MASTER

An integral decision support model to determine the optimal product-to-plant allocation and capacity planning considering volatile demand in the semiconductor industry

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Master thesis

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Abstract

This master thesis describes a research project carried out at ams AG. The project goal is to support capacity planning and sourcing decisions for the filter production lines. The research develops the best approach to determine which products to produce where and with what installed capacities. The research considers a deterministic, stochastic, and robust mixed-integer programming model. Each model is evaluated on robustness to input and demand variability by several experiments. The deterministic model showed the best results for the case of ams. The thesis describes the models, experiments, and application in a prototype decision support tool.

Executive summary

The semiconductor industry serves a volatile market in which the strategic deployment of capacity is critical. Semiconductor companies need to match their expensive capital with rapidly growing demand in an uncertain environment. The filter production of ams AG, an optical semiconductor company, consists of two lines where the strategic deployment of the capabilities is critical. The majority of the filter production runs in the facility in Europe at the moment. The current view is that development, pilots, and small volume production should remain in Europe, while mass production should move to the other facility in Asia when possible. No decision support tool exists to determine if and how the sourcing and capacity should be changed for the best cost-efficiency considering demand uncertainty.

To develop the decision support tool, we created several decision models based on relevant criteria from ams and model types from literature. Two experiments compared the models based on company data. The best performing model was implemented in a decision support tool and provided recommendations for ams. fig. 1 provides an overview of the research setup.

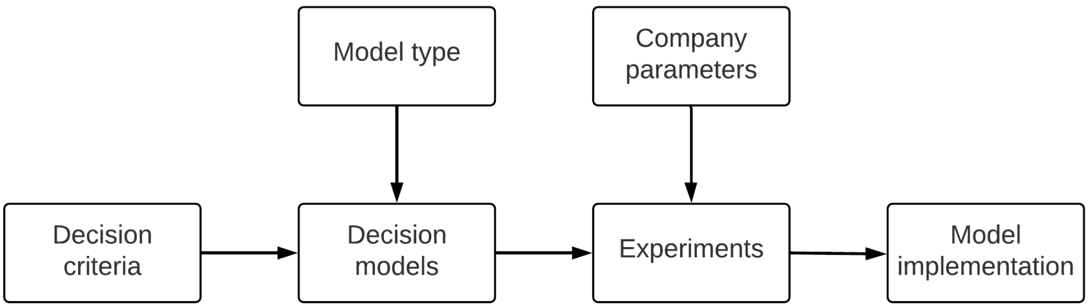

Figure 1: Research setup

We developed several decision models based on relevant criteria for ams. The capacity planning and sourcing decisions are cost-based. Therefore, the decision models minimize the costs of changing capacity, changing allocation, and producing in two different locations. In literature, a Mixed-Integer Linear Program (MILP) is the most common approach in capacity expansion and product-to-plant allocation problems. Several methods exist for incorporating uncertainty in the models. We consider the following types of mathematical programming models to solve the problem and compare performance:

- Deterministic Programming (DP): a multi-stage deterministic programming model taking no uncertainty into account. This model serves as the benchmark optimization model and is the simplest model of the three.

- Stochastic Programming (SP): a multi-stage stochastic programming model considering several demand scenarios and minimizing the expected costs.
- Robust Optimization (RO): a multi-stage robust programming model considering several demand scenarios and minimizing the maximum costs.

Two experiments were conducted to compare the models' robustness and select the best model for the situation of ams. A sensitivity analysis and simulation study test the models' robustness to the input parameters and demand input, respectively. The sensitivity analysis shows that the robust model has a higher objective value in general and is more sensitive to changing parameter values. The robust model could still make suitable decisions for the long-term in an uncertain environment. The simulation study solves the models iteratively in a rolling planning setting. Table 1 shows the simulation study results in an environment with the same demand variability as the filter line products of ams. The table shows that other than expected, the stochastic model does not outperform the deterministic model on average performance, and the robust model does not outperform the deterministic model on worst-case performance. End-of-horizon effects in the model and iteration insufficiency in the simulation may have caused the counter-intuitive results, which does not alter that the deterministic model fits this problem and the situation of ams well. We recommend using the deterministic model with several demand scenarios as support to the decision process. The model performed best in the experiments and has the additional benefit of simplicity.

The deterministic model confirms that the current view on allocation planning, a production shift towards the facility in Asia, is an optimal choice for several demand scenarios. Practically, this means moving as many products to the facility in Asia as possible by other restrictions and increasing capacity led by demand requirements.

Table 1: Performance of the considered models

	DP (S0)	DP (S1)	DP (S2)	DP (S3)	DP (S4)	SP	RO
Average	0.0217	0.0226	0.0239	0.0157	0.0361	0.0280	0.0446
Worst-case	0.1074	0.0765	0.1025	0.0997	0.0931	0.0895	0.2268

The costs in this table are normalized. DP indicates the deterministic programming model with the scenarios used as input demand between brackets.

To conclude, we answer the main research question:

How to determine the optimal product-to-plant allocation and the associated capacities considering different demand scenarios?

Determining the optimal product-to-plant allocation and the associated capacities is a recurring decision process that needs a decision support tool and expert judgment. The planning process is dynamic, and therefore, a prototype decision support tool applies the deterministic model with demand scenarios to alterable input defined by the decision-maker. We recommended using the decision support tool when making or reviewing capacity or sourcing decisions. The tool shows the decisions and their consequences according to the model as well as the benchmark. Additionally, the tool provides scenario analyses to show the decisions and consequences of the model and benchmark in different demand situations.

Preface

In front of you lies the master thesis "An integral decision support model to determine the optimal product-to-plant allocation and capacity planning considering volatile demand in the semiconductor industry" describing the thought process that led to the problem solution and recommendations for ams AG. It has been written to fulfill the master's in Operations Management and Logistics with the special master's track Manufacturing Systems Engineering. This master thesis marks the end of my years as a student. I look back on an instructive and enjoyable time made possible by the professors and my fellow students. The research for the graduation project was both challenging and educational, and comprised all my main interests. I enjoyed the process, but I could not have done this without a number of people.

First of all, I would like to thank Ton de Kok, who provided me with critical feedback and valuable discussions. He did support not only the result but also the learning process with his enthusiastic guidance. Furthermore, I would like to thank Ivo Adan, my second supervisor, for giving another perspective on the problem and taking the time to discuss it in detail. Moreover, I would like to thank Edgar van Campen and Ben Wouters from ams for our weekly meetings and interesting discussions. They gave me the opportunity to learn in practice and provided me with the support I needed. I am grateful for the trust and freedom that I got, making it a pleasant cooperation.

Furthermore, I am thankful for my friends and family who supported me through my complete studies. My student life could not have been so diverting and successful without the people surrounding me.

Enjoy reading,

Saskia Keet, March 5, 2021

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List of Acronyms

GAP Generalized Assignment Problem

WAP Weighted Assignment Problem

DP Deterministic Programming

SP Stochastic Programming

RO Robust Optimization

MIP Mixed-Integer Program

MILP Mixed-Integer Linear Program

FSP Filter Sputter

Chapter 1

Introduction

A semiconductor company's strategic deployment of capital is critical. Rapid demand growth, expensive capital, and volatile demand in the industry drive the decisions' importance. The rapid demand growth forces companies to make decisions fast. The installed capacity should suffice to satisfy customers, while low utilization of the capacity is a waste of investment. Volatile demand complicates finding the capacity needed that meets the changing demand.

Ams is a semiconductor company with more than 9,000 employees worldwide, headquartered in Premstätten (Austria). The company generated a 2 billion USD revenue in 2019 with a 32% year-on-year growth. New product development and new customer attraction result in the growth of the company.

Ams makes and develops optical sensor solutions and sensor integrated circuits (ICs) for manufacturers worldwide that make products and technologies such as smartphones and mobile devices, but also smart homes and buildings, industrial automation, medical technology, and driver-assisting vehicles. The solutions excel in applications requiring extreme precision, dynamic range, high sensitivity, and low power consumption in small form factors.

This research focuses on the strategic deployment of the filter production line capabilities. The line mainly equips spectral sensors with interference filters. Spectral sensors measure the colors within a specific wavelength range of the light. Typical applications of the sensors with interference filters are ambient light color measurement, smoke detection, blood value measurement, and lateral flow tests.

1.1 Company background

In general, a spectral sensor's production consists of five steps deployed over the company's global production network: CMOS wafer production, wafer post-processing, wafer probe, assembly, and test. Figure 1.1 shows the production steps, locations, and material flows. The production of CMOS wafers occurs at the internal facility in Europe and external partners in Asia. The wafer post-processing- and probe-phase for the production of filter products occur in the two internal production facilities, either in Europe or Asia. There, the filter line places the interference filters and organic coatings on the wafers. The wafer prober identifies non-functional ICs on the test floor of the same facility. Subsequently, the wafers with filters go to the customer or an external partner for assembly in either the USA, Europe, or Asia. The assembly phase consists of cutting the wafers into individual ICs and packing them in a case

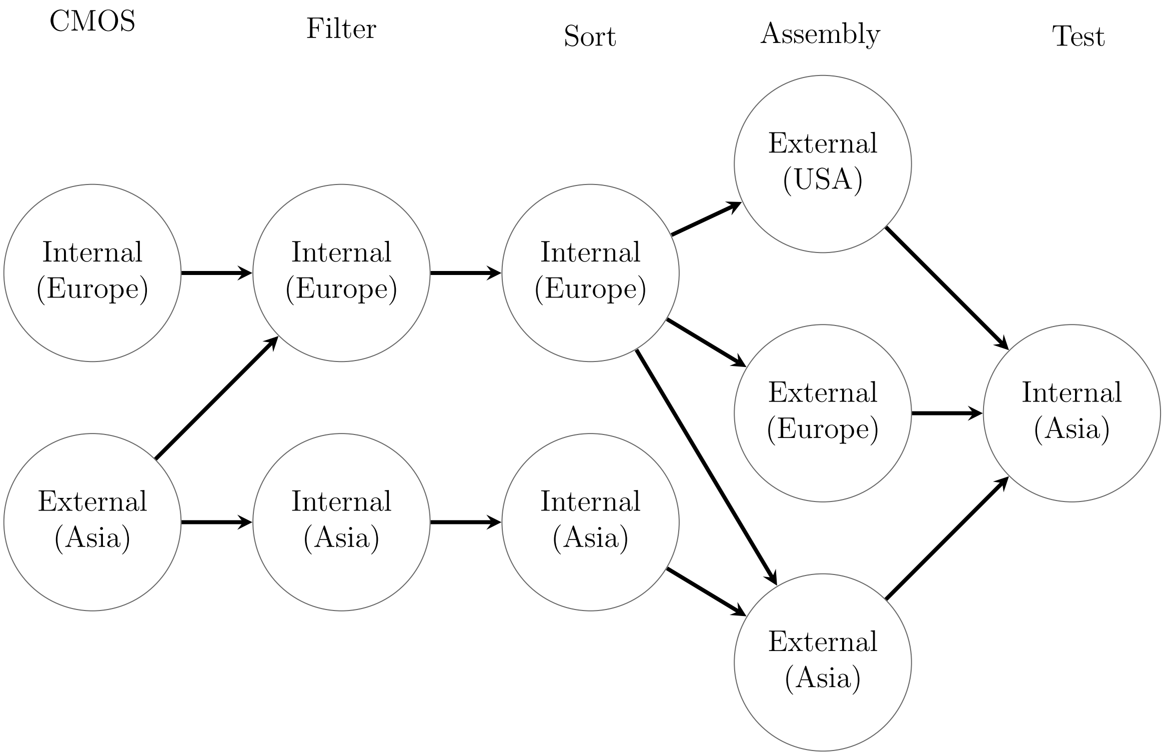


Figure 1.1: Supply chain topology

that supports the connection between the IC and a circuit board. The testing of the final product takes place at an internal testing facility in Asia.

Next to structuring interference filters and organic coatings on a CMOS wafer for spectral sensor production, new technologies will use the filter production line. The deposition of filters and coatings on glass is such a technology and has a different supply chain.

1.2 Problem background

The filter step is a capital-intensive production process, meaning that the capital expenditures on facilities and manufacturing equipment are high. Therefore, the strategic deployment of the production lines is of high importance to ams. Ams has two filter production lines with enough installed capacity and is busy ramping volumes. Demand growth increases the load on the lines. The filter lines' strategic deployment comprises a trade-off between the locations taking into account the current situation.

The production cost difference between the locations drives the trade-off. The majority of the products run in the fabrication plant in Europe (FAB 1), and only a couple of high-volume products run in the fabrication plant in Asia (FAB 2). Recently, a management decision is made to change the sourcing strategy of filter products. The decision entails that the mass production location changes to the FAB 2 facility. New products will ramp at this facility, but the existing products' mass production will remain in FAB 1. The demand for the existing products remains over the coming years. However, at some point, the existing product portfolio disappears. The planning resulting from this rule-of-thumb serves as the benchmark of this study.

The products and underlying technologies should be qualified for a facility to enable the production of the associated products. The qualification ensures the quality of the production process and, thereby, the product. The customer decides in collaboration with ams if the quality is sufficient. If ams wants to change the sourcing or production process of a product, research is needed, and the customer must approve.

A shift in volumes between both locations results in capacity changes. The current practice is that demand is leading in capacity planning. Capacity is increased just in time, and only the base demand forecast is taken into account.

The model would be a straightforward consideration of all decision criteria if demand would be known with absolute certainty. However, the demand volatility and the changing product portfolio bring uncertainty. New product development and in-sourcing of key technologies and products contribute to the changing product portfolio. The introduction of new filter technologies brings new products to enter new markets. As said before, the change in the configuration is associated with high capital expenditures. Therefore, the sourcing strategy should be not only cost-efficient but also future-proof.

1.3 Problem definition

The majority of the filter production runs in FAB 1 in Europe at the moment. The current view is that development, pilots, and small volume production should happen in FAB 1, while mass production should move to FAB 2 when possible. No decision support tool exists to determine if and how the sourcing and capacity should be changed for the best cost-efficiency considering demand uncertainty.

1.4 Research design

1.4.1 Goal

This research aims to develop a decision support model and prototype tool that determine which products to produce where and with what installed capacities while minimizing the long-term costs of operations and reconfiguration. Besides the maximum throughput of the installed capacity, the capacity needed in a facility depends on the demand for a facility in a given configuration. Therefore, the model should be robust to demand uncertainty.

The main company deliverable is a prototype tool that gives valuable insights into the optimal configuration and capacities with the underlying model. A practical manual and recommendations on using the tool in the existing decision process should accompany the tool. The MSc thesis describes the thought process that led to the model, tool, and implementation of the model with recommendations.

1.4.2 Research questions

In line with the project goal, the main research question is:

How to determine the optimal product-to-plant allocation and the associated capacities considering different demand scenarios?

The following sub-questions lead us to the answer to the main research question:

1. What are the relevant criteria for the decision model?
2. What type of decision model is appropriate?
3. What model type allows ams to take robust decisions taking into account demand uncertainty?
4. How can the decision model be implemented in the decision process?
5. What is the difference between the current practice and the recommended solution?

1.5 Relevance of the research

This research develops a reusable model for supporting product allocation and capacity expansion decisions. For ams, the model applies to filter production, which has a growing demand forecast over the coming years. Ams currently investigates other target markets. Since demand is non-stationary and new products arise at ams all the time, the problem stays relevant.

Although the primary goal is solving the company problem of ams, the problem is not only faced by ams. In literature, many papers about product-to-plant allocation and capacity expansion originate from semiconductor company problems. The semiconductor industry has several distinguishing aspects, due to which both problems become interesting. The high production volumes, the high costs and long acquisition lead times of tools, the rapid change of technologies, and high capacity variability make the allocation crucial (Chien, Wu, & Chiang, 2012; Swaminathan, 2000; Zhou & Li, 2016). Therefore, this research could be useful for other companies with similar characteristics.

1.6 Research method

The research conforms with the operations research (OR) process of Sagasti and Mitroff (1973), as depicted in Figure 1.2. Sagasti and Mitroff (1973) apply the general systems theory (GST) to operations research by seeing the research activity as a system with components. The components are research phases, which are connected by relations. The 'science' component is not a research phase but supports the other steps with scientific knowledge. The rest of the section will explain the different phases and apply them to this research.

In the problem situation phase, we gained a better understanding of the problem and the surrounding situation. We gathered data about the production system and the costs involved in capacity change, product qualification, and operations.

In the conceptualization phase an abstract model structure for the problem was created. To abstract, we defined what are relevant criteria to base decisions on. Literature helped to select decision modeling approaches. The requirements were set, and problem assumptions were made.

Once the conceptual model was established, we identified the controllable and uncontrollable variables and defined them in operational terms. The objective(s) and

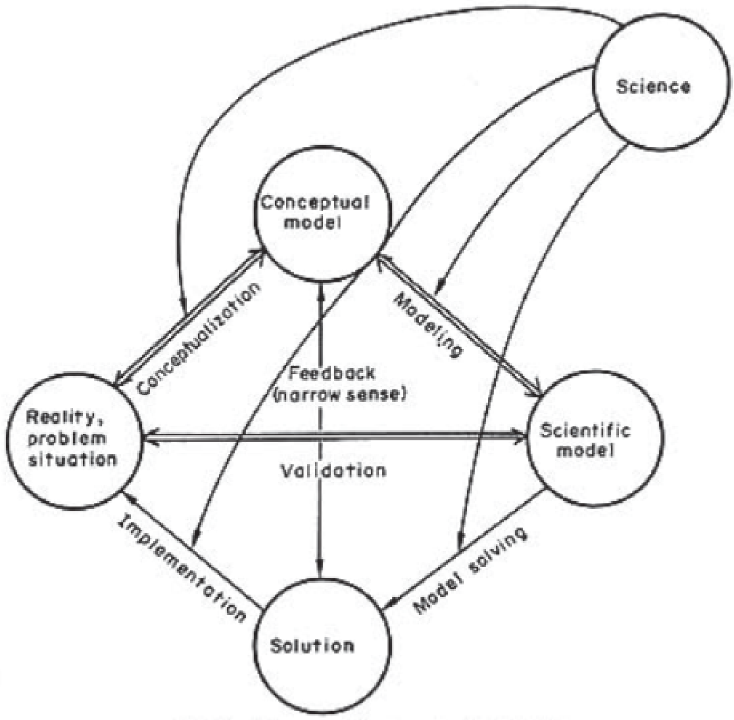


Figure 1.2: The operations research process (Sagasti & Mitroff, 1973)

constraints were formalized with mathematical expressions. We verified if the model matches the conceptual model's requirements. To validate which model fits the situation of ams best, two experiments were conducted. First, a sensitivity analysis tested the model's robustness to input changes, i.e., how much the parameter settings affect the outcomes. Second, The models were tested in a realistic environment. The models were implemented in a real-life situation with uncertain demand by a simulation. This test environment showed the models' behavior in the problem situation, enabling us to choose the model that is most robust to the degree of demand uncertainty of the filter products.

