate as the current basestock levels do. The improvement potential is computed by subtracting the required investments in the second column by the current required investments $RI(\mathbf{S}^{tw,NPI})$ =€53,292.

Table 5.5: Required investment and improvement potential for the basestock levels generated by our model (adjusted)

V	$RI(\mathbf{S})$	$RI(\mathbf{S}^{tw,NPI}) - RI(\mathbf{S})$
$V_d = 0$	€20,456	€32,837
$V_{d,di}^{low}$	€20,872	€32,420
$V_{d,di}^{medium}$	€24,786	€28,506
$V_{d,di}^{high}$	€26,852	€26,440

Table 5.5 shows a high improvement potential for applying our model to make stock decisions for NPI spare parts instead of the current method. It shows that approximately 60,8% can potentially be saved in case of very optimisitc demand rate uncertainty $V_{d,di}^{low}$ and approximately 49,6% can potentially be saved in case of very pessimistic demand rate uncertainty $V_{d,di}^{high}$. By evaluating the basestock levels and characteristics of a sample of parts, the reasons for these differences can be explained. These values are shown in table 5.6

Table 5.6: Current and proposed basestock levels with relevant part characteristics (adjusted)

Part Number	λ_i	c_i^p	d_i	$\mathbf{S}^{tw,NPI}$	$\mathbf{S}^{V_d=0}$	$\mathbf{S}^{V_{d,di}^{low}}$	$\mathbf{S}^{V_{d,di}^{med}}$	$\mathbf{S}^{V_{d,di}^{high}}$
SERV.438.4xxxx	0.01	€0.003	ca	6	4	4	5	5
SERV.662.9xxxx	0.01	€1.370	gf	1	2	2	3	3
SERV.502.3xxxx	1	€5287.366	ca	1	0	0	0	0
SERV.476.2xxxx	0.0001	€7.945	gf	0	1	0	0	1
SERV.476.2xxxx	0.0057	€0.394	lt	1	1	1	1	1
SERV.476.5xxxx	0.0384	€3.600	gf	1	1	1	1	2
SERV.476.2xxxx	0.009	€0.069	gf	1	2	2	3	4
SERV.502.3xxxx	0.0001	€0.343	gf	4	0	1	1	1
SERV.502.4xxxx	0.5	€3678.363	ca	1	0	0	0	0
SERV.662.9xxxx	0.2	€0.073	gf	0	2	3	4	4

These differences are the result of the system approach we apply to our model. Accordingly, expensive spare parts are stocked more in the current situation than proposed by our model. SERV.502.3xxxx and SERV502.4xxxx from table 5.6 are the two most expensive instances of this and therefore substantially contribute to the difference in the required investment. Oppositely, our model proposes higher basestock levels for cheap parts compared to the current situation. Furthermore, based on SERV.662.9xxxx and SERV.662.8xxxx, our model proposes higher basestock levels for cheap parts as the demand rate uncertainty increases. In that case, the demand process constructed by our model expects a higher failure rate. Accordingly, the system approach of our model stocks these parts in higher quantities.

Question 2

For the results to are necessary to answer the second business case question, we will look at the basestock levels $\mathbf{S}^{V_{d,di}^{low}}$, $\mathbf{S}^{V_{d,di}^{med}}$,$\mathbf{S}^{V_{d,di}^{high}}$ and the corresponding required investment $RI(\mathbf{S})$, which were computed for answering question 1. We refer to these as the base case scenario. According to these basestock levels and required investments, we derive the top-10, top-50 and top-100 most expensive parts that are stocked at least once and have the lowest possible demand predictability gf, "gut feeling". For these parts we evaluate the effect of increasing the demand predictability on the required investment $RI(\mathbf{S})$. We do this for the demand predictability of design specifications ds and lifetime tests lt. This basically denotes the effect of extra time being devoted by D&E on extra design specifications or lifetime tests for specific parts. The results for this are shown in table 5.7.

Table 5.7: Required investment for adjusted demand predictability (adjusted)

Scenario	$RI(\mathbf{S}^{V^{low}_{d,di}})$	$RI(\mathbf{S}^{V^{med}_{d,di}})$	$RI(\mathbf{S}^{V^{high}_{d,ifr}})$
Base case	€20,872	€24,786	€26,852
Top-10 specifications	€20,872	€24,542	€26,390
Top-50 specifications	€20,872	€24,121	€25,846
Top-100 specifications	€20,872	€24,010	€25,520
Top-10 lifetime test	€20,872	€24,542	€26,315
Top-50 lifetime test	€20,872	€24,121	€25,793
Top-100 lifetime test	€20,872	€23,853	€25,347

Table 5.7 shows that increasing the demand predictability for the 10 to 100 most expensive parts in case of low demand rate uncertainty has no impact on the required investment $RI(\mathbf{S})$. When this is done for medium demand rate uncertainty, an improvement potential of approximately 0.5% to 1.3% is generated for extra design specifications. For extra lifetime test this is approximately 0.5% to 1.6% . The improvement potential in case of high demand rate uncertainty is the highest. Extra design specifications on 10 to 100 parts generates an improvement potential of approximately 0.8% to 2.5%. In addition, extra lifetime tests on 10 to 100 parts generates an improvement potential of approximately 1.0 % to 2.9%.

Question 3

For the results to are necessary to answer the third business case question, we will look at an aggregate fill rate target β^{obj}, DTWP target $DTWP^{obj}$ and a logistical system unavailability target UA^{obj}. For this, we need to determine the target values for these particular optimization targets. Since we want to evaluate the impact of demand rate uncertainty on the optimization targets, we derive the target values based on our model with deterministic demand rate. Accordingly, we can observe the effect when demand rate uncertainty is increased.

Based on the current performance of the EUV systems in Taiwan, as shown in table 5.1, we decide to set the aggregate fill rate target β^{obj} equal to A. Based on the optimization for this target, we can derive $DTWP^{obj}$ and UA^{obj}. The outcome variables for the optimization of aggregate fill rate target $\beta^{obj} = A$ are shown in table 5.8.

Table 5.8: Outcome variables for the optimization of aggregate fill rate target $\beta^{obj} = A$ (adjusted)

$\beta^{obj} = A$						
V	$\sum \mathbf{S}$	$RI(\mathbf{S})$	$DTWP^{sto}(\mathbf{S})$	$UA^{sto}(\mathbf{S})$	$\alpha^{sto}(\mathbf{S})$	Λ
$V_d = 0$	30.3	€27,611	B -0.4%	C -1.0%	1.2	24.1
$V_{d,ifr}^{low}$	32.2	€28,489	B -0.1%	C -0.7%	1.2	24.3
$V_{d,ifr}^{medium}$	40.7	€35,020	B -0.7%	C -0.1%	1.3	26.7
$V_{d,ifr}^{high}$	44.0	€38,336	B -2.6%	C +1.4%	1.6	30.4

The results in table 5.8 show the same pattern as identified for the validation results in table 5.4: as the demand rate uncertainty increases, the expected number of stockouts $\alpha^{sto}(\mathbf{S})$ increases and therefore the service measures $DTWP^{sto}(\mathbf{S})$ and $UA^{sto}(\mathbf{S})$ decrease. This is because the demand process, that is constructed according to failure rate ranges, expects a higher yearly demand in case of higher demand rate uncertainty. This shows that, in case of demand rate uncertainty, optimization towards an aggregate fill rate target does not consistently attain the system availability that it supposed to attain. This difference increases as the demand rate uncertainty increases.

Since the whole point of service stock is to maximize the system availability, we are interested in the effect of targets for other service measures than the aggregate fill rate. We will evaluate therefore targets for service measures that are related to time instead of demand, which are DTWP and logistical system unavailability. As discussed earlier, we set $DTWP^{obj} = DTWP^{sto}(\mathbf{S}^{V_d=0}) = B - 0.4\%$ and $UA^{obj} = UA^{sto}(\mathbf{S}^{V_d=0}) = C - 1.0\%$, which can be derived from table 5.8. The outcome variables for the optimization of these targets are shown in table 5.9 and 5.10 respectively.

Table 5.9: Outcome variables for the optimization of DTWP target $DTWP^{obj} = B - 0.4\%$ (adjusted)

$DTWP^{obj} = B - 0.4\%$						
V	$\sum \mathbf{S}$	$RI(\mathbf{S})$	$\beta^{sto}(\mathbf{S})$	$UA^{sto}(\mathbf{S})$	$\alpha^{sto}(\mathbf{S})$	Λ
$V_d = 0$	28.7	€26,088	A +0.7%	C -1.0%	1.4	24.1
$V_{d,ifr}^{low}$	31.0	€27,197	A +0.6%	C -1.0%	1.4	24.3
$V_{d,ifr}^{medium}$	41.1	€35,767	A +0.0%	C -1.3%	1.4	26.7
$V_{d,ifr}^{high}$	47.3	€44,722	A -1.0%	C -1.8%	1.4	30.4

Table 5.10: Outcome variables for the optimization of logistical system unavailability target $UA^{obj} = C - 1.0\%$ (adjusted)

$UA^{obj} = C - 1.0\%$						
V	$\sum \mathbf{S}$	$RI(\mathbf{S})$	$\beta^{sto}(\mathbf{S})$	$DTWP^{sto}(\mathbf{S})$	$\alpha^{sto}(\mathbf{S})$	Λ
$V_d = 0$	28.7	€26,088	A -0.7%	B -0.4%	1.4	24.1
$V_{d,ifr}^{low}$	30.9	€27,154	A -0.6%	B -0.4%	1.4	24.3
$V_{d,ifr}^{medium}$	41.1	€34,893	A -0.2%	B -0.1%	1.4	26.7
$V_{d,ifr}^{high}$	47.3	€41,984	A +0.6%	B +0.4%	1.4	30.4

The results in table 5.9 and 5.10 show that a higher aggregate fill rate is required to satisfy the targets for DTWP and logistical system unavailability as the demand rate uncertainty increases. Also this is caused by the higher yearly demand that is expected by the demand processes that are constructed by our model for different degrees of demand rate uncertainty. In conclusion, to reach a higher aggregate fill rate, more stock and therefore higher investments are required.

From tables 5.9 and 5.10 it can also be observed that reaching a DTWP of B -0.4% and a logistical system unavailability of C -1.0%, in case of no demand rate uncertainty, requires the same basestock levels. However, as demand rate uncertainty increases, a difference emerge. For instance, in case of the DTWP target optimization, more stock and investments are required in case of higher demand rate uncertainty. In this case, not just the stockouts $\alpha^{sto}(\mathbf{S})$, but also the parts on stock contribute to the value of this service measure. As demand rate uncertainty increases, less stockouts are allowed to satisfy this target. Accordingly, higher basestock levels and investments are required. Oppositely, for the logistical system unavailability target optimization the number of allowed stockouts remains roughly the same, as only stockouts affect the value of this service measure.

5.5.2 Scenario analysis

In this paragraph we evaluate the effect of values we set for the optimization targets on the required investment $RI(\mathbf{S})$. The values that we assign to the optimization targets are shown in table 5.11. For these comparisons, we will evaluate $V_d = 0$ and $V_{d,di}^{high}$, such that we can observe the effect of demand rate uncertainty.

Table 5.11: Target settings for scenario analysis (adjusted)

Optimization targets	Values
β^{obj}(%) (A +/-)	-5.0, -2.5, +0.0, +2.5, +3.0, +4.0, +4.5, +4.8
$DTWP^{obj}$(%) (B +/-)	+7.5, +2.5, +0.0, -2.5, -5.0, -7.5, 10.0, -11.5
$UA^{obj}(\%)(C+/-)$	+0.5, -2.0, -4.5, -7.0, -7.5, -8.5, -9.0, -9.3

The aggregate fill rate target that are currently set at ASML depend on the service performance that is desired by the customer. Correspondingly, the DTWP and logistical system availability value do as well. It is therefore interesting to see the effect for setting lower and higher targets than in the base case scenario. First we will evaluate the effect on the aggregate fill rate target β^{obj}, which is shown in figure 5.2

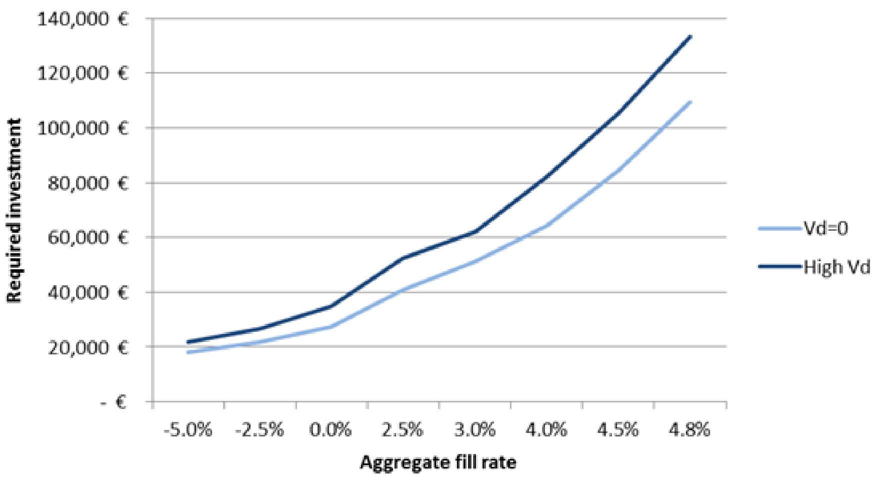

Figure 5.2: Required investment for different aggregate fill rate targets (adjusted)

As figure 5.2 shows, the required investment increases progressively as the aggregate fill rate target β^{obj} is increased in gradually smaller steps. From this it can be seen that a very high extra investment is required to reach a marginally higher system availability when the aggregate fill rate is high already. In that case, the item fill rates for cheap items are very high already, which entails higher fill rates should be reached for expensive parts. It can also be observed that the diffence in investment between the situation with demand uncertainty and known demand becomes slightly larger. This is because the difference between the situation stays the same relatively, but that translates to larger actual differences when the required investments increase to reach a higher target. Next, we look at the same effects for increasing the DTWP target and logistical system unavailability target, as shown in figure 5.3 and 5.4 respectively.

