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Tactical capacity allocation in hospitals to optimize production within the budget

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“Learning never exhausts the mind”

-Leonardo da Vinci (1452-1519)

Management summary

This research proposes a tactical planning tool which can help the Radboud UMC by creating a blueprint for a tactical-level operating room planning and control model, so that operating room (OR) and ward capacities can be specifically distributed over the next 2-3 months for the elective care, over the specialties ENT, URO, and GYN, taking into account the available capacities and budget goals. The tactical level is mentioned as one that needs to be created in healthcare as it often leads to standards that determine which and how much capacity and other resources are periodically allocated to the various tasks, departments, specialties, and patient groups. However, while tactical level planning is significant, not much attention has been paid to it to date.

The problem for the specialties is that the strategic plan for capacity distribution and the actual realisation of used capacity tend to significantly differ from each other. The reasons for this are as follows. Each year, all specialties of Radboud UMC must indicate how many care products per department(subsequently referred to as a “pillar” in the rest of the report) they expect to need Based on this information, the Radboud UMC then negotiates a budget ceiling with each health insurer. Then, based on all budget ceilings, capacities are distributed among the departments in form of a master plan. The problem is that this budget is created and distributed well before a healthcare year begins. As a result, the master plan and the realisation differ, and the available OR- and bed capacity is not fully used. This problem, however, can be prevented by using tactical planning, which is still under development at the Radboud UMC.

The main goal of this research is to create a tactical-level operating room planning and control approach that can create a blueprint that distributes OR and ward capacities over the next 2-3 months over the relevant specialties, taking into account the available capacities and budget goals.

The proposed approach for implementing the blueprint consists of eight steps. First, a forecast is made to determine the expected patient demand based on the waiting list and historical data. For the second step, a connection is made between patients on the waiting list and their presumed care product, for the financial results. Third, costs and revenue per predicted care product per patient are predicted. In the fourth step, the available hours per department per pillar for the ORs for the next 12 weeks are checked and adjusted according to seasonality. As a fifth step, a constructive heuristic is created that will form a planning schedule for the 95% capacity for each week for the expected patient demand. The heuristic should take into account patient characteristics, such as urgency, duration of treatment, length of waiting list, and cost and revenue. For the sixth step, it is checked whether patients are late when only 95% capacity is used. If patients are late, they are first scheduled on the basis of urgency under the 5% capacity reduction. The 5% capacity is then redistributed to the departments based on the expected patient demand. If there are no late patients or if there is still capacity left after the late patients have been scheduled, the seventh step is applied. In the seventh step, a local search heuristic is applied over the 5% capacity. The aim is first to schedule as many patients as possible and then to meet the revenue goals. The eighth and final step is to add up the number of capacity required per week in each department, to support creation and scheduling of patient blocks.

As a result of the 8 step model, a blueprint will be displayed by the model with a table that indicates which (expected) patients should be scheduled per week per department and per pillar. The original idea in this study is to reduce 5% of capacity per pillar per department. A key part of this research is therefore to establish whether this solution delivers the best result. Therefore, the proposed model has also been tested with a 0% and 10% reduction in capacity.

Testing the model clearly shows the benefit that redistribution of a small amount of capacity can have. With a 5% reduction, 56% of the patients, who would otherwise be late, could still be treated on time, while with the 10% reduction, all but two patients could be treated on time. Table 0-1 shows how many patients can be helped in total per reduction level. The increase in patients that can be helped under higher reduction is explained by the fact that capacity is now allocated to the pillars that need it at the moment. When 0% reduction takes place, fewer patients can be helped because the pillars where patients need to be helped lack sufficient capacity. Despite a 10% reduction having better results, the initial 5% reduction is still maintained. This is because 10% reduction is currently not realistic to implement: if so much capacity were to be allocated to certain pillars, it would not be used, as there simply won't be enough doctors available.

Table 0-1. The number of total patients that can be treated per capacity reduction level

Reduction	Number of patients planned over 12 weeks	Increase over 0%	Increase over 5%
0%	1076		
5%	1110	3%	
10%	1131	5%	2%

The financial data used for this study constitutes business-sensitive information that cannot be published. Therefore, the only information that can be provided regarding this matter in this report is that the financial results of the proposed model correspond to reality. Thus, the most profitable pillars in the model are also the most profitable pillars in the real life. The capacity is also distributed among the pillars when testing to optimise with a focus on the budget targets, and the more profitable pillars are, in fact, allocated the most capacity. By using the tactical plan model to make adjustments to the capacity distribution, the uncertainties intrinsic to strategic planning become less severe because they are anticipated during the healthcare year.

This research was undertaken to investigate the possibility and effects of creating a blueprint for a tactical-level operating room planning and control model for URO, GYN, and ENT departments, so that OR and bed capacities can be specifically distributed over the next 2-3 months, together with the budget goals. Therefore, this research makes an important theoretical contribution to existing research by creating a model that realises such a blueprint. The analysis shows that the model can clearly reallocate capacity between hospital departments and the number of patients; moreover, the financial results planned per pillar per week are realistic. Furthermore, the model also makes it clear what the effect can be of a capacity reduction of 5 or 10%, in terms of the total number of patients that can be helped with the same available capacity. This is partly due to the fact that data from the Covid period was used, which may give a distorted picture. Furthermore, it needs to be further investigated whether the blueprint can be made dynamic, so that it can respond more effectively to another patient mix than the forecast predicted. This study results in a static blueprint schedule which should be regularly reviewed (which can be done every three weeks for every TPO). However, dynamic blueprint schedules would make this unnecessary. Therefore, further research could investigate how capacity can dynamically be adapted when the patient mix changes. Our contribution to science is that it integrates capacity management and financial goals of a hospital without making patient groups. Furthermore, the theory (model) is applicable to other hospitals and/or departments. It is important that the right data is available or that a start is made to record the right data. Without data, the theory cannot be used,

Based on this study, the main recommendation to the Radboud UMC is to further expand the database of completed patients per urgency level, per pillar, per week, to increase the reliability of the forecast. It is also recommended to create a database of predicted care products per operation.

This will reduce the runtime of the model from 4 hours to 1 hour (as discussed in the second step of the model). Finally, it is recommended to implement the proposed blueprint model so that as many patients as possible can be helped with total available capacities of the three departments in the Radboud UMC.

Preface

Herby, I present my Master Thesis ‘Tactical capacity allocation in hospitals to optimize production within the budget’, as a final step toward finishing my master degree in Industrial Engineering and Management. Considering my study background, a bachelor’s degree in both Mechanical Engineering and Industrial Engineering & Management, I was excited to get a new challenge at RadboudUMC to put my learned skills into practice in a completely new environment and industry. Therefore, I would like to thank especially Bart van Acker for giving me this opportunity and guidance throughout my research period at the RadboudUMC. I would also like to thank the rest of my colleagues for the enjoyable and fun time I had during my thesis period.

Furthermore, I want to thank my supervisors from the University of Twente. Erwin Hans, I first want to thank you for confirming my enthusiasm to apply my master in healthcare and to help me with finding this thesis project. Next, thank you for all the enjoyable feedback moments and willingness to help me and making me feel more confident to trust my abilities and choices. I also thank Daniela Guericke for her expertise in my topic and useful feedback for both content and writing of my thesis.

Lastly, I would like to thank my family and friends who supported me during this research. Thanks to my dad for the discussions about the research and reading my thesis. I would also like to thank some fellow students, who I can also call my friends. Juul, Marije, Matthew, Ivo, Stan, Michiel, Rob, Wouter and Jesse, thanks for all the support during the pre-master and master. Although Covid emerged and covered the largest part of the master study we stayed in contact. You guys made my time at the university a lot of fun and we always helped one another when needed.

I hope you will enjoy reading my master thesis.

Robin Rust

October 2022, Loil

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Abbreviations/ Definitions	Meaning
Care product	A care product consists of all the steps (procedures) a patient undergoes during his treatment. This means that a care product can, for instance, consist of a consultation, treatment , nursing days, diagnostics, and surgery.
Inpatient	A patient who is admitted for more than one day
Outpatient	A patient who is admitted for less than one day
OR	Operation Room
ENT	Ear Nose Throat department
GYN	Gynaecology department
URO	Urology department
Pillar	A department within a specialty

1. Introduction

This report examines the problem of using tactical planning within Radboud UMC for the elective surgical patient flows to achieve the annual financial goal regarding the efficiency and quality of care. This chapter introduces the research plan. Section 1.1 provides the context and the company description, including the research motivation. Section 1.2 describes the problem context and formulates the core problem, including the scope of the research. Finally, section 1.3 provides a description of how the problem will be addressed and formulates the research question and sub-questions.

1.1 Context description

In this chapter, a general description of Radboud UMC and a brief overview of healthcare in the Netherlands is provided. Finally, the Radboud UMC and the departments selected for this research are briefly described.

1.1.1 General background

In the Netherlands, healthcare is one of the largest sectors, employing as many as 1.2 million people. The UMCs and other hospitals account for 20% of employment [1]. Healthcare costs in the Netherlands have risen sharply since the beginning of this century, from €34.8 billion at the start of the century to €90.9 billion in 2019. Due to this increase, there are also concerns about the healthcare quality. Over the years, the importance of employees has led to increased attention to personnel policy. However, until recently, not much attention has been paid to planning the deployment of employees at a tactical level: until now, planning is done only at the operational level. This is a problem, since inadequate staffing can have major consequences both for the cost and quality of care. This lack of tactical planning is one of the reasons why more and more hospitals are looking into capacity management and how it can be best applied to them [1]. However, capacity management looks at all capacity, not just the employees.

Within healthcare in general, there is a strong growing trend in capacity management, which has increased significantly. This coincides with a growing interest in the healthcare sector in process planning and control. While this interest was already in place for the financial aspects, it is now moving to the capacities within a hospital as well. This has increased significantly over the past decade. This is in part due to the increasing costs within the healthcare sector and the shortage of staff.

While capacity planning and control has not received much attention as a subject within the healthcare sector, it has a rich history within the manufacturing environment/industry. Compared to the manufacturing environment, healthcare is still far behind in terms of planning and control management.

Capacity planning and control occur at strategic, tactical, offline operational and online operational management levels [2] [3]. Of these levels, the tactical level is singled out as one most urgently needed to be created in healthcare. However, not much attention has been paid to this issue to date [2]. The significance of tactical planning is that it often leads to standards that determine which and how much capacity and other resources are allocated to the various tasks, departments, specialties, and patient groups [1]. This should also take into account the budgets for each department and specialism. The input for planning on a tactical level partly comes from strategic planning and from monitoring what is actually executed and spent within the department.

In the absence of strategic and tactical process planning, plan problems were only solved operationally (on operational level and ad hoc) which was sometimes impossible. This reduced the need for strategic and tactical planning.

1.1.2 Hospital description of the Radboud UMC

The Radboud UMC is an academic hospital in the Netherlands, located in Nijmegen. The Radboud hospital was founded in 1905 and became an academic hospital in 1956 [4]. The Radboud UMC is a renowned hospital, falling just outside the top 100 best hospitals in the world [5] [6]. It had 173,000 patients in 2020, of which 86,166 were new visits and 330,098 were control visits. Also, 29,364 operations were performed in 2020, and 22,273 patients were admitted to the hospital (clinic).

In total, the Radboud's revenue is € 1.216.968.000 in 2020. The financial result, however, is € 3.039.000 [7].

Furthermore, the Radboud has a total of 25 operating rooms, of which 5 are for outpatients and 20 for inpatients. In total, there are 52 departments.

1.1.3 PVI department

The Process Improvement and Implementation (PVI) advisory group has been a reliable and well-known part of the Radboud UMC for more than a decade. The department's role is twofold: on the one hand, it is an expert in the field of change in healthcare, providing support in the execution and implementation thereof. It also contributes to the creation of strategy and planning for implementation. In doing so, it supports the strategically chosen change themes drawn up by the Executive Board, as well as by the departmental management of the relevant departments within the Radboud UMC.

1.2 Problem description

Each year, all departments of Radboud UMC must indicate their need for each care product. Based on this information, the Radboud UMC then negotiates a budget ceiling with each health insurer. Based on all budget ceilings, capacities are then distributed over the departments, and a master plan is drawn for capacity planning. However, this budget is created and distributed well before an actual care year. This creates a strategic problem because when the care year is underway, it appears that the master plan and the realisation differ too much from each other. The allocation is made on the basis of the production plans that all departments submit to the planning and control department. Based on these production plans, the possible budget for each department for the coming care year is determined. Furthermore, this budget and required capacities of the resources are not yet properly distributed over the care year, concerning the seasonal pattern per department. In order for master planning to work properly, tactical planning is needed to reallocate capacities where necessary, thus ensuring that a Radboud-wide balance between quality and care and optimal utilisation of capacities and income is achieved. The output of the tactical planning can then be linked back to the strategic level.

A start has already been made on tactical planning within the Radboud UMC; however, the process is still in its beginning phase. Through tactical planning, strategic planning can be adjusted in time, but this is currently not happening. With the current way of working at the “tactical planning moments”, the capacities are not yet redistributed among the departments. Only the current state of affairs is discussed at TPO. As a result, a number of hospital departments lack sufficient capacity to assist all patients. On the other hand, other departments have too much capacity and do not use all that is allocated to them. Figure 1-1 presents the relevant problems along with their likely causes and connections to the core problem.

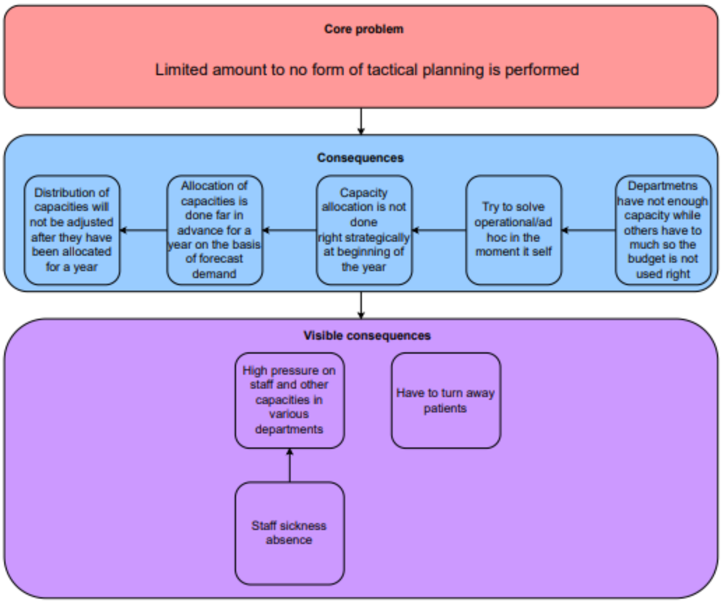


Figure 1-1.All problems and the cause of the problems to get to the core problem

When allocating the capacities, departmental production plans are taken into account. These plans are used to adjust the current OR schedule (among other things) and to determine how much bed capacity is needed by the department (or clinic). However, production plans for the next care year are normally requested by the Planning and Control Department of the Finance Department of the Radboud UMC in March or April of the current year. As a result, the actual practice may differ from the production plan and, therefore, from the OR schedule that's been drawn up. It is therefore important to monitor how much each department is doing and the corresponding costs. When a department significantly deviates from the drawn-up schedule, a new/adjusted schedule must be made. The new plan should then be done in the form of tactical planning, in order to specifically allocate capacities to a department within the margins for tactical planning.

