MASTER

Strategic Capacity Planning Under Demand Uncertainty

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Executive Summary

This thesis focuses on a production capacity expansion problem faced by a company that is active in the market of integrated photonics sensing products. The sensing systems can measure stress, strain, and temperature in real time by means of an optical fiber. The products are primarily developed for high tech applications as the sensing systems are far more accurate and versatile than conventional electrical sensors. However, due to the low system weight the products are also highly suitable for the transportation sectors such as automotive and aerospace. Within the sensing system is a module referred to as a package that converts the incoming light signal of the optical fiber into an electrical signal. Both the plug-and-play sensing systems and the packages are manufactured in-house.

This thesis focuses on the production capacity expansion of the package production line. Besides the development and production of internally designed sensing systems, the company also provides a packaging service. Here, standalone packages are produced for integration into applications of external parties. To accommodate the expected demand for the packaging service the company is currently transitioning from manual package production to mass production.

Due to the absence of historical demand of the newly emerging market, there are no indications of demand trends. For the production of packages, highly specialized and made-to-order equipment is required. Therefore, the order lead time of equipment can take up to a year from the moment an order is placed to the moment the equipment is fully operational on site. Due to the equipment order lead time the company is exposed to investment risks. To analyse the impact of the demand uncertainty the goal of this project is split into two separate objectives. The first objective is defined as:

"Provide a scenario analysis for a set of long term demand scenarios."

The first objective focuses on the analysis of a set of deterministic long term demand scenarios spanning a period of five years. The scenarios are individually analysed to determine the impact on the spatial requirements of the production facility. Here, an integer linear programming (ILP) model is developed that maximizes the gross profit by determining the optimal equipment portfolio and the required inventory levels for finished goods. Based on the results, the required floor space and inventory storage capacity are calculated.

The second objective of this project is defined as:

"Develop a tool that supports management in defining an optimal production capacity expansion strategy."

The second objective focuses on the short term strategic capacity planning. Future demand is estimated based on an order book that lists both sold orders and pending sales leads. While the sold orders provide the minimum required production capacity, the pending orders constitute the stochastic element in this project. To generate an optimal capacity expansion strategy a

Markov decision process (MDP) model is designed that identifies a global optimal expansion strategy by maximizing the expected gross profit based on selling probabilities of the pending orders in the order book. However, due to the exhaustive nature and the size of the problem, the MDP model can only find a solution for a limited number of pending orders. Therefore, a heuristic solution method is designed with the aim of reducing the required time to solve the model such that the number of considered pending orders can be increased.

Due to the increased processing speed of the heuristic, the number of pending orders in the order book is increased by 55% compared to the MDP model. Moreover, a performance analysis of the heuristic shows that based on a set of 8 order book instances, the solution accuracy is near optimal. For the order book instance in which the heuristic performs worst, the average deviation from the optimal solution found by the MDP model is 0.0055%. Looking at individual scenarios that are generated based on the order book composition, the largest deviation for an individual demand scenario is -0.1% based on the expected gross profit over the whole modelling horizon. Consequently, the solution accuracy is near optimal and the heuristic proves to be a valuable tool that can be used as support for management to define an optimal production capacity expansion strategy.

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Last but definitely not least, I would like to thank my family, friends and especially my girlfriend for their continuous support during this project.

Luuk van Bavel, February 2021

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Abbreviations

C&F	Equipment type 'Calibration & FAT'
DB	Equipment type 'Die bonder'
ESD	Electrostatic discharge
FAA	Equipment type 'Fiber array aligner'
FAT	Factory acceptance test
FBG	Fiber Bragg grating
ILP	Integer linear program
MDP	Markov decision process
MILP	Mixed integer linear program
NFA	No fiber aligning
OV	Equipment type 'Oven'
PIC	Photonic integrated circuit
SCP	Strategic capacity problem
SFA	Equipment type 'Single fiber aligner'
WB	Equipment type 'Wire bonder'

Nomenclature

Gross margin	Revenue minus material costs
Gross profit	ILP model: Gross margin minus operational, depreciation and inventory costs MDP model: Gross margin minus operational and depreciation costs

A	Set of all actions a_t
A_{s_t}	Subset of feasible actions a_t in state s_t
D	Set of all demand scenarios within the modelling horizon M
D_t	Set of all demand scenarios for period t
E_{jt}	Decision variable for number of machines j procured in period t
G	Expected long term gross profit
I	Number of unique packages i
I_{it}	Decision variable for number of packages i on inventory in period t
J	Number of unique equipment types j
K	Set containing all package types i
K^{sfa}	Subset of K containing all SFA package types i
K^{faa}	Subset of K containing all FAA package types i
K^{nfa}	Subset of K containing all NFA package types i
L	Set containing all equipment types j
M	Set containing all time periods t in the modelling horizon
N	Number of pending orders within modelling horizon M
N_t	Number of pending orders with a first delivery period t
P_{it}	Decision variable for number of packages i produced in period t
$P_s(k_{t,n})$	Selling probability of order $k_{t,n}$
S	Set of all states in the state space
S_{it}	Decision variable for number of stockout packages i in period t
T	Number of periods t within modelling horizon
Z_t	Expected added gross profit for period t
Z	Total expected added gross profit

a_t	Action containing decision variables $a_{t,j}$ for all J equipment types
$a_{t,j}$	Binary decision variable of buying additional equipment type j in period t
b_j	Production capacity of a single machine of equipment type j
c_j^{dep}	Depreciation costs for equipment type j per period t
c_j^{op}	Operational costs for equipment type j per period t
c_i^{inv}	Inventory costs for package type i per period t
$cap^r_{d,j}$	Required production capacity for equipment type j of scenario d
d	Demand scenario
d_i	Demand for package type i of scenario d
d_{it}	Demand for package type i in period t

$\vec{e}$	Equipment portfolio description of state s_t
$g_{d,j}^{add}$	Added total gross margin of scenario d when expanding equipment type j
g^{prof}	Gross profit
g_i^{mar}	Gross margin of package type i
g_d^{sfa}	SFA package type component of the total gross margin of scenario d
g_d^{faa}	FAA package type component of the total gross margin of scenario d
g_d^{nfa}	NFA package type component of the total gross margin of scenario d
g_d^p	Long term gross profit of scenario d
k_n	Pending order number n in scenario d
$k_{t,n}$	Pending order number n with a first delivery date in period t
l_j	Equipment order lead time of equipment type j
$\vec{o}$	Pending order description of state s_t for time interval $[0,t]$
$\vec{o}_t$	Vector of pending orders with first delivery date in period t
s_t	State in state space S
t_j^{bd}	Expected time required for breakdowns of equipment type j per period t
t_j^{ma}	Expected time required for maintenance of equipment type j per period t
$t_{i,j}^p$	Process time required for package type i on equipment type j
$\vec{v}$	previously taken actions description of state s_t for all equipment types
$\vec{v}_{t,j}$	Vector of previously taken actions for equipment type j in period t

Chapter 1

Introduction

Over the past years general interest in the field of photonics has risen significantly. The best known application is the fibre optic cable that we use for high speed data communication such as the internet. Unlike conventional copper wire that transports data through an electrical current, optic fibers transport information through light which allows data transmission at much higher speeds and with a bandwidth up to multiple terabytes per second. Most people are unfamiliar with the term photonics mainly because products with integrated photonics are often not primarily intended for consumers. However, the fields of application are numerous, varying from medical to military. One of the promising fields of application of photonic technologies is referred to as integrated photonics. This technology focuses on the development and manufacturing of optical chips that process light signals. These chips can be used for fibre optic sensing applications.

1.1 Fiber optic sensing

This graduation project is executed for a company that specializes in research, development, engineering and production of fiber optic sensing systems. The main focus is on the high-end medium-volume market such as research medical systems, aerospace and other comparable high-tech industries. The applications are based on a sensor that can measure strain, pressure and temperature in real time by means of an optical fiber. Research facilities in both industry and academia have been using fiber optic sensing for research and development purposes for decades as the technique is far more accurate than conventional electrical sensing and additionally the fiber is non-conductive and immune to electromagnetic interference. The technique that enables the use of optical fibers as sensing tools is called Fiber Bragg Grating (FBG). To manufacture a FBG a part of an optical fiber, generally between 5 and 10 mm along the axial length, is exposed to an UV laser which permanently changes the local refractive index of the fiber. The exposed part of the fiber with the permanently changed refractive index is called a grating. When a spectrum of light passes the grating, a specific wavelength that directly correlates to the refractive index, also called the Bragg wavelength, is reflected while the remainder of the light spectrum is transmitted unaffected as illustrated in Figure 1.1. Under exposure of strain or heat the refractive index of the grating changes temporarily, subsequently changing the Bragg wavelength. The change in Bragg wavelength can be monitored and converted into an electrical signal. A multitude of gratings with distinct refractive indices can be inscribed into a fiber which allows for independent measuring points along the length of a single optical fiber.

It has taken a long time to commercialize the technique as it was not possible to downsize the hardware to manageable dimensions that enables integration into third party systems. However, the company succeeded by developing a photonics module approximately half the size of the

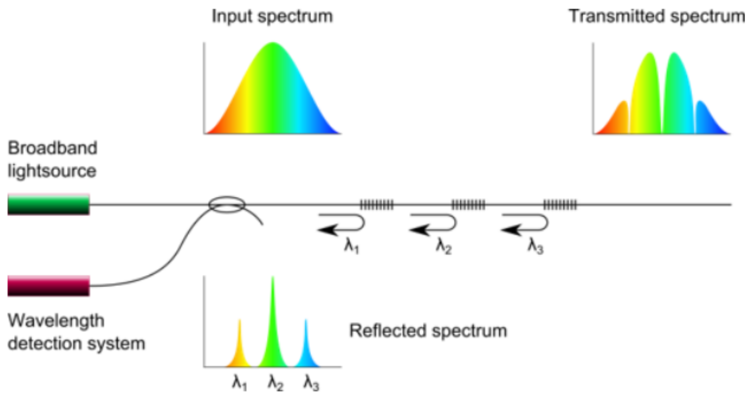

Figure 1.1: Fiber Bragg Grating principle

average smartphone that is integrated in a turnkey sensing system. In addition to succeeding in reducing the dimensions of the hardware, the company developed patented integrated photonics technology compliant with the requirements of high tech industries. Besides being more accurate than conventional electrical sensors, the diameter of an optical fiber is approximately equal to a human hair and has a significantly lower specific weight than copper wire. Due to these characteristics, fiber optic sensing is highly suitable for industries within the transportation sector such as aerospace and automotive.

The company is already collaborating with third party companies that apply internally designed sensing systems. In one of the projects the company partners with an airplane manufacturer to develop a sensing system that measures the load at the landing gear with the objective to provide data for analysis of failure modes and flight management and control. Besides measurements of stress and strain as a result of a physical load the company is also developing a system that will be used to monitor the temperature fluctuations in the battery pack of an electric vehicle of a high end car manufacturer. Fiber optic sensing systems are even being field tested in renewable energy applications such as wind turbines where optic fibers are laminated into the blades to monitor bending stress and torsional deformation to optimize preventive maintenance intervals.

1.2 Problem description

The main focus of the company in the past two decades has been on the development of photonic integrated circuits (PICs), also referred to as dies. To validate the die designs, low volume sensing system prototype series have been manually assembled and tested. With the maturing of the fiber optic sensing technology, the application of integrated photonics is assumed to increase significantly in the near future. To facilitate the forecasted gain in demand, the production capacity has to be substantially increased during the coming years.

From a high level perspective the production of fiber optic sensing systems consists of two production steps: die packaging and system assembly. To enable to receive and process a light signal, the die is integrated in what is referred to as a package, illustrated in Figure 1.2. The fiber that transports the optical signal is aligned with the die that processes the incoming light spectrum. The die is connected to a printed circuit board that converts and transports the data to a connector for export to an external device. The housing of the package protects the die against electrostatic discharge (ESD). A standalone package is essentially a spectrometer that

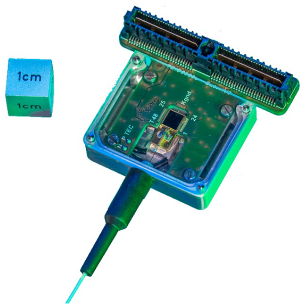

Figure 1.2: Generic package

Figure 1.3: Sensing system

requires input to generate output. Consequently, the packages are integrated into a system to be fully functional. A system, illustrated in Figure 1.3, provides a user interface and contains among others a light source required to perform measurements. From a practical perspective, the system provides the end user with a plug-and-play measuring device that can easily be integrated into third party applications.

The focus of this graduation project is on the package production process. From a manufacturing perspective, package production is very challenging due to the required high-precision positioning of components. The state-of-the-art integrated photonics technology imposes new requirements on the precision of manufacturing equipment. The critical package production steps cannot be performed with generic equipment and thus highly specialized manufacturing equipment is developed concurrently by other companies to enable the mass production of packages. Consequently, equipment is made-to-order and can take up to a year from order confirmation until first production run on site. As a result of the significant equipment order lead time, demand has to be estimated a year in advance to adapt the available production capacity as optimal as possible to the required production capacity.

Due to the high cost of production equipment, relative small production runs of packages are not commercially viable for companies to produce in-house and consequently demand exists for packaging services. Therefore, in addition to producing packages for internally designed systems, the company will provide a packaging service for third parties. The packaging service accommodates any type of packaging, provided the package design is based on a photonic integrated circuit. The packages that are produced for external companies are not internally integrated into plug-and-play sensing systems but are shipped after completion to be integrated into sensing applications elsewhere.