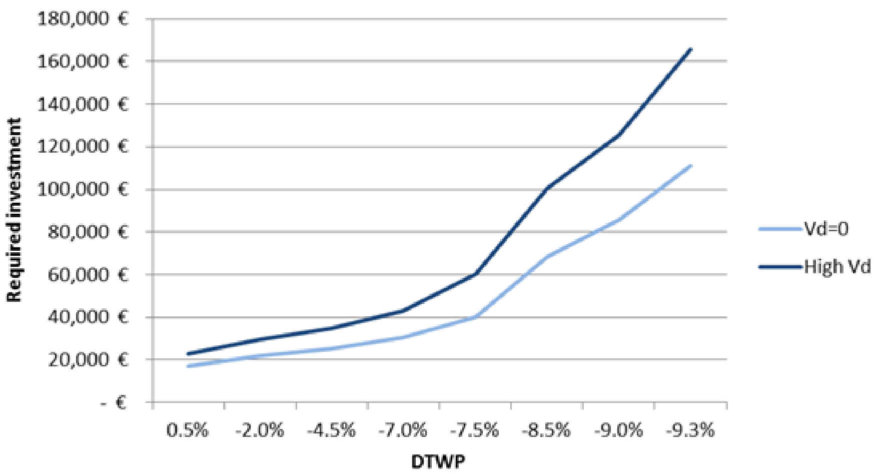

Figure 5.3: Required investment for different DTWP targets (adjusted)

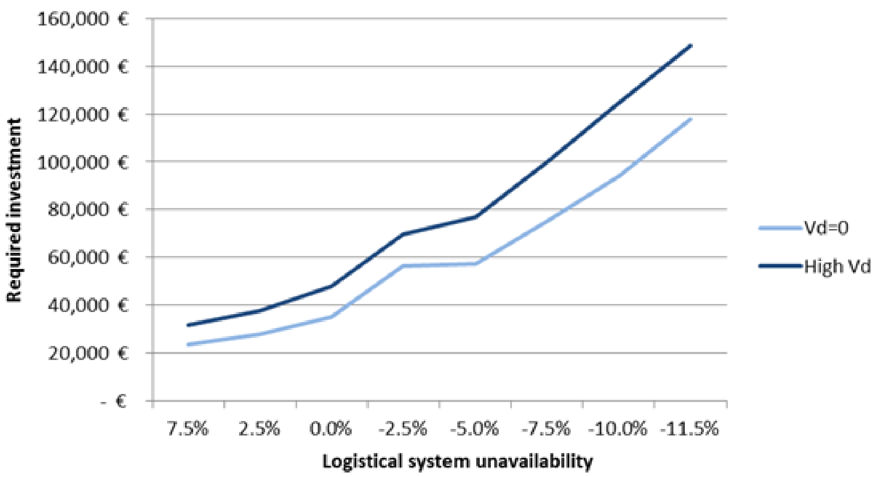

Figure 5.4: Required investment for different logistical system unavailability targets (adjusted)

As figure 5.3 and 5.4 shows, the effects for decreasing the DTWP and logistical system unavailability in graduallly smaller steps is very similar to effects seen for the aggregate fill rate target increase. It also for the same reason that this effect occurs.

5.5.3 Senstivity analysis

The input parameters depend on the location of the warehouse that is evaluated, but are also sometimes unknown for NPI spare parts. Therefore we vary the values for several input parameters values, as given in table 5.3 for the base case scenario. Accordingly, we can examine the effect of the parameters on the required investments $RI(\mathbf{S})$. The values that we assign to the input parameters are given in table 5.12. For these comparisons, we will only evaluate $V_{d,di}^{high}$.

Table 5.12: Input parameter settings for sensitivity analysis (adjusted)

Input parameters	Values
Replenishment lead time t	2,5,8,11,14,17,20,23, 26
Emergency shipment costc^{em}	100, 300,500,700,900,1100,1300,1500,1700
Emergency shipment time t^{em}	8,12,16,20,24,28,32,36,40,44,48

We vary the one of the input parameters or targets, while the rest remains the same. Besides only examing the effect of varying input parameters and target values, we are also interested to see whether differences occur between the optimization targets. Therefore we will evaluate different input parameters for the three different optimization targets at the same time.

Replenishment lead times

In ASML's multi-location inventory network, the replenishment lead time for a local warehouse depends on its location with respect to the global warehouse. Therefore the replenishment lead time for locations in Europe are completely different than those in, for instance, Asia. We are interested to see what kind of effect this has on the required investment. This effect is shown in figure 5.12.

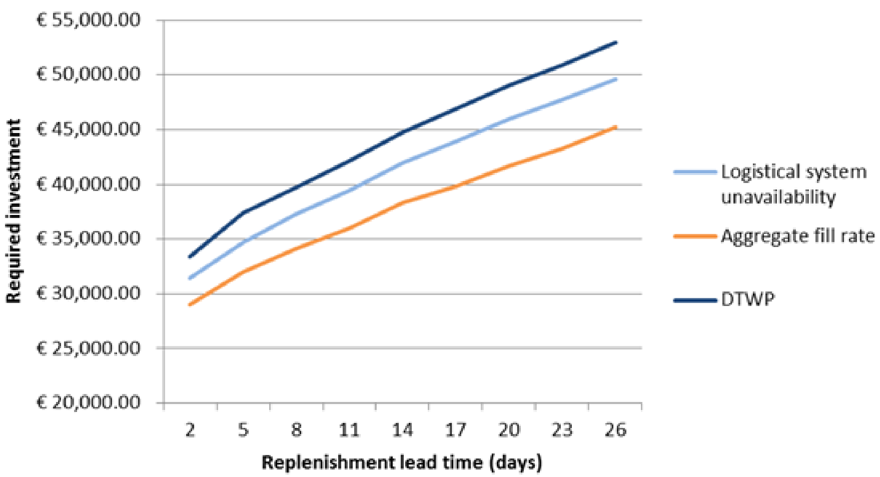

Figure 5.5: Required investment for different replenishment lead times (adjusted)

Based on figure 5.5 we see that as the replenishment lead time increases, the required investment increases similarly for all optimization targets. In case of a small replenishment lead time, a higher item fill rate is realized for a particular basestock level than in case of a large replenishment lead time. In that case, higher basestock levels are necessary to reach the optimization target and therefore higher investments are required.

Emergency shipment time and cost

Also the emergency shipment time and cost depend on the location of the local warehouse, since an intercontential emergency shipment takes more time and is more expensive than a intracontinental emergency shipment. For this reason, we will look at the effect of assiging several values to these input parameters on the required investment for the different optimization targets. This is shown in figure 5.6 for different emergency shipment costs.

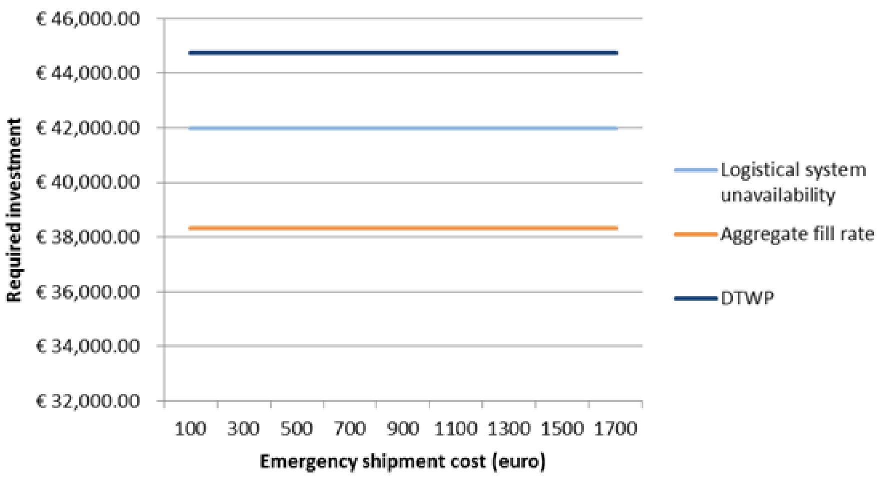

Figure 5.6: Required investment for different emergency shipment costs (adjusted)

From figure 5.6 it can be observed that an increase in the shipment cost does not affect the required investment. If the average yearly cost for all the spare parts is increased by the same amount, the proportions between these costs remain unchanged. Therefore the same biggest bang for buck will be identified everytime a basestock level is increased. Thus this leads to the same final basestock levels. Next, we evaluate the effect of different emergency shipment times.

From figure 5.7 it can be derived that a longer emergency shipment time leads to a higher required investment for reaching a DTWP or logistical system unavailability target. Since these targets directly relate to downtime, emergency shipment time is a decisive facotr. A longer emergency shipment time leads to a longer downtime when a stockout occurs. So in order the reach the DTWP or logistical system unavailability target, less stockouts may occur in case of longer emergency shipment time. Accordingly, this requires

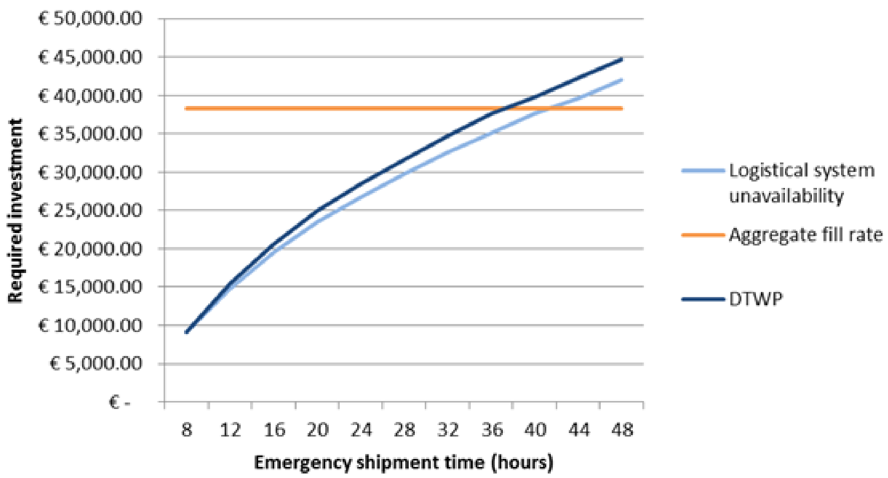

Figure 5.7: Required investment for different emergency shipment times (adjusted)

higher basestock levels and therefore a higher investment. Since the aggregate fill rate is based on demand, reaching this target is not affected by the emergency shipment time.

5.6 Conclusion and applicability for ASML

Within the introduction of this business case, we identified three business case questions to generate valuable knowledge with regard to the NPI spare parts stock decisions at ASML. In this section we answer these business case questions according to the results from paragraph 5.5.1. Furthermore, we will discuss the implications with regard to the applicability at ASML.

Within the validation of our model, we recognized slight differences compared to reality. These are caused because we do not consider common spare parts and we apply a single-location model to a local warehouse in a multi-location network. We therefore answer the business case question in terms of improvement potential. Furthermore, we evaluated low, medium and high demand rate uncertainty. We argue that the actual demand rate uncertainty at ASML is somewhere in between the low and high demand rate uncertainty.

1. *With regard to the required investment in spare parts, what is the difference between applying our model and ASML's current method for NPI spare part stock decisions?*

We applied our model to make stock decisions that yield the same perfomance as is done for the current basestock levels for the NPI spare parts in Taiwan. This showed that our model makes stock decisions that require approximately 49.6% less in case of high demand rate uncertainty and approximately 60.8% less in case of low demand rate uncertainty. This difference is partially caused by very expensive spare parts that are stocked currently and are not stocked by our model. A reason that some of these expensive parts are stocked is that these have political value. In the spare parts classification in Appendix D, we define this political value as the customer desire to have the particular part on stock. Accordingly, we design an appropriate operating policy for these parts in terms of an extension to our model.

2. *With regard to the required investment in spare parts, what is the impact of lowering demand rate uncertainty by increasing the demand predictability of certain NPI spare parts?*

For this analysis, we evaluated the impact on the required investments of carrying out extra design specifications or lifetime tests for the 10 to 100 most expensive parts with IFR's based on gut feeling. When this is done for low demand rate uncertainty, no impact is observed. However, when this is done for high demand rate uncertainty, an additional improvement potential is generated of approximately 0.8% to 2.5% in case of extra design specifications and 1.0% to 2.9% in case of extra lifetime tests. Based on the predictability variance we associate with these degrees of demand predictability, we argue that carrying out extra design specifications is more cost effective, since lifetime tests require more resources to carry out and do not generate a much larger improvement potential. Furthermore, we note that extra design specifications do not impact the NPI spare parts in Taiwan, but also the same NPI spare parts all over the world. This implies that the impact on the required investments for all NPI spare parts worldwide is larger.

3. *In case of demand rate uncertainty, what is the effect of applying a particular optimization target when making NPI spare part stock decisions?*

ASML currently optimizes towards an aggregate fill rate target, the so-called customer service degree (CSD). To evaluate the impact of demand rate uncertainty on this particular target, we also looked at targets for two service measures that directly regard the downtime of a system: DTWP and logistical system unavailability due to stockouts. As demand rate uncertainty increases, optimizing towards to the same aggregate fill rate results into higher system downtime in terms of the service measures DTWP and logistical system unavailability. This implies that the desired system availability is not consistently attained by optimizing towards aggregate fill rate in case of demand rate uncertainty. Since realizing a particular system availability is the purpose of stock decisions, we argue this should be done according to a DTWP or logistical system availability target in case of demand rate uncertainty. However, this requires that the actual downtime in terms of one of these service measures is monitored, such that its performance can be monitored as well.

To realize the improvement potentials that we identified, we developed a decision-support tool that can be utilized within ASML. In the next chapter, we will elaborate on the implementation of this tool, such that the NPL department can generate advices and support their decisions accordingly.

Chapter 6

Implementation

In this chapter it will be discussed how our model, as specified in paragraph 5.2.2, can be implemented as a decision support tool for specific situations within ASML. The decision support tool that we developed is capable of assisting spare parts planners within NPL to take stock decisions for NPI spare parts. Furthermore, it is part of the decision tree that we developed according to the analysis in Appendix D. To clarify on the application of this tool, we will focus on answering the following two questions one by one:

- When can the tool be applied?
- How should the tool be used and maintained?