1.2.1 Core problem

The core problem can be stated as follows:

> *Planning is done to a limited extent on a tactical level, which leads to a lack of flow in production because capacities are not properly allocated. This results in a lot of ad hoc planning and great pressure on the personnel.*

1.2.2 Research goal and scope

The aim of this study is to create a blueprint plan model that distributes and allocates the capacities among the hospital departments for the next 2-3 months, taking into account the available capacities and budget.

Accordingly, the main research goal is formulated as follows:

> *To create a blueprint for a tactical-level operating room planning and control model for Urology, Gynaecology, and ENT, so that OR and ward capacities can be specifically distributed over the next 2-3 months, over the specialties, taking into account the available capacities and budget goals.*

To get an accurate picture of the current situation, only the situation before Covid will be considered throughout the present study, as the latter constitutes a more normal or permanent situation.

1.3 Research design

The Managerial Problem-Solving Method has been proven to be a successful method for systematically solving various business problems [8]. The seven corresponding steps of this method are depicted in Figure 1-2.

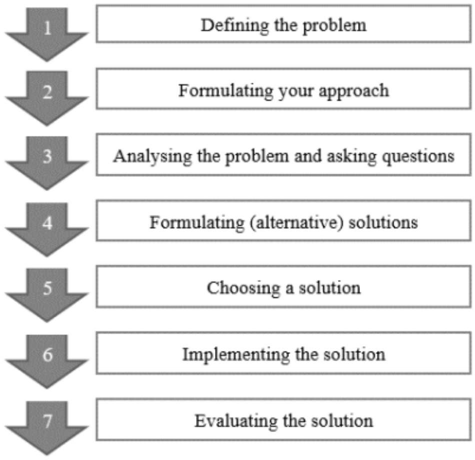


Figure 1-2. Steps of the managerial problem-solving method

The first two steps of the method have been implemented in sections 1.2 and 1.3. However, research questions must be formulated for the remaining steps, as the core problem can be solved only when all research questions have been answered.

1.3.1 Research questions

1. ***What is the current situation (before Covid) at Radboud UMC in terms of capacity and budget per department, and how does Radboud UMC perform compared to the production plans?***

The current situation can be examined with respect to five areas. The first area considers how a hospital process actually works and how capacity is determined for each department. It is also important to find out how care products tend to be structured. These points are important because they provide the basis for identifying good solution to the core problem later in the research. After an overall picture has been formed, the capabilities within the scope are examined. It is investigated how these are structured and how much capacity they receive and use. This applies to the OR but also to the clinic. It is also important to analyse the waiting list and the seasonality of the OR because these indicate the product demand and the pattern in which the OR is used. In addition, it is important to form a picture in the clinic of how many inpatients and outpatients there are and what the trend of this has been in recent years. When there are more outpatients, it means that more patients should be helped in the short time period, and the capacities should be allocated accordingly. Then, it must also be examined how the budget is established, how much turnover a care product currently generates, and how much a care product costs on average. Finally, the current method of planning must be examined.

This leads to the following sub-questions for the five areas:

I. General sub-questions
   I. What does a treatment pathway look like in general (what is the sequence of steps)?
   II. How should the capacity each department needs be determined?

   - III. How has the capacity turnover in the departments increased/decreased in recent years?
   - IV. How is a care product structured?
- II. OR sub-questions
   - I. How many OR hours does each department need?
   - II. How large are the waiting lists for the department's ORs?
   - III. Are the seasonal patterns of the ORs and the associated clinic similar, or do they differ significantly?
- III. Clinic sub-questions
   - I. How many beds does each clinic need and use?
   - II. How many patients are outpatient or inpatient?
   - III. How many admitted patients go on to the OR? What are the differences in day admission and longer-admission patients?
- IV. Budget sub-questions
   - I. How is the budget established?
   - II. How much turnover is generated per care product, on average?
   - III. How much does a care product cost, on average?
- V. Planning sub-questions
   - I. How is tactical planning currently viewed and possibly carried out?
   - II. How is the turnover of each department monitored?
   - III. How is planning currently carried out?
   - IV. How much deviation is there from the master planning?

This research question will be answered in Chapter 2.

2. ***What methods can be found in the literature to plan multiple capabilities at the tactical level for a hospital? (Chapter 3)***

3. ***What methods are required as an input to answer the core problem, and what steps are needed for the solution model? (Chapter 4)***

4. ***What is the result of the chosen solution model, and how much benefit does the hospital derive from this? (Chapter 5)***

5. ***How can the chosen solution model be implemented? (Chapter 6)***

2. Context analysis

*The best research you can do is talk to people.- **Terry Pratchett** (1948-2015)*

This chapter describes context analysis, which considers how the capacities related to the core problem outlined in the previous chapter have been built up in previous years. This includes looking at the bed capacity of the clinics (departments). In addition, the number of OR hours used per department is also analyzed. Furthermore, an overview is presented of how the budget is established and how the current year's roster is produced and monitored.

As indicated in chapter 1, context analysis will be carried out over the year preceding the start of Covid-19. This is done to get a maximally realistic picture of the normal situation within the Radboud UMC.

2.1. General description of hospital flow and the pillars of a hospital plan process

Before the current situation in the Radboud UMC can be analyzed, it is important to know how a hospital process generally works. Readers who are already familiar with this can move to section 0, where context analysis begins.

Figure 2-1 depicts an example of a possible care pathway within a hospital and what is needed to perform a particular step within that process, including those related to staff, facilities and inventory.

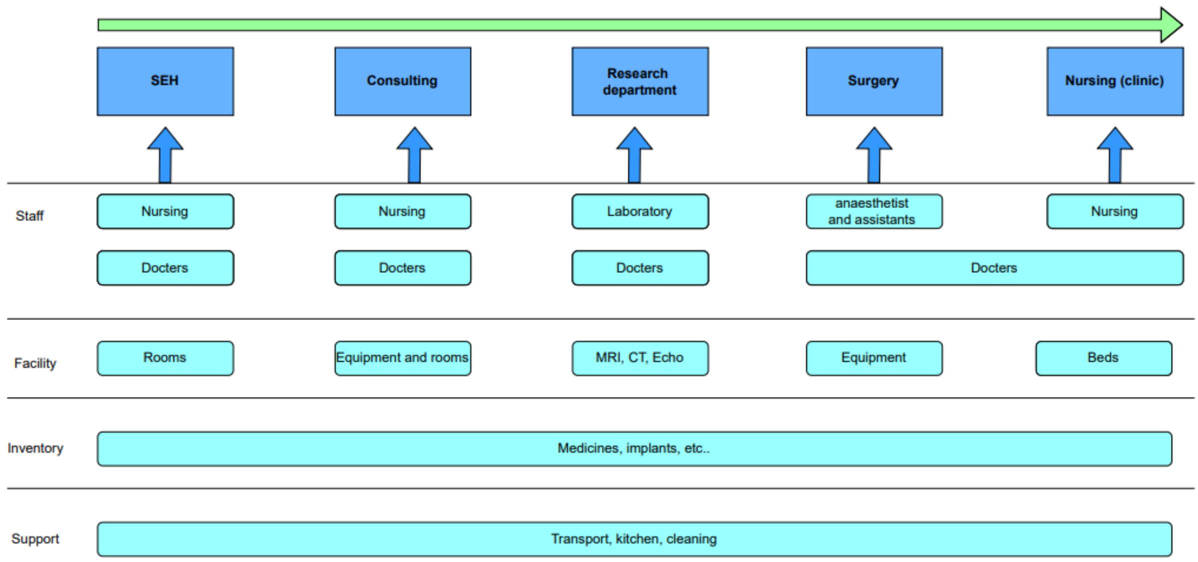


Figure 2-1. An example of a general care pathway and all the equipment and staff necessary per step

The steps for the first two components are largely fixed. As, a patient enters the emergency room or the consultation room if referred by a physician. In the subsequent steps, the process may be different for each patient. For instance, not every patient needs the same examination method or a surgery. The process followed by the patient within the hospital therefore depends on what is determined as a diagnosis in the consulting department at the beginning of the flow.

2.2. Breakdown of the departments

In this section, the three hospital departments, ENT, GYN and URO, are analyzed. First, the section looks at how many patients the departments have admitted in the years before Covid. This is done to get an idea of how much capacity the departments actually used. Furthermore, it is investigated how the admission of patients is distributed in relation to the number of patients need surgery and whether there is a trend in the number of inpatients and outpatients. Finally, the OR capacity and bed capacity of the relevant departments are analyzed. This is important for the coordination of the capacities at the planning level.

2.2.1 The pillars per department

In addition to a hospital is divided into departments, each department is also divided into several pillars. Every doctor has their own speciality, which belongs to a pillar. The capacity available per department is therefore not given in general to a department, instead, it is examined, per pillar, how much capacity it needs and then the capacity of all pillars(department) is added up to determine how much capacity a department needs. The master plan, similarly, is designed per pillar, per department and not indiscriminately over the entire department. The capacity per department is calculated later, when the capacity per pillar is set. The pillars of the departments for this study are shown in Table 2-1.

Table 2-1. The pillars per department in the RadboudUMC in 2022

Department	Pillars
ENT	Head and Neck Surgery
ENT	Otology
ENT	Rhinology
ENT	Child
GYN	Oncology
GYN	Benign gyn
GYN	Obstetrics
URO	NTX
URO	Functional
URO	Oncology
URO	Child

2.2.2 The number of patients admitted

In order to plan, it is important to have a clear picture of how much capacity each department has used in the recent years. The budget and capacity forecast is determined on the basis of historical data, and it is therefore important to analyse the historical data of the departments as well. Furthermore, for each department, the number of patients admitted in recent years before Covid was examined. The percentage of patients with an operation and the number of inpatients and outpatients were also considered. This was done to determine whether there had been a trend of patient admissions in recent years which helps estimate how many patients can be treated with the current capacities. In addition, the waiting lists of the departments are also looked at as this is the work stock for a hospital.

ENT department
Table 2-2 shows how patient admissions have been structured in recent years before Covid. For the ENT department, data prior to 2017 is not considered because the ENT department started digital tracking of all of its patients only in the middle of 2017. Prior to that, everything was done on paper.

Therefore, data from 2017 is not for the entire year. The percentage of patients entering the OR and the distribution of inpatients and outpatients is almost the same as in other years.

Table 2-2. The admission of the ENT department of the years before Covid (n>1000; RadboudUMC)

ENT patient admission breakdown	2018	2019
Total patients admitted	822	729
With OR treatment	94%	93%
Outpatient	388	381
With OR treatment	98%	95%
Inpatient	431	345
With OR treatment	91%	91%
Other	3	3

In 2019, there is an 11% decrease in admissions compared to 2018. Moreover, in the analyzed time period, at least 91% of the admissions also needed surgery.

GYN department

When examining how the patient intake of the GYN department is structured, it is notable that, like the ENT department, 2017 is not complete here, as they only started working digitally in 2017. This means that not all admitted patients are in the new database. Moreover, in the GYN department, as in the ENT department, there is an increase in the number of outpatients. However, the growth in outpatients is not as large as at the ENT. This is due to the fact that the GYN department has care products that require a longer hospital stay. Therefore, its patients are admitted for longer than one day.

URO department

URO, likewise, does not have complete data available for 2017. This also explains why 2017 has an operation rate of only 40%. The values of 86% for the number of surgeries performed per year for 2018 and 2019 are representative. The percentage of operations required for outpatients is significantly lower than in the previous two departments.

Most of the care products carried out by the URO department with surgery require patients to be in hospital for more than one day. This also explains why there is almost no increase in the number of outpatients for the URO department.

2.2.3 The number of OR capacity reserved and used

In this section, the OR capacity is analyzed. First, the number of hours per year reserved by the departments is considered, to determine whether there is an increasing or decreasing trend. Then, it is examined how many of the reserved hours are in fact used by the departments. If these numbers deviate, reasons for this possible difference are investigated.

The OR hours are determined on the basis of the reserved “plan blocks”. A “plan block” correspond to the number of hours a department has reserved for an OR. During this reserved plan block, the department can schedule it as it sees fit. Thus, in one planning block, one surgery can be performed ,while in the next planning block, several surgeries can be carried out in succession. The analyzes will also look at how many OR hours were actually used and where this possible difference could come from. This is being investigated to determine how the ORs are currently being used.

ENT department
When looking at the OR hours for the ENT department, a decreasing trend in the number of OR hours booked and used can be observed. In total, on average 7% of the reserved OR hours are not used by the department. Some of the reserved hours are not used because the fully reserved OR blocks are not used. These tend to be small OR blocks (of 2 to 4 hours). OR blocks can hardly ever be planned down to the exact minute. It also comes because an operation was cancelled at the last minute or because there is not enough bed capacity at the clinic.

GYN department
For the GYN department, it is noteworthy that in 2019, approximately 10% fewer hours were reserved and used, compared to 201s8. Furthermore, more different plan blocks have been requested in 2019. However, these were all of shorter duration than in the previous years.

Another interesting point is that in 2019, there is a 30% decrease in unused reserved hours compared to 2018. This is a considerable decrease compared to previous years. This may be due to the fact that fewer operations have been performed and more shorter plan blocks have been requested. The department has therefore planned more efficiently.

URO department
When examining the OR capacity of the URO department, it can be seen that in 2018 and 2019, URO did not use an average of 16% of the reserved hours. This is because a reserved plan block is not always fully used and there is still changeover time between patients in the OR.

In contrast to the ENT department, the URO department has seen an increase in the number of OR hours booked and used. However, there is only a 2% increase in the hours actually used. This difference can, of course, be due to the changeover times or due the plan blocks not being fully used, either because smaller surgeries were performed, or because surgeries were finished earlier than expected. Between 2018 and 2019, there is a 4% increase in the number of booked OR hours. There is also a 4% increase in used OR hours.

However, the difference between hours booked and used increases every year. Between 2018 and 2019, there is a 25% increase in the unused reserved OR hours.

2.2.4 OR waiting lists

In order to distribute the capacities in the best way possible, it is necessary to look at which department has the highest care backlog. This is done in the form of OR waiting lists. Each department has its own waiting list of patients that require treatment. These waiting lists specify which care product a patient should receive and how long they have been waiting for treatment. The duration of treatment is planned for OR time and for any length of stay in case of admission. The waiting list also indicates whether the patient is already scheduled or not.

The waiting list is important to consider because it reflects the hospital's upcoming workload. The waiting list generally consists of two types of patients: those who can be and cannot be scheduled yet. The patients who cannot yet be scheduled, do not want to be scheduled due to private reasons or still have to go through the anaesthesia procedure. Furthermore, the urgency of the patients treatment is also indicated in the waiting list. In total, there are five different urgency levels, namely: 2, 4, 6, 12, and 53. These numbers indicate number of weeks within which the patient must receive treatment.

As indicated in subsection 0, the healthcare products concerned cannot be disclosed, as this is business-sensitive information. For this reason, this data is not published in the report. However, it can be explained how a healthcare product is constructed. A care product is created after a patient is done with their treatment. So, the costs and revenue generated per patient is not known while the patient is still on the waiting list.

Since the waiting lists for the years 2017 to 2019 cannot be retrieved, the data will be based on the current waiting list of the departments. Furthermore, a distinction is made between patients who are overdue and those who will be operated on in the near future.

Waiting list: ENT department
Table 2-3 gives an overview of the waiting list of the ENT department. The data shows that 132 patients are late for surgery. There are 337 patients who will need surgery in the near future. Of the patients who are late, only 19% are scheduled for surgery. Each patient has their own care product. As expected, some care products are more common than others, as mentioned in subsection 0. However, the different costs and operating times of the various care products must be taken into account.