To obtain an interpretable solution, we solved the chosen model for the situation of ams and determined the consequences. The solution was compared with current sourcing strategy as a benchmark. Furthermore, several scenarios are calculated to show what can happen. The benchmark and scenario analysis are essential for the interpretation of the proposed model and are the base for the decisions support tool.

1.7 Research outline

Chapter 2 gives background on the products and processes of ams. Chapter 3 identifies the sub-problems, sets the scope, and researches existing models. We formulate several models in Chapter 4, which we verify in Chapter 5. Experiments test the models for which Chapter 6 describes the design, and Chapter 7 shows the results. Chapter 8 describes the decision support tool as an implementation of the model and gives an example of the benchmark and scenario analysis. Chapter 9 concludes the results, discusses the research limitations, and makes recommendations for ams.

Chapter 2

Background

This chapter examines the filter products, production process, supply capacity, forecasting, and the current product allocation and capacity planning practices.

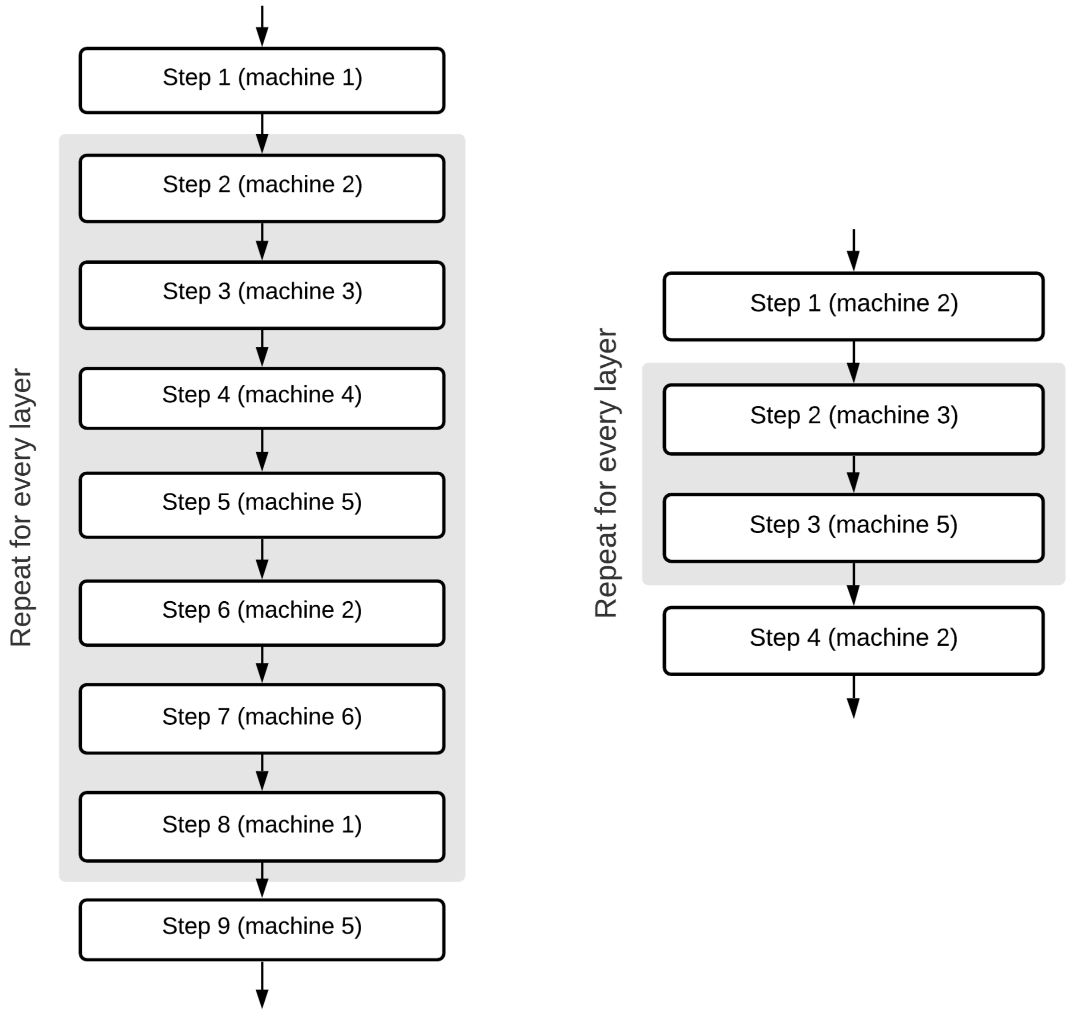
2.1 Filter products

The filter production line equips spectral sensors with interference filters. Spectral sensors measure the colors within a specific wavelength range of the light. One way to do that is to filter the light before it reaches the light-sensitive sensor. Ams equips the sensors with interference filters. The filters consist of multiple transparent layers of different materials that refract the light to cancel out specific wavelengths. The measurement of specific wavelengths is needed for ambient light color measurement in smartphones, smoke detection in smoke detectors, lateral flow tests for pregnancy testing.

2.2 Filter production process

The re-entrant job shop produces filter products in batches by doing operations on every wafer several times. The current starting material of the filter process is a CMOS wafer. The sequence of operations on the wafer for a layer depends on the type of mask layer. Currently, a filter product consists of interference filters with or without organic coatings. Figure 2.1a and Figure 2.1b show the sequence of operations for one interference or organic mask layer, respectively. The job shop consists of six machine types. The sequence is repeated for the required amount of layers. For the interference filter, this is one for every light frequency range. For the organic coating, this is always five layers of the following coatings: clear, green, red, blue, clear. Several tool groups execute the operations for every layer repetitively. Both processes use the same tool groups.

As explained before, the filter production line will also be used to deposition filters on glass, causing the filter line to grow even more. The supply chain and the production process is different from the other products. The production process of these products only uses machine 2 and 6.



(a) Interference filter (b) Organic coating

Figure 2.1: Filter process

2.3 Supply capacity

The supply capacity of a facility depends on the maximum production volume of the tools and the products' capacity consumption. The tool groups described above all have a maximum daily throughput, and the amount of tools in each group differs among facilities. Each product consumes capacity differently depending on the times it needs an operation on a particular tool group.

Machine 6, the Filter Sputter (FSP) tool, is an exception regarding capacity consumption. Next to the number of layers, the required layer thickness, and thereby, the application time on the FSP tool differs per layer type. Therefore, the capacity consumption and maximum production volume on the FSP differs a lot per product.

2.4 Demand forecast

Ams uses a monthly rolling demand forecast with an 18 month time horizon for the S&OP process. Most products are customer-specific or made for only a couple of customers. Furthermore, the demand is volatile and is, therefore, forecasted collaboratively with the customer. The demand for new products depends highly on new technology adaption, which is uncertain for both ams and the customers.

However, demand is not the only aspect influenced by the rapidly evolving technologies and markets. The filter process materials might differ, new technologies might need new capabilities, and the supply capacity might change if new products have different processing times. Furthermore, the customer's decision to use an ams filter product in their new designs is a source of uncertainty.

Chapter 3

Conceptualization

3.1 Scoping

The research focuses on supporting decisions in the mid-term production planning with a horizon of four years. It aims to determine if and how the sourcing and capacity planning should be changed for the best cost-efficiency considering demand uncertainty.

On the one hand, we can influence the cost-efficiency with low unit costs; on the other hand, we can prevent more assets, such as machines, should be bought (Figure 3.1). Closing a facility is out-of-scope since earlier internal analysis at ams has shown that this is not desired. The research is limited to the strategic deployment of the existing facilities. Buying machines can be prevented by a higher utilization or throughput of the machines. Increasing the machine throughput is not the aim of this study. The production, inventory, and back-order costs determine the unit costs. The sourcing of the products can influence the production costs. Inventory and back-order costs are caused by demand variability. Without variability of demand, we would match demand and supply exactly, and we would not need inventory and would not get back-orders. The sourcing of products may be changed.

Supply planning is the focus of this research. The demand forecast is complex and is established best by expert judgment. The demand planning is not within the scope of this research. However, quantifying demand uncertainty and forecast errors is within the scope. The demand on the filter lines is subject to a dynamic product portfolio where introduction and end-of-life of products are no exception. The demand is uncertain in volume as well as in the course of product life-cycles. Therefore, the model considers several demand scenarios obtained by collaboration with experts.

The research goal is to develop a decision support model that determines the product configuration and installed capacity with minimal costs under demand uncertainty. We recognize two sub-problems that should be solved simultaneously. The first sub-problem is the product allocation problem. In this problem, the primary decision is which products to allocate to which plant(s). These decisions result in a product configuration. The second sub-problem is capacity expansion. The main decision is how, when, and by how much to change capacity. These decisions result in an installed capacity over time. In both sub-problems, future demand plays a role. As stated earlier, demand in the semiconductor industry is volatile. Therefore, incorporating demand variability in a model is an essential aspect of the research.

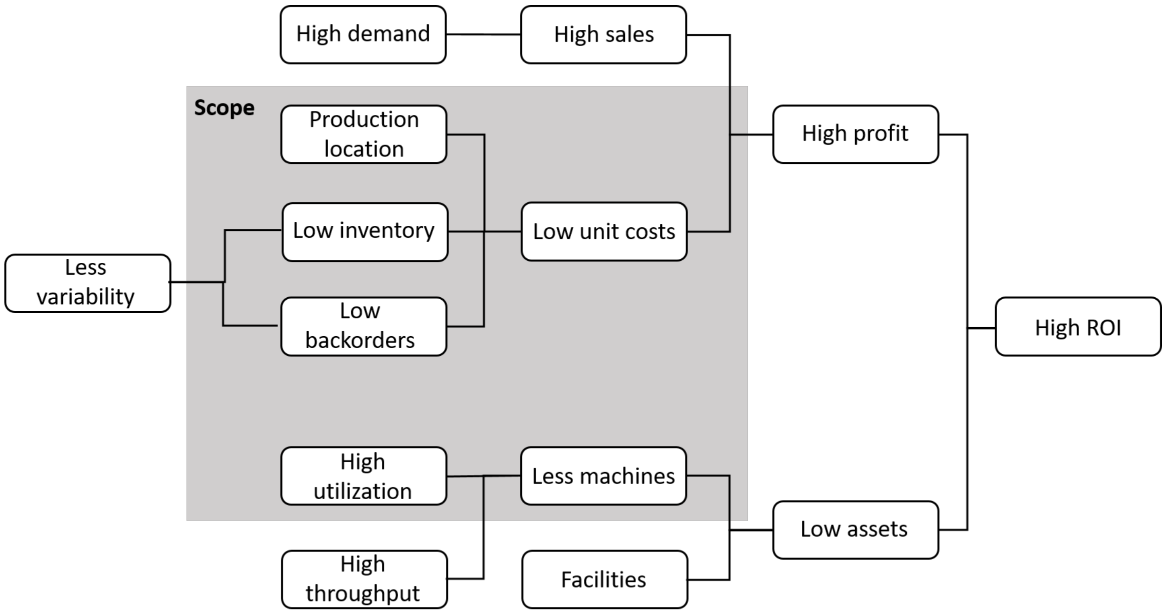


Figure 3.1: Driver diagram

3.2 Literature review

The literature review examines existing product-to-plant allocation models, capacity planning models, and modeling techniques to deal with uncertainty. The existing knowledge is a first step in answering the first two research questions: "What are the relevant criteria for the decision model?" and "What type of decision model is appropriate?".

3.2.1 Product-to-plant allocation

The product-to-plant allocation problem optimizes the allocation of demand in a fixed facility network. The problem is relevant when designing production networks, reallocating existing products, and introducing new products.

The product-to-plant allocation problem's underlying problem is the Generalized Assignment Problem (GAP) of Ross and Soland (1975). The GAP is a combinatorial optimization problem that assigns tasks to agents under assignment costs. The agents have a capacity that is consumed by a task with a capacity consumption rate. When this capacity consumption has a lower bound, the problem becomes the Weighted Assignment Problem (WAP) of Ross and Zoltners (1979). An important characteristic of both the WAP and the GAP is the possibility of assigning one task only to one agent. The Multi-Resource Weighted Assignment Problem (Ross & Zoltners, 1979), the multi-resource GAP with setups (MRGAPS) of Leblanc, Shtub, and Anandalingam (1999) and the generalized multi-assignment problem (GMAP) of Park, Lim, and Lee (1998) relax this constraint. In general, the GAP and the product-to-plant allocation are capacity-constrained. The elastic GAP of Nauss (2004) allows for violating the capacity constraints at additional costs.

The GAP can be applied to the product-to-plant allocation problem when considering the products as tasks and the plants as agents. The objective function of the product-to-plant allocation, as opposed to the GAP, minimizes several costs. Therefore, the application of the GAP in product-to-plant allocation models results in more extensive models. Benjaafar, Elhafsi, and De Véricourt (2004) and Mazzola and Schantz (1997) present applications of the GAP for product-to-plant allocation. Benjaafar et al. (2004) consider two types of product allocation under stochastic demand and production times, one with the possibility to split demand for a product among multiple facilities and one where a single facility should satisfy the demand for one product. Mazzola (1989) discusses the GAP with non-linear capacity constraints and applies it later on to the problem of multiple-facility loading in Mazzola and Schantz (1997).

The product-to-plant allocation models mentioned incur either operating costs or re-assignment costs. However, the trade-off between these costs could be of interest. Furthermore, the models assume that demand is stationary. Therefore, the models have a fixed installed capacity and have no integrated capacity planning. The costs of capacity could be relevant in the trade-off.

3.2.2 Capacity planning

Capacity planning matches the available production volumes to the demand and decides on expanding or reducing these volumes. Geng and Jiang (2009) categorize capacity planning methods in the static capacity model, the neighborhood search method, and mathematical programming techniques. Martínez-Costa, Mas-Machuca, Benedito, and Corominas (2014) present an extensive review of existing capacity planning models. The reviewed models include either opening and closing facilities, expanding or reducing installed capacities, or both, to adjust the capacity.

Since the allocation of products to fixed facilities is the main topic of this research, multi-site models aiming to decide about the adjustment of installed capacities are most relevant to this research. The capacity models assume that every facility can make all products. Some models incorporate a technology restriction, but the strategic allocation is not part of any capacity model.

Most capacity expansion problems are modeled as linear programming models. Chien et al. (2012) propose a Markov decision process capacity model for capacity expansion and claim that a Markov chain of market states represents the demand uncertainty in the semiconductor industry better than demand scenarios. Demand scenarios (opposed to a single plan) are commonly used in capacity planning (Eppen, Martin, & Schrage, 1989; Swaminathan, 2000).

3.2.3 Decision-making under uncertainty

Quantitative models try to represent reality as closely as possible. However, the reality is not always known with certainty. Therefore, it can be beneficial to take this uncertainty into account when making a decision. Deciding while assuming all input is known is the deterministic approach which ignores data uncertainty. Robust and stochastic approaches handle optimization problems with data uncertainty proactively.

Stochastic programming models the demand as a random variable, and the distribution of the random data is (partially) known or approximated well. SP assumes the probability distribution is known or has to be estimated (Gorissen, Yanıkoğlu, & Den Hertog, 2015). RO aims at finding the best solution for all possible realizations of the data that fall in the uncertainty set. Various approaches to robust optimization exist.

Mulvey, Vanderbei, and Zenios (1995) develop a general framework for RO, which models two robustness concepts, solution robust and model robust. A solution is solution-robust if it remains close to an optimal solution for all scenarios and model robust if it remains close to feasible for all scenarios. The general model formulation incorporates the inflicting objectives of these concepts.

The RO approach of Aharon Ben-Tal, El Ghaoui, and Nemirovski (2009) requires the solution to be feasible for all scenarios while finding the solution that remains the closest to an optimal solution for all scenarios. This approach is quite conservative. Therefore, Ben-Tal, Goryashko, Guslitzer, and Nemirovski (2004) extend the RO methodology with the Adjustable Robust Counterpart to overcome the issue by postponing a subset of the decision until the realization of the uncertain event.

The concept of postponing a subset of the decision does not only exist in RO. Several stochastic capacity planning models from the chemical process industry deal with uncertainty through multi-stage programming. Swaminathan (2000) and Zhou and Li (2016) developed such a model for the semiconductor industry.

Atamtürk and Zhang (2007) applies the work of Ben-Tal et al. (2004) to a network flow and design problem. Mulvey et al. (1995) show the application of their approach in a capacity expansion model. Laguna (1998) applies the RO approach of Mulvey et al. (1995) to a capacity expansion model as well and obtains the stochastic optimization solution for comparison by solving the model with all weight parameters zero.

None of the models discussed fits the situation of ams directly. Product-to-plant allocation models assume fixed capacity, whereas capacity planning models do not focus on product-facility configurations. Therefore, developing an integrated model involving both decisions serves the purpose of this research. The existing models give a first step in defining the relevant criteria for the decisions. However, the potential criteria should be checked to fit the situation of ams. A Markov decision process may be an accurate way to model uncertain demand instead of linear programming with demand scenarios in a capacity expansion problem. However, it is computationally intractable for multi-period allocation problems. Either SP or RO seems the correct modeling technique for the problem since we are dealing with demand uncertainty. These techniques' complexity may be unnecessary if a deterministic model's performance approaches the more complex models' performance. Therefore, we will develop a deterministic, a RO, and a SP model and compare their performances.

Chapter 4

Model formulation

The models in this chapter combine the product configuration and capacity expansion sub-problems. We can decide on machines' transfers between locations, the machines' purchases, and machines' sales resulting in the installed machine capacity. We can decide on the qualifying products at a facility resulting in a product-to-facility allocation. The qualification of products is an internal process ensuring the production process, and product quality meet the ams and customer standards. We can decide on the production volume of a product every period, possibly resulting in inventory and back-orders. The machine transfer, machine buy, and product qualification decisions take time to take effect. The sale of machines is immediate, and the production is done within the period. Production of a product at a facility is only allowed if that product is qualified at that facility. The facility capacity limits the production volume. The manufacturing process makes it necessary to model capacity on a machine level because the bottleneck changes due to the product-dependent capacity consumption rates.

All these decisions result in costs. In both sub-problems discussed in Chapter 3, the trade-off between one-time costs (capital expenditures) to reduce running costs (operational expenditures) plays a role. The costs named in the literature serve as a base to determine which costs are relevant for ams. Note that fixed costs are excluded from the model since including these would imply opening or closing a facility is an option. The relevant running costs for ams consist of production, holding, and back-ordering costs. The main source of production costs are labor costs which differ between the facilities. The one-time costs are machine buy, machine transfer, and product qualification costs. Additionally, we incur a benefit for selling machines. All these costs are considered quantitatively by the decision support models.

As discussed in Section 3.2, both sub-problems are known in literature and mostly modeled as (mixed-integer) linear programming models. The model can be formulated as a deterministic, stochastic or robust programming model. According to their objective, all models allocate a set of products and a set of machines to the two facilities under qualification and capacity constraints. However, a stochastic or robust model incorporates demand uncertainty, whereas a deterministic model assumes a nominal demand as certain. This chapter describes the models and the most important differences. Appendix A shows the full models.