As the tool represents our model, it supports stocking decisions for multi-item single-location problems. In the conceptual description of our model in chapter 4, we mentioned that our model supports three warehousing situations. However, the only situation that occurs within ASML's inventory network, is the situation of a local warehouse. For this situation, the tool can be applied for support in two ways: basestock level proposal for new machine(s) at a certain local warehouse or adjustment of basestock levels according to new available demand predictability information. In the first case, the latest available IFR's and demand predictability information should be used as input. Furthermore, if basestock levels already have been determined for other machines serviced by that local warehouse, these basestock levels should be taken into account as initial basestock levels in the optimization algorithm in the tool. According to this input, optimal basestock levels will be produced for the new machine(s) at that particular local warehouse.

As NPI spare parts become mature and more corresponding systems are installed, the parts gradually become the same as spare parts for volume systems. This represents the second case in which our tool can be applied. When a considerable amount of new demand predictability information becomes available, adjusted basestock levels can be determined based on a relevant demand rate uncertainty reduction. Within ASML, additional demand predictability information consists of actual part failures and cumulative machine years. However, it is complicated to indicate an exact period during which the amount of this new information is considerable.[1] As this information is monitored by Reliability Engineering, it is necessary for NPL to repeatedly communicate with these engineers within ASML.

Next, we elaborate on how the tool should be used and maintained. The input data can be entered in a pre-formatted MS Excel file, which consists of 2 sheets. The first sheet provides an explanation on how the MS Excel should be taken care of. The second sheet is where the data entering is done. This sheet contains three input sections. The first input section regards the input for the parameters with respect to the part number and price as well as installed base, replenishment lead time, emergency shipment time and cost for a particular location. This data can be retrieved from the enterpise resource planning software SAP. Data on the IFR's and the degrees of demand predictability, if available for the particular part, is entered in section 2 of sheet 2. This available data can be retrieved from the Reliability database (RDB), which is maintained and updated by ASML's Reliability Engineers. Whenever a decision needs to be supported by this tool, it is required to retrieve the updated data from these databases. In the third section, the values of basestock levels are entered that were possibly already determined before the introduction of this decision support tool. When the input is entered in the MS Excel file, it should be saved as a .csv file. Accordingly, a programmed model in R studio produces basestock levels and outcome variables, which are both saved in seperate .csv files.

[1]This has been argued by Reliability Engineers at ASML

Chapter 7

Conclusions and Recommendations

In this chapter, we state the conclusions that can be drawn from this research and provide recommendations for ASML as well as for future research. In section 7.1 we draw the conclusions. Thereafter, in section 7.2, we provide the recommendations.

7.1 Conclusions

In the introduction of this research, we stated that service stock decisions for NPI's of complex capital goods at ASML are subject to many uncertainties. However, in the literature so far, the integral combination of these uncertainties is unexplored. We mainly focused on the demand uncertainty of NPI service stock decisions. We therefore formulated the following research question:

How should ASML make service stock decisions in the early phase of the PLC, while taking into account inventory cost and system availability?

We now address the main research question by anserwing our sub questions and drawing conclusions accordingly.

1. *What are the key factors that complicate ASML's service stock decisions for NPI's compared to these decisions for volume systems?*

In order to gain an understanding of what aspects should be taken into account for decision support for NPI service stock decisions, we carried out an in-depth problem analysis of these decisions with respect to these decisions for mature volume systems.

Radically new technology of NPI's of the lithography systems is one of the major causes for the limited information for the spare parts of these systems. However, this is amplified by a short time to market orientation, which makes generating information on spare parts less important during the product development processes. The most impactful results of this are very inaccurate initial failure rates and incorrect spare parts assortment.

2. *What parameters and variables are useful for service stock decision making in the early phase of the PLC*

One very useful demand parameter is given by the initial failure rate estimation. However, to examine other useful parameters and variables, we classified the spare parts characteristics for NPI's. Based on the this classification, we argue that amongst other characteristics, the demand predictability of spare parts holds valuable information to support service stock decisions. This demand predictability of parts is linked to the presence of lifetime analyses, tests and design specifiations etc. We argue that the demand predictability of a part indicates the initial failure rate estimation of that part. In addition, just like for service stock decisions for volume systems, the part price and emergency shipment time are also relevant.

3. *What are the functional requirements for a model that supports service stock decisions for NPI's of complex capital goods?*

The functional requirements represent the objectives for the design of a model that supports service stock decisions for NPI's. The first functional requirement is taking into account the demand rate uncertainty of the NPI spare parts, such that excess and obsolescence risk of NPI spare parts is reduced and the desired system availability is achieved. This implies that the model must be capable of satisfying a particular target against minimum costs in case of demand rate uncertainty. A second functional requirement is taking into account that NPI's become mature and its installed base increases as time progesses. This implies that over time, the demand predictability of a part increases and thus the demand rate uncertainty of a part decreases to the degree similar to the demand rates for volume systems.

4. *What decision model supports determining stocking quantities of spare parts for NPI's of complex capital goods?*

We used the multi-item, single-location inventory model by van Houtum and Kranenburg (2015) and extended this by applying failure rate ranges instead of ordinary failure rates, such that demand rate uncertainty for NPI spare parts is incorporated. Basically, the higher the demand rate uncertainty, the wider the failure rate range is. These failure rate ranges are derived from the most likely, most optimistic and most pessimistic value of the failure rate for a part. The latter two values can be either obtained directly from experts or derived through the demand predictability of the spare parts and the corresponding IFR. In addition, we developed a model that optimizes towards an aggregate fill rate target and one that optimizes towards logistical system unavailability due to stockouts.

5. *What are the implications of the current way service stock decisions for NPI's are made at ASML?*

Currently the NPL department applies a manual classification method for their stock decisions for NPI spare parts. To examine the implications of this approach, we evaluated the spare parts stock decisions for the NPI's in Taiwan. Applying our model to attain the same service perfomance as the current stock for NPI spare parts in Taiwan, shows an improvement potential of approximately 49.6% to 60.8%, depending on the actual demand rate uncertainty at ASML. If D&E carries out extra design specifications on 10 to 100 expensive parts with high demand rate uncertainty, this uncertainty is reduced and an additional improvement potential is generated. For only Taiwan, a maximum improvement potential of 0.8% is realized if done for 10 parts and 2.5% if done for 100 parts.

NPI stock decisions are currently made based on an aggregate fill rate target (i.e. CSD). However, in case of demand rate uncertainty, this target does not consistently attain the service performance that it is supposed to achieve in terms of system availability. We conclude that, to consistently achieve the desired system availability, targets should be set for DTWP or logistical system unavailability due to stockouts.

6. *How should ASML apply the decision support model for NPI spare parts stock, such that certain system availability can be attained while taking account the incurred cost?*

For our multi-item, single-location inventory model with demand rate uncertainty, a tool has been developed that can be applied by NPL planners to support their spare part stock decisions for when a new machine needs to be serviced or extra demand information becomes available. This can be done by following to the decision tree in Appendix D.

7.2 Recommendations

We present the recommendations for ASML and the recommendations for future research in this section.

7.2.1 Recommendations for ASML

Implementation of the decision-support tool: Because of the importance of system availability of the NPI's at the customer and the corresponding stock investment, ASML should search for optimal values of their basestock levels of the spare parts of these systems. In this research, a multi-item, single-location inventory model has been developed that takes into account the demand rate uncertainty for NPI spare parts, such that the required investment in these spare parts can be minimized. By using the decision-support tool that has been developed accordingly, this search for optimal basestock levels can be supported whenever a new machine needs to be serviced or a considerable amount of new demand information becomes available.

CSD target: This target corresponds to the aggregate fill rate target in our model. During the business case it was concluded that an aggregate fill rate target in the presence of demand rate uncertainty does not consistently attain a desired system availability. As the demand rate uncertainty increases, the difference between desired and achieved system availability increases as well. In order to consistently attain the desired system availability when making NPI spare parts stock decisions, it is recommend to apply a target that is directly to the system's downtime. For this, our tool supports the optimization towards a DTWP target or a target for logistical system unavailability due to stockouts

Extra spare part demand analyses, tests and assessments: In our business case we showed that lowering demand rate uncertainty by carrying out extra design specifications generates a maximum improvement potential of 0.8% is realized if done for 10 parts and 2.5% if done for 100 parts. However, since the demand rate uncertainty reduction applies to the other local warehouses as well, this improvement potential is even larger in reality. So even though engineers within D&E are under the pressure of short time to market, it is strongly recommended to allocate more resources to increasing the demand predictability of expensive NPI spare parts by carrying out extra analyses, tests and assessments.

NPI spare parts control characteristics: For all the NPI spare part control characteristics that have been identified during our in-depth spare parts classification, it is argued that these require appropriate operating policies. These control characteristics and corresponding operating policies are adopted in a decision tree (Appendix D). It is recommended to apply this decision tree when spare parts stock decision need to be made, as it improves the effectiveness of the decision-making.

7.2.2 Recommendations for Future Research

Multi-location extension: In this research, we developed a multi-item, single-location inventory model to support service stock decisions for NPI's. However, if these decisions have to be made worldwide and for regions of warehouses, better decision support is provided by a multi-item, multi-location inventory model and the generated improvement potential is more accurate. Therefore it is recommended to extend our model to a model that supports the multiple locations within ASML's inventory network integrally.

Failure rate range determination: A considerable body of research has been done on the beta distribution in a PERT scheduling application, especially in terms improving the approximations of the distribution parameters. However, the PERT scheduling application is not the same as the application of resource usage. Improving the approximations of the distribution parameters under this application, improves the constructed demand process by our model. It is therefore recommended to examine this. Furthermore, we recommend to evaluate to how to improve the accuracy of the estimates for the most optimistic and most pessimistic value by making use of demand predictability of the parts. In this way, more accurate estimates are generated than when these are directly provide by Equipment Engineers.

Obsolescence risk of NPI service stock decisions: As mentioned in the introduction of this research, we have not taken into account the obsolescence risk that comes along with making NPI spare parts stock decisions. However, because spare parts represent high investments, obsolete inventory can be very costly. It is therefore recommended to examine how obsolescence risk should be taken into account in the search for optimal basestock levels of NPI spare parts.

Relaxation of Poisson demand assumption: For the ASML specific model, an assumption has been made that can possibly be relaxed for the sake of potential improvement of the model. This assumption that the demand process following a Poisson distribution. It could be interesting to see the effect when the demand follows another distribution.

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Appendix A

List of Abbreviations

BOM	Bill of materials
CFR	Current failure rate
CSD	Customer service degree
DOA	Dead on Arrival
D&E	Development & Engineering
DTWP	Downtime waiting for parts
DUV	Deep ultra violet
EC	Engineering change
EUV	Extreme ultra violet
FMEA	Failure more effect analysis
GLS	Global logistics services
IC	Integrated circuit
IFR	Initial failure rate
KD	Key Decision
NPI	New product introduction
NPL	New Product Logistics
OEM	Original equipment manufacturer
PGP	Product generation process
PLC	Product life cycle
RDB	Reliability database
SKU	Stock keeping unit
USD	Unscheduled down

Appendix B

List of Variables

a_i	Lower bound of failure rate range
$\alpha^{det}(S_i)$	The average number of stockouts for SKU i in case of a deterministic demand rate
$\alpha^{det}(\mathbf{S})$	Average yearly number of stockouts for all SKU's in case of a deterministic demand rate
$\alpha^{sto}(S_i)$	The average number of stockouts for SKU i in case of a stochastic demand rate
$\alpha^{sto}(\mathbf{S})$	Average yearly number of stockouts for all SKU's in case of a stochastic demand rate
b_i	Upper bound of failure rate range
$\beta^{det}(S_i)$	The fill rate for SKU i in case of a deterministic demand rate
$\beta^{det}(\mathbf{S})$	Aggregate fill rate in case of a deterministic demand rate
$\beta^{sto}(S_i)$	The fill rate for SKU i in case of a stochastic demand rate
$\beta^{sto}(\mathbf{S})$	Aggregate fill rate in case of a stochastic demand rate
c_i^{em}	Emergency shipment cost for SKU i
c_i^{h}	Holding cost rate for SKU i
$\hat{C}_i^{det}(S_i)$	Total yearly average costs for SKU i
$\hat{C}^{sto}(\mathbf{S})$	Total yearly average costs for all SKU's together
$DTWP^{det}(S_i)$	DTWP for SKU i in case of a deterministic demand rate
$DTWP^{det}(\mathbf{S})$	DTWP for all SKU's in case of a deterministic demand rate
$DTWP^{sto}(S_i)$	DTWP for SKU i in case of a stochastic demand rate
$DTWP^{sto}(\mathbf{S})$	DTWP for all SKU's in case of a stochastic demand rate
γ	Shape parameter of Beta distribution
Γ	Greedy ratio for Greedy algorithm
D	Set of degrees of demand predictability
d	Index of demand predictability of $D \in d$
δ	Shape parameter of Beta distribution

$f_d(x, \lambda)$	Density function of demand process with failure rate parameter λ
$f_\lambda(x)$	Density function of the Beta distribution of the failure rate range
i	Index of SKU $I \in i$
I	Set of SKU's
λ	Failure rate
$\lambda^{initial}$	Initial failure rate estimation
Λ	Total yearly demand in spare parts
m	Installed base at customer
$\hat{\mu}$	Estimation of Beta distribution mean
$RI(\mathbf{S})$	Required investment in spare parts
$\mathbf{S}$	Vector of basestock levels for SKUs $i \in I$
S_i	Basestock level for SKU i
$\hat{\sigma}^2$	Estimation of Beta distribution variance
t	Replenishment lead time
$UA^{det}(S_i)$	Logistical system unavailability due to waiting time for SKU i in case of a deterministic demand rate
$UA^{sto}(S_i)$	Logistical system unavailability due to waiting time for SKU i in case of a stochastic demand rate
$\beta^{det}(\mathbf{S})$	Logistical system unavailability due to waiting time for all SKU's in case of a deterministic demand rate
$\beta^{sto}(\mathbf{S})$	Logistical system unavailability due to waiting time for all SKU's in case of a stochastic demand rate
V	Set of predictability variance values
V_d	Predictability variance for demand predictability d
$V_{d,di}$	Predictability variance for demand predictability d, where the value depends on the height of the initial failure rate

Appendix C

In-depth analysis of Complicating Factors of Service for New Product Introductions

In this Appendix we provide an in-depth analysis of the complicating factors of service stock decisions for the NPI's within ASML. Besides that this problem is unexplored in the literature, it is not fully clear within ASML either. Therefore this analysis provides valuable knowledge with regard to the research assignment as well as additional understanding of the problem for ASML.