Table 2-3. The waiting list of the ENT department Covid (n=454; 2021-2022; RadboudUMC)

		Planned			Not planned			Total		
	Time on waitlist	# patients	OR needed hours	Admittion hours	# patients	OR needed hours	Admittion hours	# patients	OR needed hours	Admittion hours
To late	> 90	8	16	1	69	132	63	77	148	64
To late	30-90	6	9	0	1	41	4	7	50	4
To late	0-30	11	33	2	22	62	10	33	95	12
In	0-30	43	92	33	28	60	12	71	152	45
In	30-90	4	13	2	70	190	37	74	203	39
In	90-180	4	9	0	74	222	25	78	231	25
In	180-365	0	0	0	30	79	2	30	79	2
In	> 365	4	9	0	80	156	1	84	165	1
Total		80	181	38	374	942	154	454	1123	192

Figure 2-2 indicates how many patients are on the waiting list per urgency level. Red means that this number of patients is too late for the promised deadline for treatment.

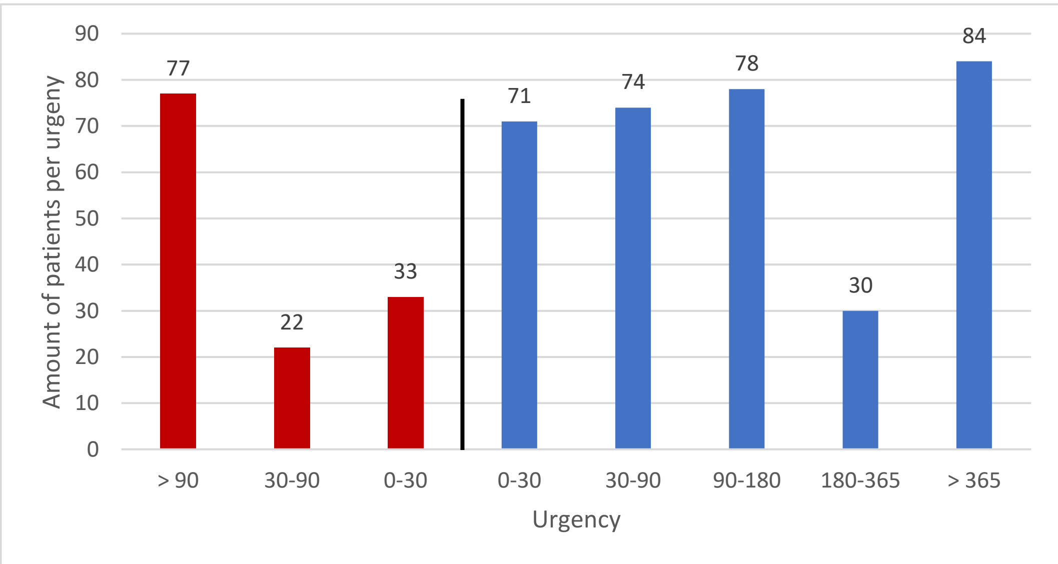


Figure 2-2. The amount of patients on the waiting list for the ENT department per urgency with amount of patients late in red and still on time in blue, (n=454; 2021-2022; RadboudUMC)

Waiting list: GYN department

Table 2-4 provides an overview of the waiting list of the GYN department. Here, it becomes clear that only 75% of the waiting list has not yet been scheduled for surgery. In total, 13% of the surgeries already scheduled are overdue, and the remaining surgeries are still ahead of the deadline. Furthermore, 17% of operations not yet scheduled are late. What is striking is that 57% of these are already more than three months overdue. When looking at the OR time required, this also concerns smaller surgeries that are less urgent. It is also noteworthy that the waiting list is much smaller than that of the ENT department and that proportionally more people have already been scheduled.

Table 2-4. The waiting list of the Gyn department Covid (n=175; 2021-2022; RadboudUMC)

		Planned			Not planned			Total		
	Time on waitlist	# patients	OR needed hours	Admition hours	# patients	OR needed hours	Admition hours	# patients	OR needed hours	Admition hours
To late	> 90	2	4.5	1	13	19.83	9	15	24.33	10
To late	30-90				6	15.08	7	6	15.08	7
To late	0-30	4	6.25	3	4	10.5	6	8	16.75	9
In	0-30	29	51.75	43	22	37.5	27	51	89.25	70
In	30-90	4	8.5	5	29	60.75	36	33	69.25	41
In	90-180				32	61.17	33	32	61.17	33
In	180-365				7	9.42	1	7	9.42	1
In	> 365	4	11.5	10	19	26	17	23	37.5	27
Total		43	82.5	62	132	240.25	136	175	322.75	198

Waiting list: URO department

Table 2-5 shows the waiting list of the URO department. This list is relatively large, compared to those of the ENT and GYN departments. It is striking that 26% of the patients have already been scheduled, which is the highest amount among the three departments. Of the scheduled patients, 27% are late. Furthermore, 24% of the unplanned patients are late, of whom 58% are more than three months late. There are also 202 patients (44%) who will not require treatment for a year but are on the waiting list.

Table 2-5. The waiting list of the URO department Covid (n=619; 2021-2022; RadboudUMC)

		Planned			Not planned			Total		
	Time on waitlist	# patients	OR needed hours	Admition hours	# patients	OR needed hours	Admition hours	# patients	OR needed hours	Admition hours
To late	> 90	11	24	25	63	109	133	74	133	158
To late	30-90	10	24	16	26	56	35	36	80	51
To late	0-30	22	58	53	19	37	34	41	95	87
In	0-30	48	113	86	35	88	80	83	201	166
In	30-90	28	51	38	52	93	72	80	144	110
In	90-180	7	13	10	37	77	69	44	90	79
In	180-365	3	3	0	24	34	26	27	37	26
In	> 365	32	58	30	202	347	217	234	405	247
Total		161	344	258	458	841	666	619	1185	924

2.2.5 Clinic capacity

The clinic is being examined because this is a place where all patients enter when they are admitted into a hospital and return post-treatment. It is therefore important to see how much capacity clinics usually need.

Each department has its own bed capacity, where patients can be admitted or recover from treatment. This bed capacity is allocated to the clinic to which the relevant department belongs. However, a department shares a clinic with several wards. For example, the ENT department shares the clinic with three other departments, and the GYN and URO share the clinic with one more department.

To determine how many beds are needed just for ENT, it is estimated how many beds are needed per hour. The number of beds occupied per department per hour is monitored by Radboud UMC. Based on this, the number of beds available per hour can be used to determine the acceptance rate of a patient. The acceptance rate is such that, if there is *X* number of beds available, Radboud UMC can say with *Y* percent certainty that it can accept all patients.

However, it is not just the departments themselves that need to be considered but the entire clinic to which they belong. This is because some departments may need more beds than what they have available. In such cases, the relevant department uses beds that are meant for the other department that does not need them at the moment. So, in order to get a good idea of how many beds are actually available, It is necessary to look at the two different departments, to which ENT and GYN/URO belong.

Table 2-6 shows the total number of departments shared by the respective clinics. It also shows how many beds are available in total at the clinic and how many beds are intended for the departments.

Table 2-6. The two clinics for the departments ENT, GYN and URO

Departments	Clinic	Amount of departments in the clinic	Total amount of beds available	Beds available for asked departments
GYN/URO	C5	3	46	38
ENT	C2	4	68	14

When looking at the clinic to which the ENT specialty belongs, the relevant department is C2. According to Table 2-6, there are 14 beds available for the ENT department on this ward. This should be more than sufficient, as in 2019 ENT should be enough for a maximum of 11 beds per day. However, it must be taken into account that this only concerns *elective* patients, so, additional beds are needed for emergency patients. Further, when looking at both the GYN and URO departments together, it is noticeable that if a 100% acceptance rate is to be achieved for both departments, a total of 30 beds is required. Again, this is only for elective patients and does not include emergency patients. Looking at Table 2-6, it can be seen that a total of 38 beds are available for the departments together. These 38 beds include the emergency patients.

2.3 Creating and using of the budget

This section first examines how a hospital budget is established, considering the steps involved and the time schedule. Next, it analyzes how each department uses its own budget. Finally, it examines how often care products occur per year and which care products generate the largest part of the revenue.

2.3.1 Creation of the budget

At Radboud UMC, the determination of the budget for the following care year begins in March. It should be noted that a care year is longer a regular, twelve-month year, and runs from 1 January to the end of April of the following year. The budget is determined based on the production plans of all departments. In a production plan, the departments indicate how many care products are expected in the next care year. A care product consists of all the procedures that a patient undergoes during their treatment. This means that a care product can, for instance, consist of care activities such as consultation, nursing days, diagnostics, and surgery. The maximum duration of a care product can be 120 days (four months). Because a healthcare product consists of several steps, a healthcare year lasts longer than a normal year. This implies that if the first action of the healthcare product was still carried out in December of this year, the total healthcare product still falls within the current healthcare year. For this reason, it was decided to make the healthcare year longer than twelve months, because when everything is running normally, a healthcare product must be completed by the end of April, if started in December.

In total, there are about five thousand care products in the Netherlands, of which around three thousand are used at Radboud UMC. To determine which type of care product a patient falls into, there is a national decision tree used both by health insurers and hospitals.

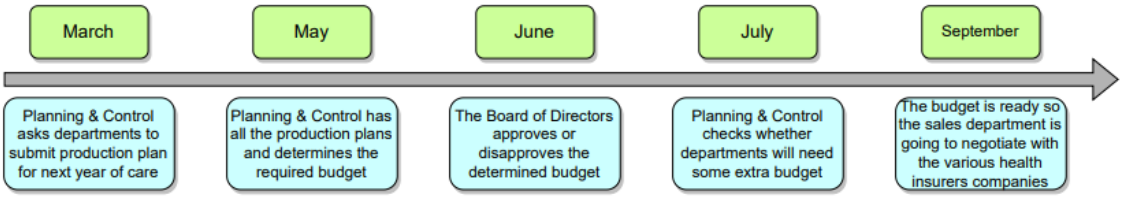


Figure 2-3. The timeline of which steps are carried out when determining the budget for the next care year

In order to form a maximally realistic budget, production plans use forecasting software to determine how much of each healthcare product is expected. After all production plans have been submitted to the Planning & Control department, who then start calculating the expected budget. Once this is done, the budget is submitted to the Board of Directors, which then approves or rejects it. When the budget is approved, Planning & Control checks with the departments whether they still think they need some extra budget. This is possible because when calculating the budget, a buffer was added. When the budget is complete for all departments, the Sales department starts negotiating with the health insurance companies.

Figure 2-3 shows a timeline of which steps are carried out when determining the budget. The budget for the coming year must already be determined in September of the current year. Because this is relatively far in advance, it is important that adjustments can be made in time, which, currently, is not yet the case.

Appendix A contains a flow chart that depicts the process of creating the budget.

2.3.2 How is revenue created per department

This section examines how much cost and revenue are incurred per care product, since these determine how much of the budget is used and which budget targets are met. However, since this information is business-sensitive, the real results cannot be published. For this reason, revenue and costs are not presented in the report. Instead, revenues and costs are examined in order to get a clear picture of which healthcare product is profitable and why. This analysis also helps clarify whether some care processes occur more often than others.

ENT department
For the ENT department, 136 care products are generated. The revenue of the ENT department increases a little each year. The budget for the coming year will be one million euros. In total, care products can occur between 1 and 260 times during the year, including those that are profitable but also those that are loss-making. While loss-making care products can occur more than once in a year, the ENT department has managed to make more profit in each year.

When considering various care products, 34 care products are needed to meet 80% of the demand for care, as shown in Figure 2-5. This means that with only 25% of the care products, 80% of the demand for care is met. When looking at the profit, it is noticeable that only eight care products are needed to meet 80% of the profit, which is profit in relation to the cost and revenue of a care product. This information is also displayed in Figure 2-4. What is also striking about this graph is that the profit after 20 care products is above 100%. Of course, this does end up at 100% again at the end. Because a number of care products do not yield a profit but a loss, the total profit of the care products decreases.

In 48% of cases, a healthcare product does not yield a profit. Of course, this is quite a lot, but it is only 26% of the total care product demand. These care products do not recur often over the years. However, even if all health care products were profitable, these 26% loss-making care products would only account for 12% of total profit.

The care products that involve surgery are generally the most profitable care products. In particular, 76% of the revenue comes from healthcare products with OR treatment. Officially, the nursing days weigh the heaviest on how much profit a care product makes. However, more than 90% of the nursing days come from surgeries.

Profit is not determined by how many OR hours are used by a department but by the types of care products that are performed. This means that if a profitable care product can be performed one extra time, because, for instance, more OR hours are available, the department would make more profit. The same applies when a loss-making care product must be performed. In such a case, the department with more work will generate less profit but will have helped more patients.

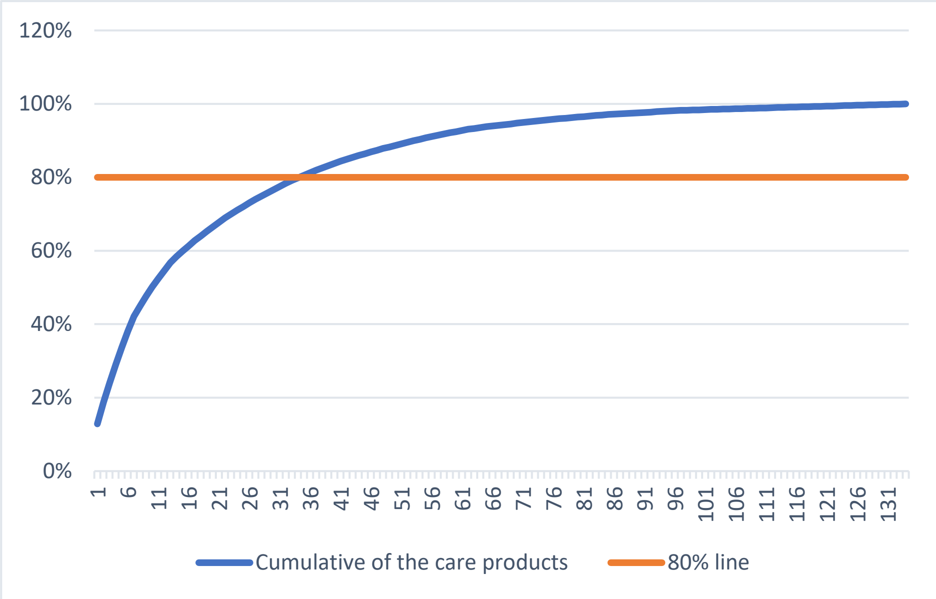


Figure 2-5.The cumulative of the amount of care products of the ENT department (n=136; 2021 – 2022; RadboudUMC

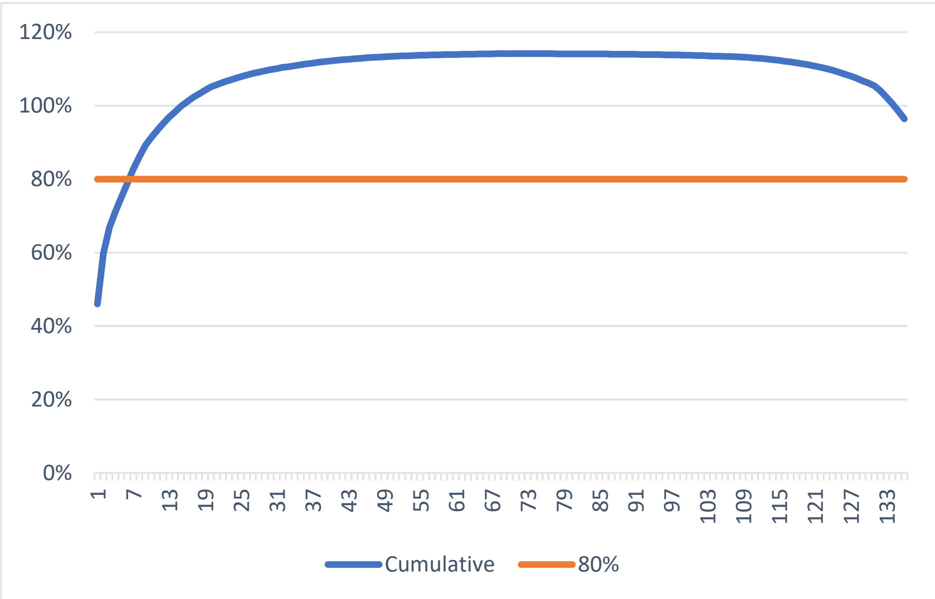


Figure 2-4. The cumulative of the profit of all the care products from the ENT department (n=136; 2021 – 2022; RadboudUMC)

GYN and URO department

For the GYN and URO departments, the same applies as for the ENT department. Both departments have profitable and loss-making care products. Thus, the GYN department has used 98 care products between 2017 and 2019, while the URO department has used 125. The GYN department only needs seven care products per year to reach 80%, compared to 21 products for the URO. Furthermore, in both departments, the revenue has increased by just over 20% in 2019 compared to 2017. Furthermore, the GYN department needs only 25 care products to carry out 80% of their required treatments. For the URO department, this requires 33 care products.