4.1 Deterministic programming model

The deterministic model considers f facilities with m machine types and p products (Table 4.1). The qualification, capacity expansion, and production decisions are made for every period in the time horizon t (Table 4.2). We assume the demand is known for the deterministic model, and we minimize the costs based on this demand. The demand for product p during period t is given with $D_{p,t}$ (Table 4.3).

Table 4.4 gives the additional output variables. The model uses $a_{p,f,t}$ to keep track of the ongoing allocation. A product starting its qualification process in period t ends its qualification process and gets its allocation in period $t + \tau_1$. The variable $k_{m,f,t}$ keeps track of the number of machines. A machine bought in period t is delivered in period $t + \tau_2$ and a machine transferred in period t is de-installed at one facility immediately for it to be delivered at the other facility at $t + \tau_3$. $i_{p,t}$ and $b_{p,t}$ account for the inventory and back-orders dependent on the demand and production for a product p in a period t. All output variables have an initial value at time 0.

The model minimizes machine buy, machine transfer, machine sell, product qualification, production, inventory, and back-order costs (4.1). It is desirable to buy and transfer machines as late as possible and to sell them as early as possible since the value of money decreases over time by its potential earning capacity. Therefore, we introduce the interest percentage (ρ) to devalue the costs of these investments over time. Since we are considering a finite-horizon problem, high amounts of back-orders and inventory could occur at the end of the horizon instead of increasing capacity. To avoid this end-of-horizon effect, the inventory holding and back-ordering costs are time-dependent, allowing them to increase over time.

Table 4.1: Model indices

P	number of different products, p = {1, ..., P}
M	number of machines, m = {1, ..., M}
F	number of facilities, f = $\{f_1, f_2\}$
T	number of periods in the time horizon, t = {1,...,T}
T_0	number of periods in the time horizon with initial period, t_0 = {0,...,T}

Table 4.2: Decision variables

$q_{p,f,t}$	$\begin{cases} 1 & \text{if qualification of product } p \text{ in facility } f \text{ is started on time t} \\ 0 & \text{otherwise} \end{cases}$
$x^{buy}_{m,f,t}$	number of machines of type m bought in facility f on time t
$x^{sell}_{m,f,t}$	number of machines of type m sold at facility f on time t
$x^{trans}_{m,f,f',t}$	number of machines of type m transferred from facility f to f' on time t
$y_{p,f,t}$	production volume of product p in facility f at time t, $t \in T$

$D_{p,t}$	demand of product $p \in P$ on time $t \in T$

Table 4.3: Input variables

Table 4.4: Output variables

$a_{p,f,t}$	$\begin{cases} 1 & \text{if product } p \text{ is allocated to facility } f \text{ on time } t \in T_0 \\ 0 & \text{otherwise} \end{cases}$
$k_{m,f,t}$	number of machines of type m in facility f on time $t \in T_0$
$i_{p,t}$	inventory of product p in facility f at time t, $t \in T_0$
$b_{p,t}$	backorders of product p in facility f at time t, $t \in T_0$

Table 4.5: Parameters

ρ	interest percentage
c_m^{buy}	costs of buying a machine of type m
c^{sell}	benefit of selling a machine
$c^{transfer}$	costs of transferring a machine
$c^{qualify}$	costs of qualifying a product
$c_{m,f}^{production}$	costs of producing a product on machine m at facility f
$c_t^{inventory}$	costs of keeping inventory for one unit of a product in period t
$c_t^{back-order}$	costs of back-ordering one unit of a product in period t
τ_1	qualification lead-time
τ_2	tool procurement lead-time
τ_3	tool transfer lead-time
v_m	the maximum production volume of a machine of type m
$g_{p,m}$	the capacity consumption of product p on a machine of type m
M	large number

$$
\begin{aligned}
\min_{x,q,y} \sum_{t\in T}(1+\rho)^{-t} \Bigg(& \sum_{f\in F}\sum_{m\in M} c_m^{buy}\cdot x_{m,f,t}^{buy} - c^{sell}\cdot x_{m,f,t}^{sell} \\
& + \sum_{f\in F}\sum_{f'\in F, f'\neq f}\sum_{m\in M} c^{transfer}\cdot x_{m,f,f',t}^{transfer}\Bigg) \\
& + \Bigg(\sum_{f\in F}\sum_{p\in P} c^{qualify}\cdot q_{p,f,t} \\
& \quad + \sum_{f\in F}\sum_{m\in M}\sum_{p\in P} c_{m,f}^{production}\cdot g_{p,m}\cdot y_{p,f,t} \\
& \quad + \sum_{p\in P} c_t^{inventory}\cdot i_{p,t} + c_t^{backorder}\cdot b_{p,t}\Bigg)
\end{aligned} \tag{4.1}
$$

The amount of machines is the amount of machines in the last period minus the amount of machines sold and transferred away now plus the amount of machine bought τ_2 periods ago and transferred to this facility τ_3 periods ago (4.2).

$$
\begin{aligned}
k_{m,f,t} = k_{m,f,t-1} + x_{m,f,t-\tau_2}^{buy} - x_{m,f,t}^{sell} - \sum_{f'\in F} x_{m,f,f',t}^{trans} + \sum_{f'\in F} x_{m,f',f,t-\tau_3}^{trans} \\
\forall m\in M, \forall f\in F, \forall t\in T
\end{aligned} \tag{4.2}
$$

The inventory position ($i_{p,t} - b_{p,t}$) in a period the inventory position of last period plus the production and minus the demand for this period given by the inventory balance constraint (4.3).

$$
i_{p,t} - b_{p,t} = i_{p,t-1} - b_{p,t-1} + \sum_{f\in F} y_{p,f,t} - D_{p,t} \qquad \forall p\in P, \forall t\in T \tag{4.3}
$$

A product's qualification at a facility is the allocation of that product at that facility last period plus the qualification done τ_1 periods ago (4.4).

$$
a_{p,f,t} \leq a_{p,f,t-1} + q_{p,f,t-\tau_1} \qquad \forall p\in P, \forall f\in F, \forall t\in T \tag{4.4}
$$

A product can only be produced at a facility if the product is qualified for that facility (4.5).

$$
y_{p,f,t} \leq a_{p,f,t}\cdot M \qquad \forall p\in P, \forall f\in F, \forall t\in T \tag{4.5}
$$

The capacity consumption volume cannot be more than the maximum supply capacity (4.6). The maximum supply capacity gets determined by the number of machines and the throughput of the machines. The capacity production volume is determined by the capacity consumption rate of a product and the production volume summed over all products.

$$
\sum_{p\in P} y_{p,f,t}\cdot g_{p,m} \leq v_m\cdot k_{m,f,t} \qquad \forall m\in M, \forall f\in F, \forall t\in T \tag{4.6}
$$

The allocation and qualification variables are binary (4.7).

$$
\begin{aligned}
a_{p,f,t} &\in \{0,1\} \qquad \forall p\in P, \forall f\in F, \forall t\in T \\
x_{p,f,t} &\in \{0,1\} \qquad \forall p\in P, \forall f\in F, \forall t\in T
\end{aligned} \tag{4.7}
$$

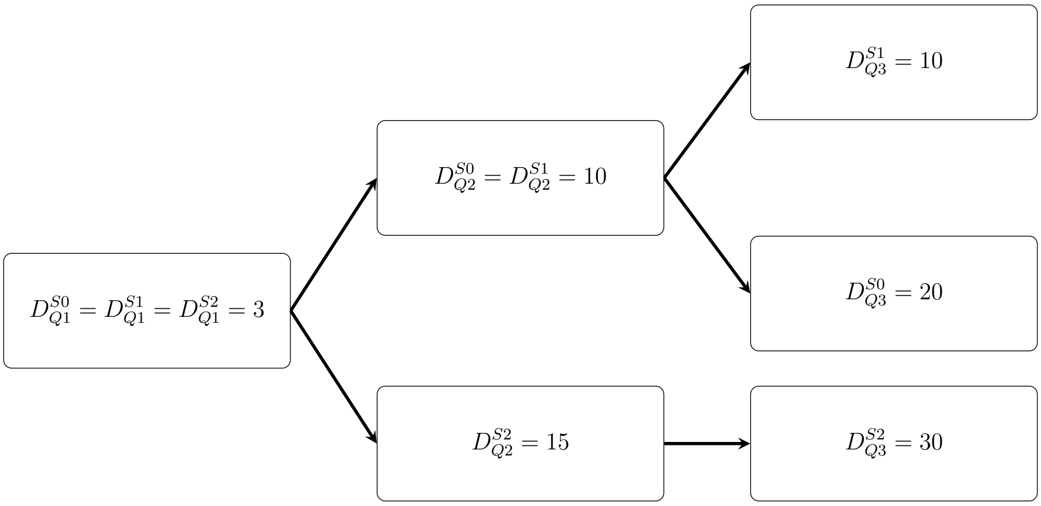


Figure 4.1: Scenario tree example

The production, back-ordering, inventory, and the number of machine variables are continuous (4.8). Note that the amount of machines does not need to be integer since the variables that can change this amount are integers.

$$\begin{aligned}
&k_{m,f,t} \in \mathbb{R}_+ && \forall m \in M, \forall f \in F, \forall t \in T \\
&y_{p,f,t} \in \mathbb{R}_+ && \forall p \in P, \forall f \in F, \forall t \in T \\
&b_{p,t} \in \mathbb{R}_+ && \forall p \in P, \forall t \in T \\
&i_{p,t} \in \mathbb{R}_+ && \forall p \in P, \forall t \in T
\end{aligned} \tag{4.8}$$

The machine variables are non-negative integers (4.9).

$$\begin{aligned}
&q^{buy}_{m,f,t} \in \mathbb{N}_0 && \forall m \in M, \forall f \in F, \forall t \in T \\
&q^{sell}_{m,f,t} \in \mathbb{N}_0 && \forall m \in M, \forall f \in F, \forall t \in T \\
&q^{trans}_{m,f,f',t} \in \mathbb{N}_0 && \forall m \in M, \forall f \in F, \forall f' \in F, \forall t \in T
\end{aligned} \tag{4.9}$$

4.2 Stochastic programming model

The deterministic model is the base for the stochastic programming model. We assumed that the demand is known for all products over the entire time horizon for the deterministic model. After the first period, multiple demand realizations are possible. We call each possible realization of demand a demand scenario s with a probability P_s.

We demonstrate the use of the demand scenarios with the scenario tree of Figure 4.1. The most left node represents the demand in the first period. This demand is known and the same for all demand scenarios. Each arrow from a node represents another demand realization in the next period. At the first node, three scenarios are possible to realize in the future, but the number of scenarios decreases as time passes. The decisions in the SP are conditional on which demand scenario realizes. However, for scenarios with the same demand history - represented as one node in the figure - the conditional decisions should be the same. We define V_t as a pair of scenarios that share a node at time t. To ensure the same decision is made for scenarios with the same demand history till that period ($(s_1, s_2) \in V_t$), we introduce the non-anticipation constraints (Birge & Louveaux, 2011) for all decision variables as given in (4.11). Table 4.6 gives the additional notation for the stochastic formulation. Furthermore, all decision variables and demand parameters are duplicated for all scenarios, and all constraints should hold for all scenarios.

The SP uses the same cost categories as the deterministic model. However, the stochastic model minimizes the expected costs over all demand scenarios (4.10). Since we minimize the expected costs, the objective weighs each demand scenario with its probability P_s.

Table 4.6: Stochastic model new variables

S	Set of scenarios s, S = {1,2,...}
V_t	Pair of scenarios (s_1, s_2) where s_1 and s_2 have the same demand history until time t
$D_{p,t,s}$	Demand of product p on time $t \in T$ in scenario s
P_s	Probability of scenario s occurring

$$\begin{aligned}\min_{x,q,y} \sum_{s\in S} P_s \sum_{t\in T} (1+\rho)^{-t} & \Bigg(\sum_{f\in F}\sum_{m\in M} c_m^{buy} \cdot x_{m,f,t,s}^{buy} - c_m^{sell} \cdot x_{m,f,t,s}^{sell} \\ & + \sum_{f\in F}\sum_{f'\in F, f'\neq f}\sum_{m\in M} c_m^{trans} \cdot x_{m,f,f',t,s}^{trans} \Bigg) \\ & + \Bigg(\sum_{f\in F}\sum_{p\in P} c_p^{qualify} \cdot q_{p,f,t,s} \\ & + \sum_{f\in F}\sum_{m\in M}\sum_{p\in P} c_{m,f}^{production} \cdot g_{p,m} \cdot y_{p,f,t,s} \\ & + \sum_{p\in P} c_t^{inventory} \cdot i_{p,t,s} + c_t^{backorder} \cdot b_{p,t,s} \Bigg)\end{aligned} \tag{4.10}$$

$$\begin{aligned} y_{p,f,t,s_1} &= y_{p,f,t,s_2} && \forall (s_1,s_2)\in V_t, \forall p\in P, \forall f\in F, \forall t\in T \\ q_{p,f,t,s_1} &= q_{p,f,t,s_2} && \forall (s_1,s_2)\in V_t, \forall p\in P, \forall f\in F, \forall t\in T \\ x_{m,f,t,s_1}^{buy} &= x_{m,f,t,s_2}^{buy} && \forall (s_1,s_2)\in V_t, \forall m\in M, \forall f\in F, \forall t\in T \\ x_{m,f,t,s_1}^{sell} &= x_{m,f,t,s_2}^{sell} && \forall (s_1,s_2)\in V_t, \forall m\in M, \forall f\in F, \forall t\in T \\ x_{m,f,f',t,s_1}^{transfer} &= x_{m,f,f',t,s_2}^{transfer} && \forall (s_1,s_2)\in V_t, \forall m\in M, \forall f\in F, \forall f'\in F, f'\neq f \forall t\in T \end{aligned} \tag{4.11}$$

4.3 Robust optimization model

The deterministic model is also the base for the RO model. As with the SP, we assume that the demand after the first period is uncertain. We use the scenarios and non-anticipation constraints (4.11) of the SP in the RO model. The difference between the SP and RO models is in the objective function. The objective of the RO model does not weigh the probability of every scenario. Moreover, the RO model minimizes the maximum costs over all possible demand realizations (4.12), which is also called the min-max or worst-case approach. To solve the robust optimization problem as a MILP, we introduce the auxiliary variable Z. Z serves as an upper-bound to the objective function under each scenario (4.13). The objective becomes to minimize Z (4.14).

Table 4.7: Robust model new variables

S	Set of scenarios s, S = {1,2,...}
V_t	Set of scenarios s_1 and s_2 with the same demand history until time t
$D_{p,t,s}$	Demand of product p on time $t \in T$ in scenario s
Z	Auxiliary variable, $Z \in \mathbb{R}$

$$\begin{aligned}\min_{x,q,y} \max_{s \in S} \sum_{t \in T} (1+\rho)^{-t} \Bigg(& \sum_{f \in F} \sum_{m \in M} c_m^{buy} \cdot x_{m,f,t,s}^{buy} - c_m^{sell} \cdot x_{m,f,t,s}^{sell} \\ & + \sum_{f \in F} \sum_{f' \in F, f' \neq f} \sum_{m \in M} c_m^{trans} \cdot x_{m,f,f',t,s}^{trans} \Bigg) \\ & + \Bigg(\sum_{f \in F} \sum_{p \in P} c_p^{qual} \cdot q_{p,f,t,s} \\ & + \sum_{f \in F} \sum_{m \in M} \sum_{p \in P} c_{m,f}^{production} \cdot g_{p,m} \cdot y_{p,f,t,s} \\ & + \sum_{p \in P} c_t^{inventory} \cdot i_{p,t,s} + c_t^{backorder} \cdot b_{p,t,s} \Bigg)\end{aligned} \tag{4.12}$$

$$\begin{aligned}\sum_{t \in T} (1+\rho)^{-t} \Bigg(& \sum_{f \in F} \sum_{m \in M} c_m^{buy} \cdot x_{m,f,t,s}^{buy} - c_m^{sell} \cdot x_{m,f,t,s}^{sell} \\ & + \sum_{f \in F} \sum_{f' \in F, f' \neq f} \sum_{m \in M} c_m^{trans} \cdot x_{m,f,f',t,s}^{trans} \Bigg) \\ & + \Bigg(\sum_{f \in F} \sum_{p \in P} c_p^{qual} \cdot q_{p,f,t,s} \\ & + \sum_{f \in F} \sum_{m \in M} \sum_{p \in P} c_{m,f}^{production} \cdot g_{p,m} \cdot y_{p,f,t,s} \\ & + \sum_{p \in P} c_t^{inventory} \cdot i_{p,t,s} + c_t^{backorder} \cdot b_{p,t,s} \Bigg) \leq Z \qquad \forall s \in S\end{aligned} \tag{4.13}$$

$$\min_{x,q,y} Z \tag{4.14}$$

Chapter 5

Model verification

In this chapter, we determine that the model implementation represents the conceptual model. Several verification tests demonstrate that the models function as they should. The models of Chapter 4 are solved with a computational model in Python using Gurobi. The tests verify the mathematical as well as the computational models.

The verification consists of four tests with the base parameters as given in Table 5.1. For the first three tests, we give two cases, A and B, to show two different decisions. Case A uses the base parameters, and case B deviates from some of these parameters. We solve the cases for the deterministic model for four periods. Test 1 demonstrates that the model chooses between inventory and back-ordering based on costs. Test 2 shows that the model prefers transferring a machine if the load of the lines allows it. Test 3 demonstrates that the model would prefer the location with the lowest production costs when deciding where to qualify new products. For the fourth test, we give only one case, which we solve for the three different models. Test 4 demonstrates the differences between the deterministic, stochastic and robust programming models in the capacity expansion decision.

Test 1 This test demonstrates the model choices when keeping inventory is cheaper than back-ordering and the other way around. We expect that building inventory upfront is preferred when the inventory holding costs are lower than the back-ordering costs (case A). Furthermore, we expect that back-ordering is preferred when the back-

Table 5.1: Parameter base settings

Parameter	Value	Parameter	Value
c^{buy}	500	ρ	0.1
c^{sell}	1	τ_1	3
$c^{transfer}$	100	τ_2	2
$c^{qualify}$	150	τ_3	1
$c_f^{production}$	$[2, 1]$	υ	20
$c^{inventory}$	50	g_p	1
$c^{back-order}$	100	M	10,000

Table 5.2: Results test 1

	Test 1A				Test 1B			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Supply	20	20	20	20	20	20	20	20
Demand	5	25	10	15	5	25	10	15
Production	10	20	10	15	5	20	15	15
Inventory	5	0	0	0	0	0	0	0
Back-order	0	0	0	0	0	5	0	0

ordering costs are lower than the inventory holding costs. Consider a situation with one facility, one product, one machine type where capacity is fixed to 1 machine, and a capacity shortage occurs in the second period. Case A uses the input values of Table 5.1. Case B changes the input costs to $c^{inventory} = 100$ and $c^{back-order} = 50$.