We carry out this analysis by comparing the service stock decisions of NPI's with those for volume systems. We therefore start with providing a short introduction of service stock decision-making for volume systems in section C.1. Subsequently, we describe the complicating factors of this for NPI's in section C.2. Finally, we construct a Cause and Effect diagram that represents the entire problem.

C.1 Service Stock Decisions for Volume Systems

This section is concerned with describing the service stocking of volume systems at ASML and thus generating an insightful background for the next section. To enable determining the basestock levels of the global warehouses, emergency hubs, continental warehouses and local warehouse integrally, Van Aspert (2015) decomposed the network of warehouses of ASML into two segments: the field stock planning and the global warehouse stock planning. This decomposition is incorporated into one planning model under the name of SPartAn, which stands for Spare Parts Analyzer. The underlying SPartAn process is depicted in figure C.1.

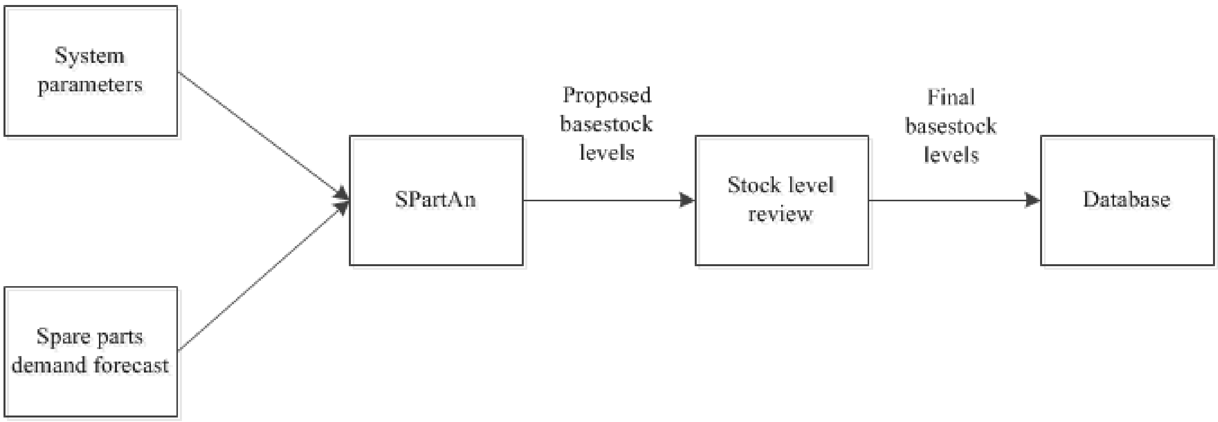

Figure C.1: SPartAn process

To properly make a spare parts stock planning, reliable forecasts of the spare parts demand are fundamental.The forecasting methodology that ASML utilizes for this is based on a Exponential moving average of every quarter for the last three years. This implies that the forecast is based on the last 12 quarters of demand data with decreasing weight. Thus forecast F_t for quarter t can be formulated as follows:

$$F_t = \alpha \times (Y_{t-1} + (1-\alpha) \times Y_{t-2} + (1-\alpha)^2 \times Y_{t-3} + ... + (1-\alpha)^{12} \times Y_{t-12})$$

where Y_t can be obtained by:

$$Y_t = \frac{Usage\ Q_t}{Installed\ Base\ Q_t}.$$

For most volume systems the formula can always be applied over 12 quarters of data. However, it should be noted that for newer systems it is likely that there is no usage for 12 quarters yet. In that circumstance, an initial failure rate (IFR) can be applied as well, which is estimated by an Equipment Engineer. So in case of a new system, the forecast of these parts is based on this initial failure rate and the available demand date so far. Then gradually, as more usage occurs and the installed base life increases, the forecast is increasingly based on actual usage.

C.2 Complicating factors of New Product Introduction Service Stocking

The discussion in this section is based on multiple extensive interviews with ASML employees that are involved with the problem complexity, such as Equipment Engineers, Reliability Engineers and NPL employees. For a more clear explanation, the discussion revolves around four topics. In paragraph C.2.1 we evaluate the impact of radically new technology. In paragraph C.2.2, we look at what complicating factors are caused by a short time to market orientation. In paragraph C.2.3, we examine the effect of service tools. Finally, in paragraph C.2.4, we mentioned several specific complicating factor. Moreover, if possible, several descriptive statistics are provided based on data from ASML databases to support the discussions within the categories.

The content of this section and more specific issues regarding the problem are represented in a Cause and Effect diagram, which is shown in section C.3. It summarizes the discussion in this section and clearly shows how the issues and effects are related to each other.

C.2.1 Radically New Technology

As aforementioned, ASML pays a lot of attention to its breakthrough technology based on EUV. As it is a radically new technology, the development of systems carrying this technology is very complex for the D&E department. However, according to this, also several complicated issues emerge for service stock decisions. These issues are elaborated in this paragraph.

Within ASML' s lithography systems, the distinction is made between specific and common parts. Here, common parts are defined as parts that are also included in older generation sytems. As redesigns of EUV systems are very large, it mainly contains specific parts instead of common parts. Therefore commonality between several systems is very low. Overall, technical information on commonality between particular parts is very useful to determine how usage within different capital goods affect demand (Driessen, Arts, van Houtum, Rustenburg and Huisman, 2015). This implies the opportunity to derive spare parts demand information from older generation systems is limited.

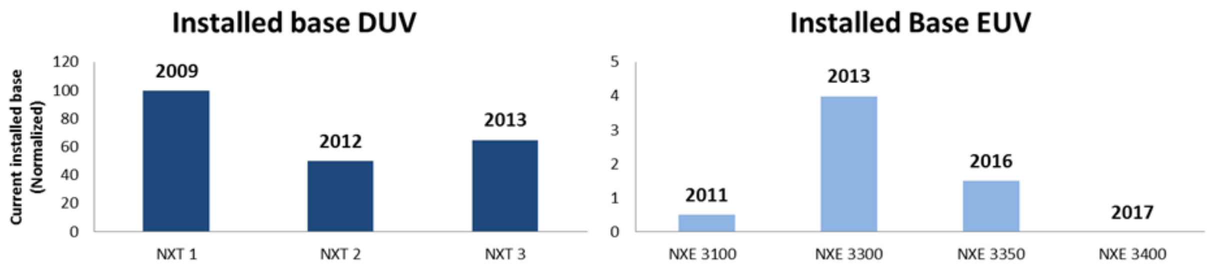

Figure C.2: Installed base of ASML's latest DUV and EUV systems (Normalized)

Another implication of EUV being a radical new technology is that the installed base of EUV systems is very small and young (see Figure C.2, with the years of introduction on the bars). This limits the available spare parts demand information and negatively affects the accuracy of the IFR estimations. In case historical demand data is lacking, standard forecasting techniques cannot be applied (Fortuin, 1984), as is done for volume systems. Since the quality of the proposed stock levels by SParTan greatly depends on reliable usage forecast, the application of the estimated IFR's for NPI's in SParTan yields very unreliable results. This complicates making service stock decisions for these parts.

EUV as a radically new technology also influences the suppliers of the parts, the EUV-technology requires parts that are also radically new for a substantial amount of suppliers. Besides coping with development challenges, other business aspects of these parts are complicated for these suppliers as well. An instance of this is the part price. The first part price indications provided by the part supplier are occassionaly inaccurate and parts might be subjected to uncertain scale benefits. Another uncertainty is generated by the new buy lead time of the part. If a supplier has to manufacture a part for the first time, the new buy lead time is inaccurate. Similarly to new buy lead time uncertainty, is the repair time uncertainty. Because EUV is a new technology, many unknown failure modes occur in case of part failure. If a supplier has to repair a part for the first time, they are possibly unfamiliar with the failure mode of that part failure. Also these inaccuracies complicate the service stocking decision making for NPIs. Because suppliers are more familiar with DUV system parts, this uncertainty occurs to a much smaller extent.

Besides the supplier, also ASML is unfamiliar with these failure modes and as a result, mistakes are made frequently during the diagnostics phase of a service action. This implies that parts are replaced because of different reasons than actual part failure. For instance, these reasons can be replacement for diagnostics or suspected failures. ASML registers these as parts failures, even though these parts have not failed because of machine load. This means that the historical failure information does not fully represent the reasons for corrective maintenance. So in addition of the historical failure information being scarce, it is also unreliable, which harms the quality of the initial failure estimations. For volume systems, ASML is more familiar with the failure modes, which causes less uncertainty in the service stocking decision making.

The last implication of EUV being a radically new technology lies with the customer. Customer orders are not fully confirmed in the early phase of the PLC. A reason for this is that a customer only confirms an order if its convinced of the machine capabilities. So if a trial period on a similar machine yields satisfactory results, the order of a new is confirmed. If not, the order is postponed. Resultanlty, the installed base in the early phase is not certain in terms of timing, quanities, locations and configurations of machines. Not knowing these logistical aspects evidently complicates the service stocking decision making for the machines for unconfirmed orders. As customers are already conviced of the capabilities of ASML's volume sytems, this is not complicated for the service stocking of these systems.

C.2.2 Short Time to Market

For the lithography systems with the new EUV technology, time to market is vital, since chips of the newest generation represent an exponentially higher value than their predecessors (Stein, 2012). Thus it often leads to a substantial competitive advantage. Even though this partially applies to the DUV technology as well, the focus for those systems is more on quality. But with profitablity and a good market position as big upsides, this short time to market orientation has many organizational disadvantages. These will be discussed in this paragraph.

Because of the short time to market orientation within ASML, the D&E department mainly focuses on achieving high machine performance in a short time. As a result, other important aspects of capital goods development, such as machine availability, are at risk of receiving less attention. Just like for volume systems, D&E engineers construct an IFR. This is mainly based on available lifetime analyses, lifetime tests and design specifications. However, due to the time pressure, several important aspects of this IFR estimation are deficident and this significantly lowers the quality of these estimations. This entails that the resources for lifetime testing are limited. In for instance the aviation and car industry, extensive life testing is a liablility due to safety issues of persons. However, this applies to the lithography industry to a much smaller extent. Time constraints also limit the ability to do lifetime analyses. These analyses can be done in several ways. For instance, failure data can be utilized to do a Crow-AMSAA analysis or a Weibull analysis. Lifetime analysis can also be done qualitatively. One way this is done at ASML, is through design specifications during the detailed design phase of the parts. Another example is Failure Mode Effect Analysis (FMEA). This is a useful way to identify failure modes of specific parts. However, also qualitative lifetime analyses require a lot of time and effort to yield accurate results. So because of the time to market orientation, these analyses can only be done for a collection of spare parts.

Besides the available information, the risk of less focus on machine availability also affects the method that is applied for IFR estimation. Time pressure and unequal project resource allocation cause that different estimation approaches are being applied by the Equipment Engineers within the different D&E projects. In addition, no generic estimation approach has been defined. However, based on the available information, every Equipment Engineer indicates their confidence in their IFR estimation. They provide a subjective indication of the confidence of the estimation in form of Guess, Medium and High.

Another implication of the time to market orientation for the EUV technology is a continuously changing system design. As discussed before, the innovation and diffusion of ASML's lithography system overlaps considerably. This combined with ASML's design principles lead to a large amount of EC's. As can be derived from the diagram in Appendix E, the EC process is lenghty and cross-sectional. Moreover, it shows that the NPL department is involved in this process fairly late and therefore the extent of the EC is ambiguous untill completion of the EC. This implies that a NPI spare parts planner does not know whether the part in dispute will be obsolete in the near future or not.This together with the large amount of EC's leads to stock decisions that cause inventory obsolescence. For the mature volume systems, EC's are only implemented if the improvement increases a strict threshold. Resultantly, there are much less EC's in that circumstance and inventory obsolescence is less of an issue.

GLS and D&E are completely different departments and as a result, mutual understanding of each other's processes and procedures is lacking. One of the results of this is that D&E is not completely familiar with the logistical consequences of decisions they make. This combined with time to market pressure, leads to the risk of less focus on service BOM identification and documentation, which negatively affects the correctness of the service BOM. The first issue that occurs according to this is that, when initial stock decisions are supposed to be taken, the service BOM wrongly represents the configuration of the machine as designed . This implies that several spare parts and service tools in the service BOM are redundant or missing. So with uncertainty in the set of stock keeping units (SKUs), the initial stocking decisions are much more complicated. Another service BOM-related issue is the misidenitifaction of spare parts. During the translation of the machine BOM to the service BOM, several machine parts are wrongly identified as spare part. Moreover, it also ocassionally occurs that machine parts are not identified as spare parts while those should have been. Also this leads to uncertainty when stocking decisions need to be made. Due to less time to market pressure, the service BOM is of much higher quality and accordingly, the issues are not significant for service stocking of volume systems.

C.2.3 Service Tool Complexity

Both spare parts and service tools are required to solve costly machine downtime. This applies to both volume systems as NPI's. However, service tools and spare parts are being planned separately for both types of systems. This paragraph describes why this planning is done separately and what the effect of this is, with emphasis on NPI's.

When deciding on a stocking location and quantity of spare parts, it is known beforehand that this spare part is only used during one breakdown. This is in contrast with service tools. Namely, after solving a breakdown, a service tool undergoes one of the following steps:

- Return to warehouse
- Shipment to another machine that requires maintenance
- Shipment to another machine that needs to be installed
- Calibration and certification and a local or continental warehouse

This implies that there are multiple demand types for service tools. In addition, service actions require multiple different types of tools. This complexity is one of the reasons that spare parts and service tools are being planned separately by ASML. This is an issue for volume systems as well as NPI's. However for NPI's, this complexity is not the only reason. Another reason is that the relationship between all the spare parts and service tools is frequently not defined for NPI' s. This is partially caused by delayed completion of service procedure definition. A service procedure can be described as the way in which particular spare parts needs to be replaced using which service tools. Before such a service procedure can be defined properly by D&E, the service tool design should be finalized and tested. Because service tools are frequently used by personnel, these have to satify certain safety requirements. This means that the testing of those service tools can be lengthy, which delays the service procedure definition. Another cause for the undefined relationship is poor alignment between spare parts and service tools databases in terms service procedures.