2.4 Current method in strategic, tactical, and operational planning

This section examines how planning is currently carried out in hospital departments. It looks at what the current focus ares are and how far in advance the patients are planned. It also considers how TPOs are currently handled. The planning is also examined to determine how a year is structured based on the master planning.

2.4.1 Current operational-planning approach

Scheduling is done based on the urgency of the treatment. Due to the urgency, it may happen that more urgent patients who wait less time are scheduled earlier. Furthermore, planning is finalized one week in advance. It may happen that a patient has to be cancelled at the last minute, because, for instance, the patient is too sick to get treated, or because there are not enough beds, and the patient has no place to go for surgery. This due the fact that the capacities are not sufficiently adjusted to each other. The planning staff tries to schedule a maximum of five clinical patients per day for surgery (a higher number is not possible). The bed capacity is matched as closely as possible to the number of patients to be operated on in the specific day.

2.4.2 Current tactical-planning approach

Currently, there is a TPO for the departments between every six or ten weeks. This is done with the planning, head of nursing, and head of surgery, who assess the state of the departments. An explanation is given as to why the master plan may not have been achieved. During the TPO it is also discussed how the planning can be achieved. These discussions, however, normally don't look at how the capacities can be distributed. This is because it is the TPO for the department's self and not for all departments.

There are also TPOs for capacities, which deal with the distribution of the respective capacity for the department that the TPO is for. For example, there is a TPO for the OR, which examines how the ORs have been used during the past quarter and whether this corresponds to the actual situation. At a later stage, the intention is also to better distribute the capacities between the pillars, so that the relevant capacities are used more efficiently. However, the TPO is now mainly used to update everyone on the state of affairs.

2.4.3 Current strategical planning approach

The planning and capacity utilisation (subsections 0 and 0) indicates that a year is not divided equally. This is shown in Figure 2-6. Figure 2-6 shows the number of surgeries carried out per week. Note that this is not equally distributed over a year. This is because the master plan for a year already takes into account predetermined reductions. These reductions are the same every year for the holidays. For example, during the holidays, the ORs are generally reduced by 30%, and during public holidays, such as Christmas, they are completely closed, with only the emergency room staying open. The departments sometimes also have to attend a conference several times a year, in which case the OR, again, is reduced (with the amount of reduction depending on how many of the team's members attend the conference).

These reductions must therefore also be taken into account when capacities are distributed among the various departments. Figure 2-6 shows the seasonality of the specialties from 2018. Here, one can clearly see how much the number of operating hours fluctuates per week over a year, in the form of seasonality.

When it comes to the distribution of capacities, the OR is leading, since the types of performed operations determine how many beds per department are needed. The OR also determines how many staff must be present. This applies both to the OR and the associated clinic. In addition, a department will also run fewer consultancies when it has fewer OR hours available – otherwise more patients come in needing treatment than the department has capacity to treat. So, these patterns all depend on seasonality and planned reductions.

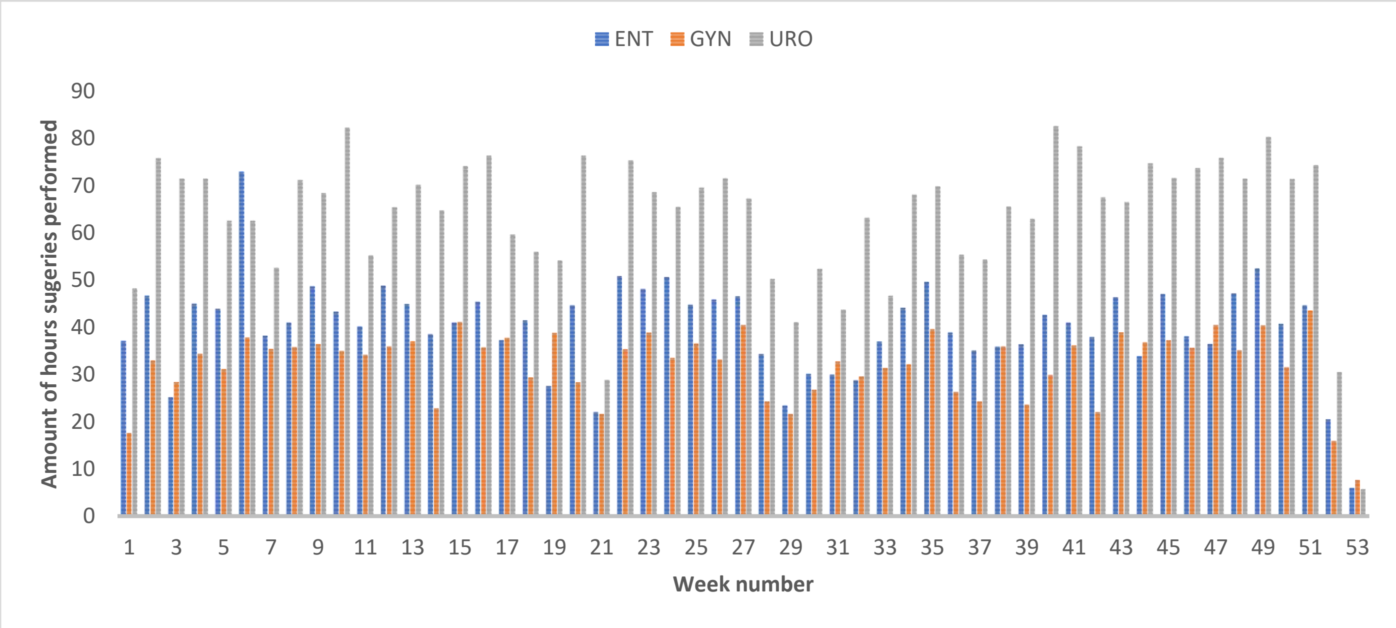


Figure 2-6. The amount of hours surgeries performed per week in 2018 in the specialties(n=798; 2018; RadboudUMC)

2.4.4 Comparison of planning to execution

In order to determine how well master planning of a year has been done, it can be compared with what has actually been realised. Figure 2-7 below shows the master planning and realisation of the ENT department from 2022 to date. While this time period is meant to be beyond the scope of the study, the master planning from 2017 to 2019 can no longer be traced. Due to these limitations, a choice was made to present the current master plan and realisation for 2022.

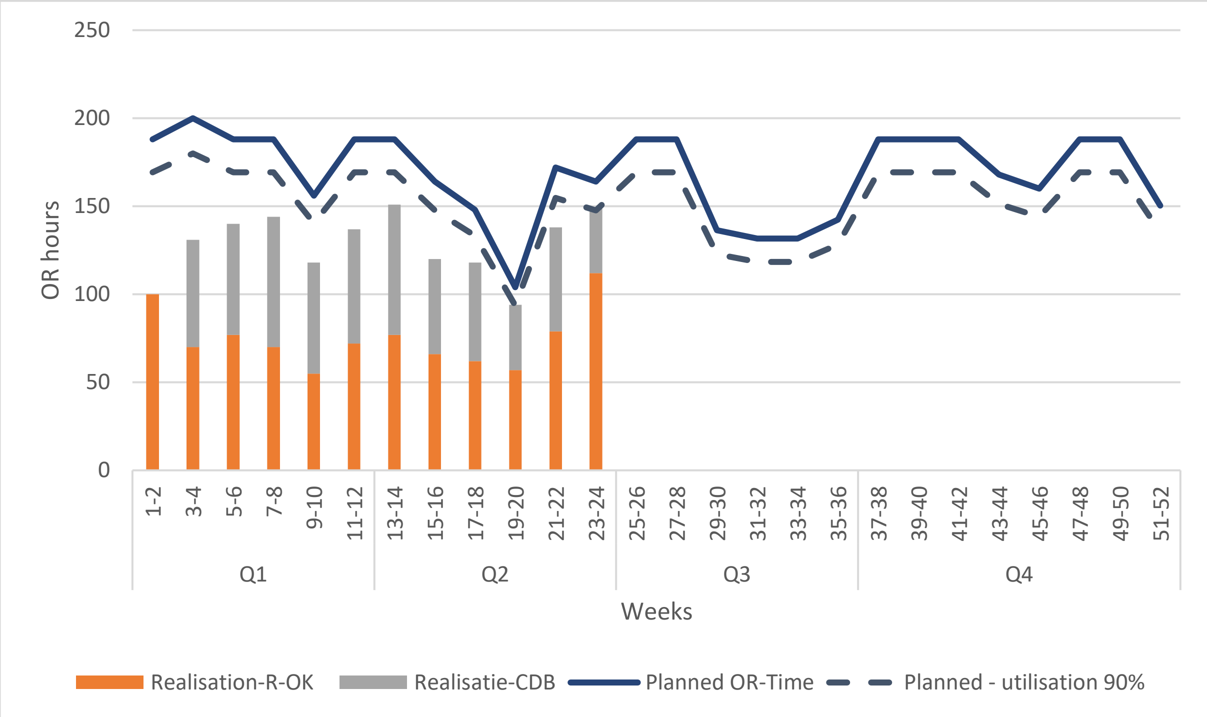


Figure 2-7. Master planning in relation to realisation (n=500; 2022; RadboudUMC)

As is evident in Figure 2.7, the ENT department is already quite behind on the master plan. This is due to several reasons. First, there is a relatively high shortage of staff at the department, either due some staff sick with Covid or because the staff is overworked by the Covid pressure experienced in recent years by the Radboud UMC. Furthermore, more operations than usual have not yet been scheduled. This is mainly due to the anaesthesia department. Due to Covid, this department has not fully staffed for quite some time, and as a result, the patients cannot be prepared for surgeries. In the normal workflow, everything has to be arranged with the anaesthesia department first before a patient can be scheduled for surgery. In addition, each department must still hand in capacity because of Covid in 2022, which means the production plan cannot be met. Finally, Radboud UMC's goal is to use the OR for 90% of its scheduled hours. If there is more than 90% utilisation, this is considered a bonus: this number is usually quiet difficult to achieve as it can sometimes take fifteen minutes or more before a new patient is in the OR for the next operation.

2.5 Conclusion

Strategic planning for the upcoming healthcare year is usually carried out eight months in advance. This creates uncertainties in the supply of patients and whether the capacities allocated to a particular department are actually needed or sufficient. When the capacities are assigned to a department incorrectly, patient waiting lists may increase, since there are now more patients than expected based on strategic planning. Moreover, final budget targets may not be met if a department has been allocated too much capacity which ended up not being used. These unused capacities could have been better reallocated to a department with a surplus of expected patients. Besides, the available capacities can (temporarily) be different than expected due to the illness or absence of staff.

To anticipate this, adjustments must be made to the elective care on a tactical level. Therefore, the new expected patient demand for the next three months should be taken into account, and a new capacity distribution must be determined in order to make adjustments. The departments must also be examined in terms of which care products they are likely to treat, as the care products determine how much turnover a department generates over a period of time. The number of hours a department spends on its own has no effect on the generated revenue this. Therefore, this research is important to propose an appropriate method to distribute the capacities during the TPOs. This, in turn, will enable the departments to use the capacities according to their current circumstances, and so the total budget can be better used and managed, and the strategic goals can be met.

3. Literature review

*Nothing has such power to broaden the mind as the ability to investigate systematically and truly all the comes under the observation in life. – **Marcus Aurelius** (121-180)*

In this chapter, the second research question will be answered:

"What methods can be found in the literature and used for a solution model to plan multiple capabilities at the tactical level?"

To answer this question, section 0 outlines the need for tactical planning worldwide and offers a brief description of tactical planning. Section 0 discusses possible methods of tactical planning within the healthcare sector. Section 0 discusses tactical models used in the manufacturing industry, and section 0 discusses different machine-learning techniques. Machine learning is considered because this technique can be used well for forecasting data and classifiers. Section 0 discusses the literature relevant for validating a tactical plan model. Finally, section 0 identifies the literature that can be applied to solve the problem.

3.1 The purpose of tactical planning

Planning and control in the healthcare sector have received increased attention over the past decade(s) due to a growing demand for healthcare and expenditures [9] [10]. For instance, Larsson et al., (2019) state that there are capacity management challenges in the United Kingdom, the Netherlands, Australia, Canada, New Zealand, Belgium, and Scandinavia [11]. Silvester et al., (2004) suggests that healthcare capacity planning processes need to better balance resource supply and patient demand.

Capacity-planning processes are hierarchically structured following the strategic, tactical, and operational production planning [12] [13]. When looking at strategic planning, this type of planning is about the long-term horizon. Accordingly, strategic planning sets the boundaries for tactical planning. Tactical planning focuses on the mid-term horizon, which, in turns, sets the boundaries for the short-term horizon operative planning [14].

Tactical planning is seen as a key process within manufacturing companies. This because tactical planning enables holistic planning by balancing demand and supply, and enforcing integration and coordination among departments, business strategy, operational planning, and in the supply chain [15]. Despite its importance, the tactical planning level is also the one that is neglected the most. The problem is further compounded by the fact that it still seemingly hard to define the boundaries between strategic, tactical, and the operational levels. This results in unclear or vague statements [16].

Although planning and control are gaining increasing attention in the healthcare sector, they already have a rich tradition within the manufacturing industries [17]. Within the manufacturing, planning and control address decisions on the acquisition, utilisation, and allocation of production resources to satisfy customer requirements in the most efficient and effective way. Planning and control comprise an integrated coordination of resources (staff, equipment, and materials) and product flows, in such a way that the organization's objectives are realised [18]. Because planning and control have such a rich tradition in the manufacturing industry, and they started to receive attention in the healthcare sector only in the last two decades, the latter is still lagging behind. One of the reasons mentioned by Hans et al., (2011) for this is that the healthcare organizations are professional organizations that lack cooperation between, or commitment from, all involved parties. Another is that the information required for planning is often not available. And yet another reason is that healthcare providers, such as hospitals, consist of autonomously managed departments, and managers tend not to look beyond their own departments [9].

Importantly, while healthcare is trailing behind the manufacturing industry, the solution for healthcare cannot be completely taken over by the manufacturing industry. This is because the solution model characteristics should match the characteristics of the hospital [19].