Market trends indicate that global demand for photonic integrated circuits (PICs), the collective term for the product group that includes packages, will grow exponentially. Market research companies estimate that the global demand up untill 2025 will increase with a compound annual growth rate of 26.4% (Mordor Intelligence, 2018). However, the market for PICs has not been consolidated yet and is highly competitive and fragmented. Combined with the company's main focus is on the relatively small high-end medium-volume sensing applications segment, estimating the exact demand for the next years constitutes a major challenge in formulating a well timed production capacity expansion strategy. Additionally, the industry in general is relatively new and thus there is no historical demand that can be used to estimate future demand. The only indicator for future demand is the internal order book, which lists individual sales leads with associated selling probabilities for several projects.

Equipment procurement is capital intensive and thus the expected profit should outweigh the initial investment. Once confirmed, an equipment order cannot be cancelled and reselling equipment is assumed to be impossible due to the made-to-order specifications in a highly specialized industry. Therefore, the main objective of this graduation project is to design a model that assists management in formulating an optimal equipment expansion strategy that considers the uncertainty in demand.

1.3 Objectives

There are two main stakeholders in the graduation project, the company and Eindhoven University of Technology. Both parties involved have different objectives that should be aligned in order to successfully perform the project. First the objectives from the company are discussed after which the academic perspective on the objective is elaborated.

1.3.1 Company objectives

The main company goal is twofold. The demand uncertainty complicates both short and long term decision making and therefore two objectives have been formulated. First the long term objective is discussed:

"Provide a scenario analysis for a set of long term demand scenarios."

For the scenario analysis, the company provides four long term demand scenarios that vary in both product mix and order quantity. Each scenario is analysed separately to assess the impact of the spatial requirements and finished goods inventory storage on the production facility. The planning horizon of each scenario is five years which results in high uncertainty whether the scenarios accurately approximate the future demand development. However, the purpose of the scenario analysis is not to aid in the equipment acquisition process but to obtain high level insight into the required facility resources for the distant future. The results of the scenario analysis are intended to make a rough estimation of the spatial requirements for finished goods inventory storage and production facility. In addition, the results can be used to identify the time period in which the current production facility cannot accomodate the expected demand anymore in term of available floor space.

"Develop a tool that supports management in defining an optimal production capacity expansion strategy."

The second objective of the company is the development of a model that supports the short term decision making process concerning the procurement of new production equipment. The model should aid to the decision making process by yielding an optimal procurement strategy given a set of potential demand scenarios. To generate these demand scenarios, an order book is provided that lists up to date sales leads with a corresponding selling probability. The order book can be seen as a rolling demand forecast that is updated periodically based on information provided by the marketing and sales department. Likewise, the model should be run periodically to generate an optimal equipment procurement strategy for the period in which the model is run.

1.3.2 Academic objectives

Secondary to the company objectives are the academic objectives. In general, the main academic objective of a graduation project is to contribute to academic literature by closing a research gap. The research gap is identified in Chapter 2 and aims on modelling the demand provided in the order book. None of the reviewed articles model orders individually which is required in this project. The model should describe orders individually which leads to a challenge in keeping the model tractable.

This graduation project focuses on the expansion of the production capacity of the production line from a strategic level (see Section 1.5.1). Simultaneously with this project, a second graduation student is writing a thesis focusing on the performance of the production line on operational level. While input parameters such as maximum production line utilization are often estimated for strategic capacity problems, the concurrence of two theses focusing on the same topic from both a strategic and operational level offers a chance to greatly improve the accuracy of the optimal model solution. The analysis of the production line on operational level provides the optimal utilization which can be used as input for the model that is elaborated in this graduation project.

1.4 Research questions

For performing effective research, appropriate research questions are required that guide the project in a structured manner. The objectives defined in Section 1.3 are translated into a main research question that should be answered at the end of the graduation project. The central research question for this project is defined as:

"How to provide an optimal strategic capacity planning given uncertainty in product demand?"

Answering the research question in a sophisticated and comprehensive way requires decomposition of the problem. Therefore, the main research question is decomposed in subquestions that aim to provide a clear solution procedure in consecutive phases. The first subquestion focuses on the availability of information that should serve as input parameters for the project.

1. What information is available regarding the product and production equipment? What are important variables in the decision making process when acquiring new equipment?

Subquestion two investigates the provided demand data. The order book lists sales leads that should be converted to usable input for modelling purposes. The sales leads have a corresponding selling probability however, given an order book with n sales leads, the set of all demand scenario combinations grows exponentially with 2^n. Consequently, the set of all combinations is likely to be reduced to keep the model computationally tractable.

2. How to translate the sales leads in the order book into manageable modelling input for the optimization model?

Subquestion three will be the most time and resource intensive part of the graduation project. The problem formulation of the project is translated into a mathematical model that can quantify the best equipment acquisition strategy. This subquestion also focuses on whether the same model can be used for both the scenario analysis and the equipment acquisition decision making tool.

3. How to mathematically model the capacity planning problem? What variables and constraints are considered in the model? What should be considered in the objective of the model?

How to solve the mathematical model is investigated in subquestion four. Optimization models are known to be hard to solve and thus, if the problem proves to be NP-hard or takes too long to solve exactly, existing solution procedures such as heuristics and metaheuristics are analysed.

4. How to solve the model efficiently? What computation time is permissible to be commercially applicable? If needed, what procedures exist to find near-optimal solutions?

The last subquestion, number five, focuses on the implications of the solution provided by the model. A sensitivity analysis is applied to check the robustness of the model to identify the practical applicability.

5. What solutions are obtained by the model? How reliable are the solutions provided by the model? What insights can be provided to the company? Are there any trade-offs that the company should consider?

Consecutively solving the subresearch questions stated in this chapter provides a structured way to solve the main research question and will yield a substantiated solution to the problem stated by the company.

1.5 Scope

The problem at hand can be approached from many different angles. To keep the problem manageable project boundaries are defined in this section. First the level of decision making is defined in section 1.5.1. Based on the applicable level of decision making, section 1.5.2 elaborates on the assumptions and consideration of this project and lastly the exclusion criteria are defined in section 1.5.3.

1.5.1 Strategic production planning

This project is classified as a production planning problem. Which product is produced on what machine at which time is of great importance for operational efficiency. However, given the planning horizon of the assignment that spans several years, not all details can be taken into account. Anthony (1965) proposed a hierarchy framework that identifies three levels of organisational decision making: strategic, tactical, and operational. Strategic decisions focus on long term goals, often 3 plus years ahead, and on this level resources are allocated to achieve those goals. Decisions at the strategic level serve as a framework for lower level decision making. Tactical decisions aim on mid term goals, often focusing on a planning horizon of roughly 6 months to a year and meant to manage big projects or semi annual production targets. Operational level decision making focuses daily operations such as production planning and aims to optimize these activities in terms of time, resources and people. Summarized, daily and weekly decision making focuses on details while strategic decision making aims at broad long term goals.

As illustrated in Figure 1.4 the hierarchical decision making framework is applied top-down starting on the strategic level. Decisions that are made at strategic level have an indirect yet significant impact on performance on both tactical and operational level. For the company the equipment acquisition planning determines the approximate production capacity, which is optimized on tactical and operational level. Consequently, a well performing operational production planning requires an optimal strategic production planning. Therefore, this thesis focuses on strategic production planning and aims at optimizing equipment acquisition. Solving a problem at this levels requires generalizing and simplifications of details that are considered on operational and tactical level to keep the problem comprehensible and solvable. Specific examples are provided in Section 1.5.2.

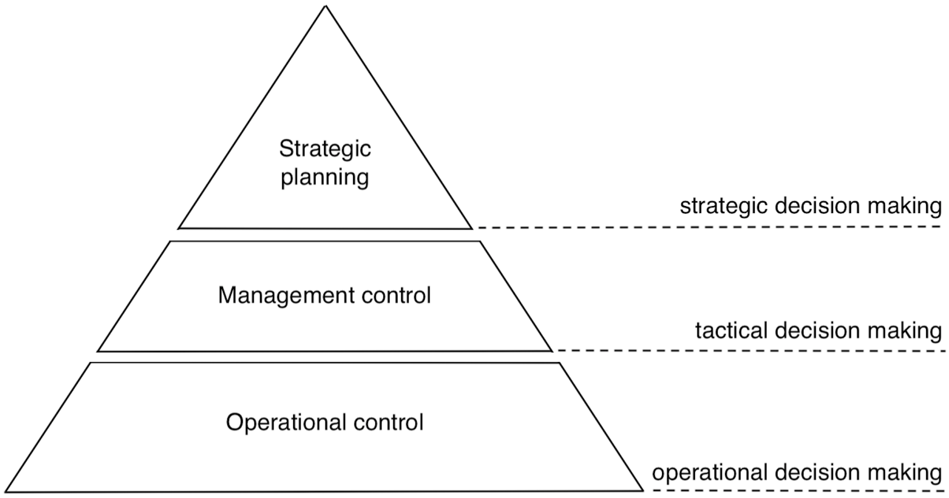

Figure 1.4: Hierarchy of management activities (Anthony, 1965)

1.5.2 Assumptions and considerations

As described in Section 1.5.1 the project aims to provide valuable insight in the production planning on strategic level. To achieve that goal, assumptions are made about details on tactical and operational level to keep the level of complexity of the problem manageable.

- The project is approached from equipment perspective. Product processing performance indicators as process time variability, cycle time and waiting time are not considered. Product process time is assumed to be deterministic and the cumulative process time of product demand in a period determines the required production capacity.
- The graduation project solely focuses on the package production line; however, system assembly is considered in the spatial requirements of the production facility. Package production and system assembly currently share the same production facility and demand increase for internally designed sensing systems increases both the required system assembly capacity and the package production capacity.
- The model is designed as a single stage problem. Other contributors in the supply chain such as suppliers and distributors are not considered in the model. Consequently, the assumption is that raw materials required for production are available at all times and that no logistic issues such as delays exist when shipping to customers.
- The problem at hand focuses solely on production capacity expansions. The production equipment that is required for the production of packages comprises of state-of-the art technology that is made-to-order. Combined with the fact that the company operates in a newly developing niche market, it is assumed to be very hard to sell or rent out production equipment and therefore production capacity reduction is not considered in this project.

1.5.3 Exclusion criteria

- Although operators are required for transportation of products between process steps, planned preventive maintenance and unplanned breakdowns, they are not considered in this project. The required operator workforce will be defined in the project that is performed simultaneously with this project, which focuses on the operational decision making regarding the package production line.

- The company states that due to the capital intensive production equipment, investments in new equipment are well considered before procurement. Therefore, large orders that require significant production capacity are assessed individually by management. Thus, the model designed in this thesis should focus on the relatively smaller orders that jointly require additional production equipment.

1.5.4 Schematic overview

A schematic of the scope of the project is illustrated in Figure 1.5

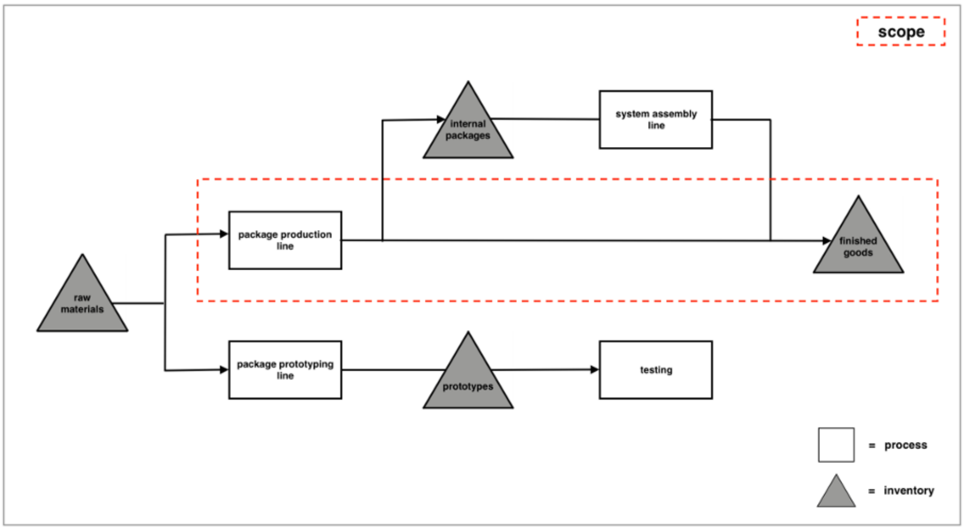

Figure 1.5: Project scope.

Chapter 2

Literature study

Expanding production facilities under demand uncertainty is a well researched topic within operations research. Referred to as strategic capacity planning (SCP), the field has received considerable attention in past decades. Most applied research is conducted in wellestablished, capital intensive environments such as the semiconductor industry (Çatay et al., 2003; Geng et al., 2009; Wang and Wang, 2013; Chien et al., 2018). Besides the semiconductor industry, comparable studies have been applied in industries such as additive manufacturing (Antomarchi et al., 2019) and the food processing industry (Lim et al., 2013). No published research has been conducted in integrated photonics but the modelling methods are broad applicable on any manufacturing company that is faced with demand uncertainty while expanding their production equipment portfolio.

Due to the relatively high cost of production equipment, a minor improvement in the capital investment strategy can result in significant savings (Geng and Jiang, 2009). The main problem that is encountered is demand uncertainty. A reactive equipment acquisition strategy cannot be applied as the order lead times of made-to-order production equipment often takes up to a year. Consequently, management is compelled to apply a proactive strategy which is subject to uncertainty in future demand. SCP provides a modelling framework that aims to find the optimal equipment expansion strategy while presented with various possible demand scenarios. In general, SCP problems are solved with either linear programming or a Markov Decision Process. In the remainder of the literature study we first elaborate on existing literature on equipment acquisition strategies for deterministic long term demand scenarios in Section 4.2 referred to as company objective 1 in Section 1.3.1. Secondly, in Section 2.2 we investigate modelling methods in literature to define optimal equipment acquisition strategies for stochastic demand scenarios referred to as company objective 2 in Section 1.3.1.