Conclusively, complex differences between spare parts and service tools combined with frequently ambiguous spare parts and service tools relationships, cause that ASML plans their spare parts and service tools separately for volume systems as well as new product introductions. "Whenever tools and parts are considered separately, a separate target must be set for both, which leads to suboptimization that negatively impacts the service level" (Vliegen, 2009). This implies that the DTWP might be longer when spare parts and service tools are planned separately. This finally leads to a higher system unavailablity due to logistical operations.

C.2.4 Specific Complicating Factors

Several factors that complicate service stocking for NPI's are quite specific and cannot be catergorized into topics. However, these factors still have a huge impact on the complicatedness. These factors are elaborated in this paragraph.

Within ASML, many mistakes are made in the configuration of the NPI systems at the customer. However, at this location ,service engineers do not always have the resources that are necessary for administration of their work, such as internet connectivity and time. As a consequence, the administration of the machine "configuration-as-maintained" at a particular customer is not always correct. An issue that arises is that machine configurations, according to the administration, contain a failed part and its replacement part. Another issue is that customer-specific configuration differences are not documented properly. As a result of these issues, spare parts and service tools are stocked in the wrong location. The same mistakes are made for volume systems, but these are less detrimental. Because of the large installed base of volume systems, stocking spare parts and service tools in the wrong location can be dealt with more easily.

Political influences can be seen as another complicating factor. Political influence can be defined by strategical choices that always overrule the proposed stock levels by SParTan to satisfy part specific customer desires. For instance, among many others, this can be caused by so-called Dead on Arrivals (DOA's). These can be defined as spare parts that are ordered to carry out a service action, but arrive in a dysfunctional state. In several cases, this is unacceptable for the customer and therefore demands that it will never happen again by stocking more than required. Another cause for political influences is the customers'perception of specific machine parts. For these parts customers always insist upon certain stocking decisions. As the causes are random, it is hard to expect what the customer influence will be with regard to the spare part stocking. For volume systems, this influence is even greater. In those cases, more DOA's have occured and the customer understands the machine better.

Besides influencing customer desires, DOA's directly influence the system availability. If an ordered spare parts arrives in a dysfunctional state, the service action cannot completed. Consequently, a new spare part has to be ordered and this means a longer time down time. Similarly, spare parts unexpectedly break during a service action. Accordingly, a new spare part has to be ordered, which leads to additional machine unavailability.

The last complicating factor is that the supplier input on failure insights of the part they developed is limited. The first reason for this regards the supplier's knowledge about the context of use. Especially when a part is ASML specific and/or mechanical, the failure insights is hard to figure out in a short time frame. For example for electronical parts, suppliers can derive an indication by examing the components individually. Another reason is knowledge protection. Several ASML suppliers do have some failure insights available, but do not want to share this information.

C.3 Cause and Effect Diagram

The Cause and Effect diagram, that can be constructed according to the discussion in the previous section, is shown in figure C.3.

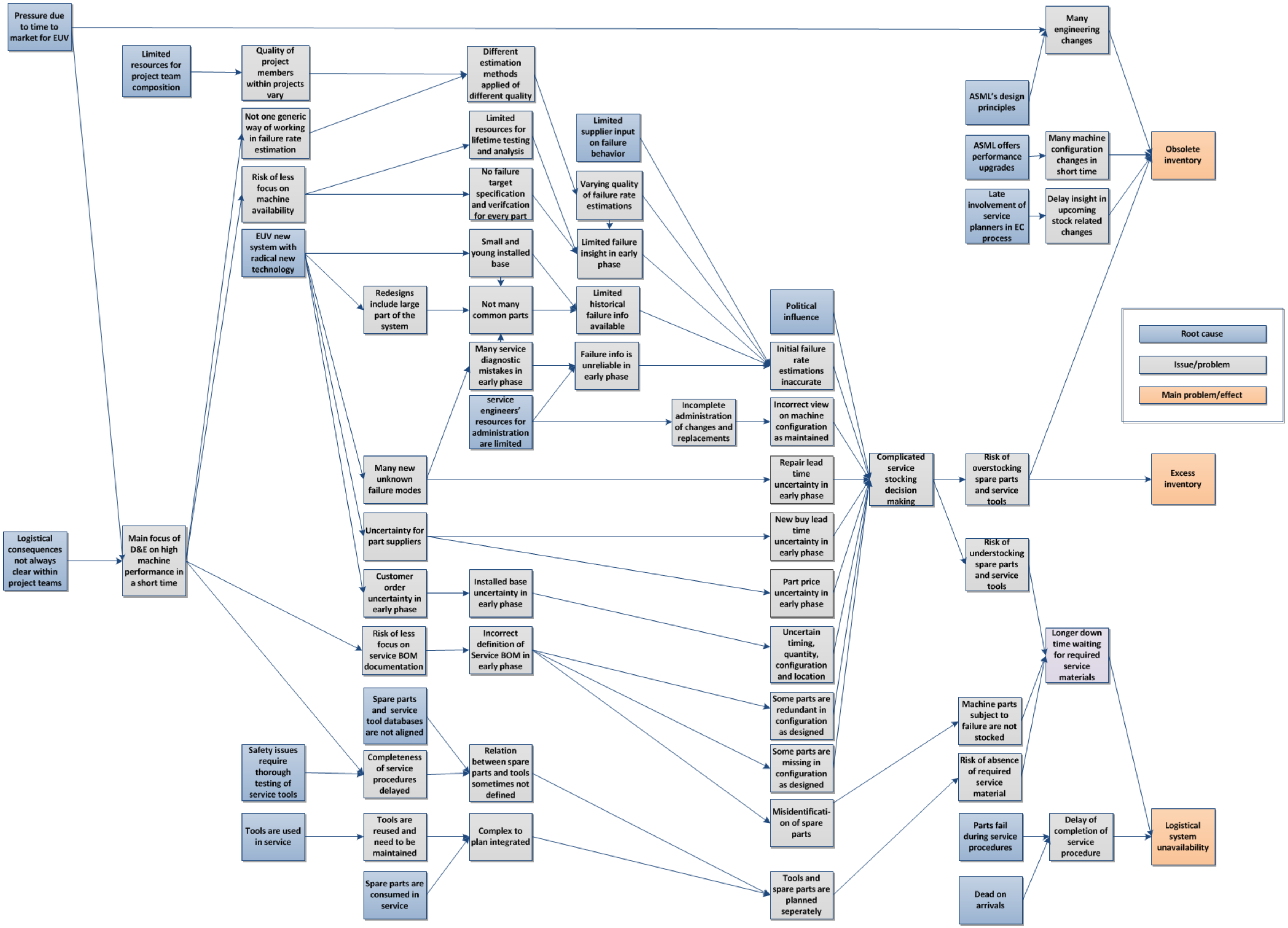

Figure C.3: Cause and Effect diagram

Appendix D

In depth classification of spare parts characteristics

In Appendix C we pointed out that many factors cause the spare part stocking for NPI's of complex capital goods to be highly varied and uncertain. That is why "a classification of spare parts is helpful to determine service requirements for different spare parts classes, and for forecasting and stock control decisions" (Bacchetti & Saccani, 2012). Furthermore, it clarifies on all the available information for NPI spare parts. Therefore, this section will concern the analysis and classification of the spare parts characteristics for NPI's of complex capital goods. The discussion in this Appendix is based on multiple extensive interviews with ASML employees that are involved with the NPI spare parts complexity, such as Equipment Engineers, Reliability Engineers and NPL employees.

We will first select an appropriate classification framework and classify the spare parts characteristics according to this framework. This is done in section D.1. Thereafter, in section D.2, we elaborate in what way we take the spare parts characteristics into account with regard to development of our model. In section D.3, we provide extensions to our model for several spare parts characteristics. Finally, in section D.4, we provide a spare part stocking decision tree that adopts all identified spare parts characteristics and shows how spare part stock decisions should be made.

D.1 Analysis and classification

In their work, Bacchetti and Saccani (2012) summarized the literature on classification methods for spare parts according to various categories. For this, they evaluated the employed classification criteria as well as the applied classification techniques. As this evaluation provides a complete overview of all methods, we can identify the spare parts classification method that best suits the stock control of new product introduction spare parts by carefully assessing each method.

The cause and effect diagram in Appendix C shows that many factors complicate the spare parts stock decisions for NPI's of the complex capital goods. This entails that multiple classification criteria are required such that sp all complicating factors. Based on these complicating factors, a criterium regarding demand uncertainty is essential. Another important feature to look at is the classification technique that needs to be applied. The discussion in chapter 3 pointed out that the information with regard to the spare part characteristics is entirely based on expert knowledge because demand data for new spare parts is absent. As quantitative classification methods considerably rely on this data, we choose to apply qualitative classficiation method. By taking the required features of the classification method into account, the method proposed by Huiskonen (2001) is considered to be the most extensive and therefore we follow the particular method.

The purpose of the study by Huiskonen (2001) is "to analyze the different development requirements and opportunities for the logistics management of a large variety of maintenance spare parts". For this, he argues that it is required to analyze various control characteristics of spare parts and design appropriate operating policies for relevant combinations of these control characteristics. This is achieved by evaluating the effects of different control characteristics on the constituting elements of a logistics system design. This method is represented in Figure D.1.

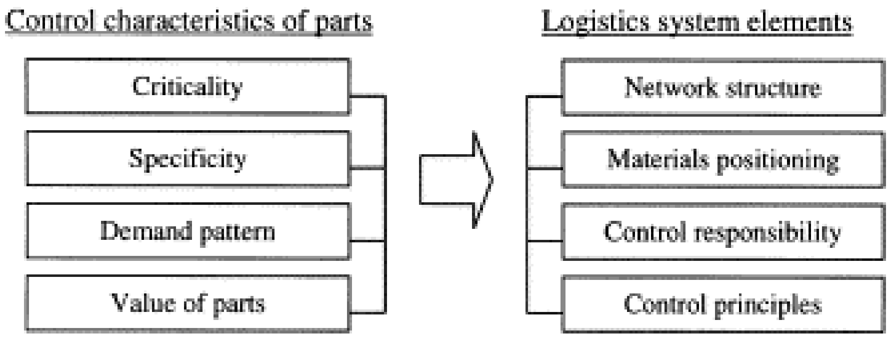

Figure D.1: Spare parts classification framework (Huiskonen,2001)

To keep the development work of a logistical system manageable, Huiskonen (2001) limits the classification criteria to the most distinctive ones: criticality, specificity, demand and value. So the NPI spare parts control characteristics are categorized based on these criteria. Accordingly, the corresponding effect on the logistics system elements will be evaluated.

D.1.1 Criticality

Following Huiskonen (2001), process criticality is related to the consequences of a part failure when a spare part is not readily available. When applying this to ASML's lithography systems, the impact of failures can be looked at from a system availability perspective and from a service perspective.

When looking at process criticality from a system availability perspective, the consequence of failed part depends on the failure mode, which can be defined as the reason for failure. A failure mode can either lead to downtime of the entire system, to degraded performance of the system or to remaining functionality of the system. When relating this to the framework in figure D.1., this mainly affects the materials positioning in the inventory network. These impacts on the materials positioning can be described as follows:

1. In case of downtime of the entire system, the spare part(s) should be positioned in a local warehouse such that it can be supplied immediately and the failure can be corrected.
2. In case of degraded performance, for a short period of time a failure can be tolerated. Meanwhile, the spare part(s) can be supplied from a continental or local warehouse.
3. In case of remaining functionality, the failure can be corrected and the spare part(s) can be delivered after a significant amount of time from a continental or even global warehouse.

When evaluating process criticality from a service point of view, the consequence of a part failure also depends on the position of the component in the lithography system. The total repair time of a failure consists of failure diagnosis, part extraction, part replacement, system re-assembly and system recovery. Especially the time required for part extraction depends heavily on the position of that part in the system. For ASML's EUV systems, this extraction time ranges from a couple of minutes to half a week. Since the part extraction needs to be completed before part replacement can be started, the required part extraction time is equal to the tolerable arrival time of the required replacement part. So with regard to the framework in Figure D.1 , the position of the component in the system also influences the materials positioning in the inventory network. These impacts can be described as follows:

1. In case the extraction time is significantly smaller that the continental shipment time, the part is required to be stocked locally to avoid long downtime.
2. In case the extraction time significantly exceeds the continental shipment time, the part can be stocked in a continental warehouse to create pooling benefits.

D.1.2 Specificity

Within the specificity category, Huiskonen (2001) makes the distiction between user-specific and standard parts. Based on these two subcategories, the expert knowledge in the early phase of spare parts control can be classified with regard to criticality.

User-specific components

Following Huiskonen (2001), user-specific components are specifically manufactured parts that are only used by particular users, which is the case for the majority of the components within ASML's lithography systems. He argues that, in contrast to standard components, suppliers are unwilling to keep stock these special and low volume parts. This implies that the responsibility of availability and control should be the result of the user' s initiative. The PGP shows that ASML recognizes this responsibility. In this process, Key Decision 10, the spare part stocking decision, ASML takes into account that the supplier lead time of these components is considerably large. Accordingly, Key Decision 10 is planned to be taken 6 months before the shipment of the system is planned. Based on the framework in figure D.1, this mainly affects ASML's inventory control principles. Besides supply complexity, user-specific component can also lead to service complexity. Several user-specific components within ASML lithograpy system are complex to such a degree, that for the repair of those components a specialized production engineer has to be flown in from one of the production facilities. Similar to the effect of long part extraction times, this also impacts the materials positioning in the inventory network.

Standard components

Standard components can be defined as parts that are widely utitlized by many other users and therefore also widely available on the market. Examples of these parts are simple electrical components (e.g. switches, sensor and lightning) and simple mechanical components (e.g. chains and bearings), but also bulk materials such as screws. These parts are readily available from various suppliers and therefore require other control principles.

D.1.3 Demand Pattern

The demand pattern of parts includes the aspects of volume and predictability (Huiskonen, 2001). As discussed in the literature review by Doumen (2016), the aspect demand predictability is a substantial issue for spare parts for NPI's. This can also be observed from the discussion in Appendix C and the corresponding cause and effect diagram. In this the volume and predictability of demand patterns for NPI spare parts.