3.2 Tactical planning in healthcare

Tactical-resource and admission-planning approaches can be either static or dynamic. Static approaches tend to result in the long-term plans that are often cyclical. Dynamic approaches, in contrast, result in the intermediate-term plans in response to the variability in demand and supply [20]. Thus, Brailsford et al., (2011) argue that implementing a dynamic approach results in lower access times and higher resource utilisation [21].

Tactical planning is a key element for hospital planning and control that concerns mid-term allocation of resource capacities. In contrast to planning at a strategic level, tactical and operative planning uses the actual expected number of patients instead of the forecast [22]. Furthermore, tactical planning is not done for the entire hospital but for a subset of care processes, for instance, for one subset of specialties or only one specialty.

To anticipate changes in demand, it is important to know the waiting lists, resource availability, expected demand, and the number of patients served in prior periods [20]. So, in general, tactical resource and admission planning approaches in healthcare do not consider multiple departments and resources and instead focus only one specialty, such as operation rooms [23] [24]. There are only a few publications that integrate decision making for multiple resources and departments but none who look at the whole hospital [25].

When looking at tactical planning in the healthcare sector, Hulsfhof et al., (2012) propose that tactical planning addresses the organization of the operations/execution of the healthcare delivery process (i.e., the 'what, where, how, when and who'). Furthermore, Hulsfhof et al., (2012) offer a useful outline of the necessary steps involved in tactical planning. Thus, they argue that as the first step in tactical planning, patient groups need to be characterized based on disease type/diagnose, urgency, and resource requirements. As a second step, the available resource capacities, settled at the strategic level, are divided among these patient groups. Then, a blueprint for operational planning can also be created when the allocation of time slots is added to the tactical planning. After the addition of time slots, resources can be assigned to different tasks, specialties, and patient groups. Furthermore, temporary capacity expansions, like overtime or hiring staff, are also part of tactical planning [26].

Currently, block scheduling is commonly used to allocate capacity in hospitals, which includes three consecutive steps. The first step is to identify the patient groups. The second step is to subdivide the resource capacities over the identified patient groups. Lastly, planning blocks are assigned in the form of different capacities to create a schedule [27]. So, tactical level gives a blueprint appointment schedule, and on the operational level, patients will be definitively scheduled. This may be because patients have to come more often and then they can be scheduled on one day because some patients from the blueprint cannot come on the expected week [26].

Furthermore, Hulshof et al., (2012) describe different classifications of patients who can be present in a care path and what is necessary for each planning level per classification. Three of the described classifications fall within the scope of the research of this thesis, and are "Ambulant patients", "Surgical care service", and "Inpatients care service". Hulshof et al., (2012) also mention solution methods for each classification planning level. The ambulant classification on a tactical level consists of multiple stages. Examples include the composition and sequence of these stages as the route of a patient. With the surgical care service the tactical capacity allocation is the objective to get the optimum trade off from patient access time and the utilisation of surgical and postsurgical resources. Lastly, for the inpatient care services, the tactical bed reallocation needs to ensure that the fixed capacities are employed, such that inpatient care is provided to the right patient groups [26].

To solve a tactical planning problem, a Markov Decision Process (MDP) can be used. The MDP can be used for patient admission plans for multiple resources and multiple patient groups with various care process. Here, the patient process is modelled as an MDP. However, according to Nunes et al., (2009) a MDP is not a suitable method because it is not yet suitable for realistic sized problems.

When planning on a tactical level in a hospital, there are many uncertainties regarding the patient demand [28]. To overcome these uncertainties, robust optimization (RO) can be applied. RO creates plans that can meet targets in spite of demand uncertainties. The RO makes general assumptions that there is uncertainty in new patient demand, without knowledge of the exact probability distribution [28].

Aslani et al., (2021) states that if data uncertainty is ignored during the model development process, and the realisation of data is different from the nominal values, several constraints may be violated, and an optimal solution found using the nominal data may, in practice, not be optimal or even feasible. The alternative approach is RO. The quality of a robust approach is evaluated based on two criteria: remaining feasible despite changing parameter values and the cost of doing so. The cost of a robust solution is attributed to potential over-conservatism and is measured by evaluating a trade-off between the robustness and the optimal objective value.

Another advantage of RO, apart from taking into account uncertainty, is that it has good computational traceability in comparison to scenario-based approaches [29]. A disadvantage of the RO method is that it is overly conservative and computationally intractable. These obstacles can be overcome through a polyhedral uncertainty set, in which the level of conservatism is controlled by a defined budget of uncertainty [30] [31]. By using a defined budget of uncertainty, the RO approach can provide a feasible solution.

Nguyen et al., (2015) used the RO method to develop a robust tactical capacity planning (RTCP) model to ensure care accessibility in the presence of uncertainty in demand in an outpatient clinic. The goal of the research was to minimize the maximum required physician time for the worst-case realisation of demand in an uncertainty set, using a uncertainty set for demand and budget [32]. It is important to clarify that the price of robustness presents the trade-off between the additional cost and the feasibility of the robust solution in terms of different budgets of uncertainty [28].

3.3 Tactical planning in the manufacturing industry

As mentioned earlier, there is a rich history of tactical planning in the manufacturing industry. Therefore, it is fruitful to investigate which models tend to be used and are available for this purpose.

A commonly used method for tactical planning is the "Rough Cut Capacity Planning" method, or RCCP. The RCCP addresses medium-term capacity planning problems. At this level, projects are split up into relatively large work packages, which are planned over time, taking into account the availability of scarce resources. The usual objective is to minimize the make span. The RCCP method uses the time buckets of weeks to split up the time horizon, allowing it to plan resources per job per week.

There are two basic kinds of RCCP methods. These are resource- and time-driven RCCP. The resource-driven method focuses on minimizing the lateness of the jobs, while the time-driven RCCP focuses on minimizing the use of irregular capacity [33].

There are several variants of the RCCP model beyond the two types that are just discussed. Schutten et al., (2004) have explored different RCCP methods. In their research, three different RCCP models have been formulated and tested on the basis of a case study with the Royal Netherlands navy dockyard. The study found that the second formulated RCCP heuristic was the best – this was the "Enum" heuristic, which consists of five steps. With this heuristic, an infeasible solution is made feasible. The method has been tested with 450 instances and solved about 75% of the cases to optimality [34]. The RCCP does assume that it is applicable primarily to large projects that need to be planned on a tactical level. However, this is not primarily the case for a hospital, since a patient is not a large project (at least not in the sense that's relevant for the RCCP). This can be a disadvantage if this solution method is chosen.

Another way to conduct tactical planning is described by Carvalho et al., (2016). Carvalho et al. propose a deterministic solution based on their previous (2015) work; however, this time their model has been extended to make the model robust to uncertainty in the data. This adjustment is motivated by the fact that real-world planning problems involve uncertainties (in terms of demand, revenues, costs, production rate, capacity, etc.) [35] [36]. Making a planning model robust will have an effect on the stability and performance of a production system by affecting due date achievement, efficient resource allocation, and the usage of a nonregular workforce [37]. The deterministic model of Carvalho et al., (2016) is used to solve an "engineer to order" (ETO) problem and uses the theory of Bertsimas et al., (2004), mentioned earlier, who use sets of uncertainty for the data [31]. This has the advantage of not needing to know the on the probabilistic distributions of the uncertain data. Moreover, it preserves the linearity of the original deterministic model [36]. The formulated model was tested with three different levels of uncertainty compared to when no uncertainty is used (RO is 0 then). The results show that the model should minimize the effort needed in the replanning process when RO is used [36].

3.4 Machine learning techniques

Machine learning is a subfield of artificial intelligence (AI). In the mid-2000s, the progress in the machine learning field started to accelerate drastically [38]. Machine-learning algorithms are self-learning: they derive knowledge from data in order to make predictions, instead of requiring humans to manually derive rules and build models from analyzing large amounts of data. As a result, machine learning offers a more efficient alternative for capturing the knowledge in data for gradually improving the performance of predictive models and making data-driven decisions [38]. Because of the efficacy of machine-learning algorithms, computers are able to continually improve their performance by learning from past experiences.

Machine learning consists of three basic types: supervised, unsupervised, and reinforcement learning. Figure 3-1 shows the three types in perspective and indicates what can be achieved with different types of machine learning.

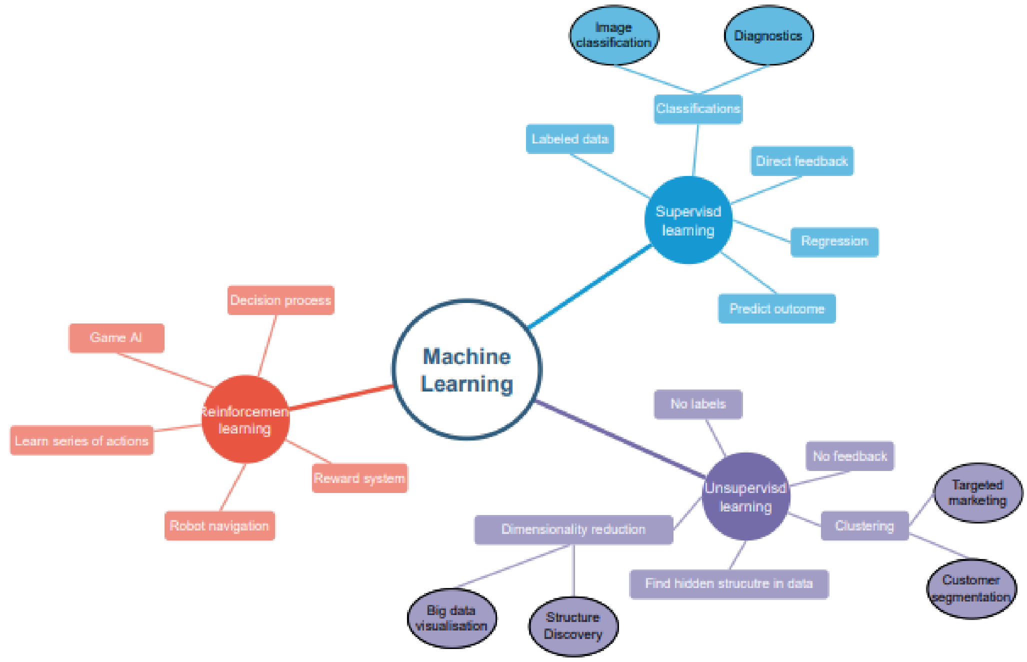


Figure 3-1. Types of Machine Learning and some indications of what can be achieved per type [38] [58]

For both prediction steps in the model described in section 0, supervised learning can be used in both instances. Supervised learning is the only one of the three types of machine learning that can make a prediction based on labelled data, which is the case for step 2. For step 1, a regression model can be used. The classification and regression methods are often used in a supply chain management setting, because of their predictive power [39]. It is recommended that multiple methods are tested on the same data to determine which prediction method works the best for the problem in question [40] [41].

For the first prediction of the expected patient demand, to complete the already existing waiting list, differing regression models will be tested. These models are considered supervised learning methods according to Figure 3-1. Regression models are used to predict target variables on a continuous scale, but also have applications to make a forecast [38]. Traditional methods, such as exponential smoothing, were also considered for demand forecasting. However, there is only data available from 2021 onwards, which is relatively little to establish good seasonal patterns and a trend for the urgency levels that are needed for traditional methods. Therefore, only machine learning is considered.

The regression models that will be tested are: K-Nearest Neighbour (KNN), Extreme Gradient Boosting (XGBoost), Random Forest, and Linear regression. Linear regression is considered both a machine learning and a traditional prediction model [42]. The four different models will be tested using the mean squared error (MSE). The MSE is useful for comparing different regression models and is the average value of the error of the prediction. This means the regression model with the lowest MSE score is the best method for this particular dataset [38]. The formula for the MSE is:

$$mse = \frac{1}{n} * \sum_{t=1}^{n} (y^i - \hat{y}^i)^2$$

KNN

KNN is a memory-based classifier and does not require a model to be fit. It is in general a simple method to classify data and is based on a distance function that measures the similarity between two instances. KNN is also known as a "lazy learner", not because of its apparent simplicity, but because it does not learn a discriminative function from the training data but memorizes the training dataset instead. The earlier mentioned distance functions are usually calculated with the Euclidean distance function, which is formulated as follows [38]:

$$d(x^{(i)}, x^{(j)}) = \sqrt[p]{\sum_k |x_k^{(i)}\ x_k^{(j)}|^p}$$

The main advantage of a KNN memory-based approach is that the classifier immediately adapts as one collects new training data [38] [42].

XGBoost

XGBoost builds an additive model in a forward stage-wise fashion; it allows for the optimization of arbitrary differentiable loss functions. In each stage n-classes regression trees are fit on the negative gradient of the loss function, e.g., binary or multiclass log loss. Binary classification is a special case, where only a single regression tree is induced [43] [44].

Random forest

By using the Law of Large Numbers, a random forest can overcome the overfitting and high inaccuracy that can occur while using a single decision tree. A random forest is essentially a large collection of de-correlated trees, where each tree casts a vote for the predicted class. The prediction with the majority of votes will then be the final decision [45] [46].

Linear Regression

Output value based on a linear combination of input values. The goal of linear regression is to model the relationship between a single feature (explanatory variable) and a continuous-valued target (response variable). This applies to simple linear regression. However, when there are multiple explanatory variables, the model becomes multiple linear [38]. The formula for multiple linear regression is:

$$y = \sum_{i=0}^{n} w_i * x_i = w^T x$$

In the literature, the classification techniques that are frequently used and discussed are: K-Nearest Neighbour (KNN), Decision tree, Random Forest, Support Vector Machines (SVM), and Naïve Bayes classification [38].

Decision tree

Decision tree algorithms are greedy algorithms that are able to discover features and extract patterns in large databases. Furthermore, based on the features in the training dataset, the decision tree model learns a series of questions of infer of the class labels of the data. This, together with the intuitive interpretation, is one of the reasons why decision trees are used extensively in data analysis. Moreover, decision trees are popular because of their robustness and low complexity. In most cases, decision trees produce comprehensible models with satisfactory accuracy levels [38] [47].

SVM

Another classification technique is SVM. Here *n* numbers of features are plotted as points in an *n*-dimensional space. These points are then split into classes by category, based on the side of the hyperplane on which they fall [48].

Naïve Bayes

This classification is based on the Bayes' Theorem, which is a probability theory which is able to determine the posterior probability. The equation used for this theorem is: [49]

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

Here P(A) is the probability of A; P(B) the probability of B; and P(B|A) the conditional probability of B given A.

Testing the classification models

To test the performance of the five models described above, a simple technique is used, and namely, the train-test split, where the whole dataset is used and split in an 80% train- and 20% test set. This is done on the dataset of the care products. Since the results of all health care product codes are already known, it makes it possible to test whether the predictions of the classification models are suited for the prediction of the data.

The care product data set comprises five years of data and will continue to grow over the years. To test their performance, the models are tested for accuracy, precision, and the F1 score. Furthermore, in order to make the best use of the classifier types, cross-validation is also used to find the optimal settings of the parameters.

3.5 Validate and test the solution approach

The performance of a tactical blueprint schedule can be tested using a simulation model. Another option, according to the literature, is to use numerical examples.

3.5.1 Simulation method

A simulation model can be used to show the effects of the chosen capacity-allocation method. In addition, a simulation model can show the performance of a stochastic model or approach perfectly. Finally, a simulation model can show the patient flow, and there are various queuing methods possible [50] [51]

3.5.2 Numerical examples method

To validate and test the performance of the capacity allocation methods they have formulated, Aslani et al., (2021) and Nguyen et al., (2015) both use numerical examples. A big advantage of numerical examples is that their computation takes less time than a simulation method.