2.1 Long term scenario analysis

The first company objective is to gain high-level insight into the implications of various demand scenarios on the production facility (i.e., 5 years ahead). Therefore, the company requests a set of demand scenarios that intentionally vary in product mix and order size to be analysed to assess the impact in terms of required financial and spatial resources. Since the scenarios vary intentionally there is no added value in considering variation in demand and thus the assumption is that the demand scenarios are deterministic.

In general, deterministic SCP problems are solved using linear programming models (Sabet et al., 2019; Martínez-Costa et al., 2014; Geng and Jiang, 2009). Whether the problem is solvable in a feasible time span depends on the size of the problem. Provided the problem can be solved, deterministic linear programming models yield an exact optimal solution when presented with deterministic parameters (Antomarchi et al., 2019). This research more specifically focuses on an integer linear program (ILP) given all the decision variables in the model are integers (i.e., sold packages, inventory, stockout packages).

Deterministic integer linear programs within SCP environments have been developed as far back as 1984 when Luss published an article that aims to find an optimal equipment procurement policy in a multi resource, multi product, single production facility environment. In the model, Luss (1984) considers costs for capacity expansion, idle capacity holding and capacity storage. As solving methods became more efficient, deterministic SCP models have become more extensive. Nearly three decades later, the article of Lim et al. (2013) considers twice the amount of cost factors and seven times as much constraints.

Due to the natural uncertainty in future demand, deterministic models are intrinsically limited in finding an optimal solution compared to stochastic models. However, a trade-off exists in solution accuracy as deterministic models can include considerably more decision terms and constraints than stochastic models (Sabet et al., 2019). Consequently, deterministic solution methods are still being applied to solve SCP problems. Recent research shows that SCP models have become more extensive due to the increased processing speeds of computers and improved solving algorithms. Antomarchi et al. (2019) apply a deterministic SCP model which combines uncertainty elements from several stochastic models variables to identify the variables with the most impact on the optimal solution in a sensitivity analysis. The results from the deterministic model are used to indicate the variables to consider in the design of a stochastic model.

Additionally, the solution accuracy of an arbitrary model depends on the quality of input parameters. High quality input improves the solution accuracy while low quality input degrades the solution accuracy. Assuming the input information is of high quality, a positive correlation exists between the completeness of a model and the model accuracy. The available model input for the project is limited which constrains the completeness of the model. However, if we compare the set of products, the set of resources and the time horizon considered in this project with the reviewed literature there is a significant increase in the number of decision variables, referred to as V_{ijt}, that are to be considered (see Table 2.1). All sets of indices in this project are equal or larger than previous research with the set of time periods being seven times larger than the second largest time horizon. Consequently, the number of decision variables in this research is significantly larger. Thus, although the model is expected to be simple in term of considered costs and imposed constraints, the challenge will be in the size of the model size considering the number of decision variables. If the deterministic long term scenario analysis model proves to be unsolvable with a regular commercial solver an algorithm might be required that approximates the optimal value.

Table 2.1: Decision variables of reviewed literature.

	Products (i)	Resources (j)	Time periods (t)	V_{ijt}
Luss (1984)	2	1	3	6
Lim et al. (2013)	1	6	12	72
Sabet et al. (2019)	1	2	10	20
Antomarchi et al. (2019)	5	5	12	300
This project	15	6	96	8640

2.2 Strategic capacity planning

Considering the previous section, the deterministic long term demand scenarios are sufficient to indicate the required future resources in a broad sense. However, due to the lead time of production equipment, decisions are required on equipment procurement on the short term. The order book lists sales leads that have a certain probability of selling, referred to as pending orders. These orders can be converted into demand scenarios that can be considered in an optimization model. Within operations research, optimization of strategic capacity planning (SCP) problems considering multiple demand scenarios is generally performed with either stochastic programming or dynamic programming.

Stochastic programming is an often applied method for SCP that simulates demand scenarios with an associated probability to find a single optimal solution (Kandiraju et al., 2016; Gupta and Grossmann, 2011; Geng et al., 2009; Barahona et al., 2005). In these articles, the demand scenarios are either distribution-based (Geng et al., 2009), based on pessimistic, nominal and optimistic scenarios (Kandiraju et al., 2016) or based on a primary scenario with some less likely scenario variants based on the primary scenario (Barahona et al., 2005). In summary, all articles have some mean demand and apply variation to generate scenarios. However, in this project one pending order can be as large as all other pending others in terms of production volume per time unit and thus the probability of receiving one specific order can be of major significance to the equipment procurement strategy. Consequently, a procurement strategy that satisfies the average expected production capacity is undesired as it can be a sub-optimal strategy for both scenarios. Moreover, stochastic programming optimizes the equipment procurement policy to be optimal over the complete simulation horizon. In this project it might be more beneficial to prioritize the immediate rewards over the long term rewards considering the reliability of the order book decreases with the projected future period.

A more appropriate method to solve the SCP problem is dynamic programming which was conceptualized in 1957 by Bellman. Dynamic programming, also referred to as a Markov decision process (MDP), focuses on finding an optimal equipment procurement strategy for the present situation. Instead of yielding an equipment procurement policy that is optimal for the full planning horizon as with stochastic programming, MDP aims to find an optimal procurement strategy solely for the situation here and now. For every possible strategy to choose from, the model determines the expected revenue based on the expected future demand and the assumption that all future procurement strategies are optimal. Comparing the expected revenue of all strategies easily identifies the optimal strategy. Following a certain expansion strategy in the present impacts the equipment portfolio in the future and consequently decisions are interdependent but also irreversible. In most models, present and future rewards are valued equally. However, for models with a distant or even infinite modelling horizon or with uncertainty that increases with time, a discount factor can be introduced that prioritizes present rewards over future rewards (Bhulai, 2002). We refer to a model with a trade off between present and future rewards as a discounted rewards model. The goal of the MDP model is to find an optimal expansion strategy that maximizes the expected total (discounted) reward over the whole modelling horizon.

2.2.1 Demand modelling

Virtually all SCP problems in literature consider demand as a stochastic variable due to the intrinsical uncertainty of the future. Rajagopalan et al. (1998) simply model demand in time dependent increments, while demand in Nguyen and Wang (2019) is modelled as low, medium or high following a certain probability. Chien et al. (2012) and Wu and Chuang (2010) both model demand as market states that change states over time following a transition probability generated from historical and forecast data. The main similarities of demand modelling in the reviewed articles is the assumption that: (1) demand can be aggregated and (2) current demand is independent of demand in previous time periods.

The market segment in which the company operates serves only a very limited number of customers due to the highly specialized products. Placement of a single order can be of significant impact on the required production capacity. Moreover, most orders are multi-period orders meaning that for a single order there are multiple shipping moments separated by a certain time interval. This order property requires the model to consider the demand for an arbitrary multi-period order in the present if the order has been sold in a previous time period. Consequently, the demand in an arbitrary time period depends in part on the outcome of stochastic elements (i.e. demand) in preceding time periods. Thus, an academic challenge in this project is to model the MDP in a way that does consider the demand dependencies.

2.2.2 Solution strategies

Originally, MDP problems are solved to optimality with the value iteration (VI) algorithm as shown in (Puterman, 1994). The algorithm, also referred to as backward induction, can be seen as a brute-force search or exhaustive search algorithm as it considers all states to find an optimal solution for the current period. However, the state space of MDP problems grows exponentially with the number of actions and demand scenarios. Solving the problem by enumeration can become intractable due to the curse of dimensionality (Bellman, 1957).

The original VI algorithm is still applied to solve SCP problems (Lin et al., 2014; Chien et al., 2012), however, several adaptations have been proposed to solve problems that become intractable for the original algorithm. Wu and Chuang (2010) revise the VI algorithm by reducing the set of applicable actions. Instead of evaluating all possible actions in every iteration, their algorithm reuses previously calculated values which significantly reduces the computational effort. Nguyen and Wang (2019) apply a state reduction approach that eliminates unreachable states based on the problem characteristics. Additionally, the computational burden is further relaxed by applying a parallel computation technique. This method divides the main problem into subproblems that are sent to different computer processors to be solved after which the optimal results are sent back to the main computer.

2.3 Research proposal

The literature review conducted in this chapter indicates that the field of strategic capacity planning has received quite some attention in the past decades. This is in part due to the capital intensive investments that often accompany the execution of strategic decisions. Virtually all reviewed research indicates that the level of optimality for decisions on strategic level has a major impact on the expected earnings. Optimal decision making can result in huge revenues while suboptimal strategies may lead to a negative balance (Geng and Jiang, 2009).

For the long term scenario analysis a trade off will be made between simplicity and modelling horizon. To illustrate the variation of finished goods inventory levels a monthly time interval is considered. Following Table 2.1 this leads to a model with an above average amount of both integer and binary variables. To account for the additional computation time, the mathematical ILP model itself will be relatively simple. However, the ILP model is mainly meant as an indication for distant future developments, such as production facility expansion and finished goods inventory capacity requirements and will not be used as a support tool in the development of an equipment procurement strategy.

The main challenge of this graduation project is the strategic capacity planning model that, in comparison to the long term scenario analysis, is specifically designed to support management in developing equipment procurement strategies. Based on the reviewed literature, SCP research is mostly performed in established industries where historical demand can be extrapolated to estimate future demand. In this project however, demand is modelled as individual orders. Consequently, model states should describe the status of all individual multi-period orders with a first delivery date between the first modelling period and the present period. Due to the made-to-order equipment, the relatively long equipment order lead time should be considered in the model. Especially if in a later stage the model should consider the value of money as function of time. An arbitrary state should therefore describe previously made equipment procurement decisions if said equipment has not been shipped and delivered yet. The expectation is that without any model constraints the multi-equipment production process in combination with the order lead time will lead to the model becoming intractable.

To reduce the computational burden, the logic from the article of Wu and Chuang (2010) can be applied by reducing the set of procurement actions under consideration in an arbitrary system state. Prior to model runs, it is possible to determine the maximum required equipment portfolio based on the required production capacity for the scenario that all orders within the planning horizon are sold. This information can be used to indicate beforehand whether ordering additional equipment in a certain system state will yield any profit based on the present equipment portfolio and equipment yet to be delivered due to the order lead time. In addition, we intuitively know that equipment delivered after the model planning horizon will not generate any profit and additionally these actions are removed from the set of procurement actions. Consequently, the required computational time for finding the optimal procurement action for an arbitrary state will reduce. This method is in line with the state reduction approach applied in (Nguyen and Wang, 2019). Reducing the set of possible actions reduces the set of reachable successor states and thus the total number of system states reduces which in turn leads to a lower computational effort.

Chapter 3

Company case setting

This chapter is dedicated to the description of the problem environment. All available information regarding production equipment, products and demand process is presented and discussed in detail in an effort to identify modelling factors that could complicate the problem at hand. The information presented in this section aims to answer subquestion 1 elaborated in Section 1.4. First the production equipment characteristics are elaborated more extensively and secondly, product differentiation and demand are discussed.

3.1 Production process

Due to a high product mix with varying process times a continuous process with conveyor belts is difficult to achieve. To maximize the throughput the of the production line, production equipment is equipped with pre-processing and post-processing product buffers to ensure that equipment can operate continuously. This type of production line setup is common practice in microelectronics manufacturing with a high product mix.

During the design and setup of the automated production line new packages have been developed that can read the optical signal of multiple fibers with a single die. These fibers are merged in a so-called fiber array that provides a single connector to the package. Aligning and securing a fiber array to a package requires a different type of specialized equipment and thus an additional equipment type, a fiber array aligner, should be considered in the project. Thus, the product requirements determine the required production steps and in addition to two types of fiber aligning equipment, there are also products that do not require an optical fiber to read a incoming signal and thus these production steps can also be skipped. However, independent of the required productions steps the sequence of production steps is identical for every package type as is illustrated in Figure 3.1.

The goal is to align the available production capacity with the required production capacity. The challenge that arises is that the decision to procure production equipment has to be made months before the precise demand is known. Most of the production equipment comprises of state-of-the-art technology and is made-to-order. Therefore, the order lead time of equipment can be a high as a full year. The specified order lead time represents the time delay between the confirmation of the order and the moment the equipment is installed and operational in the production facility. Thus the order lead time includes all time required for (re-)design, manufacturing, assembly, testing, factory acceptance test and site acceptance test.

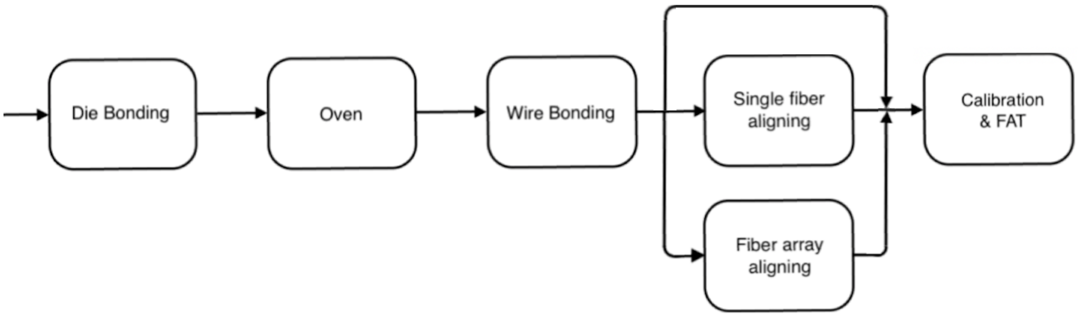

Figure 3.1: Schematic of automated production line.