Demand predictability

"Predictability of demand is related to the failure process of a part and the possibilities to estimate failure patterns and rates by statistical means" (Huiskonen, 2001). From a control perspective, parts can be divided into parts with a predictable wearing pattern and parts with random failures.

With regard to parts with a predictable wearing pattern, preventive replacements can be executed at the moment that a certain degree of wearing is exceeded (Kranenburg & van Houtum, 2015). Based on ASML' s lithography systems, this wearing pattern can be predicted beforehand or monitored through system conditions software within the systems. The predictors for this pattern specifically depend on the technical characteristics of the part. For instance, some parts are damaged by continuous exposure to a particular temperature and some parts wear due to a particular amount of production cycles. Because failures can be predicted, the required replacements can be scheduled in advance. This significantly affects the control principle of provisioning these spare parts. Based on the wearing characterstics, Reliability Engineers can indicate the appropriate time period for time-phased planned maintenance.

With regard to parts subjected to random failures, the demand predicitability is much more complicated, especially for spare parts for new product introductions. As Fortuin (1984) argues, historical demand data for spare parts in its initial life cycle phase cannot be obtained yet or is very limited. This is also concluded in the discussion in chapter 3 and Appendix C. In case historical demand data is available for a part or its predecessor, Reliability Engineers are enable to apply two types of analyses. The first of these two is a Weibull analysis. For many mechanical and electronic components, the failure rate function has a bathtub shape (Xie & Lai, 1996). They claim that in practice Weibull distributions proved to be very flexible in modelling lifetime distributions like the bathtub curve. This bathtub curve and its implication are represented in figure D.2.

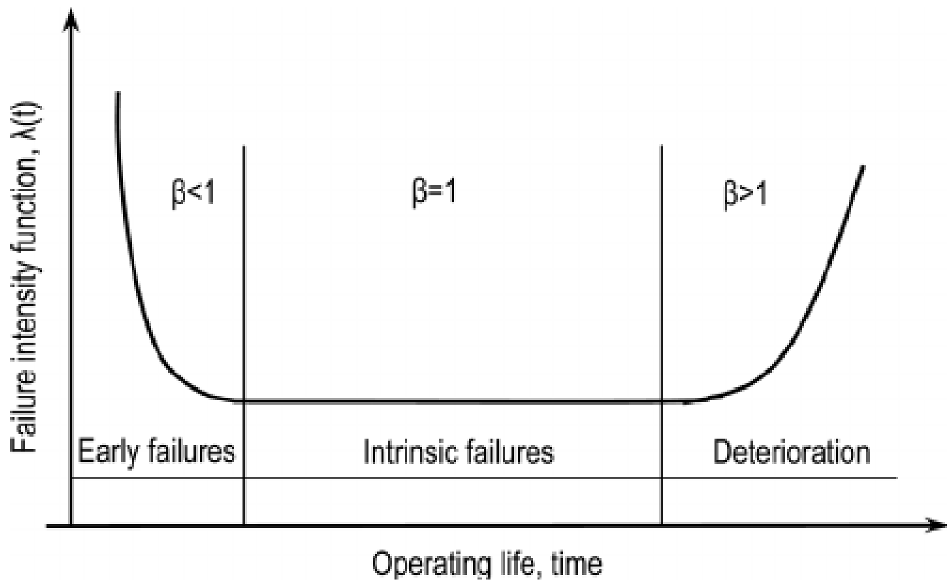

Figure D.2: The bathtub curve (Xie & Lai, 1995)

The failure rate intensity function $\lambda(t)$ is presented by equation $\lambda(t) = e^{-(\frac{t}{\eta})^{\beta}}$. Here η denotes the characteristic life, which is the lifetime at which 63% of the population failed, and β denotes the Weibull slope parameter. As shown in figure E.3, the value of the Weibull slope parameter β can be interpreted as a particular failure origin. For instance, if $\beta < 1$, the failures of those parts are (mostly) early failures, also called infant mortalities.

The parameters of the failure rate intensity function can be estimated based on a given set of failure time data. So based on the estimated beta parameter, it can be interpreted when the majority of the failures will occur.

The second type of analysis Reliability Engineers at ASML apply when failure data is available, is the Crow AMSAA model, which is based on the work by Crow (2004). He distinguishes reliability growth models between test-fix-test models, in which corrective actions are incorporated during tests of the particular product, and test-find-test, in which corrective ations are delayed until the end of tests of the particular product. Crow (2004) combines these models into a test-fix-find-test model. The application of this model enables to generate reliability growth information, such as a failure rate. As ASML does have a considerable test phase within their product development process, Reliability Engineers apply this model to the first years of the field operation phase. Resultantly, they are able to estimate failure rates based on failure time data. The difference between Weibull analysis and the Crow AMSAA model is that Weibull analysis approaches failures from a lifetime perspective and Crow AMSAA from a reliability perspective.

In case demand data for spare parts or its predecessors are absent, failure insights have to be obtained differently. Based on the part design, insights on failure intensities can be generated as well. During the design specification phase, a System Architect, a Function Owner and Project lead devise specifications from several perspectives which has to be satisfied by the part's performance. They do this for the most important parts in the module they are responsible for. One of these specification perspectives is availability and therefore they also specify a failure rate target. If later in the design process this failure rate target seems to be exceeded, the design choices are assessed and verified based on their feasibility. This is done according to a lifetime test.

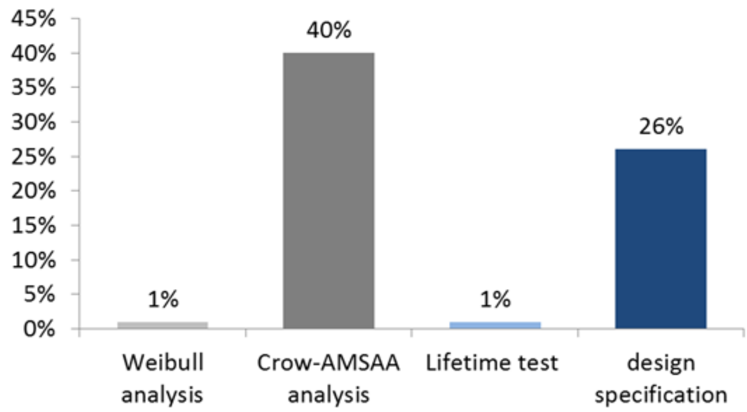

Figure D.3: Demand predictability information at ASML

Figure D.3 shows the percentage of parts for ASML EUV systems that have information on the types of analyses, tests and specifications described above. From this can be derived that not all parts have information on these analyses, test and specifications. However, these parts also require initial failure rate estimations. In this situation, an Equipment Engineer can contact the supplier of the part for their estimates. But due to customer-specificity of ASML parts and time to market pressure, their estimates are often inadequate. Another option is the"gut feeling" of the Equipment Engineer and his/her colleagues. Based on their expertise, the product type, the product materials and the context of use of the part, they provide an estimation accordingly.

For ASML, the demand predictability impacts the accuracy of the initial failure rate estimations. In chapter 4, we discuss how this impacts the demand and the material positioning in the inventory network in terms of stock control decisions. Conclusively, ASML's degrees of demand predictability can be listed as follows:

- Weibull analysis
- Crow-AMSAA analysis
- Lifetime test
- Design specification
- "Gut feeling"

Demand volume

Huiskonen (2001) recognizes that among spare parts there is typically a large amount with very low and irregular demand. This also applies to ASML's NPI spare parts. The reason for this can be best explained according to the bathtub model represented in figure D.2. One of ASML's design principles aims for designing a part such that the deterioration phase starts later than at least 7 years of operating lifetime. In addition, they focus on minimizing the "random" intrinsic failures, which depends on production quality, robust design for unforeseen overstress and human errors in system use and maintenance. So these aspects receive a lot attention during ASML's Product Generation Process. However, these type of failures cannot be excluded completely. This, therefore, influences the control principles and material positioning within the logistics system of ASML. Inventory for parts like these can be kept very low and can be placed in a more central location.

D.1.4 Value of parts

The value of a part is a very commonly used characteristic for classifying spare parts. However, in the context of ASML, value can be defined in two ways: monetary and political value.

Monetary value

Huiskonen (2001) argues that a high monetary part value forces the different parties within the chain to find other solution than holding these parts on stock. However, ASML' s lithography system are not entirely make-to-order items, which implies that stocks have to be held within the chain. This requires adjusted solution in terms of materials positioning in the inventory network. For high monetary value parts, it is too costly to stock in all local warehouses. That is why it is more cost effecient to stock these in a more central location. For low monetary value parts, this is the contratry.

Political value

As discussed in Appendix C , several spare parts have a particular political value that is driven by customer expectations and desires in terms of stock. Meeting these expectations and desires positively influence customer satisfaction and therefore are essential to be met from a senior management point of view. This entails that meeting these expectations and desires overrule any other perceptions on the part with regard to the elements in the logistics system. For instance, if an optimal spare parts stocking plan suggests particular basestock levels, these can still be adjusted accroding to the customer expectations and desires. So in terms of the framework in figure D.1, a different control principle is applied when parts have a high political value, which leads to adjusted materials positioning.

D.2 Modeling of spare parts control characteristics

In section D.1 we classified the control characterics for the NPI spare parts at ASML. According to Huiskonen (2001), operating policies for a combination of relevant control characteristics of spare parts have to be designed appropriately. Therefore we need to elaborate how we consider these characteristics in our research and whether we design approriate operating policies or not. An overview of the type of consideration within our research is provided in table D.1.

Table D.1 shows that a considerable amount of the characteristics are considered in the development of the decision support tool. It also shows that no appropriate operation policies non-critical failures and predictable wearing are designed in this research. In the next section, we define extensions to our tool that represent the operating policies for the remaining characteristics.

Table D.1: Overview of spare parts characteristics and type of consideration within research

		Type of consideration		
Category	Control characteristic	Decision support tool	Extension to tool	Out of scope
Criticality	Critical failures	X		
	Non-critical failures			X
	Part extraction time		X	
Specificity	User-specific parts	X		
	Common parts	X		
	Service specialist requirements		X	
Demand pattern	Predictable wearing pattern			X
	Random failures	X		
Value of parts	Monetary value	X		
	Political value		X	

D.3 Model extensions for spare parts characteristics

In section D.2 we indicated in what way we consider the identified NPI spare parts control characteristics in our research. Several of these are considered in terms of extensions to the decision support tool we develop in chapter 4 and 5. In this section, we desribe these extensions.

D.3.1 Political value parts

As mentioned before, basestock levels for parts with political value can be overruled because of customer desires with regard to stock. This implies that a particular basestock level S_i is desired and thus finding the optimal basestock level for those parts is not necessary. These can be set before the start of the optimization process according to what the customer desires. Let $I^{pol} \subseteq I$ be the subset of all SKUs that have a political value. Then $S^{pol} = (S_1, \ldots, S_{|I|})$ for all $i \in I^{pol}$. This vector can then be added to the initial basestock vector. For instance, step 1 in the optimization problem for a logistical system unavailability target then becomes:

Step 1

1. Set $S^{pol} = (S_1, \ldots, S_{|I|})$ for all $i \in I^{pol}$

2. $S_{(i,min)} := argminC_i^{sto}(S_i)$ for all $i \in I \setminus I^{pol}$.
3. Set $S_i = S_{(i,min)}$ for all $i \in I \setminus I^{pol}$
4. $\mathbf{S} = (S_{1,min}, \ldots, S_{|I|,min}) + S^{pol}$
5. $\boldsymbol{E} := \{\mathbf{S}\}$.
6. Compute $C^{sto}(\mathbf{S})$ and $UA^{sto}(\mathbf{S})$

D.3.2 Specialist service requirements and large part extraction time

A substantial amount of parts require an extraction time that exceeds the continental shipment time. Similarly, several other parts require a specialist for carrying out the repair action, for whom the arrival time exceeds the continental shipment time. Both these spare part control characteristics influence the material positioning in a multi-location inventory network. By stocking these parts continentally instead of locally, these parts do not cause any extra downtime. In addition, because a continental warehouse serves other warehouses and/or more customers, pooling benefits are generated.

Let t_i^{ex} denote the required extraction time of SKU i and t_i^{con} denote the continental shipment time of SKU i. Also, let $I^{long} \subseteq I$ be the subset of all SKU's that have a longer extraction time than the continental shipment time:

$$I^{long} = \{I | t_i^{ex} > t_i^{con}, \forall_i \in I\}$$

Similarly, let t_i^{spec} denote the required travel time for the service specialist to get to the customer site. Also, let $I^{spec} \subseteq I$ be the subset of all SKU's that have a longer service specialist travel time than the continental shipment time:

$$I^{spec} = \{I | t_i^{spec} > t_i^{con}, \forall_i \in I\}$$

Now that I^{long} and I^{spec} have been defined, we need to elaborate how stock decisions should be made for these sets of spare parts. SKU's $i \in I^{long}$ or $i \in I^{spec}$ still should be generally included in the optimization problem of our single-location model with demand rate uncertainty. However, after applying the single-location model to a local warehouse and generating the proposed basestock levels, the basestock levels S_i for SKU's $i \in I^{long}$ and SKU's $i \in I^{spec}$ can be allocated to the nearest continental warehouse. In this way these parts still contribute to the service perfomance in the local warehouse and pooling benefits for the rest of the multi-lcation inventory network are created.

D.4 Decision tree for NPI spare part stock decisions

In this section we provide the decision tree that should be applied when making NPI spare part stock decisions. It contains takes into account all the spare part characteristics that were described in section D.1 and indicates what operation policy should be applied. In this decision tree a hierarchy of the operating policies is incorporated. This implies that particular operating policies overrule others.

Before we show this decision tree, we elaborate on how it should be interpreted. One starts with a particular spare part and answers the questions that are asked in the decision tree. If the answer to a particular question is yes, one carries out the corresponding operating policy according to which the stock decision is made. Next, this is done for another spare part and so on.