3.6 Literature to be used

Chapter 3 presents an answer to the second research question (subsection 0) concerning literature review. First, research findings that can be applied to the problem described in section 1.2 will be named. Then, the solution model will be described.

Literature reviewed in present study clearly shows that tactical planning is necessary for achieving strategic goals. Furthermore, Cardoen et al., (2010) argue the actual number of expected patients' needs to be used for tactical planning instead of a forecast. This is in conflict with other studies that argue that tactical planning is still to be done on the basis of a forecast. Furthermore, the literature states that tactical planning is normally not used for several departments at once in general. However, for the solution model of this paper, this will have to be done.

Both Hulshof et al., (2012) and Cardoen et al., (2010B) state that a blueprint appointment schedule needs to be made for a tactical planning solution. For this blueprint, a number of characteristics of the patients must be known, such as diagnose, suspected care product, urgency, and resource requirement. Furthermore, it must also be known who/what is on the waiting list, expected demand, and resource availability. By means of the patient characteristics, patient groups can be defined that then can be planned and resources can be divided.

Furthermore, both the regression and the classification methods will be applied with machine learning technology. The KNN, XGBoost, Random Forest, and Linear Regression models are the regression methods that will be tested. For the classification method, the KNN, Random Forest, Decision tree, and Bayes rule will be tested.

4. Model description

Research is seeing what everybody else has seen and thinking what nobody else has thought.
– ***Albert Szent-Györgyi*** *(1893-1986)*

In this chapter, the third research question will be answered:

"*How is the chosen solving model structured, and what modelling methods are required as an input to answer the core problem?"*

To answer this question, section 0 first states the assumptions made for the model. Section 0 describes the solution model and explains the steps necessary for solving the core problem. In subsection 4.2.1, the choice of machine learning forecast models is determined. Subsection 0 explains how the costs and revenue per care product are determined, with the different costs and revenue per health insurance company. Subsection 0 presents the basic solution to the core problem, and subsection 0 discusses the optimization method with a focus on the budget. The last step of the model is explained in subsection 0. The final section (4.3) draws conclusions regarding the proposed model.

4.1 Assumptions made for the model

Before the model can be worked out, the assumptions made must be considered. These assumptions are made because of the missing data or because the model can become unnecessarily complex.

The assumptions made for the proposed model are as follows:

1. To determine the surgery numbers and the time per surgery needed for the predicted patients, a normal distribution is assumed, and the surgery numbers that occur most frequently with the corresponding times are chosen.
2. For the predicted patients on the waiting list, start weeks and deadline weeks are added for the high urgency patients to form a realistic picture.
3. The costs for the care products are assumed to be normally distributed, and the mean of the costs and revenue is used.
4. No distinction is made between the outpatients and inpatients because it is not possible to make this distinction in the waiting list.
5. The forecast is based on the number of patients that are treated during the Covid years, what is not a real reprehensive couple of years but no more data is available.
6. A master plan is adopted but does not take seasonality into account for the financial results, so, all weeks have the same capacity as indicated by the master plan.
7. Changeover time between patients in the OR has not been taken into account. The changeover time can be included in the desired OR utilisation.
8. All patients can be operated on and have gone through all the necessary steps, such as an pre-anaesthetic interview.

4.2 Model description

There seems to be no mention in the literature on tactical planning in relation to the budget and reallocation of the resource capacities. As already discussed (see subsection 0), about 93% of patients require surgery, only the waiting list for the OR is considered, as this is the only data that can be linked to the pillar to which a patient belongs. The importance of knowing which pillar a patient belongs to will be explained later in this chapter. The connection to the pillars is also done because this involves the clinic too and not the other capacities. As a result, the focus will be only on the established scope.

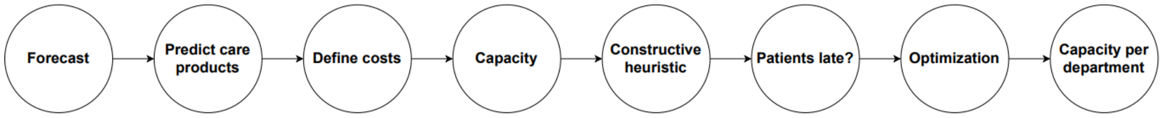


Figure 4-1. All the steps needed to make the solution model to solve the core problem

In order to reach a tactical blueprint schedule, several steps have to be executed. Figure 4-1 shows all the steps for the solution model schematically and the order in which these steps should be performed.

The first two steps of the model require a prediction model and will be computed using machine learning. Step 3 requires cost analysis, made in subsection 0. Step 4 needs the master plan as an input, and steps 5-8 require the results of the first four steps of the model as an input. These steps will be discussed in more detail below.

The first step is to determine the expected patient demand. This is done on the basis of the waiting list and the historical production of recent years. Historical data is used for a forecast that have to be made for this as well. This is because the model should be good representative for three months, and patients with high urgency will not appear on the waiting list after two weeks. Therefore, a forecast must be made so that the (predicted) high-urgency patients are also scheduled for the remaining weeks, so that the waiting list and blueprint planning becomes as realistic as possible.

After the number of patients is predicted, an operation must be determined to predict the surgery time and care product for a patient. As described in subsection 0, 80% of the demand is realised with 25% of the care products, so, the chance that a patient needs further care products is relatively small. Therefore, the choice has been made to only apply the care products for the 80%. From the operations that together supply 80% of the demand per department, a random operation code is chosen and assigned with expected operation and intake time to the predicted patient. Machine learning is used to make this prediction. Furthermore, for the patients who are already on the waiting list, the required capacities are already known, because the surgery is already known.

The second step is to make a connection between the patients on the waiting list and their presumed care product. As described in section 0, care products are assigned to a patient only after treatment. This is because a care product contains all the steps that have been completed. However, the care product must now be linked to the patient sooner if the budget is to to be taken into account. Here a trade-off has to be made between two tested methods, namely a machine learning method and a method where the general care product database is used. Subsection 0 will explain why a trade-off between the two methods is necessary. Then, the third step predicts the healthcare costs and revenue generated for the predicted healthcare product. by means of the care product.

To execute steps 2 and 3, connections must be made between multiple datasets, and data must be added (and prepared) to the waiting list. Figure 4-2 shows the types of datasets to which the waiting list needs to connect in order to perform steps 2 and 3. Figure 4-2 also shows which data is not needed for steps 2 and 3 and the final set-up for the modified waiting list.

Figure 4-2 shows which databases are needed to create the final waiting list, at the bottom is shown which data from which database is used in the final waiting list. Here, it is noticeable that no data from database 4 is used. This is because it is only used to make the connection with database 5 for the care product code and cost, and without this intermediate step, this connection for the costs is not possible. Furthermore, connections are indicated between the databases, with the exception of database 3, since here the data was added in Epic. The data from database 3 is already available but is not yet applied in the current waiting list because this is not yet necessary in the current situation.

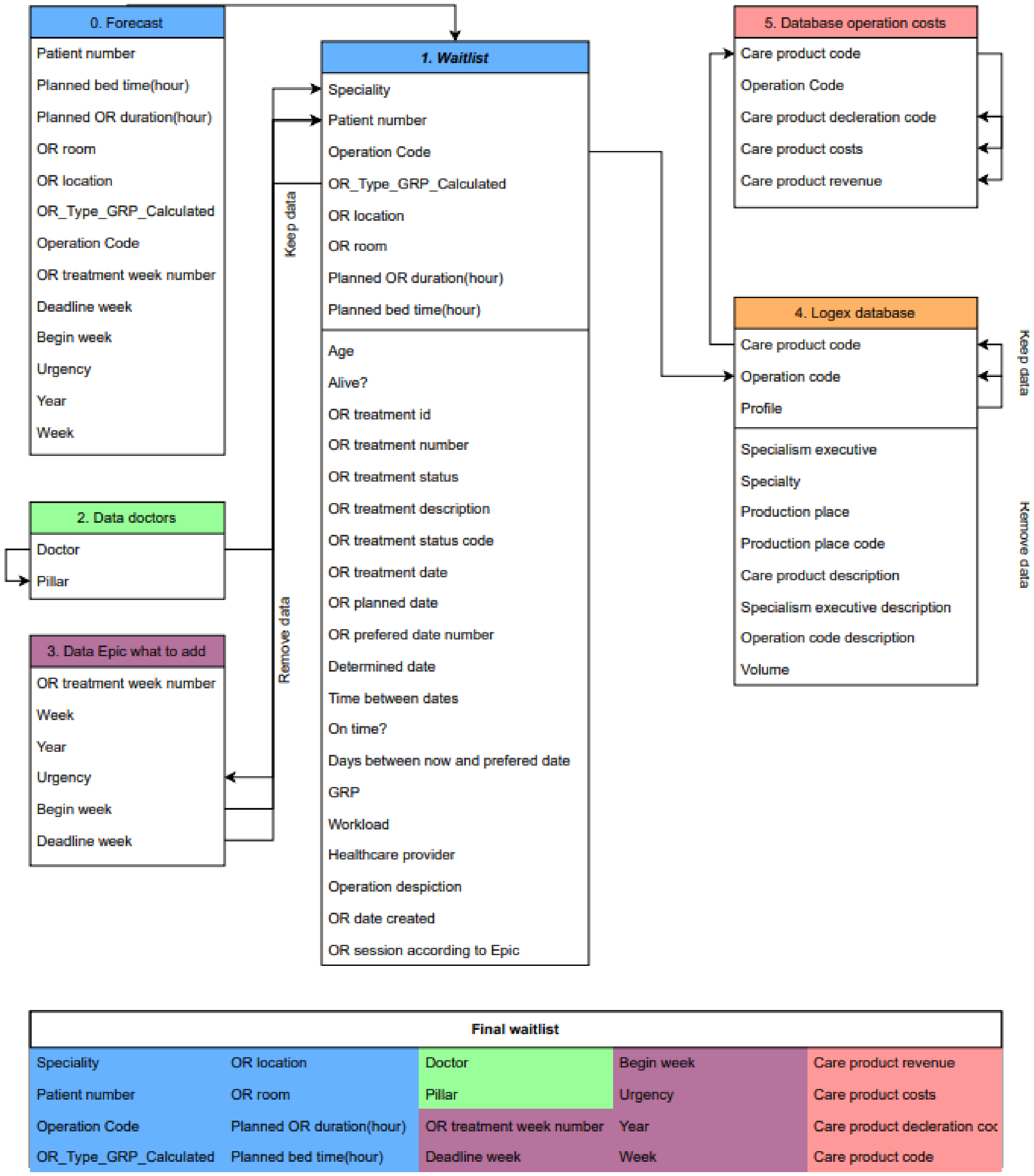


Figure 4-2. The connection between the databases and the resulting final waiting list

The fourth step is to check the available hours per department per pillar for the ORs for the next 12 weeks against the master plan. By using the availability of the ORs as input for the model, the seasonality of the OR availability can be taken into account. This is important because seasonality can vary every year and tends to vary across departments per pillar. The planners of the departments are asked to give the available capacity. In order to make a new capacity distribution, a 5% reduction is made to the stated availability per pillar of the OR's. The 95% will not be optimised financially, because this is where the patients with the highest urgency are scheduled and should not be treated later, as will be described in the fifth step.

As a fifth step, a constructive heuristic is created that will form a planning schedule for the 95% capacity for each week for the expected patient demand. This should take into account certain patient characteristics, such as urgency, duration of treatment, length of waiting list, and cost and revenue. The build-up of Step 5 is shown in a flow chart in Figure 4-3.

The sixth step is to check whether patients are late when only 95% capacity is used. If patients are late, they are first scheduled on the basis of urgency in the 5% capacity reduction. The 5% capacity is then redistributed to the departments based on the expected patient demand. If there are no late patients or if there is still capacity left after the late patients have been scheduled, the seventh step is applied.

The seventh step is to apply a local search heuristic over the 5% capacity. The aim is to first schedule as many patients as possible and then to meet the revenue goals.

The eighth and last step is to add up the number of hours required per week in each department, so that patient blocks can be created and scheduled.

This optimised planning after step five then serves as a blueprint for the operational planning and can be adjusted later with respect to which patients come and when, and whether they can come more often on a day if needed.

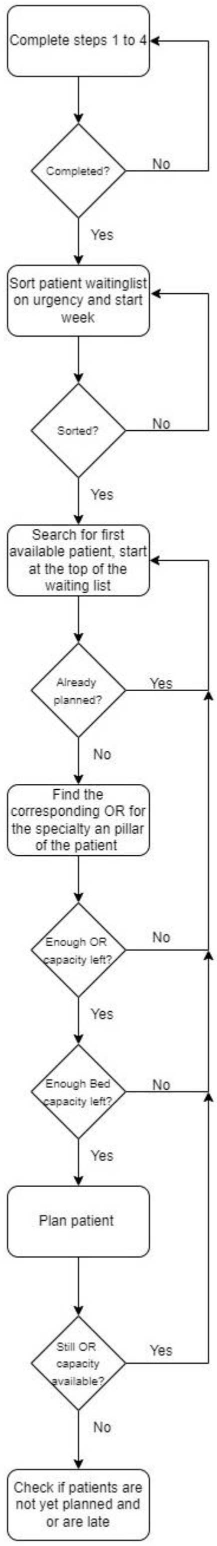


Figure 4-3. Flow chart step 5 of the solution model

4.2.1 Model step-by-step

Forecasting patients for the waiting list

Four regression models described in section 0 were tested and validated per urgency level using the mse score with the 80-20 rule described in section 0. As an input for the forecast, the dataset is used where all treated patients of the past 2.5 years are listed. In doing so, the dataset must first be expanded for each pillar (which is not yet the case in the current situation), and this is done in the same way as shown in Figure 4-2. Each urgency level has been examined, as different parameter settings are needed for each urgency level in order to achieve the most accurate prediction. The results, after testing the models and determining which parameter settings the models work with best with are shown in Table 4-1.

Table 4-1. The mse score of the regression predict models for the urgency levels for the waiting list

	Urgency levels in weeks				
Regression model	2	4	6	12	53
KNN	13.5	3.1	10.9	5.5	5.9
XGBoost	13.8	3.3	16.8	8.6	10.6
Random Forest	9.4	0.5	7.6	4.4	6.6
Linear Regression	9.2	4.3	10.4	6.9	5.9

Based on data presented in Table 4-1, it is concluded that the Random Forest regression model is the best predictor model overall (lowest mse score). When the urgency levels are considered separately, only the urgency levels within 2 and 53 weeks of operation are improved by using the Linear Regression method. Therefore, the choice was made to use Linear Regression for these two urgency levels and to use the Random Forest method for the other levels. This combination of methods is done in order to obtain the most accurate prediction possible.

After the prediction is ready, it will be added to the waiting list. Should it happen that patients with a certain urgency level are already on the waiting list, they will be removed from the forecast, as this would otherwise create a distorted picture of too many patients. Then, the most frequent OR operation numbers are linked to the predicted patients, so that an operation time and laying time is known. Furthermore, the predicted patients are numbered from 1 to X and thus assigned a fictitious patient number, to indicate that these are predicted, rather than actual , patients later on in the blueprint planning stage.

The number of extra patients added to the waiting list per urgency level per pillar

To determine how many patients should be added per urgency level, the number of patients on the waiting list per urgency level and the number of patients in the forecast were considered. The results of how many patients should be added are shown in Table 4-2. The full table is shown in Appendix C, showing the number of patients per week number that should be added according to the prognosis. Table 4-2 shows the number of patients added the three departments in total. The patients who are added with a high urgency (2, 4 and 6) are assigned a week number in which they are predicted to get on the waiting list. This is done to ensure that the waiting list looks as realistic as possible. If no week

Table 4-2. The number of patients that is predicted per specialty per urgency level

	2	**4**	**6**	**12**	**53**
ENT	90	22	28	46	96
GYN	90	1	42	27	65
URO	48	0	72	54	93

were to be indicated for patients with urgency level 2, they will all be scheduled for the first week, which is not possible in reality.