3.2 Demand process

The goal of the project to find the optimal capacity expansion policy depends fully on the expected demand. Due to the uncertainty in demand, it is crucial to pre-estimate the required production capacity correctly from a cost perspective. The absence of historical data makes it impossible to extrapolate data and estimate trend lines. The information regarding demand for both package production for internally designed systems and the packaging service for external parties that is available is based on estimations and sales leads provided by the sales department. Thus, rather than providing an estimated average demand, the available information concerning future demand is provided in an order book that lists individual orders.

3.2.1 Order book

For every individual order, the order book lists a number of properties. An illustrative, randomly generated example of the order book is provided in Figure 3.2. The most important property from a modelling perspective is the selling probability. The selling probability indicates the chance the order will be sold. For orders with a selling probability of 100% the order is already sold and can be considered a deterministic parameter. However, for orders with a selling probability $< 100\%$ it is currently unknown whether the order will be sold or cancelled. These orders are referred to as sales leads. The probability of a sales lead depends on the current stage of sales meetings, a low probability indicates a slight interest from a customers perspective while a high probability indicates the sale is almost final. Due to the uncertainty, the sales leads are considered stochastic variables.

The demand is provided in time periods of months while the majority of the orders in the order book specify a quarterly delivery interval such that the at the end of every quarter (i.e., March, June, September and December) a peak in demand is identified. However, due to the exemplary function of the order book example this characteristic is not illustrated in Figure 3.2. For every individual order, the delivery batch size specifying the number of packages and delivery dates are indicated with cells with a red fill. A green fill indicates an order is active but in between delivery periods. Sold long term production orders provide certainty considering the continuity of production and cash flow. However, these orders can also result in significant financial losses if the expected order is cancelled in a late stage of negotiations in the event the company prepared for the expected increase in required production capacity with investments in production equipment.

Order number	Package type	Selling probability	jan-21	feb-21	mrt-21	apr-21	mei-21	jun-21
1	type 1	100%	100	100	100	100	100	100
2	type 2	100%	0	0	20	0	0	20
3	type 1	60%	0	0	50	50	50	50
4	type 3	30%	0	0	0	0	100	100

Figure 3.2: Order book example.

3.2.2 Demand scenario tree

The demand from the orders in the order book cannot be aggregated into a reliable mean expected demand per time unit due to the severely limited set of orders. The individual orders differ in both selling probability and quantity and consequently the sale or cancellation of a single order can be of significant impact on the expected mean demand. Therefore, the orders are modelled individually which results in the formation of a demand scenario tree as illustrated in Figure 3.3 which is based on the order book example in Figure 3.2. Recall from the previous section that orders with 100% selling probability are considered deterministic model input and thus order number 1 and number 2 provide a lower bound on the expected demand. The main focus is on the sales leads indicated by the selling probability of order number 3 and number 4 which cause the number of demand scenarios to increase exponentially.

The first delivery period of order number 3 in the order book example in Figure 3.2 is in March 2021. Depending on whether order number 3 is sold or cancelled, two demand scenarios exist. Two months further into the future, the first delivery period of order number 4 is May 2021. Again two demand scenarios exist depending on whether order number 4 is sold or cancelled. Provided that in May 2021 already two possible demand scenarios exist due to order number 3, the number of demand scenarios increases to four. Thus, the number of demand scenarios increases exponentially with every additional sales lead in the order book. Depending on the number of sales leads n in the order book, the number of demand scenarios at the last modelling period within the considered modelling horizon is 2^n.

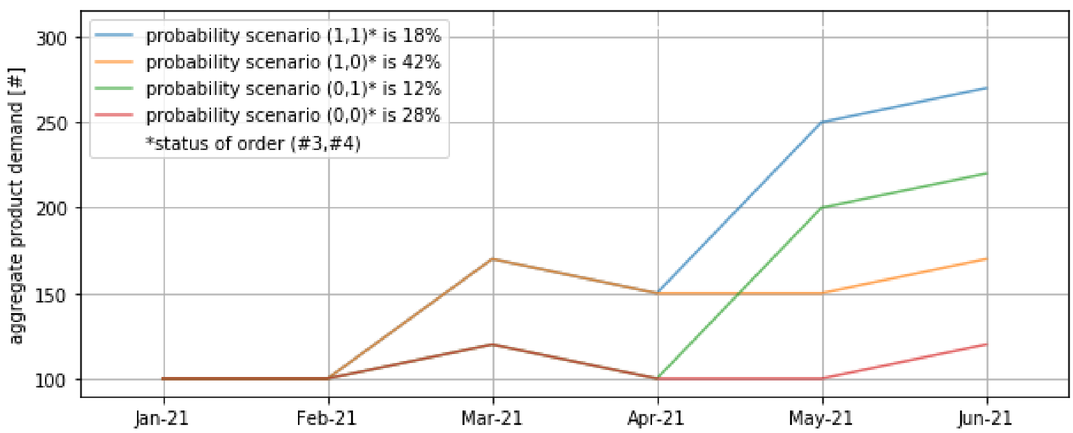

Figure 3.3: Exemplary demand scenario tree.

Chapter 4

Modelling

This chapter translates the problem description into mathematical models that aim to optimize the company objectives. Prior to defining the mathematical formulation of the models the general modelling objective is defined and the general parameters that apply to both models are elaborated in Section 4.1. Next, Section 4.2 aims at solving the first company objective specified in the section 1.3.1. Here, an integer linear programming (ILP) model is defined that aims to identify the required production resources in the distant future. In Section 4.3 the second company objective is translated into a optimization model by means of a Markov decision process (MDP). This model optimizes the equipment procurement timing with the goal of supporting management in drafting a optimal production capacity expansion strategy for short term decision making.

4.1 General objective and parameters

The two models that are described in the following sections of this chapter are distinctly different in applied method but the main objective is identical: to identify the optimal equipment procurement strategy. Here, optimal refers to the expected maximal financial gain a strategy can generate. To quantify and evaluate an equipment procurement strategy, the total costs of the respective strategy are weighed against the expected future earnings. The sum of both elements is referred to as the gross profit and the optimal procurement strategy is the strategy that yields the highest expected gross profit. Due to the shared main objective, the majority of modelling assumptions and parameters are equal for both models. Therefore, the properties that are equal for both models are elaborated in this section. Model assumptions and parameters specific to either the long term scenario analysis LP model or the strategic capacity planning MDP model are clarified in their respective section.

1. *Parameter indices*

   The majority of the parameters considered in both models apply to a specific type of package or production equipment. Therefore, a single parameter with distinct values for unique objects should be able to distinguish between said objects. The distinction is made with discrete indices that are linked to the respective object. The considered indices in the models represent the package types i, equipment types j and time periods t respectively indicated by

   $i \in K$ here, $K = \{1, 2, ..., I\}$ where I is the number of unique package types,
   $j \in L$ here, $L = \{1, 2, ..., J\}$ where J is the number of unique equipment types,
   $t \in M$ here, $M = \{1, 2, ..., T\}$ where T is the number of modelling periods.

2. *Income parameters*

   Both models aim to maximize the expected gross profit G by finding the optimal equipment procurement strategy. The gross profit is defined as the revenue minus the costs that can be directly related to individual products such as material costs and production costs. Remaining costs that can not be directly related to individual packages, referred to as overhead costs, are not within scope for this project. For every sold package, the model earns a gross margin g_i^{mar} that represents the earnings. The gross margin consists of the package revenue subtracted with the material costs. Thus, the aggregated gross margin based on the number of sold packages represents the income component.

3. *Cost parameters*

   The production costs are included in the model with two separate cost components. The operational costs c^{op} represent the periodical costs for maintenance, repairs and spare parts required to operate the production equipment. The depreciation costs c^{dep} represent the procurement costs of equipment. The depreciation costs are periodical costs that are linear with operational lifetime.

4. *Equipment production capacity*

   All equipment types have a periodic production capacity b_j which is based on the periodically available production time h. To determine the periodic production capacity, there are several components to consider. First is the expected time required for maintenance t^{ma} and breakdowns t^{db}. Secondly the number of parallel processes p^{par} should be considered and lastly the equipment yield y and the utilization u are both considered in fractions. Based on the mentioned components, the periodic production capacity is defined as

   $$b_j = (h - t_j^{ma} - t_j^{bd}) \cdot p_j^{par} \cdot y_j \cdot u_j \tag{4.1}$$

5. *Package process time*

   Depending on the number and type of components that are required to assemble a package, a package process time is defined. The package process time is defined individually for each required process step j with $t_{i,j}^{p}$ for all package types i.

6. *Package demand*

   To generate gross margin, packages need to be produced and sold. Which type of packages and what respective quantities should be produced depends on the forecasted demand. Based on the individual orders in the provided demand scenario, the demand for each package type i is aggregated and the total quantity of demand for package type i in period t is defined as $d_{t,i}$.

7. *Lost sales*

   The situations in which the required production capacity, as a direct results of demand, is higher than the available production capacity is referred to as undercapacity. A suboptimal expansion strategy can result in undercapacity meaning demand can only be fulfilled partially. If this situation occurs, the unfulfilled demand is assumed lost as we assume there is no backordering or outsourcing.

4.2 LP model for long term scenario analysis

In this section a mathematical model is designed to analyse the impact of a set of long term demand scenarios on the required production resources for the distant future. The goal of the analysis is to provide an indication for the required production capacity, the subsequent required floor space in the production facility and the required inventory capacity for finished packages. The results of the model will not be used as an aid in decision making processes but are meant to illustrate the implications of future scenarios. Consequently, the demand scenarios are modelled as being deterministic. As mentioned in Chapter 2 the classical approach to strategic capacity problems (SCP) is to design a linear programming optimization model (Geng and Jiang, 2009). Due to the assumption that the demand input is deterministic, the accuracy trade-off between deterministic and stochastic models becomes irrelevant. Consequently, a deterministic model would be most appropriate to model the problem as the absence of stochastic elements allows a deterministic model to process more decision variables compared to its stochastic counterpart (Sabet et al., 2019).

The LP model cannot be defined solely based on the assumptions and parameters described in Section 4.1. Besides the general modelling assumptions and parameters that apply to both the LP model and the MDP model, additional specific modelling assumptions and parameters are required to fully define the model. The remaining undefined parameters model assumptions are elaborated below.

1. *Periodic time interval*

   The complete modelling horizon of the long term scenario analysis is represented by the time interval $[1, T]$. The time interval is divided in a number of equal discrete time steps t, referred to as period. At the end of every period t, the model must decide on the optimal equipment expansion strategy for the observed time step. Thus the number of decision moments and subsequent decision variables in the LP model depend on the number of discrete time steps within the complete modelling horizon. One of the goals of the LP model is to identify the required inventory capacity for finished packages. Recall from section 3.2.1 that the majority of the orders in the order book are multi period orders with a quarterly or semi annual delivery interval. However, the data specified in the order book is provided on a monthly basis and consequently the result is a peak in the cumulative demand at the end of every quarter. To make optimal use of the available production capacity, the excess production capacity required as a result of the demand peak should be distributed over periods with spare production capacity to minimize the required overall production equipment portfolio. Therefore, to illustrate the consequence of the uneven distribution of demand over time and the resulting inventory, the length of time period t in the LP model is equal to one month.

2. *Inventory costs*

   Besides the cost components for production equipment depreciation and operational expenses an additional component for inventory costs c_i^{inv} is included in the model. The inventory costs are the costs to keep a finished package in storage for a single time period.

3. *Initial equipment portfolio*

   The expansion strategy of the equipment portfolio is based on the initial equipment portfolio that is available at the first period of the modelling horizon under consideration. In the initial equipment portfolio, the number of available machines of every equipment type are indicated with n_j.

4.2.1 Integer linear programming model

To determine the optimal equipment procurement strategy the LP model is enabled to make decisions. Thus, in addition to the previously defined model parameters, a set of four decision variables is introduced. The decision variables are defined as

- $P_{t,i}$ — The number of produced packages of type i in period t,
- $I_{t,i}$ — The number of finished packages of type i in inventory in period t,
- $S_{t,i}$ — The number of stockout packages of type i that can not be produced due to limited production capacity in period t,
- $E_{t,j}$ — The number of additional machines of type j required in period t.

Based on the associated earnings and costs for the decision variables, the model aims to maximize the gross profit over the whole modelling horizon. However, the type of decision variables also determine the type of LP problem. Given that all decision variables refer to objects that cannot be divided into fractions (i.e., packages and machines) the model is defined as an integer linear programming (ILP) model. The ILP model for the long term scenario analysis is defined as:

$$G = \max \sum_{t=1}^{T} \sum_{i=1}^{I} (d_{t,i} - S_{t,i}) g_i^{mar} - I_{t,i} c_i^{inv} - \sum_{t=1}^{T} \sum_{j=1}^{J} \left(n_j + \sum_{z=1}^{t} E_{z,j} \right) \cdot (c_j^{op} + c_j^{dep}) \tag{4.2}$$

Subject to:

$$P_{t,i} + I_{(t-1),i} - I_{ti} + S_{t,i} = d_{t,i} \qquad \forall i \in K,\ \forall t \in M, \tag{4.3}$$

$$\sum_{i=1}^{I} I_{t,i} \leq \max \left\{ \sum_{i=1}^{I} d_{t+1,i}, \sum_{i=1}^{I} d_{t+2,i} \right\} \qquad \forall t \in M, \tag{4.4}$$

$$\sum_{i=1}^{I} P_{t,i} t_{i,j}^{p} \leq b_j \left(n_j + \sum_{z=1}^{t} E_{z,j} \right) \qquad \forall j \in L,\ \forall t \in M, \tag{4.5}$$

$$E_{t,j}, P_{t,i}, I_{t,i}, S_{t,i} \in \mathbb{N} \tag{4.6}$$

The expected gross profit G is maximized in the objective function (4.2) by hedging the gross margin against the inventory costs, the operational costs and the equipment depreciation costs for all modelling periods $t \in M$. Here, G represents the actually obtained gross profit as the demand scenarios are deterministic. Constraint (4.3) ensures that all demand $d_{t,i}$ for package type i in period t is accounted for by assuming the demand has either been produced indicated by decision variable $P_{t,i}$ or is assumed as a lost sale, referred to as a stockout, indicated by decision variable $S_{t,i}$. To distribute peak demand over multiple periods, decision variable $I_{t,i}$ allows finished packages to be carried over to the next period as inventory. To prevent inventory to be carried over for more than a three month period, Constraint (4.4) is imposed that ensures that the maximum inventory level of period t cannot exceed the maximum demand for the two consecutive periods $t+1$ and $t+2$. Without this constraint, the model can be inclined to stock finished packages in inventory for periods in the distant future depending on the inventory carry-over cost which is undesired behaviour.