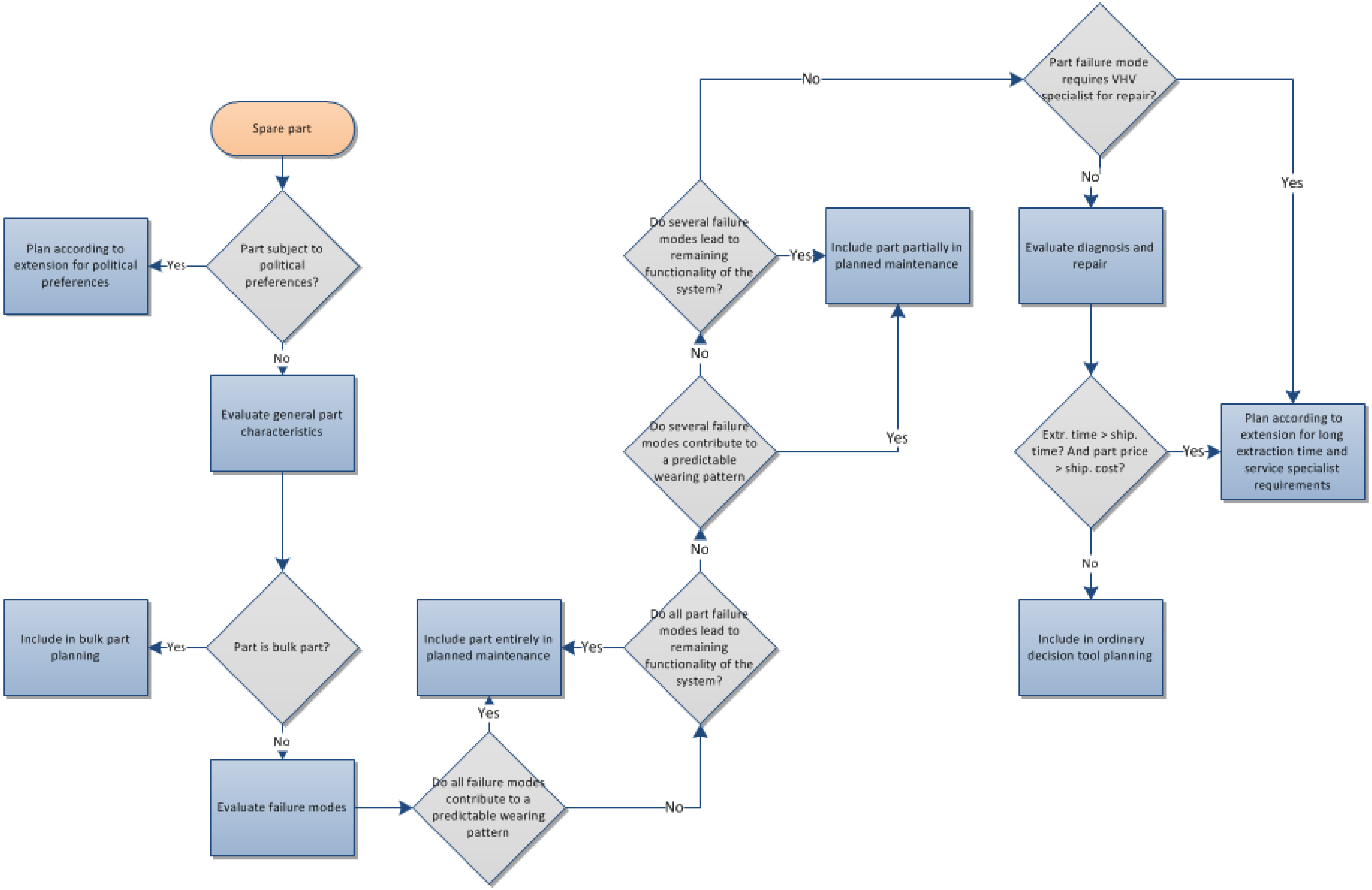

Figure D.4: Decision tree for NPI spare part stock decisions

Appendix E

EC-process

In this Appendix we provide a swimming lane diagram that represents the EC-process from a NPL point of view. This diagram is shown in figure E.1.

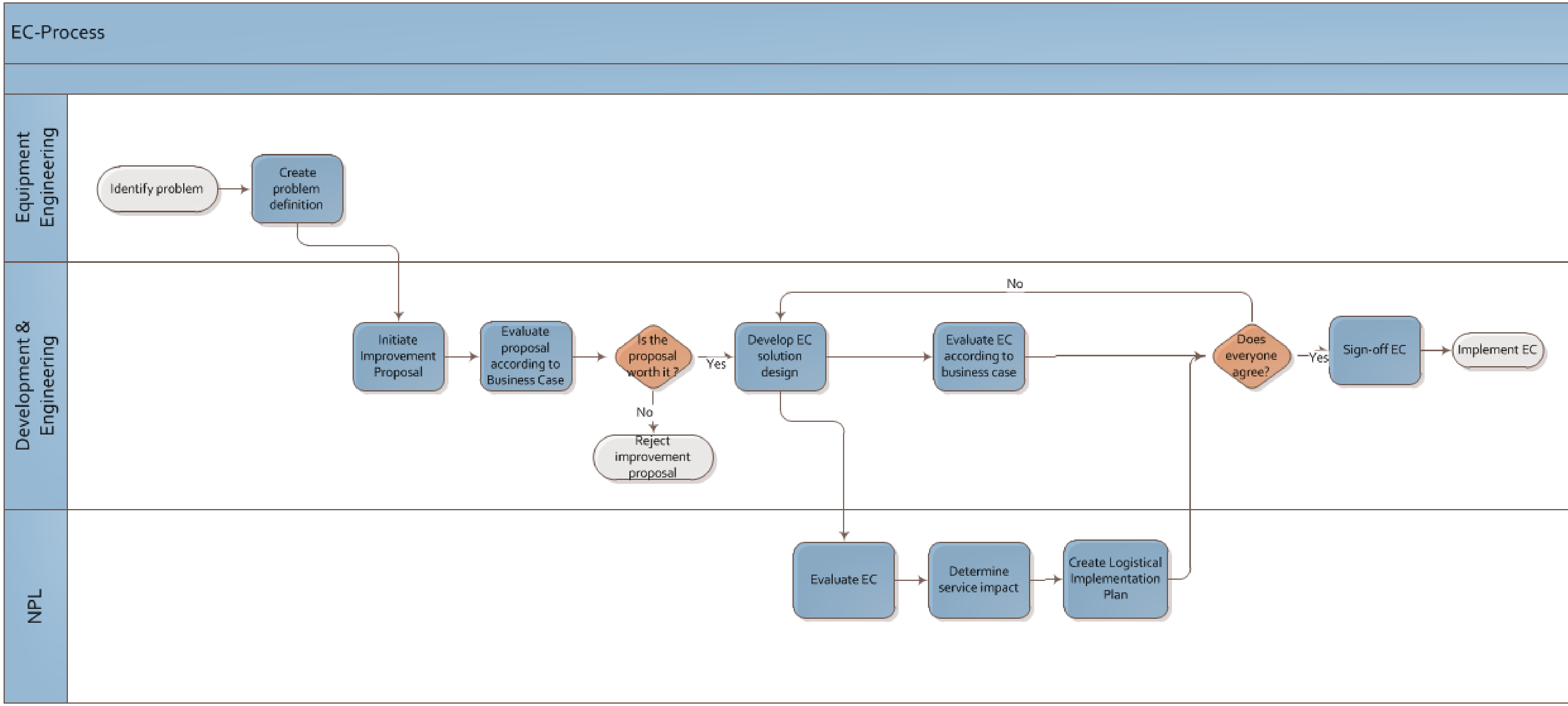

Figure E.1: EC-process

Appendix F

Analysis of initial and current failure rates

This Appendix shows the analysis of the initial and the current failure rate of the newest DUV system and an EUV system. This analysis suits three purposes:

- To confirm the presence of demand uncertainty
- To see on which type of system the demand uncertainty is the greatest
- To support the failure rate range determination

First we analyze how the failure rates changed over the year, which is represented in table F.1. Let $\lambda_{initial}$ denote the initial failure rate and $\lambda_{current}$ denote the current failure rate. The results in table F.1 tell us that approximately 75% of the initial failure rates is overestimated. As hardly any initial failure rates remain the same, 25% of the initial failure rates is underestimated.

Machine	$\lambda_{initial} = \lambda_{current}$	$\lambda_{initial} > \lambda_{current}$	$\lambda_{initial} < \lambda_{current}$
DUV	1%	73%	26%
EUV	0%	75%	25%

Table F.1: Initial failure rate vs. current failure rate

Next, we are interested in to what extent the initial failure rates changed for both the machines. For this we compare the average initial failure rate $\bar{\lambda}_{initial}$ and the average current failure rate $\bar{\lambda}_{current}$. We also generate the Mean Squared Error (MSE) and the Mean Absolute Error (MAE). Finally, we carry out a one-sided, two-sample t-test to see whether there is a significant difference between $\bar{\lambda}_{initial}$ and $\bar{\lambda}_{current}$.

Table F.2. shows that for the DUV machine the current failure rates are significantly lower than the initial failure rates. This does not apply to the EUV machine failure rates.

			Statistical measures		
Machine	$\bar{\lambda}_{initial}$	$\bar{\lambda}_{current}$	MSE	MAE	t-test
DUV	0.0495	0.0153	0.0583	0.0434	0.0019
EUV	0.1424	0.1379	0.8772	0.2067	0.4359

Table F.2: Statistical measures of comparisons

However, table F.2 shows that the errors between the initial and current failure rates are much higher than for the DUV machine, which implies higher demand uncertainty.

Finally, we are interested how much the initial failure rates changes in terms of a factor (i.e. how many times higher or lower). With overestimated initial failure rates, we know that these can become only one factor lower, as failure rates cannot be negative. Therefore, we only evaluate the factors for underestimated failure rates. The results are shown in table F.3.

		Height of initial failure rate						
Machine	Measure	E-6	E-5	E-4	E-3	E-2	E-1	E+0
DUV	Min	-	-	3.2E-1	1.6E-2	3.0E-3	1.1E-1	-
	Max	-	-	2.8E+2	9.5E+0	1.0E+1	5.0E-1	-
	Mean	-	-	3.0E+1	2.2E+0	1.8E+0	3.7E-1	-
EUV	Min	7.4E+4	1.3E+2	1.4E+1	2.5E+0	2..4E+0	4.0E-2	1.7E+0
	Max	8.5E+5	1.3E+4	5.7E+3	8.6E+2	1.4E+3	2.2E+2	1.7E+0
	Mean	2.8E+5	4.4E+3	8.5E+2	1.1E+2	2.2E+1	1.1E+1	1.7E+0

Table F.3: Differences for underestimated initial failure rates

The major conclusion that can be drawn from table F.3 is that the height of the factor depends on the height of the initial failure rate estimation. Furthermore, it can be observed that the factors for the DUV machine are considerably lower than those for the EUV machine. This observation can be explained according to the actual failures that occur. In case an actual failure occurs, this has a larger impact on a failure rate was estimated as low initially than on a high IFR.

Appendix G

Settings for predictability variance

In section 5.3 it was discussed that we examine three different settings for the predictability variance. These settings will be provided in this Appendix. We determine the settings for the IFR-dependent predictability variance, based on the results in Appendix F. By taking into account the amount of overestimated and underestimated failure rates, but also the factors from table F.3, we establish predictability variance settings $V_{d,ifr}^{low}$, $V_{d,ifr}^{medium}$ and $V_{d,ifr}^{high}$. These are shown in table G.1, G.2 and G.3. Here, $V_{d,ifr}^{low}$ to demand rate uncertainty for the DUV machine and $V_{d,ifr}^{high}$ corresponds to the demand rate uncertainty for the EUV machines.

Table G.1: Low IFR-dependent predictability variance setting

	Height of IFR					
Demand predicatiblity d	E-5	E-4	E-3	E-2	E-1	E+0
Weibull analysis	0.05	0.05	0.05	0.05	0.05	0.05
Crow-AMSAA	0.10	0.10	0.10	0.10	0.10	0.10
Lifetime test	0.10	0.10	0.10	0.10	0.10	0.10
Design specification	25	10	2	1	0.50	0.25
Gut feeling	200	50	3	1.5	1	1

Table G.2: Medium IFR-dependent predictability variance setting

	Height of IFR					
Demand predicatiblity d	E-5	E-4	E-3	E-2	E-1	E+0
Weibull analysis	0.05	0.05	0.05	0.05	0.05	0.05
Crow-AMSAA	0.10	0.10	0.10	0.10	0.10	0.10
Lifetime test	0.10	0.10	0.10	0.10	0.10	0.10
Design specification	50	25	5	2.5	1	0.50
Gut feeling	1500	500	50	12.5	2.5	1

Table G.3: High IFR-dependent predictability variance setting

	Height of IFR					
Demand predicatiblity d	E-5	E-4	E-3	E-2	E-1	E+0
Weibull analysis	0.05	0.05	0.05	0.05	0.05	0.05
Crow-AMSAA	0.10	0.10	0.10	0.10	0.10	0.10
Lifetime test	0.10	0.10	0.10	0.10	0.10	0.10
Design specification	100	50	10	5	2	1
Gut feeling	3000	1000	100	25	5	1.50

Appendix H

Proofs for $\beta_i^{sto}(S_i)$, $\alpha_i^{sto}(S_i)$, $UA_i^{sto}(S_i)$ and $DTWP_i^{sto}(S_i)$

In this Appendix, we give the proofs that are required for $\beta_i^{sto}(S_i)$, $\alpha_i^{sto}(S_i)$, $UA_i^{sto}(S_i)$ and $DTWP_i^{sto}(S_i)$ for Poisson distributed demand, such that these can be applied appropriately in the business case at ASML. We will discuss these one by one. In our model, the item fill rates $\beta_i^{sto}(S_i)$ are maximized by increasing S_i until an aggregate fill rate target $\beta^{sto}(\mathbf{S})$ is satsified. This implies that the formula for $\beta_i^{sto}(S_i)$ should be increasing and concave on its whole domain as a function of S_i. So the following must hold: $\beta_i^{sto'}(S_i) \geq 0$ and $\beta_i^{sto''}(S_i) \geq 0$.