Table 5.2 shows the results for cases A and B. In case A, pre-building 5 units in Q1 is preferred to cope with the capacity shortage. In case B, back-ordering is preferred over keeping inventory, and the capacity shortage is coped with by back-ordering in Q2 and producing 5 units more in Q3.

Test 2 This test demonstrates the machine buy and transfer decisions when capacity is needed at one facility, and the other facility is under-loaded (case A) or loaded (case B). We expect a machine transfer to the facility that needs capacity is preferred if the other facility is under-loaded (case A). We expect that buying a machine for the facility that needs capacity is preferred if the other facility is loaded (case B). Consider a situation with two facilities, two products, and one machine type where P1 is allocated to FAB 1, P2 is allocated to FAB 2, and the allocation is fixed. Both facilities start with 2 machines, machines can be bought or transferred, and a capacity shortage occurs at FAB1 in Q3. The input parameters for both cases are as given in Table 5.1. Case A has a low demand for P2, and case B has a high demand for P2.

Table 5.3 shows the results for cases A and B. In case A, the model would transfer one machine from FAB 1 to FAB 2 in Q2, whereas in case B, the model would buy one machine for FAB 2 in Q1. The machine transfer lead-time is one period, whereas the machine buy lead-time is two periods. Test 2A of Table 5.3 reflects this: the machine transfer decision is made in Q2, installed capacity is decreased immediately, and the installed capacity is increased one period later. The same holds for Test 2B of Table 5.3: the machine buy decision is made in Q1, and the installed capacity is increased two periods later.

Test 3 This test demonstrates the qualification of new products. Consider a situation with two facilities, three products, and no capacity restrictions. P1 is allocated to FAB1, P2 is allocated to FAB2, and a new product, P3, gets introduced in Q4. P3 can be qualified either in FAB1 or FAB2. We expect that the model qualifies P3 at the facility with the lowest production costs. Case A uses the input values of Table 5.1. Case B changes the input costs to $c_{FAB1}^{production} = 1$, $c_{FAB2}^{production} = 2$.

Table 5.3: Results test 2

	Test 2A				Test 2B			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Demand P1	5	25	45	50	5	25	45	50
Demand P2	15	15	15	15	35	35	35	35
Supply P1	40	40	60	60	40	40	60	60
Supply P2	40	20	20	20	40	40	40	40
Machine buy FAB 1	0	0	0	0	1	0	0	0
Machine transfer FAB 2 to 1	0	1	0	0	0	0	0	0
Machines FAB 1	2	2	3	3	2	2	3	3
Machines FAB 2	2	1	1	1	2	2	2	2

Table 5.4: Results test 3

	Test 3A				Test 3B			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Allocation P3-FAB1	0	0	0	1	0	0	0	0
Allocation P3-FAB2	0	0	0	0	0	0	0	1
Qualification P3-FAB1	1	0	0	0	0	0	0	0
Qualification P3-FAB2	0	0	0	0	1	0	0	0

Table 5.4 shows the results for cases A and B. In case A, the model qualifies P3 for FAB2 in Q1. In case B, the model qualifies P3 for FAB1 in Q1. As expected, in both cases, the model chooses the facility with the lowest production costs. As intended, a qualification started in Q1 ends in Q4 and causes the product to be allocated to a facility. Table 5.4 shows this for both tests. Production is only allowed when qualification has ended, and the product is allocated to the facility (Q4).

Test 4 This test shows the difference between the deterministic, stochastic and robust programming models in the capacity expansion decision. We expect that the deterministic model makes choices as seen before, that the robust model makes choices based on the scenario with the most demand, and that the stochastic model falls between the other two models. Consider a situation with one facility, one product, and one machine type. Both facilities start with 2 machines, and more machines can be bought. Suppose we use the input values of Table 5.1 and define three demand scenarios as in Table 5.5. S0 is the base scenario, S1 is a scenario with 50% of the base scenario demand, and S2 is a scenario with 150% of the base scenario demand.

We solve the deterministic, stochastic and robust model. Table 5.6 shows the optimization results. We see that the deterministic model chooses not to buy a machine

Table 5.5: Demand scenarios test 4

Scenario	Probability	Q1	Q2	Q3	Q4
S0	0.7	5	25	45	40
S1	0.15	5	12	22	20
S2	0.15	5	37	67	60

Table 5.6: Results test 4

	Deterministic				Stochastic				Robust			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Supply	40	40	40	40	40	40	60	60	40	40	80	80
Machine buy	0	0	0	0	1	0	0	0	2	0	0	0
Machines	2	2	2	2	2	2	3	3	2	2	4	4
Production	5	30	45	40	5	25	45	40	5	25	45	40
Inventory	0	5	0	0	0	0	0	0	0	0	0	0

and build inventory instead. The stochastic model buys 1 machine, and the robust model buys 2 machines. If the worst-case occurs, buying two machines in Q1 is the only option to avoid capacity shortage. Buying no machine or 1 machine would give a capacity shortage of 47 or 7, respectively. Note that the inventory holding and back-ordering costs are relatively high compared to the machine buy costs, making buying a machine favorable over holding inventory.

The inventory or back-order, capacity increase, and product allocation decisions separately work as expected. Hence, the model is working as intended. In the rest of the study, we assume the integrated models make the right decisions.

Chapter 6

Design of experiments

Two numeric experiments are conducted to see the models' behavior and gain insights to answer the third research question, namely: "What model type allows ams to take robust decisions taking into account demand uncertainty?". The sensitivity analysis and simulation study test the models' robustness to parameters and demand changes, respectively. This chapter describes the input and the methods used in the experiments. The next chapter shows the results.

6.1 Input parameters

The model solution is based on the input from ams (Table 6.1). As the product demand input, the model uses the quarterly aggregated consensus forecast with a horizon of 14 quarters. Beyond this horizon, no accurate information is available. By using the demand forecast, we implicitly consider the introduction and end-of-life of products. Furthermore, the machine buy costs per machine type, the machine transfer costs, the product qualification, and the production costs are known but confidential.

The capacity consumption rate and maximum production volume of the FSP tool (M6) are measured in hours, whereas for the others (M1-M5), the planned throughput in units is used. The capacity consumption rate is dependent on the number of layers of a product. The FSP tool has 24/7 production with an up-time of 80%. The other tools' maximum production volume is the maximum net throughput per period. The capacity already accounts for engineering-time, down-time, and queuing effects. The capacity consumption differs per product and machine.

The costs for the transfer and procurement of tools include installation costs. The selling benefit is set to one euro since it is uncertain if a machine can be sold. The low benefit causes a machine to be sold if it is not needed anymore, not for its benefit. Conditioned storage locations for the wafers mainly cause the inventory holding costs. The costs are variable depending on the amount stored, and the fixed part is negligible. Furthermore, holding inventory has an obsolescence risk, estimated as a percentage of the sales costs.

In the consideration between holding inventory and back-ordering or buying a machine, an end-of-horizon effect occurs. The holding and back-ordering costs at the end of the horizon do not outweigh the one-time costs, resulting in doing nothing instead of investing. If we would increase the horizon, we would never choose to build up inventory or back-orders instead of increasing capacity. Therefore, we increase the holding and back-ordering costs in the last year to force the decisions, even though

Table 6.1: Parameter input

Input parameter	Notation	Value
Products	P	{P1,...P55}
Machines	M	{M1,...,M6}
Facilities	F	{FAB1,FAB2}
Time periods	T	{2021Q1,...,2024Q2}
Time with initial period	T_0	{2020Q4,...,2024Q2}
Scenarios	S	{S0,...,S4}
Scenario probabilities	P_s	[0.7,0.075,0.075,0.075,0.075]
Interest rate	ρ	0.14 per year
Machine sell income	c^{sell}	1
Inventory holding costs	$c_t^{inventory}$	$\begin{cases} 74 & \text{if } t \in \{2021Q1, ..., 2023Q2\} \\ 5,000 & \text{if } t \in \{2023Q3, ..., 2024Q2\} \end{cases}$
Back-ordering costs	$c_t^{back-order}$	$\begin{cases} 148 & \text{if } t \in \{2021Q1, ..., 2023Q2\} \\ 10,000 & \text{if } t \in \{2023Q3, ..., 2024Q2\} \end{cases}$
Qualification lead-time	τ_1	3
Tool procurement lead-time	τ_2	2
Tool transfer lead-time	τ_3	1
Initial machines FAB 1	$k_{m,FAB1,2020Q4}$	[2,1,1,2,2,34]
Initial machines FAB 2	$k_{m,FAB2,2020Q4}$	[2.5,2,2,3,3,22]
Production volume	v_m	[2800,770,576,1200,500]
Initial inventory	$i_{p,2020Q4}$	$0\ \forall p \in P$
Initial back-orders	$b_{p,2020Q4}$	$0\ \forall p \in P$

we do not know the demand after the time horizon.

As explained in Chapter 4, the demand scenarios represent the demand uncertainty in the stochastic and robust model. All products have some demand variability. However, sampling a low-, base-, and high-demand scenario for every product would result in 3^{55} scenarios. Reducing this number by considering only the scenarios where a maximum of one product can have low or high demand, 111 scenarios remain. This would result in a stochastic model with 784,104 variables and 5,152,796 constraints. Solving with a time-limit of 5 minutes leaves an optimality gap of 94%. For the robust model, approximately the same holds. Therefore, it is computationally intractable to model all products' demand deviations as scenarios. Hence, we investigate if sampling five scenarios for the products based on the two most uncertain technologies is sufficient for making a model that gives robust solutions. We test the model in an environment with uncertainty for all products to analyze performance.

Table 6.2: Demand scenarios

Scenario	Description	Probability P_s
S0	Base demand	0.7
S1	Technology 1 products 50% of base demand	0.075
S2	Technology 1 products 150% of base demand	0.075
S3	Technology 2 products 50% of base demand	0.075
S4	Technology 2 products 150% of base demand	0.075

We sample scenarios for the products of ams with the most uncertain demand. Multiple products are based on the two most uncertain technologies making up for a large part of demand. Technology 1 exists of one product (P1), and technology 2 exists of six products (P19, P20, P28, P29, P30, P31). For these technologies, we define a scenario with low demand (50%) and a scenario with high demand (150%), resulting in four scenarios besides the base scenario (Table 6.2).

6.2 Optimization

The sensitivity analysis and simulation study solve the models multiple times. We implemented the models using Python 3.7.4. The experiments were performed on a Dell Latitude 7490 notebook with an Intel Core i7-8650U CPU 1.90GHz processor and 8GB RAM. Gurobi 9.0 with standard settings solves the models. Gurobi combines multiple algorithms efficiently. Since the variables for the number of machines are integer, the models are MILP and are solved by the branch-and-bound algorithm. If the maximum computation time is not enough to prove optimality, it leaves us with a gap between the lower and upper-bound: the optimality gap.

6.3 Sensitivity analysis

The demand is the most uncertain input parameter in the model. However, for model robustness, it is essential to know the sensitivity to the other input data as well. We study the effect of changing one parameter at a time while keeping the demand input the same.

The sensitivity analysis determines how the decision variables respond to changes in the model input. It is hard to compare individual decisions because the impact of each decisions is not the same. Therefore, we quantify the amount of change with the change in the objective function. The model is solved iteratively for changing parameter values. We look at the change in the objective value when varying the parameter values.

The models have to run multiple times for the sensitivity analysis, which takes very long. Therefore, we allow an optimality gap and warm-start the models with the prior model's solution. Appendix B explains what warm-start is, why it is used, and reports the differences with solving without warm-start.

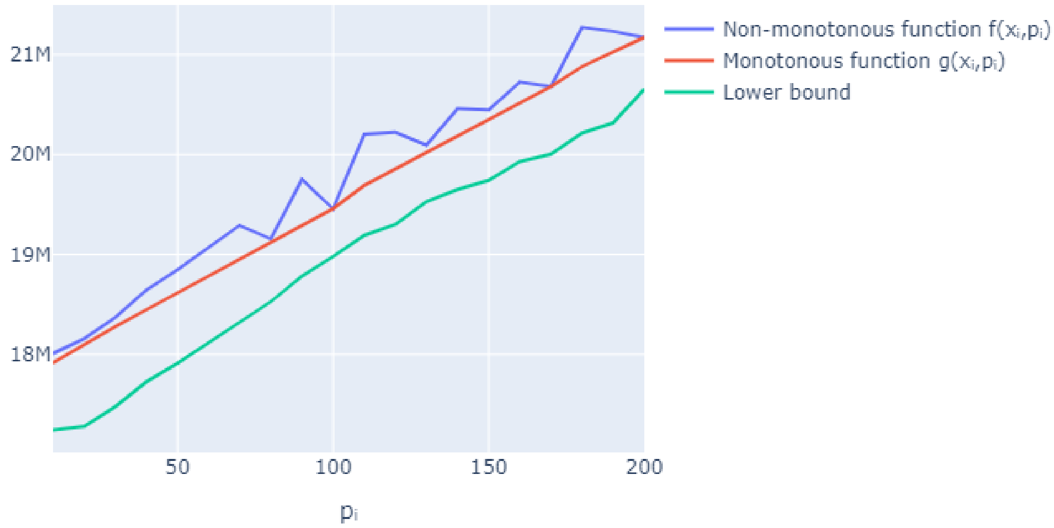


Figure 6.1: Sensitivity analysis method example

Solving the model iteratively with an allowed optimality gap results in a non-monotonous function of the objective value as a function of the parameter. The solution given by solving the model allowing an optimality gap is not proven to be optimal. Therefore, we formalize a generic method for deriving a monotonous function for the local sensitivity analysis of MILP models with an optimality gap.

We know that the optimal objective value without an optimality gap as a function of all parameters should be monotonous. First, we optimize the model with an optimality gap for the considered range of parameter values. The result is a non-monotonous function f dependent on decision x_i and parameter value p_i. We observe whether the objective function should be monotonically increasing or decreasing. Then, we define function g as the monotonous function dependent on decision x_i and parameter value p_i. We define $p_i \leq p_{i+1}$ resulting in $f(x_i, p_i) \leq f(x_{i+1}, p_{i+1})$ as the condition for increasing functions. If the condition holds, the function till $f(x_{i+1}, p_{i+1})$ is monotonous, so the monotonous function adopts the values: $g(x_i, p_i) = f(x_i, p_i)$. If the condition does not hold, the function decreases. As we know that the optimal objective function should be monotonous, the decrease is only possible if the decisions prior to this point are worse than x_{i+1}. Therefore, we calculate the objective value $f(x_{i+1}, p_j)$ for all $p_j \in [p_0, p_i]$. Since we make adjustments for all parameter values p_i where the condition does not hold, we check whether the new objective value is an improvement to the existing one. Therefore, $g(x_j, p_j) = \min[g(x_j, p_j), f(x_{i+1}, p_j)]\ \forall p_j \in [p_0, p_i]$.

Figure 6.1 shows the non-monotonous function f and the monotonous function g created by applying the described method for an example for the machine transfer cost sensitivity of the stochastic model with a maximum optimality gap of 5%.

In the case of ams, we consider a relative deviation of plus and minus 100% with steps of 10% around the nominal parameter value. The relative deviation makes the sensitivity of several parameters comparable and enables us to not only test the sensitivity of scalar parameters (interest percentage), but for vector (machine buy costs) and matrix parameters (production costs) as well. The stop criterion for the sensitivity analysis is a gap of 5% or 900 seconds run time.

6.4 Simulation

The simulation tests the model's sensitivity to changes in demand. The results of running the models once tell us the theoretic decisions (first-stage decisions and belonging recourse actions) and objective values. However, our goal is not to find the model with the lowest theoretic costs but the model that performs best under demand uncertainty. To determine the models' differences, we simulate the models for several periods in a rolling scheduling environment. The rolling scheduling simulation simulates the situation in practice where demand uncertainty and forecast updating occur every period. We start with the newest forecast as an input to the optimization models. We only take the first-stage decisions from the models' solutions and determine their costs. (6.1) gives the formula for the actual costs made in the period. We continue to the next period where decisions take effect according to their lead-time and the actual demand for the period is revealed. The forecast is updated again and all periods in the simulation horizon follow these steps. Figure 6.2 shows the events in the simulation.

$$
\begin{aligned}
TC_t = & \sum_{f \in F} \sum_{m \in M} c_m^{buy} \cdot x_{m,f,t}^{buy} - c^{sell} \cdot x_{m,f,t}^{sell} \\
& + \sum_{f \in F} \sum_{f' \in F, f' \neq f} \sum_{m \in M} c^{transfer} \cdot x_{m,f,f',t}^{transfer} \\
& + \sum_{f \in F} \sum_{p \in P} c^{qualify} \cdot q_{p,f,t} \\
& + \sum_{f \in F} \sum_{m \in M} \sum_{p \in P} c_{m,f}^{production} \cdot g_{p,m} \cdot y_{p,f,t} \\
& + \sum_{p \in P} c_t^{inventory} \cdot i_{p,t} + c_t^{backorder} \cdot b_{p,t}
\end{aligned}
\tag{6.1}
$$

The simulation study requires some additional input next to the input of Section 6.1. The simulation will imitate the situation of ams as well as possible. Therefore, the forecast's fluctuation when updating the forecast, the demand uncertainty, and the probability and frequency of new product introductions serve as an input to the simulation study. We used historical data about the forecast and actual demand to determine the filter products' demand uncertainty. To be precise, we used the forecast of one quarter before the actual demand was revealed. We calculated the percentage difference between the forecast and the actual demand. The data points out that the percentage difference between the actual demand and last quarter's forecast is normally distributed with $\mu = 0.1$ and $\sigma = 0.5$ (Figure 6.3). The D'Agostino-Pearson, Shapiro-Wilk, and Anderson-Darling normality tests confirmed the normality of the data on a 1% significance level.