Maximizing the gross profit requires the model to find the optimal trade-off between earnings and incurred costs. Constraint (4.5) reflects said trade-off with respectively the dependency between the maximum number of packages than can be produced in period t and the available production capacity in period t. Every package type i has an associated process time $t^{proc}_{i,j}$ that indicates the time required to process package type i on equipment type j. If the available production capacity is insufficient, the model can procure an additional machine of equipment type j with binary decision variable $E_{t,j}$. For period t, the total production capacity of equipment type j is determined by the sum of the initial number of machines n_j at $t = 0$, and the number of machines procured between $t = 1$ and $t = t$. The total number of machines is multiplied with the periodical production capacity b_j of a single machine to determine the total production capacity. Lastly, Constraint (4.6) ensures that all decision variables are restricted to be integer values.

4.3 MDP model for strategic capacity planning

This section defines the strategic capacity planning model that aims to support management in defining an optimal equipment procurement strategy. In the literature study in Chapter 2 a Markov decision process (MDP) is identified as the optimal method to solve the problem at hand. A MDP is modelled by a set of time dependent system states of which the interdependencies resemble a scenario tree as illustrated in Figure 4.1. Assume in this simple example there is only one product type, one equipment type, no equipment order lead time, and two demand scenarios every period t. The decision maker is allowed to make a binary decision a_t every period t, referred to as an procurement action in Figure 4.1, to either procure one additional machine (+1) or do nothing (0). Based on the current state s_t and the chosen action a the model receives a reward $r(s_t, a)$. For each decision in period t, the model responds by randomly transitioning to one of two reachable states in period $t + 1$, based on the probability of the respective pending order status. Provided the transition probabilities are known, the model can determine the average expected reward over future periods. Thus, the optimal equipment procurement strategy is the action policy that maximizes the expected sum of rewards over the whole modelling horizon.

The actual MDP model that represents the problem under consideration in this project is more extensive and complex than the example illustrated in Figure 4.1. Therefore, to reduce the required computational time of the MDP model, the following assumptions apply:

1. *Periodic time interval*

   Like the ILP model, the modelling horizon of the MDP model is represented by the time interval $[1, T]$. The time interval is divided in a number of equal discrete time steps t, referred to as a period. Here, a period is defined as a three month time interval, also referred to as a yearly quarter. As opposed to the deterministic ILP model, the MDP model must consider multiple demand scenarios which requires exponentially more computation time. Therefore, the monthly demand is aggregated to quarterly demand to partially counteract the additional required computation time as a result of the stochastic demand.

2. *Inventory levels of finished packages are not considered*

   Due to the extension of period t from monthly to quarterly, the peak in cumulative demand at the end of every three month period is no longer visible. Therefore, we assume that a quarter is a single production period and demand is evenly distributed within that period. Consequently, considering inventory levels of finished goods is not required for the MDP model which reduces the required computational time of the model.

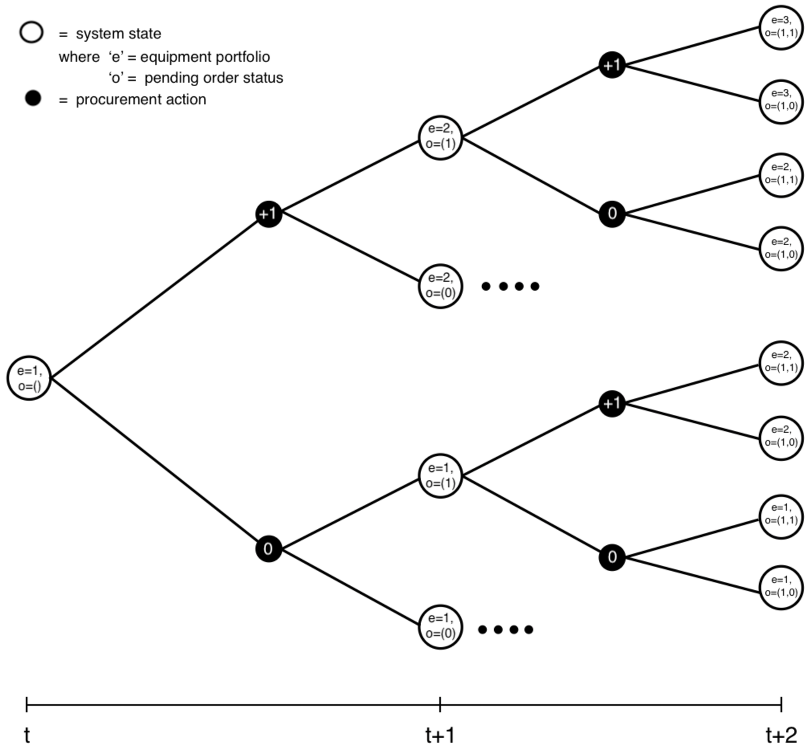

Figure 4.1: Graphical representation of a simple MDP model.

The remainder of this section elaborates on the main elements and processes of the MDP model of this project. Successively the state space, the action space, transition probability and state reward are defined. Lastly, the optimization method is elaborated such that the MDP model can be solved to optimality. To validate the MDP, the model is run for a simplified problem instance, which is defined and manually verified in Appendix A.

4.3.1 State space

The total set of reachable states in the MDP within discrete time interval $[1, T]$ is referred to as the state space. We refer to the state space as set S. For the set of states in period t we define a subset $S_t \subseteq S$. For every state $s_t \in S_t$ the set of reachable states after transitioning is a subset of S_{t+1}. The set of reachable states for state s_t depends on the respective state description. Every state s_t in the state space must comply with the Markov property meaning that the conditional probability of future states only depends on the present state and is independent of any preceding states. Consequently, all information regarding events in the past required to fully describe a current state, should be stored in the state description in order to satisfy the Markov property. Consequently, there are three variables that are required to describe a state in the state space of which the first is the current equipment portfolio. To determine the available production capacity in an arbitrary state, the number of machines per equipment type is specified. The number of available machines of equipment type j is indicated by e_j. Therefore, the equipment portfolio in state s_t is described by vector $\vec{e}_t$ following

$$\vec{e} = (e_{t,1}, e_{t,2}, ..., e_{t,J}) \tag{4.7}$$

The second property the state description must include is the current demand. Important to note is that the demand description only includes orders that have a selling probability < 100% and thus are considered a stochastic element in the model, referred to as pending orders. Recall from section 3 that most orders are multi period orders, meaning that a single order often has multiple delivery moments. Consequently, the model must keep track of the outcomes of stochastic elements in preceding time periods. That is, if the model assumes an order has been sold in a predecessor state of the observed state, the observed state should also consider demand for that specific order. Thus, the state description of an arbitrary state in period t should include the order status of all preceding orders considered in predecessor states within time interval $[0, t]$.

Individual orders are indicated by $k_{t,n}$ where t indicates the first delivery period and n differentiates between orders with the same first delivery period following $n \in \{1, 2, .., N_t\}$ where N_t indicates the total number of orders with the same first delivery period t. Individual orders are binary variables indicating the order is cancelled or sold with $k_{tn} = \{0, 1\}$, respectively. Thus, the set of pending orders with a first delivery date in period t is denoted as

$$\vec{o}_t = (k_{t,1}, k_{t,2}, ..., k_{t,N_t})^* \tag{4.8}$$

Provided that state s_t must consider the realisation of all previously pending orders with a first delivery date within time interval $[0, t]$, the state order description is defined with vector $\vec{o}$ following

$$\vec{o} = (\vec{o}_1, \vec{o}_2, ..., \vec{o}_t) \tag{4.9}$$

Lastly, due to the lead time of production equipment, procurement decisions that are taken in previous periods should be defined in the state description. The lead time of equipment in number of periods is denoted by l_j and procurement actions for equipment type j in period t are referred to as $a_{t,j}$. Depending on the lead time, the vector of previously taken procurement actions for equipment type j is defined as

$$\vec{v}_{t,j} = (a_{t-l_j,j}, a_{t-l_j+1,j}, ..., a_{t-1,j}) \tag{4.10}$$

However, the state description must include the previous procurement decisions of all equipment types and thus the complete action description for state s_t is an vector of vectors denoted as

$$\vec{v} = (\vec{v}_{t,1}, \vec{v}_{t,2}, ..., \vec{v}_{t,J}) \tag{4.11}$$

All three variables required to describe an arbitrary state are now individually defined with respectively equations (4.7), (4.9), and (4.11). Combined, the variables can represent every system state $s_t \in S$ with the full state description that is defined as follows

$$s_t = (\vec{e}, \vec{o}, \vec{v}) \tag{4.12}$$

The number of states in the state space S grows exponentially with the number of considered considered variables. The variables for the state equipment description in equation (4.7) and

*Note that if $N_t = 0$ the set $\vec{o}_t$ is empty.

state action description in equation (4.11) are predefined by the number of unique equipment types and the respective lead time. However, the state demand description in equation (4.9) is defined by the number of pending orders within modelling horizon [0,T]. Thus, the size of the state space S, and subsequently whether the model is solvable in a reasonable time span, depends on the number of pending orders.

4.3.2 Action space

Every period t the decision maker must make a decision for all equipment types j on whether to procure additional equipment. Due to the equipment order lead time l_j equipment ordered in period t is delivered at the start of period $t + l_j + 1$. Thus, the decision maker must look $l_j + 1$ periods ahead to determine the expected demand and to estimate the required production capacity. If the available production capacity of the respective future period is expected to be insufficient, additional equipment can be procured to increase the production capacity. Recall from section 1.5.2 that large orders are not considered in this project. Therefore, the focus of this model is on relatively smaller order and thus the equipment portfolio can periodically be expanded by one additional machine of every equipment type. Consequently, the individual action per equipment type is a binary decision variable with two possible actions, either doing nothing or procuring one additional machine, denoted with $a_{t,j} = \{0, 1\}$, respectively. Thus, for every period the decision maker has to make J separate procurement decisions which combined form the action a_t indicated with

$$a_t = (a_{t,1}, a_{t,2}, ..., a_{t,J}) \tag{4.13}$$

The set of all feasible actions a is referred to as the action space and indicated with A. Recall from section 3.1 that this project considers six production equipment types ($J = 6$). Consequently, the decision maker has to make six separate procurement decisions every period. The action space A grows exponentially with the number of equipment types and considering the two possible options for individual equipment procurement action $a_{t,j}$, the action space A for this project contains 2^6 feasible actions a_t as is illustrated in Table 4.1.

Table 4.1: Action space A

a_t	$(a_{t,1}, a_{t,2}, ..., a_{t,6})$
1	(0,0,0,0,0,0)
2	(0,0,0,0,0,1)
3	(0,0,0,0,1,0)
...	...
64	(1,1,1,1,1,1)

Considering all feasible actions in action space A for every state s_t becomes an exhaustive exercise for large problem instances. To reduce the computational burden, the number of actions under consideration for state s_t is reduced by generating $A_{s_t} \subseteq A$. Subset A_{s_t} filters all redundant actions from action space A based on the state description of state s_t. That is, prior to the model run, the model calculates the maximum demand that must be fulfilled for every period t in the hypothetical situation that all pending orders are sold. Based on the maximum demand, the upper bound of required production capacity and consequently the maximum number of machines of every equipment type is calculated. The maximum required number of machines of type j in period t is defined as $e^{max}_{t,j}$. Based on this parameter, the model can predetermine whether there is added value in considering action a_t in state s_t. For every equipment expansion decision $a_{t,j} \in a_t$ the model checks whether the sum of the currently available number of machines of type j plus the machines that are already ordered but are not yet delivered due to the order lead time l_j is equal or higher than the maximum number of machines required in future period $e^{max}_{t+1+l_j,j}$. If so, expansion option $a_{t,j}$ should not be considered and therefore action a_t should not be considered.

Secondly, subset $A_{s_t} \subseteq A$ filters all procurement actions of equipment that will be delivered outside the modelling horizon $[1, T]$. For equipment that is delivered after the last period T, no profit can be generated and thus there is no value in considering the respective procurement action. Important to note here is that while actions might be filtered due to a delivery period outside the modelling horizon, this does not definitively means that the procurement action is not required in the respective time period. If the model is run x time periods later, the delivery period of the previously filtered procurement action might now be within the new modelling horizon $[1 + x, T + x]$ and consequently the procurement action should then be considered. Considering both filters that are described here, subset $A_{s_t} \subseteq A$ is mathematically defined as

$$A_{s_t} = \{ \ a_t \mid a_t \in A \land \left(e_j + \sum_{x=0}^{l_j} a_{t-x,j} \leq e^{max}_{t,j} \forall \ a_{t,j} \in a_t \right) \land (t + l_j + 1 \leq T \forall \ a_{t,j} \in a_t)\} \quad (4.14)$$

4.3.3 Transition probability

The transition probability of state s_t to state s_{t+1} is partly deterministic and partly stochastic. The deterministic, controllable, part of the transitioning probability depends on action a_t made by the decision maker as discussed in the previous section. Action a_t determines all equipment related variables in the state description which are the state-equipment description and the state-action description indicated with respectively equations (4.7) and (4.11). The stochastic part of the transition probability of state s_t to state s_{t+1} depends on the realisation of demand. For state s_t, pending orders with a first delivery date in time interval $[0, t]$ have already realized, either being sold or cancelled. However, the realisation of pending orders with a first delivery date in an arbitrary future period is still unknown. For the transition of state s_t to state s_{t+1} the stochastic part of the transition probability depends on the set $\vec{o}_{t+1}$ that contains the pending orders with a delivery date in period $t + 1$.