Prediction of care products per patient

In order to predict care products per patient, two possibilities have been investigated. The first option uses machine learning, and the second option uses the general database of care products. These two options are elaborated on below.

Option 1: The machine learning model for the prediction of the care product

To determine which of the four classification models is most suitable for predicting the care product code, the operation code of the surgery should be considered. This is because the operation code concerns the OR waiting list for which the prediction is to be made and constitutes the only similarity between the two datasets. The scores of the classification models are shown in Table 4-3. Hereby, the models have already been tested, and cross-validation has taken place in order to find the best possible parameter setting per classifier type.

Table 4-3. The accuracy score of the classification predict models to predict the care product per patient

Classification model	Accuracy	Precision	F1-score
KNN	60%	53%	54%
Randomforest	63%	56%	56%
Decision tree	62%	56%	56%
Bayes rule	12%	5%	7%

Table 4-3 shows that the Random Forest classifier is the most appropriate with 63% accuracy. This may seem like a bad score, but this is due to the fact that care products that occur infrequently are difficult to predict on the basis of the operation in the OR only. This was also evident in subsection 0, where only 34 healthcare products supplied more than 80% of the demand for the ENT department. This large difference in numbers makes it difficult for a model to predict the less common care products. Accuracy will also improve when the model looks at the total process and what a patient has already gone through, and not just the OR treatment.

Looking further into the predicted data in the train & test set, it is noticeable that the care products that occur more frequently are predicted more reliably. The relatively lower score of 63% is therefore mainly due to the infrequent care products. When looking only at the ENT department, at the 34 care products that supply more than 80% of the demand, the predictions are much more accurate than the earlier 63%. Of these 34 care products, only fifteen occurred more than 60 times in the last five years. The other products occur less frequently, with some of the 34 most common care products even occurring only once. Due to the low frequency of more than 75% of care products, it is very difficult to predict these infrequent care products. However, it can be assumed that the waiting list contains mainly patients who need care products that occur more frequently. For care products that have occurred more than 60 times in the last five years, the prediction accuracy is 78%. Moreover, for the ten most frequent products of a department, there is an even higher prediction accuracy of 80%.

Option 2: Predicting care product per patient with the general databases of care products

In total, there are about 5000 care products listed in a general database. This database shows per healthcare product which transaction codes belong to it and how often these operations belong to this healthcare product. To determine which healthcare product likely belongs to which patient, the database can be searched for each operation code and the healthcare product in which the operation occurs the most can be selected, because this has the greatest chance that the patient will have this healthcare product. However, it must be taken into account that, as with the machine learning method, only the operation codes are known. If all the steps were known, prediction accuracy would probably be much higher. When this method is applied, the accuracy can be determined by applying it to the historical data of the transactions and the corresponding care products, and an accuracy of 81% can be achieved. However, this method takes at least two hours to perform due to the large database and the need to search for each patient on the waiting list. Therefore, a decision must be made on whether the time it takes to perform this method is worth the extra accuracy, as the machine learning method takes about five minutes.

For present research, it is therefore decided to continue with the results of the method using the general care product database because of its higher accuracy.

4.2.2 Defining care product cost and revenue

Now that probable care products have been linked to patients, probable costs and revenues can also be linked to the patients. Because separate agreements have been made with each health insurer about the same care products, costs and revenues will differ per care product.

It can be assumed that all patients on the waiting list are normally distributed. Therefore, the average of costs and revenues is taken. This is because using twice the standard deviation in a normal distribution gives a confidence level of about 95%. Applying three times the standard deviation can increase the confidence level to about 99% [52].

4.2.3 Developing a constructive heuristic

Now that all the necessary data is known, an initial solution can be created. It should be noted that this solution will not focus on the budget yet, because patients are of primary importance and the budget comes second.

The build-up of the constructive heuristic is shown in a flowchart in Figure 4-3. The constructive solution is constructed by first sorting the waiting list patients according to urgency level and start week (for urgency levels, see Table 4-1). For the constructive heuristic, patients with the highest urgency level are placed on the waiting list first, with lower-urgency patients placed at the end of the waiting list. Furthermore, planning must take into account the speciality of the department. So it is not possible for an ENT patient to be scheduled for a URO OR.

To make the model as realistic as possible, current master planning is used for OR and bed capacity only. Furthermore, since no overtime can be scheduled, patient planning must therefore fall within the available hours of the master plan.

From the capacity of the master planning, 5% per department will be reduced and combined to a total amount of capacity that can be used for all departments and will be reallocated later. Subsequently, the remaining 95% of the departments are filled with patients. This is done on the basis of the urgency and the patient's first week, as described earlier. After checking whether there is still room in the 95% capacity for a patient somewhere, the planning for this 95% is definitively stored in the model and will not change anymore. Next, the patients on the waiting list are checked to see if they will be treated too late in the current planning. Should the patients, indeed, be treated too late, they will first be scheduled in the capacity of the 5% reduction of the master planning. The patients who will be late are scheduled in the same way as the patients already scheduled in the previous 95% capacity. When all the patients who are late are scheduled, they are stored in the model, and the schedule does not change anymore. The next step is to see if there is any capacity left from the 5% reduction. If there is any capacity left, it is scheduled in the same way as the previous patients, but in the next step of the model an optimization heuristic is used to optimize the scheduling of the patients in order to meet the budget targets. If not all late patients are scheduled and there is no capacity left to reallocate, the planning blueprint is completed, and it is no longer possible to optimize the blueprint for the budget goals, because the care for the patients comes first.

The 5% capacity reduction offers the possibility of redistributing capacity among the departments as there are no further restrictions. First, planning is based on possible late patients. Because there are no departmental restrictions on the reduced capacity, a department can be allocated more capacity than it has handed in, because it has more patients who would otherwise be treated too late. In the event that no patients will be treated late with only the 95% capacity planning, or if there is any capacity left from the 5% reduction, the capacity will be redistributed based on the financial goals. However, this depends on the size of the waiting list, as the fewer patients on the waiting list, the more the financial targets can be taken into account.

4.2.4 Optimization heuristic

If there is still capacity left from the 5% reduction, budget target can be considered, as shown in Figure 4-4. In order to ensure that the budget target is met in the best possible way, the initial planning of the remaining capacity will be optimized. The simulating annealing (SA) technique is used for this optimization, by swapping patients who are planned and not yet planned. The effect of the swap operator is shown in Figure 4-5.

The move operator is not used because the planning is already filled out as much as possible. The capacity already filled is also controlled by checking whether another patient fits into the remaining capacity. Furthermore, there are no restrictions in the optimization planning except that the new patient must fit into the capacity, as there may be no overtime in the planning.

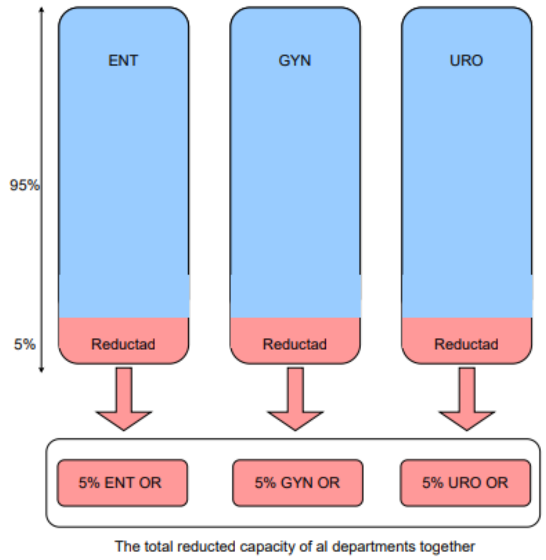


Figure 4-4. A visual representation of the departments that all give up 5% of their OR capacity to be combined

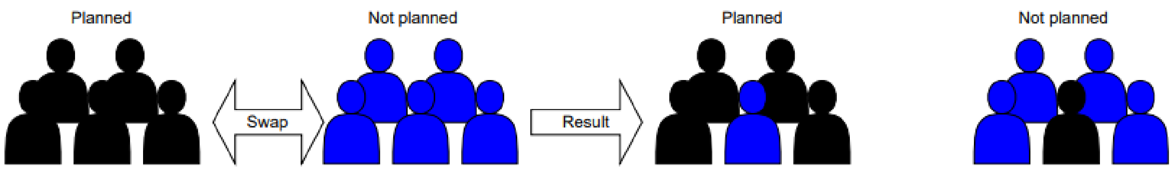


Figure 4-5. The visual representations of the swap operator

Kirkpatrick et al., 1983 SA algorithm is one of the most preferred heuristic methods for solving the optimization problems. A simple optimization algorithm compares iteratively the outputs of the objective functions running with current and neighbouring point in the domain so that, if the neighbouring point generate better result than the current one, it is saved as base solution for the next iteration. Otherwise, the algorithm terminates the procedure without searching the wider domain for better results. An algorithm is prone to be getting trapped in local minima or maxima. Instead, SA algorithm proposes an effective solution to this problem as incorporating two iterative loops which are the cooling procedure for the annealing process and Metropolis criterion [53] [54] [55]. Here, the final planning will be presented in the form of a table and can be compared to the initial planning of the reduced capacity.

The SA method is applied to the group of patients who do not yet need to be scheduled. Therefore, there are no restrictions on which patients can be exchanged. The move operator is also tested next to the swap but does not add enough difference in the results to be used in the final model. This is because the capacity utilisation in blueprint planning is already as good as it can be, no extra patients can be added and no overtime is allowed.

The settings of the SA parameters are shown in Table 4-4.

Table 4-4. The settings for the local search heuristic SA

Parameter	Setting
Start temperature	100
Decrease factor	0.9
Temperature lowerbound	0.5

By testing the SA method with multiple settings for the parameters, the final values of the parameters were determined. The goal is to get a reliability of 95% or higher that the optimal solution has been found. The testing started by first setting the start temperature to the high value of 1000 to see how the results change, with the aim of generating more revenue. After trying different decrease factors, a value of 0.9 was found to be sufficient. While this value may initially seem too high, when the SA method is used for the full 5% reduction capacity, it has a run time of 16 minutes.

The new solution is calculated over the entire schedule and not just the two newly exchanged patients. This was chosen because the model calculated the total solution within a few seconds, and it was therefore decided not to only look at the patients who are swapped. This means that the SA method is not incrementally built.

4.2.5 Determining the capacities needed per department

To determine the required capacity per pillar per department, blueprint planning was considered. Here, blueprint planning will be presented in table form and will indicate, per week, per department, and per pillar, which patients should be planned for a specific week. The capacity of the patients for that week is known and is added up for all patients in order to calculate the number of OR hours and beds needed for each department. At the same time, a calculation is made of how much revenue a department would generate per week if the blueprint planning were adhered to.

4.3 Conclusion

This chapter describes the solution model, which consists of eight steps. Furthermore, the assumptions made regarding the waiting list and the distribution of costs per care product are discussed.

For the first step (*forecast*), a forecast model has been determined for each urgency level, namely, linear regression for urgency levels 2 and 53 and Random Forest for urgency levels 4,6, and 12. For the second step (*presumed care product*), a trade-off has to be made regarding whether a longer model runtime is acceptable or if, instead, when machine learning method is chosen, an overall lower accuracy is acceptable. For the model, the care product database is chosen because this has a higher accuracy, indicating that it gives a better prediction for the presumed care product. In the constructive solution, it is first considered which patients needs care and then the financial goals, so that the interests of the patients are placed above all in the model. The constructive solution fills 95% of the available OR capacity and only looks at the urgency of the patients and the start and deadline weeks when patients need to be treated. The remaining 5% capacity per department will be reduced and combined to a total amount of capacity that can be used for all departments and will be reallocated later in the optimization heuristic. The 5% capacity reduction offers the possibility of redistributing capacity among the departments as there are no further restrictions. First, planning is based on possible late patients. Because there are no departmental restrictions on the reduced capacity, a department can be allocated more capacity than it has handed in because it has more patients who would otherwise be treated too late. In the event that no patients are treated late with only the 95% capacity planning, or if there is any capacity left from the 5% reduction, the capacity will be redistributed based on the financial goals.

5. Results

It does not matter how beautiful your theory is, it does not matter how smart you are. If it does not agree with experiment, it is wrong.- ***Richard P. Feynman*** *(1918-1988)*

This chapter presents the results of the model described in chapter 4 and answers the following sub-question:

"What is the result of the chosen model, and how much does the hospital benefit from this?"

The chapter first explains how the model has been validated and verified and then provides a description of the blueprint plan. Section 5.1 discusses the validation and verification of the model. Section 5.2 explains the experimental design to test, if the 5% reduction is indeed the best setting for the planned capacity reduction. Section 5.3 looks at the general overview of the blueprint, the results of the experiments, and the redistribution of the capacity. In section 5.4, the financial results of the model are examined and compared with the goals set by Radboud UMC, starting with the overview of the general results and then taking a deeper look at the pillar level. Section 5.5 provides a conclusion.

5.1 Validation and verification

The model is validated by checking the results with experts in the field. Thus, the blueprint planning has been validated by the planners to determine whether a realistic number of patients is scheduled per week. While this was shown to be the case, the 90% utilisation due to patient changes in the OR also must be taken into account. Despite this, the blueprint offers a good assessment of the situation, including the number of patients that can be scheduled in a week.

The financial side of the model has been validated by a business controller who, among other things, is in charge of making the production plan for the ENT department and also has insight into other hospital departments. It has been confirmed that the financial results of the model are positive and that it gives a realistic picture of the goals of the relevant departments. The redistribution of part of the capacity of the departments means, however, that a department's goals cannot be achieved, but they must then be adjusted because the overall goal can be achieved. The same applies to the reallocation of capacity between the pillars of a single specialty.

5.2 Experimental design

During this research, a decision was made to apply a 5% reduction for capacity reallocation as this is expected to be a realistic amount of capacity that can be applied in practice. However, it should also be explored whether this kind of reduction does deliver a better result or if instead another percentage reduction works better. Therefore, a total of three experiments settings are carried out in terms of how much the basic capacity is reduced.

First, a short 0% reduction is tested to get a baseline result with which the effect of the reduction can be tested. The 5% reduction is then tested to see if it delivers any benefits. A 10% reduction is also tested to determine if higher reduction delivers better results than a 5% reduction. A reduction of more than 10% is not tested because it is not realistic to redistribute so much capacity: if over 10% of capacity were to be redistributed, it could not be used by the departments, and ORs would not be used efficiently or not used at all.

The experiments conducted in the present study will focus on how many patients can be helped with the same amount of total capacity and how many patients will be treated late (since the fewer patients are treated late, the better). All experiments are conducted with the same data set.

The input dataset for the experiments is the newly created waiting list dataset, as shown in Figure 4-2.

5.3 Blueprint schedule and the current waiting list

The blueprint will be displayed by the model with a table, which shows which actual or projected patients should be scheduled per week per department and per pillar. The characteristics of the blueprint table are shown in Table 5-1.

Table 5-1. The characteristics of the blueprint plan with an example patient

Specialty	Pillar	Patient number	Operation	Start week	Deadline week	Urgency	Operation Time OR[hour]	Time occupies a bed[hour]	Revenu	Costs	Profit
ENT	Otology	1	681878	1	3	5	2	0	€ 755.00	€ 584.71	€ 170.29

The blueprint itself is not included in the report as it contains patient information that cannot be published for privacy reasons. As indicated in the assumptions in section 0, the actual waiting list will be even more extensive in practice than what has been forecast. Despite this, the model can be adequately tested because the waiting list is sufficiently extensive for the period of 12 weeks in the model.