The simulation considering a normally distributed relative forecast error with $\mu = 0.1$ and $\sigma = 0.5$ is defined as case 3. Table 6.3 shows all test cases with the amount or

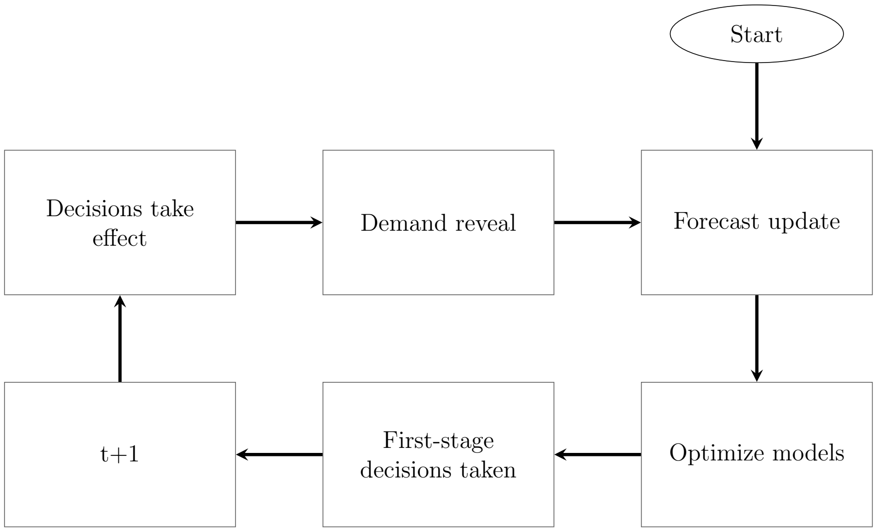


Figure 6.2: Simulation steps

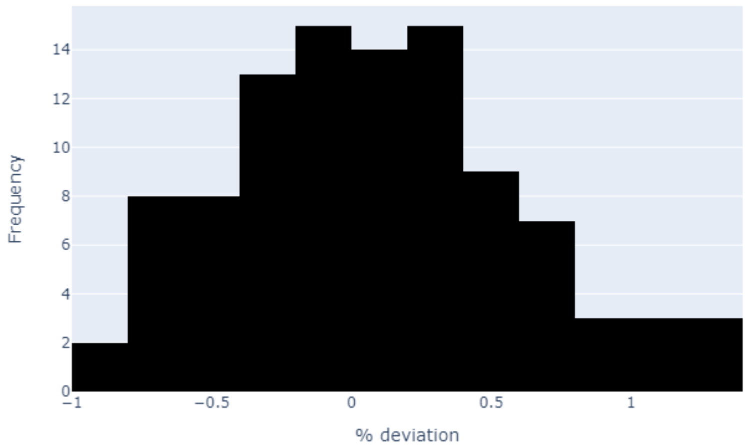


Figure 6.3: Distribution of % deviation from forecast

Table 6.3: Test cases

Case #	Uncertain products	Relative demand deviation
1	All	$N(0.1, 0.0)$
2	All	$N(0.1, 0.4)$
3	All	$N(0.1, 0.5)$
4	All	$N(0.1, 0.6)$
5	All	$N(0.1, 1.0)$
6	All	$N(0.1, 1.5)$
7	All	$N(0.1, 3.0)$
8	None	
9	Technology 1	-0.5
10	Technology 1	0.5
11	Technology 2	-0.5
12	Technology 2	0.5

distribution of the relative forecast error. We perform other simulations with higher and lower standard deviations than case 3 (case 1-7). These cases are used to test which model performs best under which level of uncertainty. For validation, we test the performance in case one of the demand scenarios occurs. Case 8-12 represent demand scenarios 0-4. These cases assume only demand uncertainty for the products considered by the scenario.

Ams employs a rolling demand forecast mechanism to use the most recent and, thereby, most accurate information for decision-making, such as capacity expansion decisions. The simulation uses a similar mechanism to meet reality for the experiments. This means the forecast gets an update every period based on the forecast fluctuations in the past determined by historical data. The fluctuations are dependent on the forecasting distance.

Since the models have to run multiple times for the simulation, the simulation can take very long. Therefore, we set a maximum on the optimality gap and use last quarter's solution as a warm-start. Appendix B explains what warm-start is, why it is used, and reports the differences with running without warm-start. The stop criterion is a gap of 5% or 120s seconds run time.

We compare the different models by calculating several performance measures. The measures, such as average costs and worst-case costs, give insight into the model differences. Simulating several iterations is necessary to obtain reliable measures.

Chapter 7

Results of experiments

Following the methodology of Chapter 6, we present the sensitivity analysis and simulation study results. We discuss the third research question: "What model type allows ams to take robust decisions taking into account demand uncertainty?"

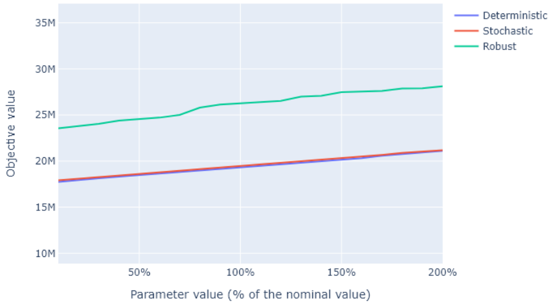
7.1 Sensitivity analysis

Figure 7.1 gives the sensitivity analysis results for the machine buy and transfer cost parameters. The sensitivity analysis results for the other parameters show similar effects (Appendix C). The obvious difference between the models is the magnitude of the objective value, indicated by the line's height. All lines of the robust model lie much higher than the lines of the deterministic and stochastic model. The stochastic model has a slightly higher objective value than the deterministic model. The line-height says nothing about the sensitivity of the model. The sensitivity of the models can be compared by looking at the slopes of the lines. The figures show no significant difference between the deterministic and stochastic models in the slope of the lines. The objective value of the robust model increases faster for positive related parameters and decreases faster for negative related parameters. Figure 7.1b shows a very steep line for the robust objective as a function of the machine buy costs. The machine buy costs is the main contributor to the difference between the robust model and the other models. Altogether, the robust model is more sensitive to the input parameters than the deterministic and stochastic models.

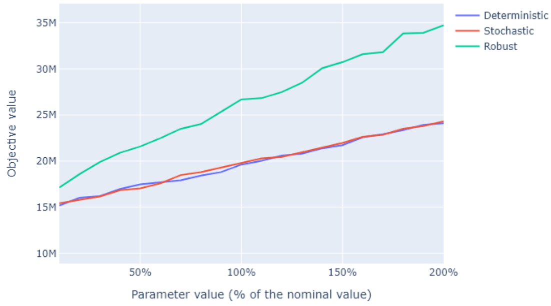
7.2 Simulation

The simulation study tested the models' performance in an environment with varying demand uncertainty. Table 7.2 presents the average performance and Table 7.3 the worst-case performance for the 12 cases. We simulated 150 iterations for case 3 and 50 iterations for all other cases. Case 3 is the most realistic case for ams according to historical data.

Looking at the average performance, the deterministic model with input scenario 0 outperformed the stochastic and robust model in all cases. Remarkably, not the deterministic model with input scenario 0, but with input scenario 3 had the best average performance in all cases, which implies that assuming a lower demand than in the forecast is beneficial. The model recommends investing less because it assumes a



(a) Machine transfer costs



(b) Machine buy costs

Figure 7.1: Sensitivity

lower demand than forecasted. However, the capacity shortage's adverse effects, such as back-orders, are not visible because the simulation has a finite horizon.

The worst-case performance shows more differences between the cases than the average performance. In case 1 (standard deviation 0), the deterministic model's worst-case performance with input scenario 0 is best. In case 2-6, the deterministic models with input scenarios 1, 2, and 3 outperformed the other models. In case 7, the case with the highest uncertainty, the stochastic model had the best worst-case performance. In case 8-12, the deterministic models outperformed the other on worst-case performance. However, in case 12, the deterministic model with input scenario 4 had the best worst-case performance, and the deterministic model with input scenario 3 had the worst worst-case performance. The worst-case performance is quite unstable over the different cases.

Since case 3 is the most realistic case for ams according to historical data, we emphasize case 3. On average, making choices according to the stochastic or robust model was 10.2% and 32.0% more costly, respectively, than the deterministic model with input scenario 0. The deterministic model with input scenario 3 was 8.3% less costly than the one with input scenario 0. Figure 7.2 gives the results' boxplots for case 3. The stochastic model performed best in 4 of the 100 iterations. The robust model performed best in 1 of the 100 iterations.

For case 3, we have a closer look at the costs' origin (Table 7.1). The deterministic model with input scenario 3 performs best on the total average costs. The low capital investments and high back-order costs indicate an end-of-horizon effect. It shows that the model's decisions had relatively low costs in total because it invested less than the other models. The back-order costs did not nullify this, and the model still comes out best.

Furthermore, the robust model and the deterministic model with input scenario 4 have high inventory holding costs. The former optimizes for the worst-case, and the latter assumes a high demand. For both models, it seems beneficial to create inventory for the high future demand explaining the high inventory holding costs for these models.

Moreover, the robust model has high capital investment costs as well as back-orders. It has been observed that in several iterations of the simulation, capacity gets critical at the end of the horizon, and the robust model covers early for capacity

Table 7.1: Costs breakdown case 3

	DP (S0)	DP (S1)	DP (S2)	DP (S3)	DP (S4)	SP	RO
Buy	0.0057	0.0020	0.0172	0.0020	0.0333	0.0086	0.0349
Sell	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Transfer	0.0691	0.0512	0.1020	0.0253	0.1703	0.1060	0.1660
Qualification	0.2733	0.2658	0.2791	0.2496	0.3173	0.3082	0.3283
Production	0.3493	0.3458	0.3480	0.3481	0.3375	0.3434	0.3359
Inventory	0.0023	0.0011	0.0067	0.0009	0.0102	0.0049	0.0089
Backorder	0.0670	0.1108	0.0531	0.0810	0.0579	0.0855	0.1261
Total	0.7666	0.7766	0.8062	0.7069	0.9266	0.8566	1.0000

The costs in this table are normalized. DP indicates the deterministic programming model with the scenarios used as input demand between brackets.

shortages by machine transfers. When in a period of transfer, overall capacity is lower for the transfer lead-time. If this creates a capacity shortage, back-orders originate. In reality, the back-orders pay off later. However, since we consider a finite horizon simulation, we see the back-orders and machine transfer, but not the pay-off in sufficient capacity later.

The sensitivity analysis showed no significant sensitivity difference between the deterministic and stochastic models. The robust model is more sensitive than the other models to parameter deviations, meaning it will be less resistant to poor data quality and input parameter assumptions. The simulation study showed that, on average, the deterministic model outperforms the models that incorporate uncertainty in all test cases. The worst-case performance was unstable over the different cases, which indicates that the number of iterations in the simulation is insufficient to draw meaningful conclusions to the worst-case performance. Therefore, we focus on the average performance and conclude that the deterministic model fits the situation of ams best. The deterministic model has the additional benefit of simplicity. Although the deterministic model with input scenario 3 seems to perform better, we do not recommend using just this model because of the end-of-horizon effects. Considering the deterministic model with several input scenarios to support the decisions is the proposed solution.

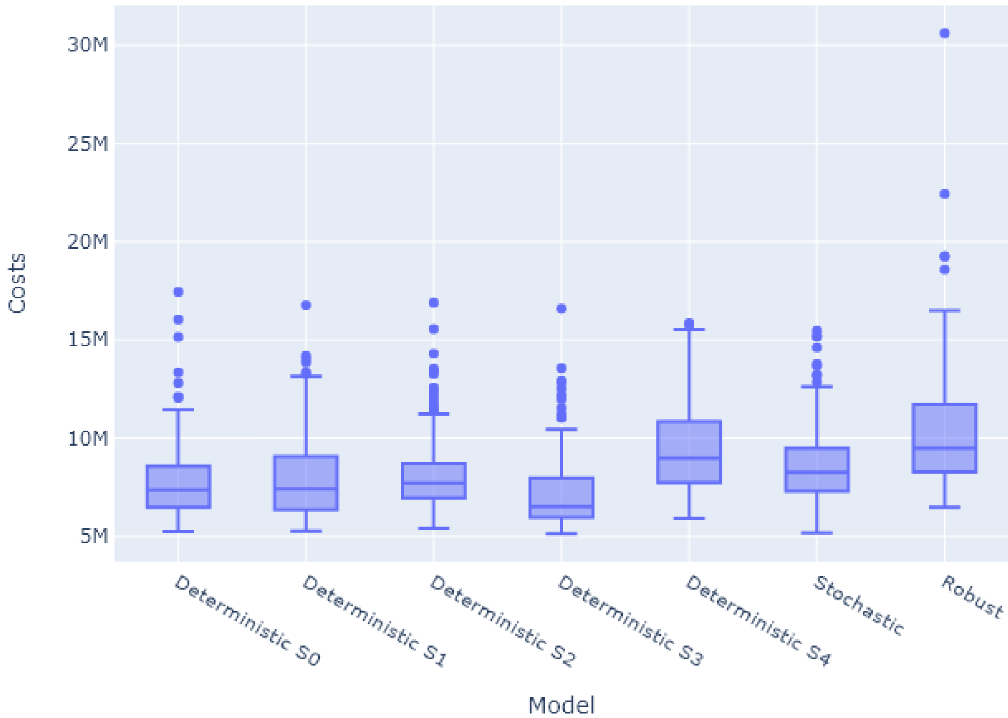


Figure 7.2: Boxplots of the simulation results for case 3

Table 7.2: Average performance

Case #	DP (S0)	DP (S1)	DP (S2)	DP (S3)	DP (S4)	SP	RO
1	0.0146	0.0140	0.0191	0.0123	0.0259	0.0205	0.0324
2	0.0166	0.0150	0.0207	0.0114	0.0312	0.0251	0.0403
3	0.0209	0.0223	0.0237	0.0154	0.0353	0.0282	0.0438
4	0.0257	0.0266	0.0249	0.0181	0.0392	0.0304	0.0418
5	0.0557	0.0620	0.0525	0.0422	0.0760	0.0718	0.0824
6	0.0875	0.1010	0.0855	0.0630	0.1089	0.1036	0.1242
7	0.4341	0.4549	0.4382	0.4064	0.4598	0.4500	0.4711
8	0.0121	0.0092	0.0175	0.0070	0.0267	0.0175	0.0347
9	0.0086	0.0050	0.0142	0.0035	0.0219	0.0123	0.0282
10	0.0134	0.0120	0.0170	0.0078	0.0263	0.0190	0.0320
11	0.0077	0.0050	0.0120	0.0000	0.0211	0.0133	0.0277
12	0.0180	0.0155	0.0229	0.0154	0.0266	0.0233	0.0314

The costs in this table are normalized. DP indicates the deterministic programming model with the scenarios used as input demand between brackets.

Table 7.3: Worst-case performance

Case #	DP (S0)	DP (S1)	DP (S2)	DP (S3)	DP (S4)	SP	RO
1	0.0347	0.0411	0.0652	0.0407	0.0576	0.0507	0.0798
2	0.0673	0.0751	0.0532	0.0643	0.0782	0.0803	0.1316
3	0.1074	0.1014	0.1025	0.0997	0.0931	0.0895	0.2268
4	0.1035	0.1131	0.0814	0.1131	0.1239	0.1249	0.1215
5	0.3049	0.3427	0.1768	0.1912	0.2947	0.3145	0.2963
6	0.7396	0.8598	0.6128	0.3832	0.6808	0.6671	0.7498
7	0.9047	1.0000	0.8625	0.8164	0.8258	0.7654	0.8781
8	0.0427	0.0410	0.0698	0.0342	0.0732	0.0373	0.0986
9	0.0252	0.0202	0.0713	0.0202	0.0555	0.0301	0.0767
10	0.0301	0.0444	0.0399	0.0338	0.0577	0.0475	0.0662
11	0.0218	0.0184	0.0434	0.0160	0.0435	0.0416	0.0749
12	0.0678	0.0723	0.0695	0.0806	0.0536	0.0755	0.0706

The costs in this table are normalized. DP indicates the deterministic programming model with the scenarios used as input demand between brackets.

Chapter 8

Implementation

As seen in the last chapter, the sensitivity analysis and simulation study examine the best model for ams. The recommended solution for ams is using the deterministic model (Chapter 7), hereafter called the model. This chapter describes the implementation of the model in practice, thereby answering the fourth and fifth research question: "How can the decision tool be implemented in the decision process?" and "What is the difference between the current practice and the recommended solution?". Furthermore, we demonstrate the benchmark comparison and scenario analysis for the current data of the ams case.

8.1 Decision support tool

Our model optimizes capacity planning and sourcing decisions for the filter line. Making these decisions is a recurring process in which the decisions are reviewed quarterly. The optimization model should be implemented in a decision support tool to use our model and compare it with the planned decisions. The insights from the model serve multiple purposes. The proposed plan can be used in several strategic review processes such as capacity planning and sourcing strategy review, and budgeting. The amounts of product qualifications, machine buys, and machine transfer can be used for budgeting purposes. The decision support tool's outcomes serve as an input for decision processes but will still need expert judgment. A field expert can consider the outcomes for several scenarios and take into account committed allocations of products.

The decision support tool supports ams in making the capacity planning and sourcing decisions by showing the model's recommended actions. Furthermore, the tool provides additional insights into the consequences of the decisions, such as costs and installed capacities. The tool provides recommended actions and consequences for the base scenario, several demand scenarios, and the benchmark. The benchmark is the current practice in which we adhere to the current allocation planning. The tool enables the decision-maker to compare the decisions and consequences for the scenarios and benchmark side-by-side. The decision support tool allows the decision-maker to base the analyses on the latest information, which is essential in the decision process.

Figure 8.1 shows the process for using the decision support tool. The decision-maker provides the consensus forecast, defines the demand scenarios, and sets the input parameters. Furthermore, the user can choose which machines to consider,

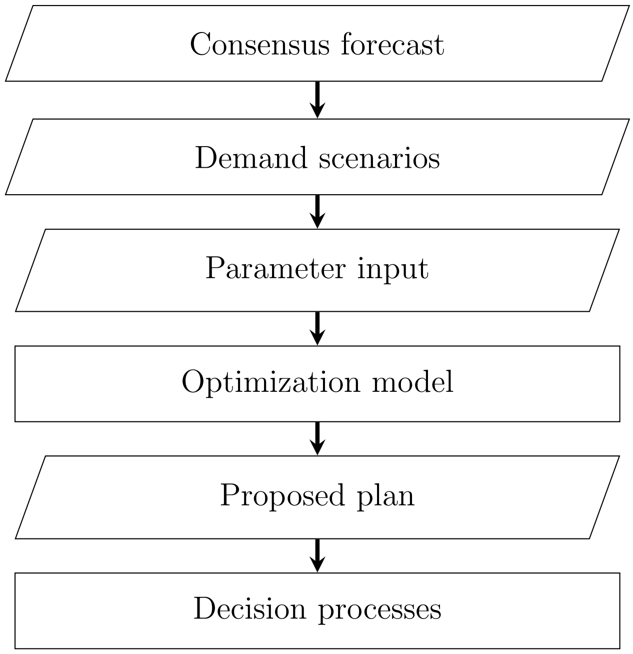


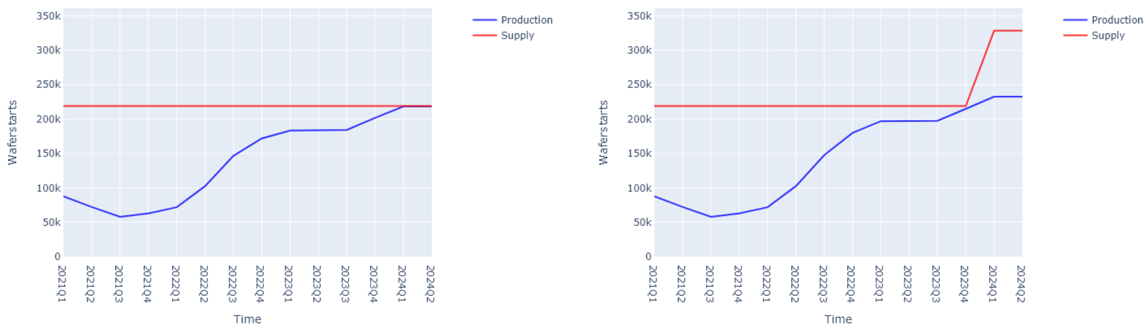
Figure 8.1: Tool use flowchart

whether scenario analyses and benchmark comparisons should be made, and whether a limit should be set on the maximum number of machines in a facility. The decision support tool solves several optimization models for our model and the benchmark for every demand scenario on the back-end. The tool processes the solution to an interpretable form, the proposed plan. After processing, the decision-maker sees several tabs in the tool. One to visually inspect the given demand input in a demand figure. Another tab visualizes the solution by several figures. The last tab provides a pivot table for a detailed look at all decisions and consequences. Appendix D gives several screenshots for the prototype tool.