The number of transitions from state s_t to state s_{t+1} depends on the number of pending orders N_{t+1}. Recall from section 4.3.1 that the status of pending orders is a binary variable denoted with $k_{t,n} = \{0, 1\}$. Thus, the number of scenarios $\vec{o}_t$ is 2^{N_t}. The transition probability for an arbitrary scenario $\vec{o}_t$ is the product of the selling and cancellation probabilities of individual pending orders $k_{t,n}$ denoted as $P_s(k_{t,n})$ and $1 - P_s(k_{t,n})$, respectively. The transition probability of state s_t to state s_{t+1} provided action a_t is mathematically expressed as

$$\begin{aligned} P^{a_t}_{s_t,s_{t+1}} &= \prod_{n=1}^{N_{t+1}} P_s(k_{t+1,n})^{k_{t+1,n}} \cdot (1 - P_s(k_{t+1,n}))^{1-k_{t+1,n}} \\ where \quad & s_{t+1} = (\vec{e}, \vec{o}, \vec{v}), \\ & \vec{e} = (e_{t,j} + a_{t-l_j,j}, ..., e_{t,J} + a_{t-l_J,J}), \\ & \vec{o} = (\vec{o}_1, ..., \vec{o}_{t+1}), \\ & \vec{v} = ((a_{t-l_j+1,j}, a_{t-l_j+1,j}, ..., a_{t,j}), ..., (a_{t-l_J+1,J}, a_{t-l_J+1,J}, ..., a_{t,J})). \end{aligned} \quad (4.15)$$

Note that if there are no pending orders with a first delivery date in period $t + 1$, $N_{t+1} = 0$

and $\vec{o}_{t+1}$ is an empty set. In this case, there is only one transition and Equation (4.15) yields a transition probability of 1.

4.3.4 Reward function

The goal of the MDP model is to yield the production capacity expansion policy that maximizes the expected long term gross profit. In order to differentiate between policies, states obtain a reward that is dependent on the respective equipment portfolio and respective pending order description. Hence, the state reward is denoted as a function of the observed state with $r_t(s_t)$. As elaborated in section 4.3.2 an action a_t is taken for every state s_t. If the action is to order new equipment of type j, the equipment is expected to be delivered $l_j + 1$ periods in the future due to the equipment order lead time l_j. Payments for the new equipment do not start until the machine is delivered and thus no immediate costs are incurred in state s_t for action a_t. As a result, the reward $r_t(s_t)$ is independent of action a_t. However, action a_t in state s_t obviously does impact the reward of successor states.

Like the ILP model, the goal of the reward function of the MDP model is to maximize the gross profit by fulfilling as much demand as possible with the available production capacity. Therefore, the state reward function is defined as a simplified version of the calculation of the gross profit in the ILP model as defined in Section 4.2. Recall that due to the aggregation of time periods from monthly to quarterly inventory levels are not considered in the MDP model. Secondly, for every state the equipment portfolio $\vec{e}$ and the status of pending orders $\vec{o}$ are fixed and thus deterministic. Therefore only two decision variables are considered in the reward optimization function of the MDP model. The decision variables are defined as

$P_{t,i}$	The number of produced packages of type i in period t,
$S_{t,i}$	The number of stockout packages of type i that can not be produced due to limited production capacity in period t.

Since the state reward only considers time period t of the respective state, the sum over the complete modelling horizon $[1, T]$, that is applied in the ILP model, is omitted. Based on the defined modelling assumptions, the state reward function is defined as

$$r_t(s_t) = \max \sum_{i=1}^{I} (d_{t,i} - S_{t,i}) \cdot g_i^{mar} - \sum_{j=1}^{J} e_{t,j} \cdot (c_j^{dep} + c_j^{op}) \tag{4.16}$$

Subject to:

$$\sum_{i=1}^{I} P_{t,i} + S_{t,i} = d_{t,i} \tag{4.17}$$

$$\sum_{i=1}^{I} P_{t,i} \cdot t_{i,j}^{p} \leq b_j \cdot e_{t,j} \qquad \forall j \in L, \tag{4.18}$$

$$P_{t,i}, S_{t,i} \in \mathbb{N} \tag{4.19}$$

The reward r_t is maximized in the objective function in Equation (4.16). Here, the income component depends on the number of produced packages and the cost component is fixed as the equipment portfolio is deterministic. The demand for package type i in period t is reflected by parameter $d_{t,i}$ which is directly derived from the pending order status of the respective state. Constraint (4.17) ensures that all demand is considered, either as a produced unit or as stockout unit. For every produced package $P_{t,i}$ the objective function generates income while a stockout package $S_{t,i}$ generates none.

The production capacity is capped by the available production equipment in Constraint (4.18). If the available production capacity is insufficient for the demand, the objective function will select the most profitable packages in the demand to be produced to maximize the reward. The least profitable packages are assumed as stockout packages and incur an indirect costs in the form of lost earnings. In the optimal situation the required production capacity as a result of the demand $d_{t,i}$ and the available production capacity as a result of the current equipment portfolio align perfectly. Here, any lost earnings due to stockout packages as a result of undercapacity are eliminated, and additionally unnecessary operational and depreciation costs for idle equipment are prevented. Lastly, Constraint (4.19) ensures that all decision variables are restricted to be integer values.

4.3.5 Model optimization

In this section, the strategic capacity planning problem as defined in the previous sections of this chapter is optimized. Optimization here means finding the optimal sequence of actions a_t for every period t, referred to as the optimal policy, such that the sum of expected rewards over the whole modelling horizon is maximized. Briefly covered in the introduction and more extensive in Section 4.3.3 is that multiple possible scenarios exist in the transition from state s_t to s_{t+1}. Each scenario has an associated transition probability that indicates the likelihood of occurring and thus the expected reward to be received in state s_{t+1} is the sum of all possible rewards multiplied by their respective transition probability. Finding the optimal action for state s_t requires the model to consider the rewards of all reachable future states within the remaining time interval $[t, T]$. Consequently, the value $v(s_t)$ of a state in period t is defined as the immediate reward plus the average expected value of successor states in period $t + 1$. This relation is known as the Bellman expectation equation (Bellman, 1957) and is defined as

$$v(s_t) = r_t(s_t) + \mathbb{E}\left[\sum_{s_{t+1} \in S_{t+1}} P^{a_t}_{s_t, s_{t+1}} v(s_{t+1}) \right] \tag{4.20}$$

The last period T within the modelling horizon in referred to as the terminal period. States in the terminal period have no successor states and thus an exception applies to the their respective value. Due to the non-existence of successor states for states in period T the value of states in the terminal period is defined as

$$v(s_T) = r_T(s_T) \tag{4.21}$$

Due to the recursive relationship in equation (4.20) the value of state s_0 is a function of the values of all reachable states within modelling horizon $[1, T]$. For problem instances with a large state space this solution method quickly becomes insolvable (Rust et al., 2006). Recall that all states in the state space must comply with the Markov property meaning that an arbitrary state in the state space is conditionally independent of any previous actions or predecessor states. Due to this property, backward induction can provide a solution procedure by dividing the main problem into sub problems which can be separately solved to reduce the computational burden. This solution method solves the MDP in reversed order, calculating the value of states in period

T first and subsequently iterates backwards to period 0, the current period. Now every state value in period T is a part of the value of predecessor states in period $T-1$. By reusing the calculated value of a state for the calculation of predecessor states, the computational effort is significantly reduced.

The goal of the model is to find the optimal equipment procurement strategy that maximizes the sum of expected rewards over the whole modelling horizon. The procurement decision a_t in state s_t is fully under control of the decision maker and thus for the model a deterministic parameter. Following the Bellmann expectation equation in equation (4.20) one can determine the expected future rewards for an arbitrary state given an arbitrary procurement decision. Consequently, using backward induction it is possible to consecutively find the optimal procurement decision for every period that maximizes the sum of expected rewards with the Bellman optimality equation (Bellman, 1957) defined as

$$v^*(s_t) = r_t(s_t) + \mathbb{E}\Bigg[\sum_{s_{t+1}\in S_{t+1}} P^{a_t^*}_{s_t,s_{t+1}} v(s_{t+1})\Bigg] \tag{4.22}$$

In Equation (4.22) a superscript asterisk is added to both the notation of the value of state s_t and the action a_t. The asterisk indicates the value for state s_t is optimal for action $a_t^* \in A_{s_t}$ that maximizes the state value. Hence, action a_t^* that maximizes the state value is the optimal equipment procurement strategy. Recall that the goal of the model is to find the equipment expansion strategy that maximizes the expected gross profit G. The state value represents the gross profit that can be earned in a respective state and thus the expected gross profit as a result of the optimal equipment procurement strategy can be defined as the optimal state value for the state at time $t = 0$ that considers all expected state values in the state space for all periods $t \in M$ with

$$G = v^*(s_0) \tag{4.23}$$

4.3.6 Complexity

The state space of the MDP increases exponentially with the number of considered variables. Solving the MDP model with backward induction is an exhaustive method that considers all details which can lead to the model becoming intractable. For the problem at hand the number of equipment types under consideration and the associated equipment order lead times, and the modelling horizon are deterministic. The number of demand scenarios however can vary depending on the number of pending orders in the order book. Assuming the average action set A_{s_t} for an arbitrary state is reduced to $a = 5$ feasible actions, and $n = 1$ order is pending for ever period within the modelling horizon of $T = 9$ quarters such that every state-action combination can transition into 2 possible successor states, the state space consists of $(a * 2^n)^{T-1} = (5 * 2)^8 = 100.000.000$ system states. Provided that for every state a reward must be determined, the required time to solve increases rapidly with the number of pending orders in the order book.

Figure 4.2 shows the required time to solve the MDP model as a function of the number of pending orders in the order book. Important to note is that the time to solve the MDP model also depends on the first delivery dates of the respective pending orders. If for a modelling horizon $[1, T]$ all first delivery dates of the pending order in the order book are at $t = 1$, the state space of the MDP model obviously is exponentially larger compared to an order book with pending orders that have an first delivery date close to $t = T$. Consequently, the MDP model run time varies depending on the order book composition. However, as indicated by the figure,

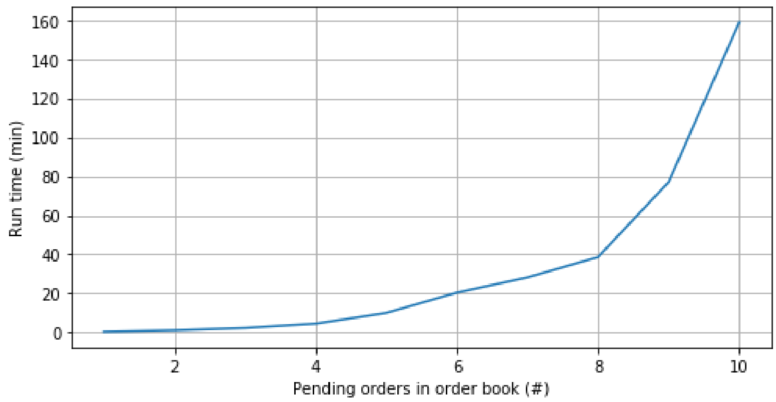

Figure 4.2: MDP model run time

in general the practical use of the MDP model is lost for large sets of pending orders. Therefore, the next chapter focuses on designing an alternative solution method that enables finding a solution for larger sets of pending orders in a feasible time span while ensuring that the optimal solution approximates the expected total reward as yielded by the MDP model.

Chapter 5

Heuristic solution method

As indicated in the previous chapter the exhaustive MDP model becomes insolvable in terms of time for larger sets of pending orders. Thus, the main goal of an alternative solution method is to find a (near) optimal solution for order book instances where the MDP model is unable to. An often used strategy for an alternative solution method is a heuristic approach. In general, a heuristic does not yield an optimal solution for all problem instances but does reduce the required time to solve the problem significantly. This chapter focuses on defining and assessing a heuristic solution method with the aim of approximating the global optimal solution yielded by the MDP model. First, the heuristic is defined in Section 5.1 after which the performance of the heuristic is assessed in Section 5.2.

5.1 Solution approach

Like the MDP model the goal of the heuristic is to generate an optimal expansion strategy. The runtime of the MDP model is dependent on the property that all feasible expansions for all periods are considered. By iterating through all expansion policies, the MDP model finds the single optimal policy that maximizes the expected gross profit. Hence, as opposed to the exhaustive approach of the MDP model that yields a global optimal policy, the run time of the heuristic can be significantly reduced by generating a sequence of local optimal expansion decisions. A local optimal expansion decision should be made based on the information that is 'locally' available. Thus, a local optimal decision cannot be based on the global expected gross profit. Therefore, the heuristic makes local decisions based on the expected *added* gross profit of the expansion of a single equipment type. These expansion decisions are taken in isolation of any other production bottlenecks in the production line which may result in a sub optimal solution but reduces the required computation time significantly.