Let $L(\lambda_i, S_i)$ denote the Erlang loss probability as a function of λ_i and S_i. Furthermore, let the probability density function of the Beta distribution be denoted by $B(\lambda_i)$. Then, the formula for $\beta_i^{sto}(S_i)$, equation 5.10, can be written as follows:

$$\beta_i^{sto}(S_i) = \int_{a_i}^{b_i} (1 - L(u, S_i))B(u)du$$

Following Karush (1957), $E(\lambda_i, S_i)$ is decreasing and strictly convex as a function of S_i. Thus, $L'(\lambda_i, S_i) \leq 0$ and $L'('\lambda_i, S_i) < 0$. Accordingly, $(1 - L(\lambda_i, S_i))' \geq 0$ and $(1 - L(\lambda_i, S_i))'' > 0$. Furthermore, as $B(\lambda_i)$ represents a probability density function, we know $0 \leq B(\lambda_i) \leq 1$. Moreover, $b_i > a_i$. Hence,

$$\beta_i^{sto'}(S_i) = \int_{a_i}^{b_i} (1 - L(u, S_i))'B(u)du \geq \int_{a_i}^{b_i} 0\, du = 0$$

and

$$\beta_i^{sto''}(S_i) = \int_{a_i}^{b_i} (1 - L(u, S_i))''B(u)du \geq \int_{a_i}^{b_i} 0\, du = 0$$

Therefore, $\beta_i^{sto}(S_i)$ is increasing and concave on its whole domain as a function of S_i.

APPENDIX H. PROOFS FOR $\beta_I^{STO}(S_I)$, $\alpha_I^{STO}(S_I)$, $UA_I^{STO}(S_I)$ AND $DTWP_I^{STO}(S_I)$

Similarly, a proof has to be provided for the amount of stockouts $\alpha_i^u(S_i)$, logistical system unavailability $UA_i^{sto}(S_i)$ and DTWP $DTWP_i^{sto}(S_i)$. In our model, the amount of stockouts $\alpha_i^{sto}(S_i)$ are minimized, such that the logistic system unavailability $UA_i^{sto}(S_i)$ and $DTWP_i^{sto}(S_i)$ are minimized as well. This implies that the formulas for $\alpha_i^{sto}(S_i)$, $UA_i^{sto}(S_i)$ and $DTWP_i^{sto}(S_i)$ should be decreasing and convex on its whole domain as a function of S_i. So the following must hold: $\alpha_i^{sto'}(S_i) \leq 0$, $UA_i^{sto'}(S_i) \leq 0$, $\alpha_i^{sto''}(S_i) \leq 0$, $UA_i^{sto''}(S_i) \leq 0$, $DTWP_i^{sto'}(S_i)$ and $DTWP_i^{sto''}(S_i)$. The formula for $\alpha_i^{sto}(S_i)$, equation 5.11, can be rewritten as follows:

$$\alpha_i^{sto}(S_i) = \int_{a_i}^{b_i} uL(u, S_i)B(u)du$$

We know that $\lambda_i \geq 0$. Hence,

$$\alpha_i^{sto'}(S_i) = \int_{a_i}^{b_i} uL(u, S_i)'B(u)du \leq \int_{a_i}^{b_i} 0\, du = 0$$

and

$$\alpha_i^{sto''}(S_i) = \int_{a_i}^{b_i} uL(u, S_i)''B(u)du \leq \int_{a_i}^{b_i} 0\, du = 0$$

Now we know that $\alpha_i^{sto'}(S_i) \leq 0$ and $\alpha_i^{sto''}(S_i) \leq 0$, we can provide the same proof for $UA_i^{sto}(S_i)$. The formula for $UA_i^{sto}(S_i)$ is given in equation 4.17 and 5.12. From this, it follows that:

$$UA_i^{sto'}(S_i) = \frac{t_i^{em}\alpha_i^{sto'}(S_i)}{m_i 8760} \leq 0$$

and

$$UA_i^{sto''}(S_i) = \frac{t_i^{em}\alpha_i^{sto''}(S_i)}{m_i 8760} \leq 0.$$

Therefore, $\alpha_i^{sto}(S_i)$ and $UA_i^{sto}(S_i)$ are decreasing and convex on its whole domain.

Finally, we provide the same proof for $DTWP_i^{sto}(S_i)$. The formula for $DTWP_i^{sto}(S_i)$ is given in equation 5.13 and can be rewritten as:

$$DTWP_i^{sto}(S_i) = \int_{a_i}^{b_i} \frac{t_i^{em}\alpha_i^{sto}(S_i) + \beta_i^{sto}ut^{norm}}{m_i 8760} B(u)du$$

We know that $\beta_i^{sto'}(S_i) \geq 0$, $\beta_i^{sto''}(S_i) \leq 0$, $\alpha_i^{sto'}(S_i) \leq 0$ and $\alpha_i^{sto''}(S_i) \leq 0$. We also know that $\lambda_i \geq 0$. Hence,

$$DTWP_i^{sto'}(S_i) = \int_{a_i}^{b_i} \frac{t_i^{em}\alpha_i^{sto'}(S_i) + \beta_i^{sto'}ut^{norm}}{m_i 8760} B(u)du \leq \int_{a_i}^{b_i} 0\, du = 0$$

and

$$DTWP_i^{sto''}(S_i) = \int_{a_i}^{b_i} \frac{t_i^{em}\alpha_i^{sto''}(S_i) + \beta_i^{sto''} u t^{norm}}{m_i 8760} B(u)du \leq \int_{a_i}^{b_i} 0\,du = 0$$

if $t_i^{em} \geq t_i^{norm}$. Based on the definition of these variables, this requirement is satisfied. Therefore, also $DTWP_i^{sto}(S_i$ is decreasing and convex.

Appendix I

Optimization algorithm for DTWP

In this Appendix we provide the optimization algorithm that corresponds to $DTWP^{sto}(\mathbf{S})$. In our model, the system unavailability $DTWP_i^{sto}(S_i)$ is minimized by increasing S_i until a logistcal system availability target UA^{obj} is satsified. This implies that the formula for $DTWP_i^{sto}(S_i)$ should be decreasing and convex on its whole domain as a function of S_i. In Appendix H, we prove this for a Poisson distributed demand process. For reaching the DTWP target, we are interested in the decrease in $DTWP_i^{sto}(S_i)$ compared to the increase in $\hat{C}_i^{sto}(S_i)$ when S_i increases by one unit. For $DTWP_i^{sto}(S_i)$, this decrease is equal to $\Delta DTWP_i^{sto}(S_i) = DTWP_i^{sto}(S_i + 1) - DTWP_i^{sto}(S_i)$. Resultantly, the corresponding greedy ratio is given by:

$$\Gamma_i^{dtwp} = -\frac{\Delta DTWP_i^{sto}(S_i)}{\Lambda\hat{C}_i^{sto}(S_i)}. \tag{I.1}$$

The optimization algorithm is as follows:

Greedy Optimization Algorithm

Step 1

1. $S_{(i,min)} := argminC_i^{sto}(S_i)$ for all $i \in I$.
2. Set $S_i = S_{(i,min)}$ for all $i \in I$, and $\mathbf{S} = (S_{1,min}, \dots, S_{|I|,min})$
3. $\boldsymbol{E} := \{\mathbf{S}\}$.
4. Compute $C^{sto}(\mathbf{S})$ and$DTWP^{sto}(\mathbf{S})$

Step 2

1. $\Gamma_i^{dtwp} = -(\Delta DTWP_i^{sto}(S_i))/(\Lambda\hat{C}_i^{sto}(S_i))$. for all $i \in I$.
2. $k := argmax\{\Gamma_i^{dtwp} : i \in I\}$
3. $\mathbf{S} := \mathbf{S} + \mathbf{e}_k$
4. $\boldsymbol{E} := \boldsymbol{E} \cup \{\mathbf{S}\}$.

Step 3

1. If $DTWP^{sto}(\mathbf{S}) \leq DTWP^{obj}$, then stop, else go to Step 2.

Appendix J

Verification results

In this Appendix, we elaborate on the verification of our model. In order to check the demand rate uncertainty in the Poisson demand process, we apply extremely low as well as extremely high predictability variance. As we expected, applying extremely low predictability variance leads to almost the exact same results as the situation with a deterministic demand rate. Extremely high predictability variance on the other leads to much higher basestock levels. Furthermore, we also check the system approach of the model. This is done by splitting the set of SKU's in half and assigning low prices to the first half, assiging high prices to the second half and vice versa. As expected, parts with a low price have a much higher contribution to the entire stock.

In order to check the demand uncertainty in the Poisson process, we apply extremely low as well as extremely high predictability variance. For this, we define the following predictability variance settings: V_d^{ver1} and V_d^{ver2}. These settings are shown in tables J.1 and J.2 respectively.

	Height of IFR					
Degree	E-5	E-4	E-3	E-2	E-1	E+0
Weibull analysis	0.01	0.01	0.01	0.01	0.01	0.01
Crow-AMSAA	0.01	0.01	0.01	0.01	0.01	0.01
Lifetime test	0.01	0.01	0.01	0.01	0.01	0.01
Design specification	0.01	0.01	0.01	0.01	0.01	0.01
Gut feeling	0.01	0.01	0.01	0.01	0.01	0.01

Table J.1: Predictability variance setting V_d^{ver1}

	Height of IFR					
Degree	E-5	E-4	E-3	E-2	E-1	E+0
Weibull analysis	20	20	20	20	20	20
Crow-AMSAA	20	20	20	20	20	20
Lifetime test	20	20	20	20	20	20
Design specification	20	20	20	20	20	20
Gut feeling	20	20	20	20	20	20

Table J.2: Predictability variance setting V_d^{ver2}

We applied these settings to our model for optimizing towards a system availability target and for optimizing towards an aggregate fill rate target. The outcome variables for this are shown in table J.3, J.4 and J.5

Table J.3: Outcome variables for the optimization of aggregate fill rate target $\beta^{obj} = A$ as verification (adjusted)

$\beta^{obj} = A$				
V	$\sum \mathbf{S}$	$RI(\mathbf{S})$	$\alpha^{sto}(\mathbf{S})$	Λ
$V_d = 0$	30.3	€27,610	1.2	24.1
V_d^{ver1}	30.3	€27,610	1.2	24.1
V_d^{ver2}	47.4	€51,367	7.6	100.6

Table J.4: Outcome variables for the optimization of DTWP target $DTWP^{obj} = B - 0.4\%$ as verification (adjusted)

$DTWP^{obj} = B - 0.4\%$				
V	$\sum \mathbf{S}$	$RI(\mathbf{S})$	$\alpha^{sto}(\mathbf{S})$	Λ
$V_d = 0$	28.8	€26,088	1.4	24.1
V_d^{ver1}	28.8	€26,088	1.4	24.1
V_d^{ver2}	84.0	€141,742	1.2	100.6

These tables show that the no uncertainty setting and setting 7 lead to the exact same results, as we expected. In addition, very high uncertainty leads to completely different

Table J.5: Outcome variables for the optimization of logistical system unavailability target $UA^{obj} = C - 1.0\%$ as verification (adjusted)

$UA^{obj} = C - 1.0\%$				
V	$\sum \mathbf{S}$	$RI(\mathbf{S})$	$\alpha^{sto}(\mathbf{S})$	Λ
$V_d = 0$	28.8	€26,088	1.4	24.1
V_d^{ver1}	28.8	€26,088	1.4	24.1
V_d^{ver2}	74.9	€120,220	1.4	100.6

results.

The second verification we executed regards the verification of the system approach. This is done by splitting the set of SKU's in half and assigning prices of €1 to the first half, assiging prices €10,000 to the second half and vice versa. We did this for both target optimizations. Moreover, $V_d = 0$ and V_d^{ver2} are applied. In table J.6, J.7 and J.8 the total required stock for the situations are shown.

Table J.6: Outcome variables of verification of system approach for optimizing towards aggregate fill rate

$V_d = 0$		V_d^{ver2}	
1st high/ 2nd low	1st low/ 2nd high	1st high/ 2nd low	1st low/ 2nd high
3.2	23.4	5.1	35.9
27.0	6.8	42.4	11.6

Table J.7: Outcome variables of verification of system approach for optimizing towards DTWP (adjusted)

$V_d = 0$		V_d^{ver2}	
1st high/ 2nd low	1st low/ 2nd high	1st high/ 2nd low	1st low/ 2nd high
2.3	21.9	8.3	63.1
26.4	4.8	75.5	20.9

Table J.8: Outcome variables of verification of system approach for optimizing towards logistical system availability (adjusted)

$V_d = 0$		V_d^{ver2}	
1st high/ 2nd low	1st low/ 2nd high	1st high/ 2nd low	1st low/ 2nd high
2.3	21.9	5.1	60.4
26.4	4.8	69.7	14.5

Appendix K

Model overview

In this Appendix we list and summarize the input parameters and outcome variables.

K.1 Input parameters

Initial failure rates

The first estimation of the failure rate of a spare part provided by engineers during the design phase.

Demand predictability information

The information that is utilized for initial failure rate estimation. This can be associated with demand analysis, tests and specifications during the design phase.

Part price

The price of a part is registered within the organization.

Holding cost rate

The yearly costs that are associated with storing the spare parts in warehouses. Since it is a rate, it is expressed as a percentage of the part price.

Installed Base

The amount of machines of different machines types that are installed at a customer site and need to be serviced through the warehouse inventory.

Replenishment Lead Time

The time that is required to replenish a certain part in a particular warehouse. This depends on the type of warehouse.

Emergency shipment time and cost

Ermegency shipments occur when demand will not be backordered in case of a stockout (Van Houtum & Kranenburg, 2015). So the emergency shipment time and cost are the average required time and average corresponding cost respectively per SKU. This depends on the location of the warehouse.

K.2 Outcome variables

Basestock levels

The basestock level represent the number of a particular SKU that should be stocked. It is used as a decision variable.

Total stock

Represents the sum of all basestock levels.

Initial purchase costs

The expenses that are occured when all spare parts, that are to be stocked, need to be bought for the first time.

Yearly average costs

The total yearly inventory costs. Consists of yearly holding cost and yearly emergency shipment costs

Stockouts

This service measure denotes the aggregate mean number of stockouts. So it counts the expected number of times one of the spare parts is not on stock when demanded.

Fill Rates

The distinction can be made between *item fill rate* and the *aggregate fill rate*. The item fill rate represents the probability that an arbitrary demand for one SKU is fullfilled immediately, whereas the aggregate fill rate represents this probability for the total group of SKU's.

Logistcal system unavailability

The percentage of total time a system is unavailable due to the waiting time for spare parts that are not on stock.