The benchmark comparison and scenario analysis give valuable managerial insights. The rest of the chapter describes the insights the decision-maker could retrieve from the decision support tool for the current situation and the most recent demand forecast of ams. Appendix E gives a complete overview of the qualification and machine move decisions for the model and the benchmark in scenario 0, and the costs for the model and benchmark in each scenario. The demand scenarios used as input to the stochastic and robust models came forward because these scenarios are likely to occur. Therefore, we show the consequences for these scenarios. We define the other input parameters as in Chapter 6 as well.

8.2 Benchmark comparison

As outlined in Chapter 1, a recent management decision determined that the mass production location changes to the FAB 2 facility. The majority of the new products will ramp at FAB 2, but the existing products' mass production will remain in FAB 1. The planning resulting from this rule-of-thumb serves as the benchmark. The general difference between the current practice and the recommended solution is that the benchmark has a fixed qualification planning, whereas our model can choose where new products will be qualified. Our model and the benchmark both optimize the



(a) Model

(b) Benchmark

Figure 8.2: Capacity planning machine 3 FAB 2

capacity planning in the same way. Thus, the model will always be less costly than the benchmark, to which extent depends on the situation.

For the current situation, the difference between the model and the benchmark is that the model allocates four products differently than the benchmark if scenario 0 evolves. The different allocation results in a different load balancing. The load balancing impacts the machine buy decision for machine 3, for which the model prevents a machine buy (Figure 8.2).

The benefit of using the model compared to the benchmark allocation planning can be expressed in a relative cost difference. If the demand develops according to scenarios 0, 1, 2, 3, or 4, the expected savings are 8.3%, 14.3%, 6.5%, 0.5%, and 12.4%, respectively. Therefore, we conclude that the model is significantly better than the benchmark.

8.3 Scenario analysis

The scenario analysis shows the differences if future demand deviates from the base forecast. Since the demand is the leading difference between the scenarios, comparing costs is of no use. Instead, we show what shift in capacity and sourcing can be expected between FAB 1 and FAB 2 if the scenarios occur in the coming years.

In the model's solutions assuming scenarios 0, 1, 2, or 3, production remains in both facilities. The model solution in scenario 4 is an exception: all production shifts to FAB 2. The benchmark for scenario 4 shows that remaining production in both facilities requires one extra machine for M1, M3, M4, and M5 (Table 8.1). The savings on machine buy costs outweigh the qualification and transfer costs.

It is noteworthy that two seemingly similar scenarios, 2 and 4, have a distinct capacity shift. The difference is in that in scenario 2 no extra machines are needed when remaining production in FAB 1 and 2 compared to shifting all production to FAB 2. Products based on technology 1 and 2 have a different capacity consumption on several machine types, which explains the different capacity needs between scenario 2 and 4.

The scenario analysis teaches us that a production shift to FAB 2 with some production remaining in FAB 1 is currently a suitable choice in most cases. The production shift means qualifying most of the new products in FAB 2 while shifting

Table 8.1: Installed capacity 2024Q2 scenario 2 vs. scenario 4

	Model S2		Model S4		Benchmark S4	
Machine	FAB 1	FAB 2	FAB 1	FAB 2	FAB 1	FAB 2
M1	1	7	0	8	1	8
M2	1	2	0	2	1	2
M3	1	2	0	3	1	3
M4	1	4	0	5	1	5
M5	1	3	0	5	1	5
M6	7	71	0	76	3	73

capacity led by demand. However, if an increase in demand causes an imbalanced line, it may be beneficial to re-qualify products to shift all production to FAB 2 instead of increasing overall capacity.

Chapter 9

Conclusion

This research developed a decision support model and prototype tool that determine the recommended long-term capacity planning and sourcing strategy. The decision models concerned include a deterministic, stochastic, and robust mixed-integer linear programming model minimizing costs. The decisions are prone to volatile demand, which the stochastic and robust models consider upfront by utilizing demand scenarios. A sensitivity analysis and simulation study determined which model allows ams to make robust decisions considering demand uncertainty. The sensitivity analysis tested the effect of parameter changes on the model outcomes. The simulation study tested the actual costs in a rolling scheduling environment with forecast updates and demand uncertainty.

The sensitivity analysis showed that the robust model is more sensitive to the input parameters than the other models. The simulation study reported that the deterministic model is most robust to demand uncertainty. According to the sensitivity analysis and simulation study, the deterministic model is the recommended solution for ams. The deterministic model can be implemented in the decision processes by incorporating it in a decision support tool. The tool allows ams to make informed decisions based on the latest data and the most likely demand scenarios. We developed a prototype of such a decision support tool.

The deterministic model confirms that the current view on allocation planning, a production shift towards the facility in Asia, is an optimal choice for several demand scenarios. Practically, this means moving as many products to the facility in Asia as possible by other restrictions and increasing capacity led by demand requirements.

Determining the optimal product-to-plant allocation and the associated capacities is a recurring decision process dependent on the demand forecast. The planning process is dynamic, and therefore, we recommend using the deterministic MILP model implemented in a decision support tool. The tool should show the decisions and their consequences according to the model as well as the benchmark. Additionally, the tool should provide scenario analyses to show the decisions and consequences of the model and benchmark in different demand situations. Experts should evaluate the planned and recommended decisions and consider committed allocations and other practicalities.

9.1 Limitations and future research

Different than expected, the deterministic model came forward as the best model for making decisions under uncertainty. However, we do not rule out that a stochastic or robust model can benefit this problem and the situation of ams. This research has limitations that are worth considering in future research.

The stochastic model does not turn out to be better than the deterministic model in a finite horizon setting. The stochastic model minimizes the expected value while numerous parallel realizations of the same experiment are needed till the behavior converges to the expected value. A similar problem occurs for the robust model. We stated that robust models function best in worst-case situations. However, determining the worst-case is difficult with a simulation. As the number of iterations grows, the worst-case gets worse. We cannot say how many iterations suffice to find the worst-case or show the stochastic model's benefit. However, the number of iterations in this research's simulation study was insufficient for that purpose. Note that in practice, the problem is not solved numerous times either. The demand realizations in the simulation may not precisely be the ones that occur in practice. However, the probability of the worst-case occurrence in practice is also minor.

This research has two limitations concerning the development of the stochastic and robust programming model. First, the models use one scenario sampling technique. The research does not compare several samples of scenarios to find the best technique. With the current scenarios used, the models incorporating demand uncertainty do not perform better than the deterministic model. Defining the scenarios differently could produce stochastic and robust models that outperform the deterministic model. Second, this research considers the min-max approach of robust optimization. However, robust optimization is a broad field with many model variants. Future work could consider min-max regret or min-max relative regret approaches.

Another drawback of the model formulation holds for the deterministic, stochastic and robust model. Capacity expansion decisions focus on future demand. Not all capital investments are utilized within the finite horizon of the MILP models. The deterministic model with a high demand scenario, the stochastic model, and the robust model secure themselves with an amount of capacity and the associated expenses that are not always utilized on the considered horizon.

The straightforward way to reduce the end-of-horizon effects is lengthening the planning horizon. Furthermore, the end-of-horizon effect could have been reduced by the way the MILP is formulated. The most significant expenses in the model are the machine procurement costs. In a different formulation, we could have included the advantage of buying more machines in the objective value by modeling the procurement costs not as a one-time expense but with the depreciation value of machines. Another possible solution is to include machines' salvage values at the end of the planning horizon in the objective function. For the latter option, it is necessary to keep track of machine lifetimes and replacements as well.

Although the model is developed for the filter lines of ams, the problem can occur in other lines, companies, or industries. The general idea and mathematical formulation of this research can be applied. However, the sensitivity analysis and simulation study have to be performed again to research the best fitting model in that specific context. Furthermore, future work could extend the model to a network problem by including the decisions on opening and closing facilities and the associated costs.

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Appendix A

Complete models

A.1 Determinstic programming model

$$
\begin{aligned}
\min_{x,q,y} \sum_{t \in T} (1+\rho)^{-t} \Bigg(& \sum_{f \in F} \sum_{m \in M} c_m^{buy} \cdot x_{m,f,t}^{buy} - c^{sell} \cdot x_{m,f,t}^{sell} \\
& + \sum_{f \in F} \sum_{f' \in F, f' \neq f} \sum_{m \in M} c^{transfer} \cdot x_{m,f,f',t}^{transfer} \Bigg) \\
& + \Bigg(\sum_{f \in F} \sum_{p \in P} c^{qualify} \cdot q_{p,f,t} \\
& + \sum_{f \in F} \sum_{p \in P} c_{m,f}^{production} \cdot g_{p,m} \cdot y_{p,f,t} \\
& + \sum_{p \in P} c^{inventory} i_{p,t} + c^{backorder} b_{p,t} \Bigg)
\end{aligned}
\tag{A.1}
$$

subject to

$$k_{m,f,t} = k_{m,f,t-1} + x^{buy}_{m,f,t-\tau_2} - x^{sell}_{m,f,t} - \sum_{f' \in F} x^{trans}_{m,f,f',t} + \sum_{f' \in F} x^{trans}_{m,f',f,t-\tau_3} \qquad \forall m \in M, \forall f \in F, \forall t \in T \tag{A.2}$$

$$i_{p,t} - b_{p,t} = i_{p,t-1} - b_{p,t-1} + \sum_{f \in F} y_{p,f,t} - D_{p,t} \qquad \forall p \in P, \forall t \in T \tag{A.3}$$

$$a_{p,f,t} \leq a_{p,f,t-1} + q_{p,f,t-\tau_1} \qquad \forall p \in P, \forall f \in F, \forall t \in T \tag{A.4}$$

$$y_{p,f,t} \leq a_{p,f,t} \cdot M \qquad \forall p \in P, \forall f \in F, \forall t \in T \tag{A.5}$$

$$\sum_{p \in P} y_{p,f,t} \cdot g_{p,m} \leq v_m \cdot k_{m,f,t} \qquad \forall m \in M, \forall f \in F, \forall t \in T \tag{A.6}$$

$$a_{p,f,t} \in \{0,1\} \qquad \forall p \in P, \forall f \in F, \forall t \in T \tag{A.7}$$

$$x_{p,f,t} \in \{0,1\} \qquad \forall p \in P, \forall f \in F, \forall t \in T \tag{A.8}$$

$$k_{m,f,t} \in \mathbb{R}_+ \qquad \forall m \in M, \forall f \in F, \forall t \in T \tag{A.9}$$

$$y_{p,f,t} \in \mathbb{R}_+ \qquad \forall p \in P, \forall f \in F, \forall t \in T \tag{A.10}$$

$$b_{p,t} \in \mathbb{R}_+ \qquad \forall p \in P, \forall t \in T \tag{A.11}$$

$$i_{p,t} \in \mathbb{R}_+ \qquad \forall p \in P, \forall t \in T \tag{A.12}$$

$$q^{buy}_{m,f,t} \in \mathbb{N}_0 \qquad \forall m \in M, \forall f \in F, \forall t \in T \tag{A.13}$$

$$q^{sell}_{m,f,t} \in \mathbb{N}_0 \qquad \forall m \in M, \forall f \in F, \forall t \in T \tag{A.14}$$

$$q^{transfer}_{m,f,f',t} \in \mathbb{N}_0 \qquad \forall m \in M, \forall f \in F, \forall f' \in F, \forall t \in T \tag{A.15}$$

A.2 Stochastic programming model

$$
\begin{aligned}
\min_{q,x,y} \sum_{s\in S} P_s \sum_{t\in T} (1+\rho)^{-t} \Bigg(& \sum_{f\in F}\sum_{m\in M} c_m^{buy} \cdot x_{m,f,t,s}^{buy} - c_m^{sell} \cdot x_{m,f,t,s}^{sell} \\
& + \sum_{f\in F} \sum_{f'\in F, f'\neq f} \sum_{m\in M} c_m^{transfer} \cdot x_{m,f,f',t}^{transfer} \Bigg) \\
& + \Bigg(\sum_{f\in F}\sum_{p\in P} c_p^{qualify} \cdot q_{p,f,t,s} \\
& + \sum_{f\in F}\sum_{p\in P} c_m^{production}, f \cdot g_{p,m} \cdot y_{p,f,t,s} \\
& + \sum_{p\in P} c_p^{inventory} i_{p,t,s} + c_p^{backorder} b_{p,t,s} \Bigg)
\end{aligned}
\tag{A.16}
$$

subject to

$$k_{m,f,t,s} = k_{m,f,t-1,s} + x^{buy}_{m,f,t-\tau_2,s} - x^{sell}_{m,f,t,s} + \sum_{f' \in F} x^{trans}_{m,f',f,t-\tau_3,s} - \sum_{f' \in F} x^{trans}_{m,f,f',t,s} \qquad m \in M, f \in F, t \in T, s \in S \tag{A.17}$$

$$i_{p,t,s} - b_{p,t,s} = i_{p,t-1,s} - b_{p,t-1,s} + \sum_{f \in F} y_{p,f,t,s} - D_{p,t,s} \qquad \forall p \in P, \forall t \in T, s \in S \tag{A.18}$$

$$a_{p,f,t,s} \leq a_{p,f,t-1,s} + q_{p,f,t-\tau_1,s} \qquad p \in P, f \in F, t \in T, s \in S \tag{A.19}$$

$$y_{p,f,t,s} \leq a_{p,f,t,s} \cdot M \qquad p \in P, f \in F, t \in T, s \in S \tag{A.20}$$

$$\sum_{p \in P} y_{p,f,t,s} \cdot g_{p,m} \leq v_m \cdot k_{m,f,t,s} \qquad m \in M, f \in F, t \in T, s \in S \tag{A.21}$$

$$y_{p,f,t,s_1} = y_{p,f,t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall p \in P, \forall f \in F, \forall t \in T \tag{A.22}$$

$$q_{p,f,t,s_1} = q_{p,f,t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall p \in P, \forall f \in F, \forall t \in T \tag{A.23}$$

$$x^{buy}_{m,f,t,s_1} = x^{buy}_{m,f,t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall m \in M, \forall f \in F, \forall t \in T \tag{A.24}$$

$$x^{sell}_{m,f,t,s_1} = x^{sell}_{m,f,t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall m \in M, \forall f \in F, \forall t \in T \tag{A.25}$$

$$x^{transfer}_{m,f,f',t,s_1} = x^{transfer}_{m,f,f',t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall m \in M, \forall f \in F, \forall f' \in F, f' \neq f \quad \forall t \in T \tag{A.26}$$

$$a_{p,f,t,s} \in \{0, 1\} \qquad \forall p \in P, \forall f \in F, \forall t \in T, s \in S \tag{A.27}$$

$$x_{p,f,t,s} \in \{0, 1\} \qquad \forall p \in P, \forall f \in F, \forall t \in T, s \in S \tag{A.28}$$

$$k_{m,f,t,s} \in \mathbb{R}_+ \qquad \forall m \in M, \forall f \in F, \forall t \in T, s \in S \tag{A.29}$$

$$y_{p,f,t,s} \in \mathbb{R}_+ \qquad \forall p \in P, \forall f \in F, \forall t \in T, s \in S \tag{A.30}$$

$$b_{p,t,s} \in \mathbb{R}_+ \qquad \forall p \in P, \forall t \in T, s \in S \tag{A.31}$$

$$i_{p,t,s} \in \mathbb{R}_+ \qquad \forall p \in P, \forall t \in T, s \in S \tag{A.32}$$

$$q^{buy}_{m,f,t,s} \in \mathbb{N}_0 \qquad \forall m \in M, \forall f \in F, \forall t \in T, s \in S \tag{A.33}$$

$$q^{sell}_{m,f,t,s} \in \mathbb{N}_0 \qquad \forall m \in M, \forall f \in F, \forall t \in T, s \in S \tag{A.34}$$

$$q^{transfer}_{m,f,f',t,s} \in \mathbb{N}_0 \qquad \forall m \in M, \forall f \in F, \forall f' \in F, \forall t \in T, s \in S \tag{A.35}$$

A.3 Robust optimization model

$$
\begin{aligned}
\min_{x,q,y} \max_{s \in S} \sum_{t \in T} (1+\rho)^{-t} \Bigg(& \sum_{f \in F} \sum_{m \in M} c_m^{buy} \cdot x_{m,f,t,s}^{buy} - c_m^{sell} \cdot x_{m,f,t,s}^{sell} \\
& + \sum_{f \in F} \sum_{f' \in F, f' \neq f} \sum_{m \in M} c_m^{trans} \cdot x_{m,f,f',t,s}^{trans} \Bigg) \\
& + \Bigg(\sum_{f \in F} \sum_{p \in P} c_p^{qual} \cdot q_{p,f,t,s} \\
& + \sum_{f \in F} \sum_{m \in M} \sum_{p \in P} c_{m,f}^{production} \cdot g_{p,m} \cdot y_{p,f,t,s} \\
& + \sum_{p \in P} c_p^{inventory} i_{p,t,s} + c_p^{backorder} b_{p,t,s} \Bigg)
\end{aligned}
\tag{A.36}
$$

subject to

$$k_{m,f,t,s} = k_{m,f,t-1,s} + x^{buy}_{m,f,t-\tau_2,s} - x^{sell}_{m,f,t,s} + \sum_{f' \in F} x^{trans}_{m,f',f,t-\tau_3,s} - \sum_{f' \in F} x^{trans}_{m,f,f',t,s} \qquad m \in M, f \in F, t \in T, s \in S \tag{A.37}$$

$$i_{p,t,s} - b_{p,t,s} = i_{p,t-1,s} - b_{p,t-1,s} + \sum_{f \in F} y_{p,f,t,s} - D_{p,t,s} \qquad \forall p \in P, \forall t \in T, s \in S \tag{A.38}$$

$$a_{p,f,t,s} \leq a_{p,f,t-1,s} + q_{p,f,t-\tau_1,s} \qquad p \in P, f \in F, t \in T, s \in S \tag{A.39}$$

$$y_{p,f,t,s} \leq a_{p,f,t,s} \cdot M \qquad p \in P, f \in F, t \in T, s \in S \tag{A.40}$$

$$\sum_{p \in P} y_{p,f,t,s} \cdot g_{p,m} \leq v_m \cdot k_{m,f,t,s} \qquad m \in M, f \in F, t \in T, s \in S \tag{A.41}$$

$$y_{p,f,t,s_1} = y_{p,f,t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall p \in P, \forall f \in F, \forall t \in T \tag{A.42}$$

$$q_{p,f,t,s_1} = q_{p,f,t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall p \in P, \forall f \in F, \forall t \in T \tag{A.43}$$

$$x^{buy}_{m,f,t,s_1} = x^{buy}_{m,f,t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall m \in M, \forall f \in F, \forall t \in T \tag{A.44}$$

$$x^{sell}_{m,f,t,s_1} = x^{sell}_{m,f,t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall m \in M, \forall f \in F, \forall t \in T \tag{A.45}$$

$$x^{transfer}_{m,f,f',t,s_1} = x^{transfer}_{m,f,f',t,s_2} \qquad \forall (s_1, s_2) \in V_t, \forall m \in M, \forall f \in F, \forall f' \in F, f' \neq f \quad \forall t \in T \tag{A.46}$$

$$a_{p,f,t,s} \in \{0,1\} \qquad \forall p \in P, \forall f \in F, \forall t \in T, s \in S \tag{A.47}$$

$$x_{p,f,t,s} \in \{0,1\} \qquad \forall p \in P, \forall f \in F, \forall t \in T, s \in S \tag{A.48}$$

$$k_{m,f,t,s} \in \mathbb{R}_+ \qquad \forall m \in M, \forall f \in F, \forall t \in T, s \in S \tag{A.49}$$

$$y_{p,f,t,s} \in \mathbb{R}_+ \qquad \forall p \in P, \forall f \in F, \forall t \in T, s \in S \tag{A.50}$$

$$b_{p,t,s} \in \mathbb{R}_+ \qquad \forall p \in P, \forall t \in T, s \in S \tag{A.51}$$

$$i_{p,t,s} \in \mathbb{R}_+ \qquad \forall p \in P, \forall t \in T, s \in S \tag{A.52}$$

$$q^{buy}_{m,f,t,s} \in \mathbb{N}_0 \qquad \forall m \in M, \forall f \in F, \forall t \in T, s \in S \tag{A.53}$$

$$q^{sell}_{m,f,t,s} \in \mathbb{N}_0 \qquad \forall m \in M, \forall f \in F, \forall t \in T, s \in S \tag{A.54}$$

$$q^{transfer}_{m,f,f',t,s} \in \mathbb{N}_0 \qquad \forall m \in M, \forall f \in F, \forall f' \in F, \forall t \in T, s \in S \tag{A.55}$$