When considering the expansion of an arbitrary equipment type, first the added gross margin is calculated based on the additional production that is enabled due to the expansion of the equipment type. Figure 5.1 illustrates this principle. The gross margin resulting from the additional demand that can be fulfilled is then compared to the costs of ownership of the respective equipment type, which in this project is limited to the depreciation costs and the operational costs. If the total gross margin is higher than the cost of ownership over a four quarter period, the gross profit is positive and the heuristic assumes the expansion as a local optimal decision. This type of solution approach can be defined as a greedy heuristic. Here, Greedy refers to the models characteristic to make local optimal decisions without considering the impact on the global optimal solution.

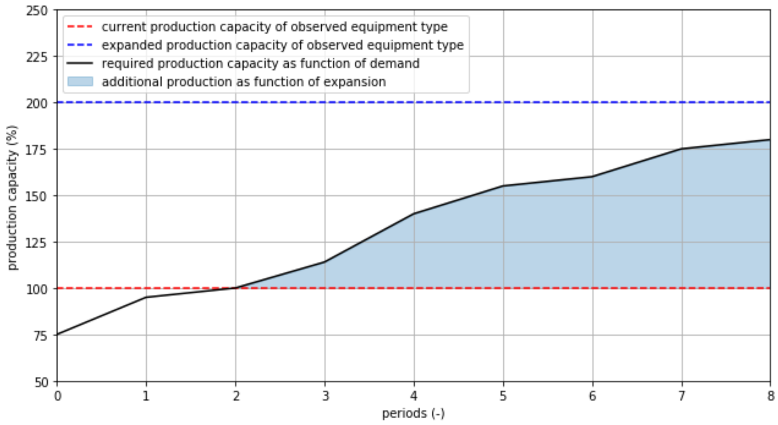

Figure 5.1: Added production capacity as function of a capacity expansion

5.1.1 Greedy heuristic

The greedy heuristic briefly described in the previous section is elaborated in more detail in this section. Important to note here is that the company specifically requested the heuristic to be designed without the use of a commercial optimization solver as is used in the MDP model. Hence, the method to calculate the gross profit deviates from the MDP model. The structure and functionalities of the heuristic are stepwise introduced below.

Step 1: initialization

Based on the pending orders in the order book, the set of demand scenarios D_t is generated for all periods $t \in M$. Depending on the number of pending orders n with a delivery date within period interval $[0, t]$, the number of scenarios in set D_t is 2^n. For each demand scenario $d \in D_t$ the required production capacity $cap^r_{d,j}$ for all equipment types is calculated based on the demand d_i for all package types $i \in K$ of the respective scenario with

$$cap^r_{d,j} = \sum_{i=1}^{I} d_i \cdot t^p_{i,j} \qquad \forall j \in L,\ \forall d \in D_t,\ \forall t \in M \tag{5.1}$$

Secondly, the heuristic generates the total gross margin under the assumption that all the demand of the respective demand scenario can be fulfilled. Here, the total gross margin is decomposed in three components due to the three production step sequences that can be distinguished for all package types which are illustrated in Figure 5.2. The decomposition is based on the production process as introduced in section 3.1. The three components of the total gross margin are calculated based on subsets of the total set of package types with

1. SFA packages as $K^{sfa} \subset K$: packages that require the single fiber aligner production step.
2. FAA packages as $K^{faa} \subset K$: packages that require the fiber array aligner production step.
3. NFA packages as $K^{nfa} \subset K$: packages that do not require fiber aligner production steps.

For the expansion decisions, the decomposition of the gross margin is important as for example a new machine of the fiber aligning type only impacts the production capacity for the SFA packages. Therefore, the heuristic calculates the gross margin for each of the three components seperately with respectively equations (5.2), (5.3), and (5.4).

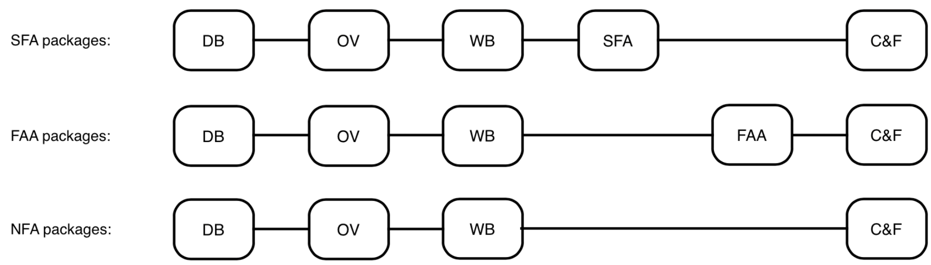

Figure 5.2: Distinguishable package production sequences

$$g_d^{sfa} = \sum_{i \in K_{sfa}} d_i \cdot g_i^{mar} \tag{5.2}$$

$$g_d^{faa} = \sum_{i \in K_{faa}} d_i \cdot g_i^{mar} \tag{5.3}$$

$$g_d^{nfa} = \sum_{i \in K_{nfa}} d_i \cdot g_i^{mar} \tag{5.4}$$

At this point the required properties of scenario d are defined. The sequence of initiation steps and the interdependencies of the variables are graphically displayed in Figure 5.3. Once the required production capacities and gross margin components are calculated for all scenarios $d \in D_t$ for all $t \in M$, the heuristic is fully initiated. Now the model consecutively iterates through all equipment types $j \in L$ for all periods $t \in M$ and executes the next steps in the model for every iteration.

Step 2: check feasibility of expansion decision
For each equipment type j, the model looks at the equipment delivery period t_d which is $t + l_j + 1$ periods ahead. If the equipment is delivered outside the modelling horizon $[1, T]$ no additional profit can be generated. Important to note here is that this modelling assumption does not definitively means no additional equipment is required for the respective time period. However, if $t_d > T$ no additional equipment is ordered and the model continues to the next iteration and repeats step 2. If the delivery period of the observed equipment type is within the modelling horizon, the model continues to step 3.

Step 3: calculate expected added gross profit for period t_d
In this step the expected added gross profit generated in the delivery period t_d is calculated for the expansion decision under consideration. The model iterates through all demand scenarios $d \in D_{t_d}$ of the equipment delivery period and calculates the percentage of demand that can be fulfilled with (1) the current production capacity and (2) the expanded production capacity based on the required production capacity calculated in the initiation phase of the heuristic in equation (5.1). The percentage of demand that can be fulfilled with respectively the current production capacity and the expanded production capacity is multiplied with the gross margin components that can be produced with equipment type j (see figure 5.2) and summed to form the total gross margin that can be earned.

The difference in total gross margin between the current and expanded equipment portfolios is the total *added* gross margin $g_{d,j}^{add}$ that is obtained for the observed scenario d if equipment type j is expanded. After the added gross margin is determined for all scenarios $d \in D_{t_x}$, the

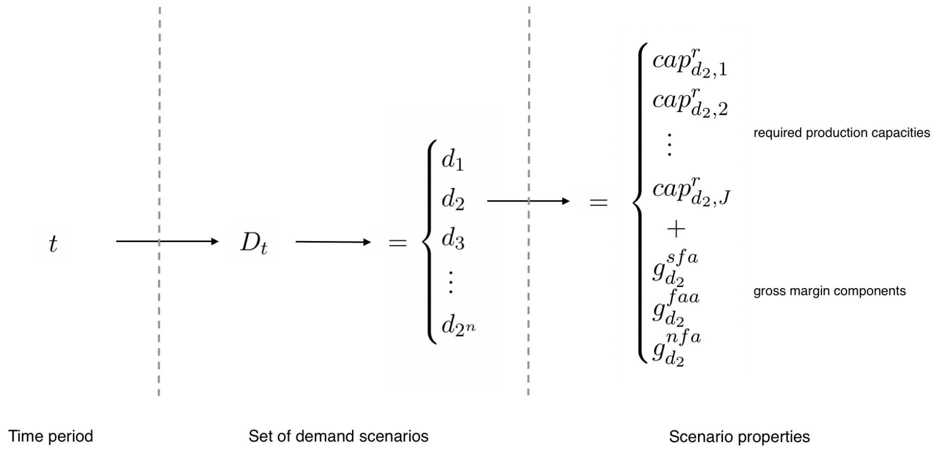

Figure 5.3: Heuristic initiation schematic

total *expected* added gross margin of the expansion is calculated as the weighted average of all possible scenarios based on the scenario occurrence probability $P(d)$. Hence, the expected added gross profit $Z_{t_d,j}$ for the expansion decision of equipment type j is calculated by subtracting the depreciation costs and operational costs from the total expected added gross margin with:

$$Z_{t_d,j} = \sum_{d \in D_{t_d}} P(d) \cdot g_{d,j}^{add} - (c_j^{dep} + c_j^{op}) \tag{5.5}$$

If the expected added gross profit is negative, no additional equipment is ordered and the model continues to the next iteration and repeats step 2. If the expected added gross profit for period t_d is positive, the model continues to step 4 to check the total added gross profit of the expansion decision for four consecutive periods.

Step 4: calculate the total expected added gross profit for 4 consecutive periods
As described in Section 5.1 an expansion decision is only considered if the total expected gross profit over a four quarter period is positive. Therefore, the expected added gross profit for the expansion decision of equipment type j is calculated for all periods within interval $[t_d, t_d + 3]$, provided the periods are within the modelling horizon $[1, T]$. Now the total expected added gross profit Z_j that is generated within period interval $[t_d, t_d + 3]$ is calculated with

$$Z_j = \sum_{t=t_d}^{t_d+3} Z_{t,j} \tag{5.6}$$

If the total expected added gross profit for four consecutive periods is positive, the decision to expand the production capacity of equipment type j is taken and the equipment portfolio in period t_d updated with an additional machine of equipment type j. If the total expected added gross profit is negative, no additional equipment is ordered. The model continues to the next equipment iteration and repeats step 2.

5.1.2 Heuristic run time

The main goal of the greedy heuristic defined in this chapter is to reduce the time required to find an (near) optimal expansion strategy. To achieve this goal, the heuristic is constrained to a limited amount of information and the expansion decisions for equipment types are taken

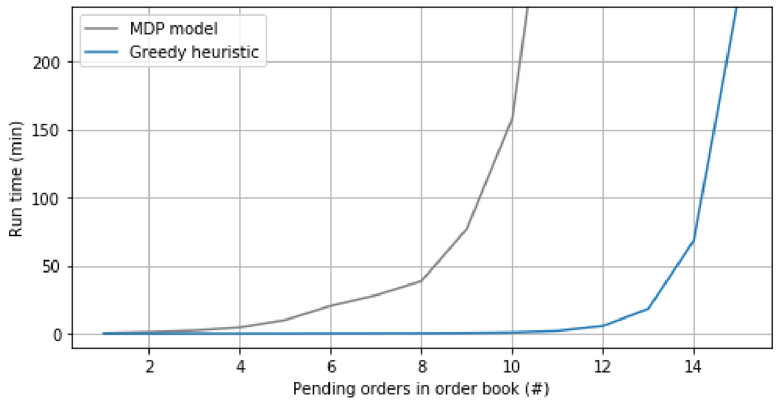

Figure 5.4: Heuristic run time

independently of each other. As indicated in Figure 5.4 this approach reduces the runtime of the heuristic significantly compared to the runtime of the MDP model. As the number of scenarios grows exponentially with the number of pending orders in the order book, the total number of additional pending orders that can be run within a reasonable time is increased by 5. Compared to the MDP model that is able to solve a problem instance with 9 pending orders in just over an hour, the heuristic is able to solve a comparable problem instance with 14 pending orders in roughly the same amount of time which is an increase of 55%. As indicated in the introduction of this chapter, the value of the heuristic is in the trade off between solution accuracy and required run time. Therefore, the next section focuses on the performance of the heuristic. Here, the solutions of several problem instances are compared with the optimal solution yielded with the MDP model to determine the solution accuracy.

5.2 Performance analysis

The value of the heuristic approach lies in the accuracy of the solution that is found. To evaluate the accuracy, the expected gross profit as a result of the expansion strategy generated by the heuristic is compared to the expected gross profit of the MDP model for a set of small demand scenarios. The assumption is that if the heuristic approximates the optimal solution of the MDP model for the small scenario instances, the heuristic will also yield (near) optimal solution for demand senarios that are too large for the MDP model to be solved within a reasonable time frame.

For both models the expected gross profit is calculated based on a single optimal expansion strategy that is the average best strategy for all demand scenarios. Finding a single best solution is the exact purpose, however, an average does not discloses any information regarding worst case situations. To obtain a complete overview of the performance of the heuristic, the model is run for every demand scenario individually. That is, based on the number of pending orders N in the order book, the set of 2^N demand scenarios D is generated. For every scenario $d \in D$ both the MDP and the heuristic calculate an optimal expansion strategy. The gross profit g_d^p resulting from the generated strategy is then compared for both models and the expected gross profit G is calculated as the weighted average of the gross profit of all scenarios $d \in D$ based on the scenario occurrence probabilities $P(d)$ with

$$G = \sum_{d \in D} P(d) \cdot g_d^p \tag{5.7}$$

Here, the scenario occurrence probability $P(d)$ is calculated based on the state transition probability of the MDP model as defined in Section 4.3.3. Every scenario d is defined as the sequential order status of N pending orders with $d = (k_1, k_2, ..., k_N)$. Based on the selling probability $P_s(k_n)$ and the orders status that is defined as $k_n = \{0, 1\}$ for respectively cancelled and sold, the occurrence probability is calculated with

$$P(d) = \prod_{n=1}^{N} P_s(k_n)^{k_n} \cdot (1 - P_s(k_n))^{1-k_n} \tag{5.8}$$

5.2.1 Required heuristic extension

Comparing the results of the MDP model with the heuristic requires a extensions to the latter. Due to design choices the expansion decisions of the heuristic are based on the expected added gross profit. Consequently, the heuristic does not generate the expected gross profit for the optimal expansion strategy by default. To determine the expected gross profit resulting from the expansion strategy yielded by the heuristic, the reward function designed for the MDP model (see Section 4.3.4) is utilized. Every scenario $d \in D$ is a deterministic demand scenario and based on the optimal expansion strategy that is yielded for the respective scenario, a deterministic equipment portfolio can be generated for all periods $t \in M$. Thus, for every period t the gross profit can be calculated with the MDP reward function where the sum of rewards of all periods equals the gross profit g_d^p of scenario d.