Appendix B

Warm-start MIP solver

The solver used, Gurobi, uses a linear-programming-based branch-and-bound algorithm to solve MILP models. The branch-and-bound algorithm uses an LP-relaxation and finds integer solutions close to the optimal LP solution. The algorithm omits the infeasible integer solutions. For a minimization problem, the feasible integer solution with the lowest objective value until that iteration serves as an upper-bound. All feasible but non-integer end-nodes serve as a lower-bound. Every iteration tries to close the gap between the lower- and upper-bound, called the optimality gap, and denoted as a percentage. When lower- and upper-bound are equal, the gap is 0% and optimality proven. Proving optimality for large-scale models can take many iterations and, thereby, a lot of computation time. Therefore, small optimality gaps are accepted.

Warm-starting the branch-and-bound algorithm gives it a head start. Warm-starting the algorithm means giving it some values for the variables, the warm-start solution, that are likely to be close to the optimal values. If the warm-start solution is feasible for the new model, the values are used to start the algorithm. The start means that the branch-and-bound algorithm uses this solution as a feasible integer node and thereby as an upper-bound.

For both the simulation and the sensitivity analysis, the models are solved multiple times with slightly different input parameters. Therefore, we could solve the model once and use the solution as a warm-start for solving the model again with slightly different data. Table B.1 shows the average computation time and optimality gap for the sensitivity analysis with and without warm-start for a complete run of the analysis. The maximum optimality gap was set to 5% with a time-limit of 400 seconds. Table B.2 shows the average computation time and optimality gap for 10 iterations with 8 time periods of the simulation study. The maximum optimality gap was set to 5% with a time-limit of 120 seconds. The models used for the first warm-start solution are excluded from calculating the averages since these models were not warm-started themselves.

The difference between running with and without warm-start in the sensitivity analysis is enormous, whereas the simulation study's difference is insignificant. The main reason for investigating warm-start was because the models have to run many times. Using the warm-start reduced the total computational time for the complete sensitivity analysis from 9.2 to 4.2 hours. For the simulation study, the difference was less significant. A simulation experiment with 8 periods and 10 iterations takes 2.1 and 2.2 hours with and without warm-start, respectively.

	No warm-start		Warm-start	
Model	Time (s)	Gap (%)	Time (s)	Gap (%)
Deterministic	2.0	3.9	1.4	4.3
Stochastic	62.5	4.0	30.0	4.4
Robust	110.7	3.6	47.8	4.2

Table B.1: Warm-start in sensitivity analysis example performance

	No warm-start		Warm-start	
Model	Time (s)	Gap (%)	Time (s)	Gap (%)
Deterministic	1.4	0.6	1.1	0.1
Stochastic	41.1	1.9	40.7	1.6
Robust	47.7	2.9	44.3	2.3

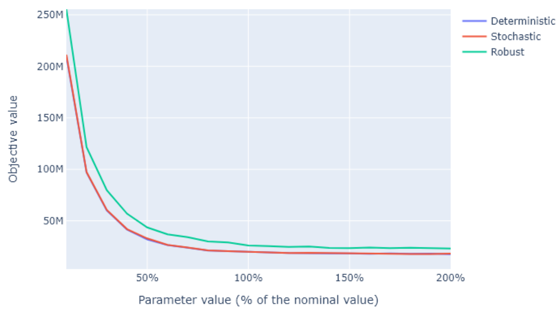
Table B.2: Warm-start in simulation study example performance

Appendix C

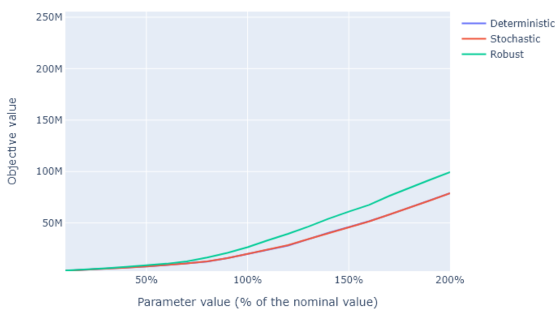
Sensitivity analysis

In the figures where the line for the deterministic model is not visible, the line coincides with the stochastic model line.

(a) Demand



(b) Machine capacity

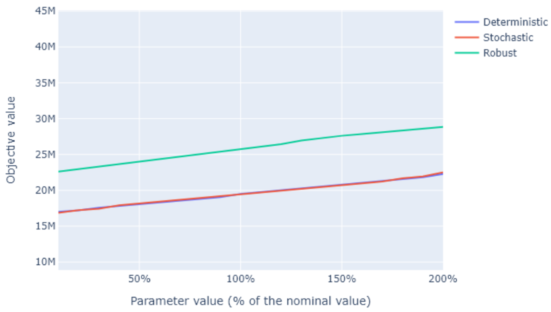


(c) Capacity consumption

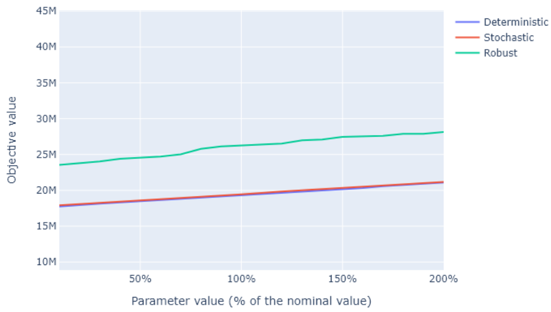
Figure C.1: Sensitivity for constraint parameters

(a) Machine buy costs

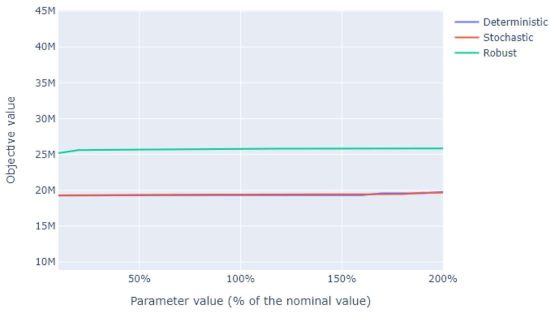
(b) Production costs



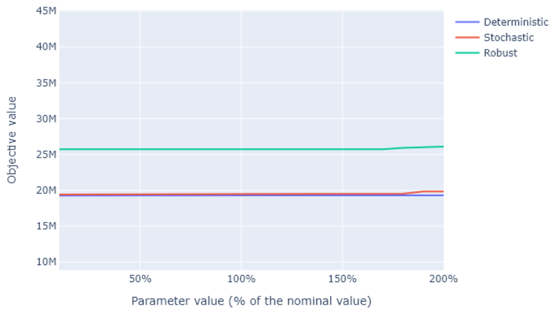
(c) Product qualification costs



(d) Machine transfer costs



(e) Holding costs



(f) Back-ordering costs

(g) Interest percentage

Figure C.2: Sensitivity for objective function parameters

Appendix D

Decision support tool

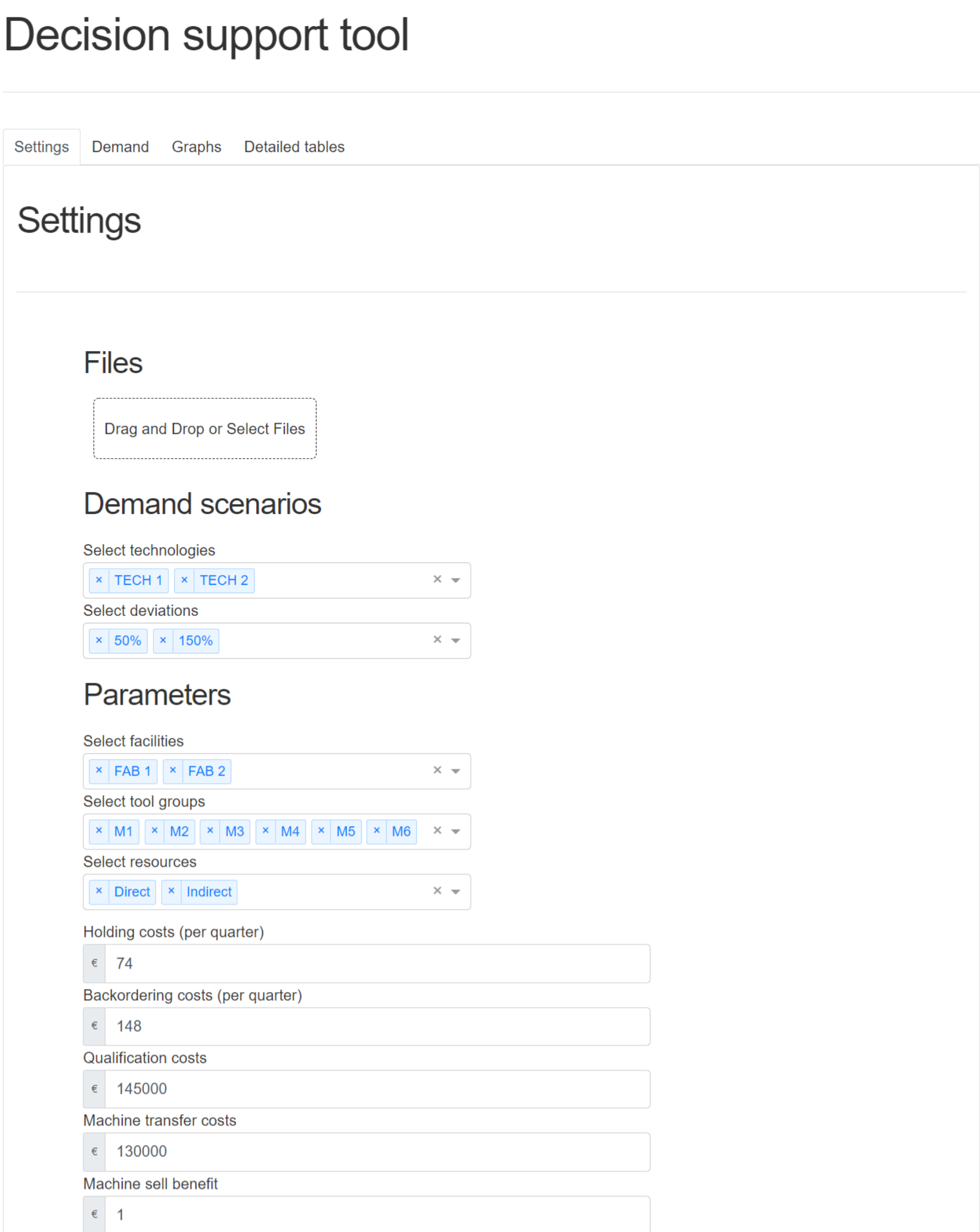


Figure D.1: Settings tab part 1

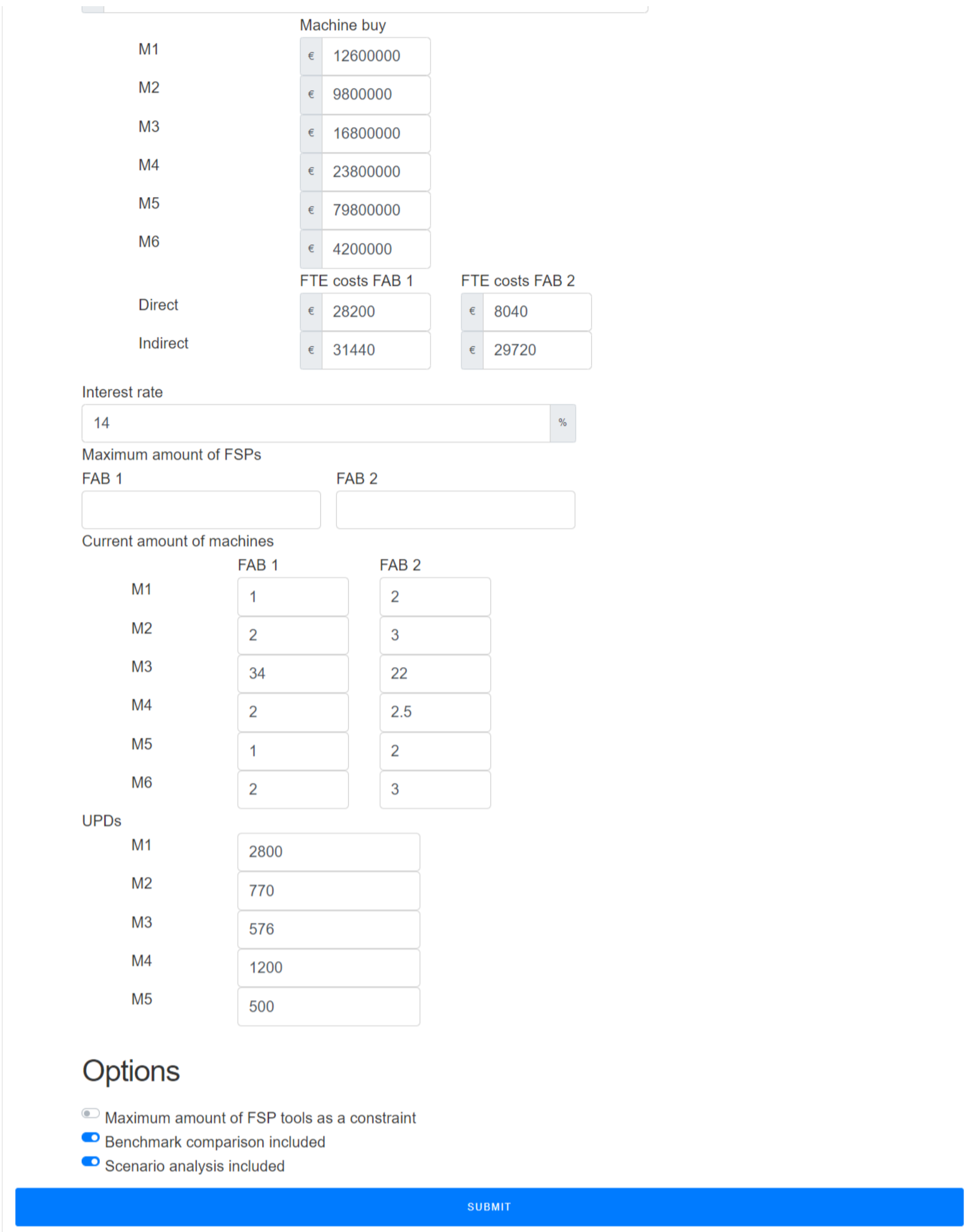


Figure D.2: Settings tab part 2

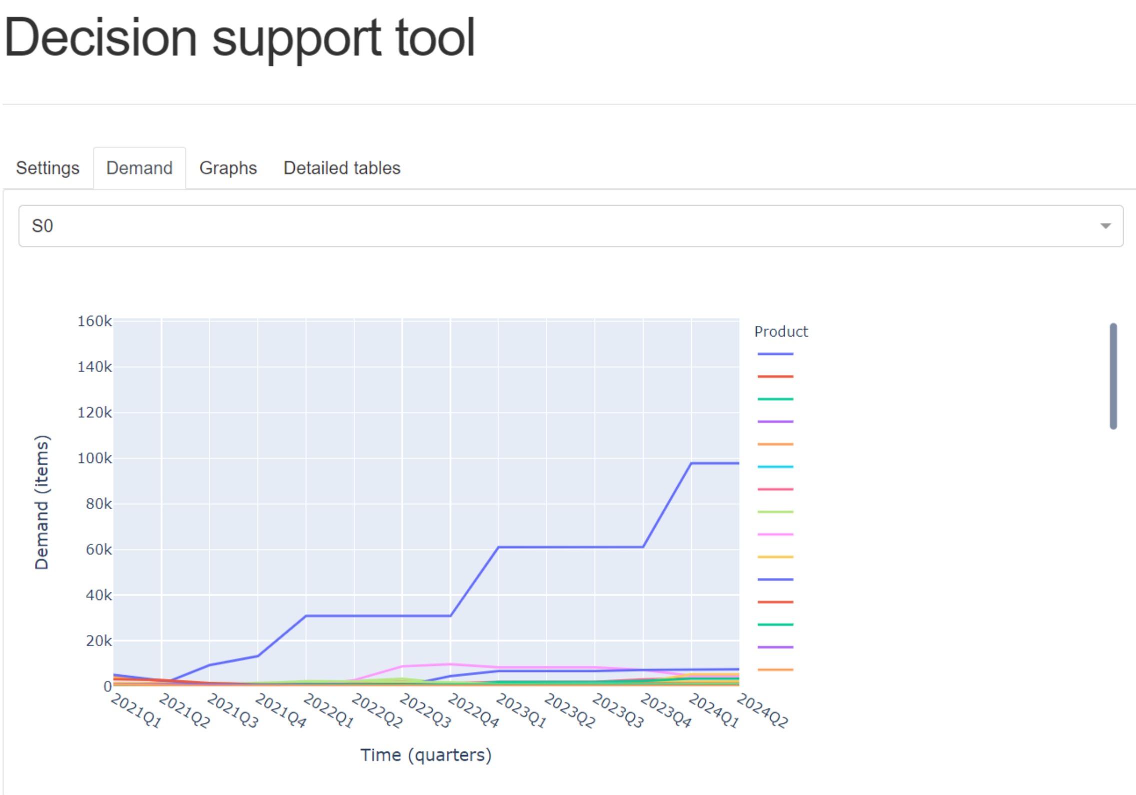


Figure D.3: Demand tab

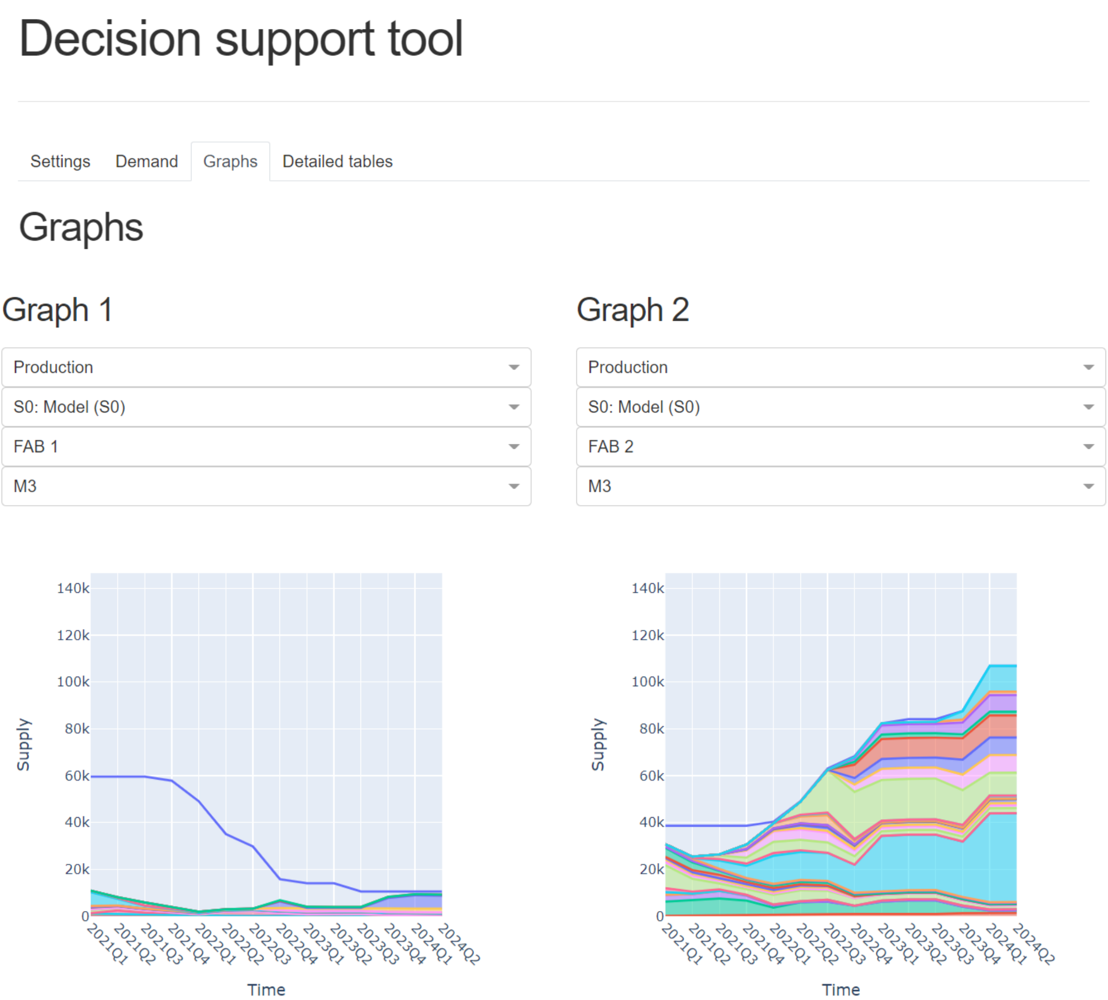


Figure D.4: Graphs tab

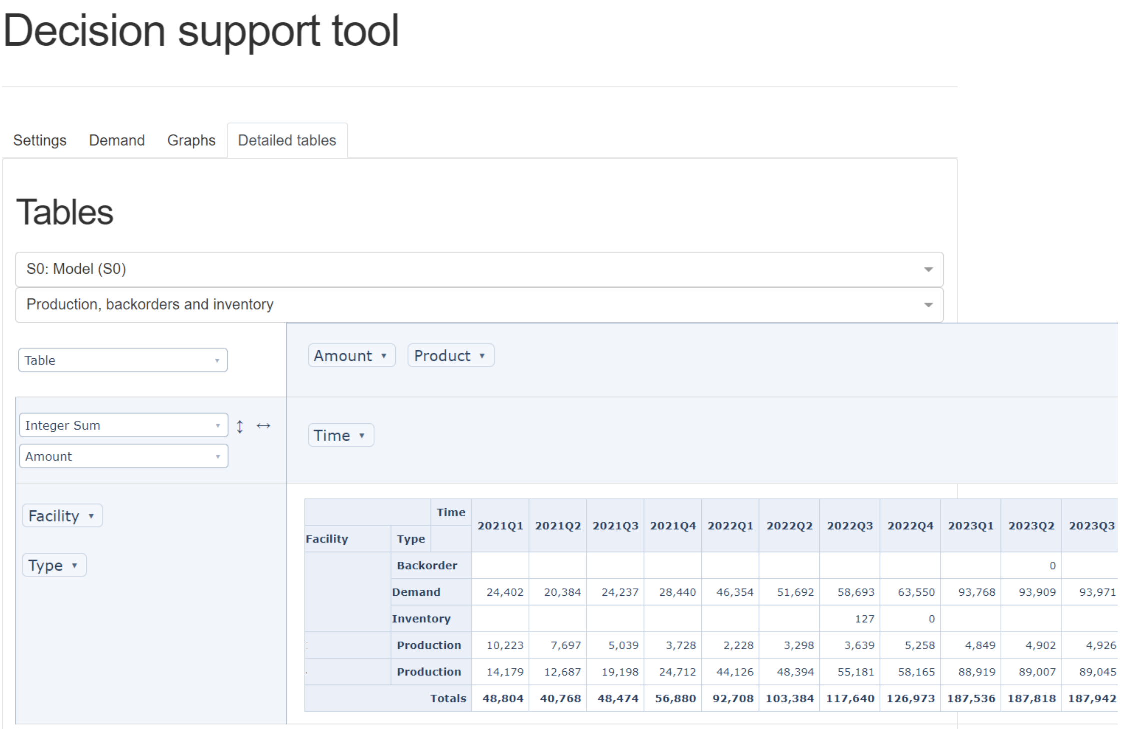


Figure D.5: Detailed tables tab example 1

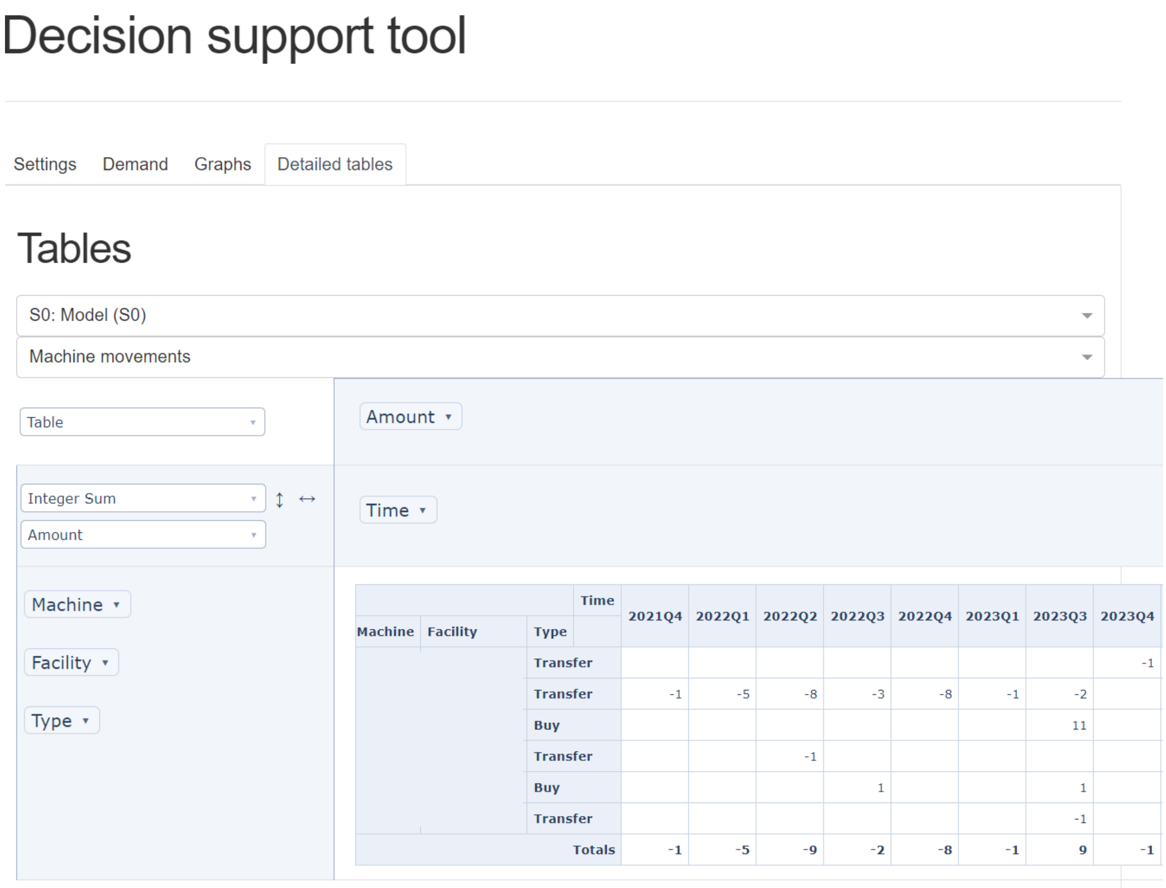


Figure D.6: Detailed tables tab example 2

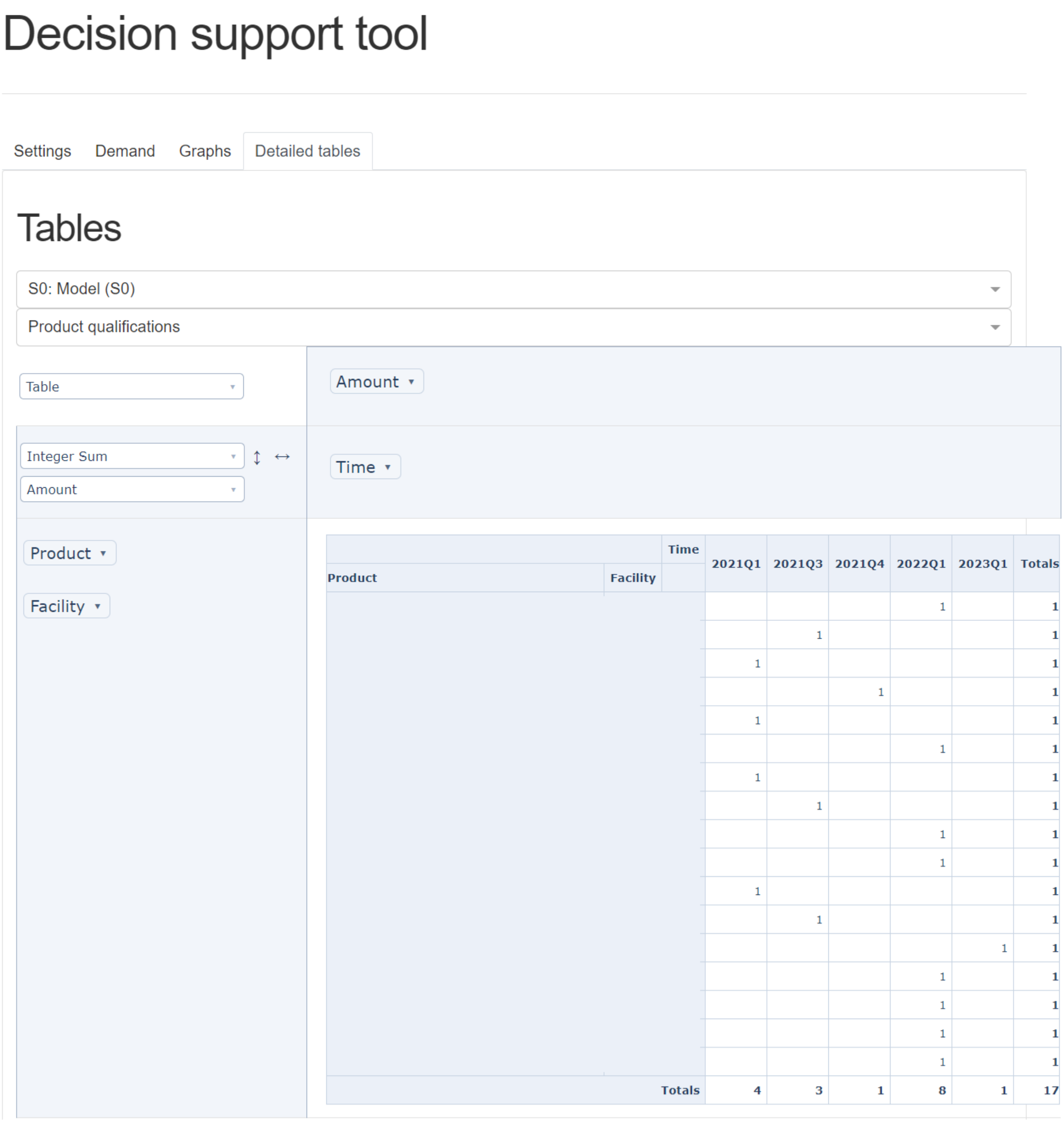


Figure D.7: Detailed tables tab example 3

Appendix E

Benchmark and scenario analysis results

Table E.1: Qualifications model vs. benchmark scenario 0

	Model						Benchmark					
Product	Facility	2021Q1	2021Q3	2021Q4	2022Q1	2023Q1	Facility	2021Q1	2021Q3	2021Q4	2022Q1	2023Q1
P8	FAB 2				1		FAB 2				1	
P18	FAB 2		1				FAB 2		1			
P19	FAB 2	1					FAB 2	1				
P20	**FAB 1**			1			**FAB 2**			1		
P21	FAB 2	1					FAB 2	1				
P22	FAB 2				1		FAB 2				1	
P23	FAB 2	1					FAB 2	1				
P25	FAB 2		1				FAB 2		1			
P26	**FAB 1**				1		**FAB 2**				1	
P27	FAB 2				1		FAB 2				1	
P28	FAB 2	1					FAB 2	1				
P29	FAB 2		1				FAB 2		1			
P30	FAB 2					1	FAB 2					1
P31	FAB 2				1		FAB 2				1	
P32	**FAB 2**				1		**FAB 1**				1	
P33	FAB 2				1		FAB 2				1	
P34	**FAB 2**				1		**FAB 1**				1	

Rows and columns with only zeros omitted.

Table E.2: Machine moves model scenario 0

			Model								
Machine	Facility	Type	2021Q4	2022Q1	2022Q2	2022Q3	2022Q4	2023Q1	2023Q2	2023Q3	2023Q4
M1	FAB 1	Transfer	0	0	-1	0	0	0	0	0	0
M1	FAB 2	Buy	0	0	0	1	0	0	0	1	0
M2	FAB 1	Transfer	0	0	0	0	0	0	0	0	0
M2	FAB 2	Buy	0	0	0	0	**0**	0	0	0	0
M3	FAB 1	Transfer	0	0	0	0	0	0	0	0	0
M3	FAB 2	Buy	0	0	0	0	0	0	0	0	0
M4	FAB 1	Transfer	0	0	0	0	0	0	0	-1	0
M4	FAB 2	Buy	0	0	0	0	0	0	0	0	0
M5	FAB 1	Transfer	0	0	0	0	**0**	0	0	0	0
M5	FAB 2	Buy	0	0	0	0	0	0	0	0	0
M6	FAB 1	Transfer	-1	-5	-8	**-3**	**-8**	**-1**	0	-2	0
M6	FAB 2	Buy	0	0	0	0	0	0	0	11	0

Machine buy in FAB 1, machine transfer from FAB 2, and machine sell in both facilities do not occur and are therefore omitted.

Table E.3: Machine moves benchmark scenario 0

			Benchmark								
Machine	Facility	Type	2021Q4	2022Q1	2022Q2	2022Q3	2022Q4	2023Q1	2023Q2	2023Q3	2023Q4
M1	FAB 1	Transfer	0	0	-1	0	0	0	0	0	0
M1	FAB 2	Buy	0	0	0	1	0	0	0	1	0
M2	FAB 1	Transfer	0	0	0	0	0	0	0	0	0
M2	FAB 2	Buy	0	0	0	0	**0**	0	0	0	0
M3	FAB 1	Transfer	0	0	0	0	0	0	0	0	0
M3	FAB 2	Buy	0	0	0	0	0	0	0	**1**	0
M4	FAB 1	Transfer	0	0	0	0	0	0	0	-1	0
M4	FAB 2	Buy	0	0	0	0	0	0	0	0	0
M5	FAB 1	Transfer	0	0	0	0	**0**	0	0	0	0
M5	FAB 2	Buy	0	0	0	0	0	0	0	0	0
M6	FAB 1	Transfer	-1	-5	-8	**-2**	**-9**	**0**	0	-2	0
M6	FAB 2	Buy	0	0	0	0	0	0	0	11	0

Machine buy in FAB 1, machine transfer from FAB 2, and machine sell in both facilities do not occur and are therefore omitted.

Table E.4: Costs model vs. benchmark in all scenarios

	S0		S1		S2		S3		S4	
Costtype	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark
Machine buy	0.1657	0.0023	0.0181	0.0871	0.3201	0.3819	0.0405	0.0405	0.3010	0.4345
Machine sell	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Machine transfer	0.0641	0.0625	0.0554	0.0553	0.0689	0.0756	0.0528	0.0495	0.0941	0.0786
Qualification	0.0852	0.0000	0.0852	0.0852	0.0852	0.0852	0.0852	0.0852	0.1203	0.0852
Production	0.3497	0.0852	0.3264	0.3274	0.3864	0.3741	0.2950	0.3011	0.3697	0.3904
Inventory holding	0.0003	0.3517	0.0003	0.0000	0.0012	0.0012	0.0003	0.0000	0.0049	0.0112
Backorder	0.0000	0.2189	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Totals	0.6652	0.7206	0.4854	0.5550	0.8618	0.9181	0.4738	0.4763	0.8900	1.0000

Costs in this table are normalized.