5.2.2 Order book compositions

To determine the value of the heuristic as a reliable substitute for the MDP model, the accuracy is evaluated based on multiple sets demand scenarios that aim to illustrate various pending order compositions in the order book. Each composition highlights different order book properties to analyse whether the solution accuracy of the heuristic significantly deviates for specific problem instances. Therefore, the analysis focuses on the four properties listed below. For each property, two demand scenarios are defined. The numerical demand for each of the eight order book compositions is provided in Appendix B.

1. *Uncertainty*
   The uncertainty of receiving orders depends on the selling probability of the respective orders. If the overall selling probability increases, the certainty of expected future demand increases and thus the expected gross profit increases. To analyse the impact of uncertainty, two scenarios are analysed that reflect respectively high and low uncertainty.

2. *Variation*
   The required production capacity depends highly on the product mix. The differences between package types in process times and required process steps might have an significant impact on the required equipment portfolio. To illustrate these differences, one scenario with a low package type mix and one scenario with a high package type mix is analysed.

3. *Quantity*
   The order size determines both the required production capacity and the earned gross margin if the order is sold. Increased order size thus increases the gap between the possible earnings and the possible losses which leads to a larger risk when defining capacity expansion strategies. To demonstrate the impact of the individual order quantities on the performance of the heuristic approach, two demand scenarios are analysed with respectively low quantity orders and high quantity orders.

4. *Order distribution*
   The timing of equipment procurement decisions depend on the distribution of the delivery dates of pending orders. If all pending orders have a first delivery date in the same period, the expected required production capacity suddenly increases significantly. However, if the first delivery dates of the individual pending orders are more evenly distributed over time, the expected required production capacity increases more subtle. For both situations a demand scenario is created that highlights both properties.

5.2.3 Solution accuracy

Based on the order book compositions that are defined in the previous section the accuracy of the heuristic is evaluated. Each composition spans a modelling horizon of 9 quarters such that the heuristic is enabled to calculate the total expected added gross profit for four consecutive quarters for all equipment types. To ensure that the MDP model yields a solution in a reasonable time frame, the order book compositions under consideration are limited to 8 pending orders. Thus, the set of demand scenarios D for each of the order book compositions consists of $2^8 = 256$ potential demand scenarios. The simulation results of all order book compositions are summarized in table 5.1. Here, the expected gross profit G of the heuristic is compared with the results yielded with the MDP model. For confidentiality purposes, only the performance in percentages relative to the results of the MDP model are specified. Overall, the accuracy of the heuristic is very high. The maximal deviation of the expected gross profit of the heuristic compared to the MDP model is -0,0055% for the high order quantity order book composition. Moreover, for 3 of the 8 compositions, the expected gross profit G as a result of the expansion strategy is equal to the solution of the MDP model and thus can be defined as a global optimum.

Table 5.1: Relative heuristic performance based on the expected gross profit G

Order book composition		Expected gross profit G		
Property	Setup	MDP	Heuristic	ΔG
Distribution	gradual	100%	99,9998%	-0,0002%
	sudden	100%	100%	0%
Uncertainty	high	100%	100%	0%
	low	100%	99,9997%	-0,0003%
Variation	high	100%	99,9983%	-0,0017%
	low	100%	99,9999%	-0,0001%
Quantity	high	100%	99,9945%	-0,0055%
	low	100%	100%	0%

However, as defined in equation (5.7) the expected gross profit G is the weighted average of the gross profit of all scenarios $d \in D$. The accuracy of the heuristic compared to the MDP model for specific demand scenarios might be significantly higher which does not show in Table 5.1. Therefore, for each order book composition the analysis results for the demand scenarios where the gross profit of the heuristic deviates from the MDP model are summarized in Table 5.2.

For all 8 order book compositions, the number of deviating scenarios varies from 0 for the low quantity order book compositions to 32 for the high quantity order book composition. While 32 out of 256 scenarios might seem high, the absolute probability that any of the 32 deviating scenarios is realized for the high quantity order book composition is 0.031%. This indicates that the heuristic mostly yields sub optimal expansion strategies for exceptional demand scenarios with a very low occurrence probability. For the sub optimal expansion strategies, the highest relative deviation between the optimal solution of the heuristic and the MDP model for a single scenario is found in the high variation order book composition. For this scenario the relative deviation is 0.19%.

Table 5.2: Heuristic performance for deviating scenarios

Order book composition		Deviating scenarios		Properties of deviating scenarios	
Property	Setup	#	%*	Max ΔG	Average ΔG
Distribution	gradual	10	0,001%	-0,1%	-0,07%
	sudden	4	0,001%	0%	0%
Uncertainty	high	12	0%	-0,03%	-0,02%
	low	12	0,008%	-0,03%	-0,02%
Variation	high	16	0,023%	-0,19%	-0,06%
	low	3	0,001%	-0,02%	-0,02%
Quantity	high	32	0,031%	-0,1%	-0,07%
	low	0	0%	0%	0%

*aggregated occurrence probability of all deviating scenarios

As indicated by the simulation results in both table 5.1 and Table 5.2 the gross profit generated with the expansion strategies from the heuristic is for the most part equal to the optimal gross profit generated by the MDP model. To illustrate the nearly equal distribution of gross profit for all scenarios $d \in D$, the order quantity high composition simulation results are plotted for both the heuristic and the MDP in Figure 5.5. Here, the x-axis specifying the gross profit is omitted for confidentiality purposes. As indicated in the histogram, the gross profit distribution for both models almost perfectly overlaps. The full simulation results of the order quantity high composition are provided in appendix C. Here, the results show that the heuristic either performs equally well as the MDP model by generating the same gross profit or performs slightly worse than the MDP model. More important, as expected the results show that the heuristic never performs better than the global optimal solution yielded by the MDP.

As discussed in the introduction of this chapter, the value of the heuristic lies in the trade-off between solution accuracy and solve time. As for solution accuracy, the simulation results indicate that the heuristic performs 0.19% worse than the MDP model in the worst case scenario. Moreover, the time required to solve the model is reduced such that the number of pending orders in the order book can be increased by 55%. Consequently, the value of the heuristic has been proved as a reliable alternative solution method for the exhaustive MDP model for the capacity expansion problem at hand.

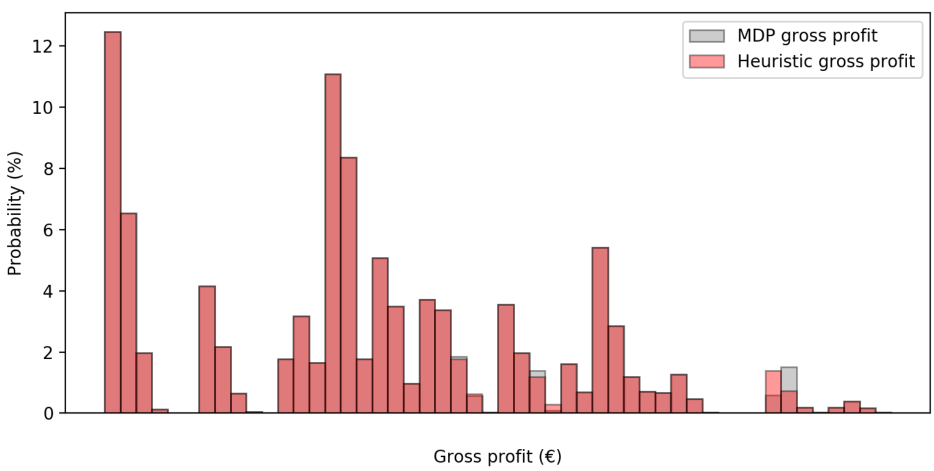

Figure 5.5: Gross profit distribution for quantity high order book composition

Chapter 6

Analysis

(this chapter is omitted due to confidentiality purposes since the case studies that are elaborated in this chapter fully consist of sensitive information. This applies to both the long term scenario analysis with the ILP model and the strategic capacity planning obtained by the heuristic based on the actual order book.)

Chapter 7

Conclusion

This chapter concludes the research performed in this thesis in which two models have been developed to assist the company in making strategic production capacity expansion decisions. Due to confidentiality purposes, only the results of the performance analysis of the heuristic compared to the exhaustive MDP model are summarized and concluded upon. Afterwards, the limitations and recommendations are defined and discussed.

7.1 Main results

The strategic capacity planning objective focuses on the procurement of production equipment. The production equipment is highly specialized machinery that is made to order and has an order lead time of up to one year. Due to the equipment order lead time the company is exposed to investment risks as production equipment has to be procured based on uncertain demand. Demand is modelled as individual orders which represent the stochastic component of future demand. To support management in making strategic production capacity expansion decisions a Markov decision process (MDP) model is designed that identifies a global optimal expansion strategy by maximizing the expected gross profit. Due to the exhaustive nature, the MDP model is capable of processing a limited order book with $n = 9$ pending orders in just over an hour. To enable the company to consider an order book with a larger set of pending orders, a heuristic solution method is designed.

The heuristic allows the order book to be increased up to $n = 14$ pending orders with an approximately equal running time. This is an absolute increase of 55% compared to the MDP model. The number of demand scenarios that are generated based on the order book grows exponentially with the number of pending orders with 2^n. Thus, for the MDP model the number of processable scenarios is $2^9 = 512$ while the number of processable demand scenarios in the heuristic is $2^{14} = 16.384$. Thus, the processing speed of the heuristic is a factor 32 faster than the MDP model.

The solution accuracy of the heuristic is measured with an analysis that is based on 8 order book instances where the solution of the heuristic is compared with the global optimal solution of the MDP model. Each order book instance consists of 8 pending orders which results in 256 possible demand scenarios. For the worst case the heuristic yields a solution with an average deviation of -0.0055% of the global optimal solution found by the MDP model. Focusing on the individual demand scenarios in which the heuristic yields a sub optimal solution, the maximal deviation is -0.1% for the respective scenario. However, considering the heuristic has been designed without the use of a commercial optimization solver, the lost gross profit due to potentially sub optimal solutions is (partially) compensated by the absence of costly software licenses.

7.2 Limitations and recommendations

This section focuses on the main limitations and assumptions made in the project.

Process times are based on estimated values
The input parameters of the heuristic regarding the package process times are based on specifications provided by production equipment manufacturers. Secondly, the heuristic considers the packages to be processed individually and irrespective of the production sequence. In reality, the packages will be processed in batches and will processed in the predetermined order of production steps. This might lead to queues in the production process and can lead to under utilization of equipment. Therefore, it is important that the behaviour of the production line is thoroughly analysed and the optimal utilization percentage of the individual production equipment types is determined once functional. These metrics should then be used as input parameters for the heuristic to update the available equipment process time.

The heuristic has limited equipment expansion options
As described in the analysis of the case study, the heuristic is limited to considering the expansion of one additional machine for every equipment type. For situations where demand increases significantly such that two or more additional machines are required, the heuristic is prone to generating sub optimal expansion strategies. In order to find an optimal expansion strategy for these order book instances, the heuristic should be extended such that multiple machines of every equipment type can be ordered. To prove the solution accuracy of the extended heuristic, the performance must be verified with the MDP model. Therefore, the action space of the MDP model must also be extended to allow multiple machines of every equipment type to be ordered at once. Unfortunately, the actions space of the MDP model grows exponentially with the number of actions. Currently, there are two possible actions for every equipment type; either procure no machine or procure one machine. This leads to an action space containing $2^6 = 64$ actions. If the possible actions are extended such that for all equipment types either no machine is procured, one machine is procured, or two machines are procured the action space increases to $3^6 = 729$ actions. Subsequently, the state space of the MDP would explode such that the model becomes infeasible even for small problem instances. A solution to this problem is to run the heuristic multiple times and for every iteration increase the initial equipment portfolio with increments of one machine for every equipment type. This method will indicate whether procuring more than one machine of a single equipment type will still yield expected added gross profit.

The heuristic considers a limited time horizon
To keep both the MDP model and the heuristic tractable the modelling horizon for the short term decision making is set to 9 consecutive quarters. For this horizon, the model calculates the optimal expansion strategy by weighing the operational and depreciation costs against the expected gross margin. However, the life cycle of the production equipment surpassed the considered modelling horizon significantly. Once production equipment is ordered the order cannot be cancelled and the depreciation costs must be paid for the complete installment period that covers the full life cycle of the equipment. Thus, only a small part of the equipment life cycle and subsequent costs are considered in the heuristic. This is true for any manufacturer that is ramping up production capacity but this difficult to measure investment risk should be taken into consideration.

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Appendix A

MDP validation

(this appendix is omitted due to confidentiality purposes)

Appendix B

Order book compositions

(this appendix is omitted due to confidentiality purposes)

Appendix C

Performance analysis example

(this appendix is omitted due to confidentiality purposes)

Appendix D

Analysis input parameters

(this appendix is omitted due to confidentiality purposes)

Appendix E

ILP model demand scenarios

(this appendix is omitted due to confidentiality purposes)

Appendix F

Case study order book

(this appendix is omitted due to confidentiality purposes)

Appendix G

Heuristic report output

(this appendix is omitted due to confidentiality purposes)