5.3.1 Results of the three experiments

The model has first been tested for a 0% reduction in capacity. Given that there is no reduction, the full (100%) capacity is filled with the constructive heuristic described in section 0. The most important point to note in this regard is that only four fewer people are treated late than in the case of a 5% reduction, as will become clear in section 5.3. These patients all belong to the same pillars, and that amount of capacity is not sufficient to treat all patients on time. However, no capacity can now be reallocated to treat these patients, as the full capacity is used. This clearly shows the benefit that the redistribution of a small amount of capacity can have. With a 5% reduction, 56% of patients, who would otherwise be treated late, could still be treated on time. When using 10% reduction, however, the number of late patients remains virtually the same, increasing only by 9 patients. This is because late patients belong to the same pillar as those under a 5% reduction and the pillars do not have sufficient capacity.

Table 5-3. The amount of patients that can be helped in total per reduction level

Reduction	Number of patients planned over 12 weeks	Increase over 0%	Increase over 5%
0%	1076		
5%	1110	3%	
10%	1131	5%	2%

What is noticeable is that when a 10% reduced capacity is redistributed according to the patients who are late, only two patients are left who cannot be planned. This is a very good result compared to the 44% of late patients who could not be scheduled under a 5% reduction in capacity. However, while he 10% reduction result is good, it is not realistic for the practice in 2022. For this amount of redistributed capacity, it must also be checked whether the doctors are available to handle this amount of extra capacity. After all, capacity can be redistributed, but if the doctors are not available, the extra capacity is of no use to a department. Table 5-3 shows how many patients in total can be helped per reduction level. It should be noted that doctors from the pillars that are allocated the capacity also needs to be available. So, with 10% reduction, the availability of the doctors should be checked first. By using the tactical plan model to make the necessary adjustments, the uncertainties in the strategic planning become less serious because they are anticipated during a care year, and more patients can be treated with the same amount of total capacity.

Table 5-4 shows the average utilisation rate of the ORs per reduction level. It becomes clear that the utilisation rate increases when the reduction level also increases. This is expected, as an increase in reduction implies that more patients can be helped. Furthermore, the utilisation rate of the ORs is relatively low, which is due to the fact that the prediction model (step 1 of the model) uses data from the Covid period. This gives a distorted picture of the reality, and in the last three weeks of the period under review, fewer patients were predicted than there was capacity for, as shown in Figure 5-2, for all three experiments. In the Covid years all three departments had to give up capacity because of Covid and therefore could treat fewer patients.

Table 5-4. The average utilisation rate of the ORs by reduction level over the 12-week time span.

Reduction	Utilization
0%	86%
5%	87%
10%	93%

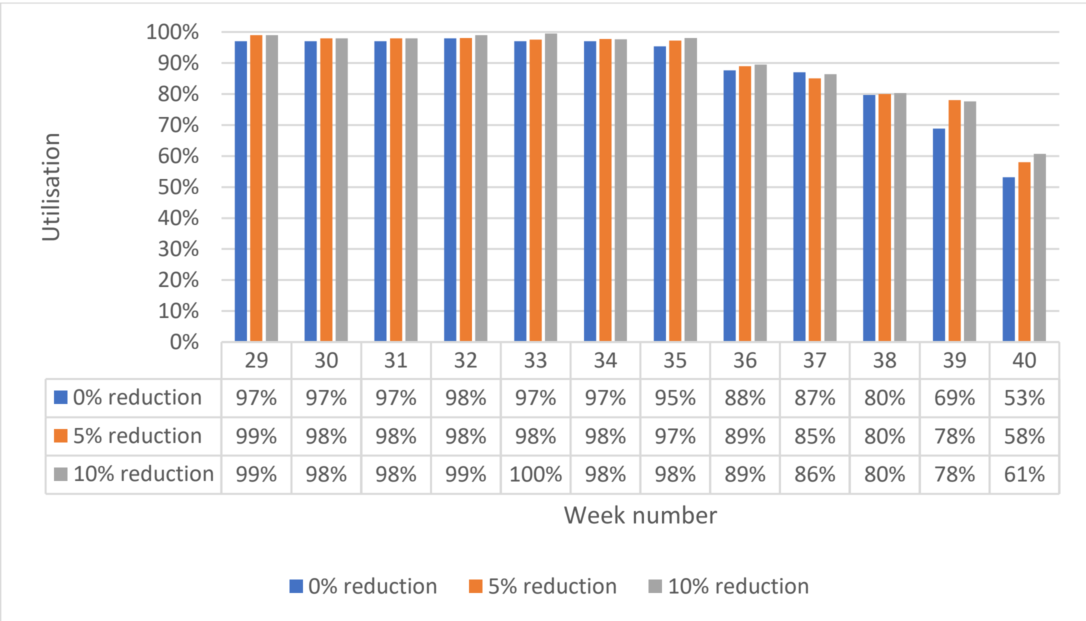
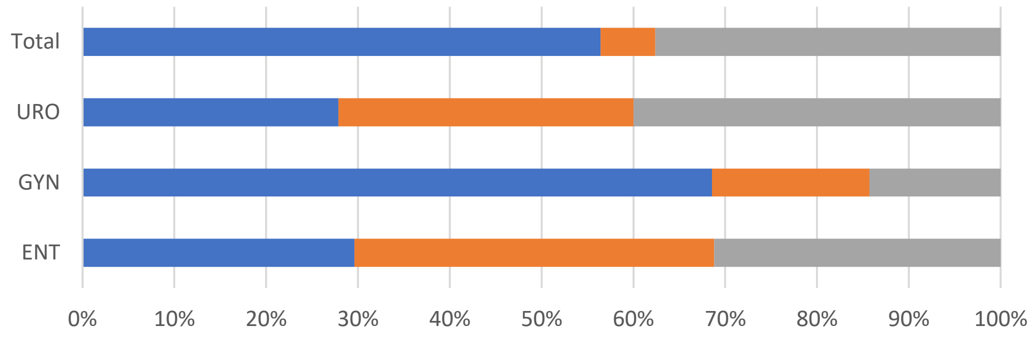


Figure 5-2.The average utilisation rate of the ORs by reduction level per week

When looking at the Figure 5-2, the utilisation of the ORs at 0% reduction is lower than at 5% and 10% reductions. This, in itself, is not strange. However, the difference is not very large, especially in the first weeks, because the capacity that is not used in the 0% reduction is capacity of pillars that have been allocated the least capacity in the master plan. From this it can be concluded that reallocating capacity has advantages in terms of OR utilisation. The difference between the utilisation of 5% and 10% reduction does not make much difference, but the 10% reduction is still not realistic as mentioned earlier in this section.

5.3.2 Experiment 2: 5% reduction results in detail

The number of patients scheduled in the blueprint per department in the 95% capacity is 57% of the total waiting list. However, 6% of patients that are not yet scheduled will be scheduled too late, and 38% are not scheduled yet.



	ENT	GYN	URO	Total
Planned	37%	24%	39%	57%
Late	49%	6%	45%	6%
Not planned	39%	5%	56%	38%

Planned Late Not planned

Figure 5-3. The percentages of patients scheduled, late and not yet scheduled from the waiting list by department and total

Figure 5-3 shows the percentages of the number of planned patients. It also shows which department has the largest share of planned patients. Furthermore, it shows how many patients are not yet scheduled and late and which ones are not scheduled but are still on time.

After the 95% capacity has been planned, the 6% of the patients on the waiting list that are currently not planned and late. It turns out that when the 5% capacity is distributed among the departments, 56% of patients who are late can still be scheduled. The effect this has on the distribution of capacity

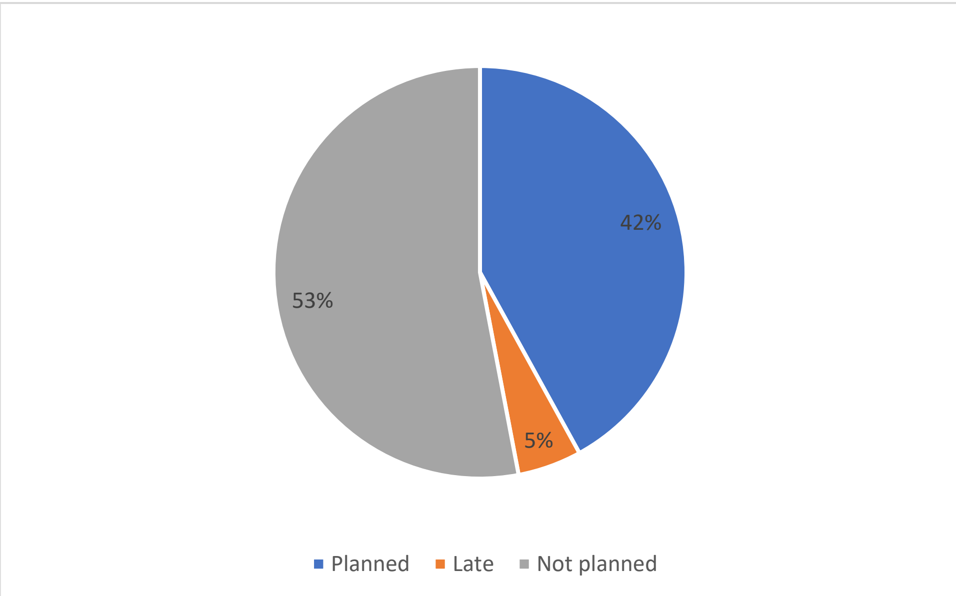


Figure 5-6. The percentage of patients planned, late and not planned of all 100% patients on the waitlist

between the departments is considered in later in this chapter. After the 56% of late patients are scheduled, there is no capacity left to schedule any more patients and the model is complete.

In the current situation, it is not possible to optimise on budget targets. Figure 5-6 shows how many of the patients on the waitlist are scheduled, late, and not yet scheduled. A part of the patients is still late, which indicates that there is insufficient capacity to provide all patients with timely care. This is a consequence of the delayed care due to Covid. The aim of the 95% capacity blueprint is to have the highest possible utilisation of OR capacity because, as indicated, this is leading. Figure 5-7, shows that the OR utilisation in the first weeks for the departments is above 95%. However, occupancy is lower in the final weeks because more patients are present than a certain pillar can cope with. To test this, a model was also created that does not take into account the pillars and only looks at the capacity of a department. The utilisation of the OR capacity in all weeks is then 98% on average, but this is not realistic because pillar capacity is determined by the number of doctors present. In addition, when looking at the seasonality of Figure 2-6, there is also less capacity used in the weeks in question, which may be because doctors from a pillar go to a conference and are not present then. It is also possible that the occupancy here is lower because the forecast of the patients has not been accurate enough, as it was made based on data from the Covid years. This means that fewer patients were predicted because the department(s) had to give up capacity because of Covid.

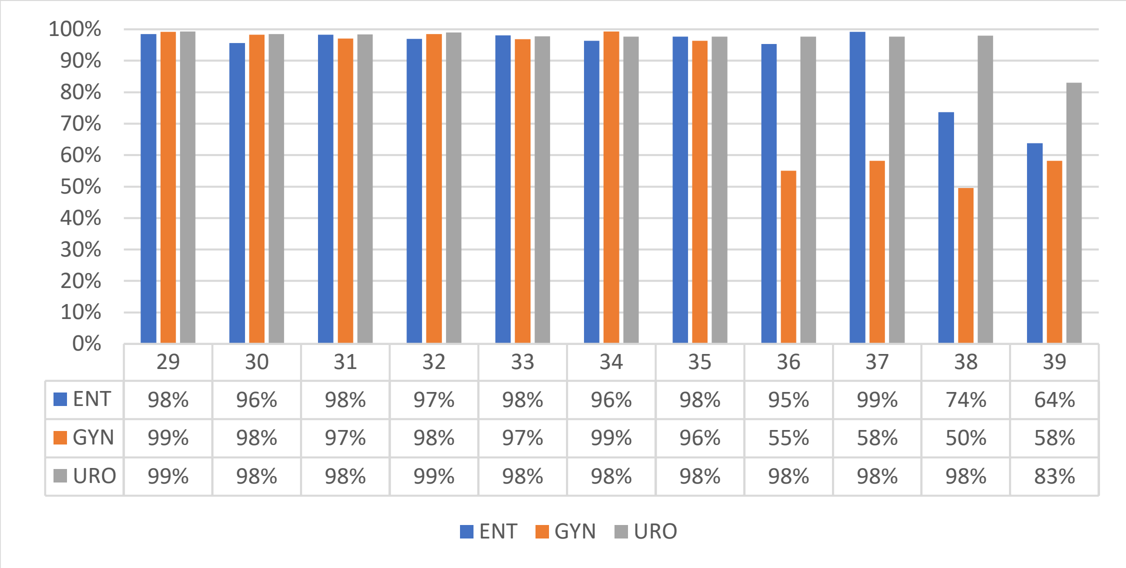


Figure 5-7. The utilisation rate of the OR for the 95% capacity

Table 5-5, shows how many hours each department gains or loses per week, compared to the original capacity distribution of the master plan are shown in Table 5-8. If a value in Table 5-5 is negative, this number of hours must be handed in. If it is positive, the department receives these hours in addition to the hours it already had according to the master plan.

Table 5-5. The number of hours of OR capacity that a department must give up or gains

Week	ENT	GYN	URO	Utilization 5% OR capacity
29	0	0	0	97%
30	6.5	-2.4	-5	93%
31	0.1	-2	1.5	96%
32	4.7	-2.4	-2.5	98%
33	3.2	-2	-1.4	98%
34	1.83	-2.4	0.5	99%
35	-1.3	-2	2.8	96%
36	2.1	-2.4	0.1	98%
37	1.4	-2	0.1	96%
38	-2.9	-1.7	4.35	98%
39	2.7	-1.3	-1.4	100%
40	-2.27	-2.4	4.35	97%

The last column of Table 5-5 (the right column) shows the utilisation rate of the reduced 5% capacity per week. The utilisation rate is 97% per week on average. The extra hours that a department receives must be divided into OR blocks after they have been added to the existing hours, because it is not practical for a department to receive an extra 3.5 hours in an OR week schedule. Therefore, it is more convenient that, for instance, the hours for two weeks are added together and become one OR block instead of two half blocks.

Table 5-6. The original distribution of the capacity of the 5% reduction per department

	Capacity reduction master plan			
Week	ENT	GYN	URO	Total
29	4.8	2	4.5	11.3
30	4.6	2.4	5	12
31	4.8	2	4.5	11.3
32	4.6	2.4	5	12
33	4.8	2	4.5	11.3
34	4.6	2.4	5	12
35	4.8	2	4.5	11.3
36	4.6	2.4	5	12
37	4.8	2	4.5	11.3
38	4.6	2.4	5	12
39	4.8	2	4.5	11.3
40	4.6	2.4	5	12

Table 5-8. The new distribution of the capacity of the 5% reduction per department

Week	ENT	GYN	URO
29	4.8	2	4.5
30	11.1	0	0
31	4.9	0	6
32	9.3	0	2.5
33	8	0	3.1
34	6.43	0	5.5
35	3.5	0	7.3
36	6.7	0	5.1
37	6.2	0	4.6
38	1.7	0.7	9.35
39	7.5	0.7	3.1
40	2.33	0	9.35

When examining the pillar level, it can be seen the pillars Otology and Rhinology are allocated extra hours when the ENT department gets extra capacity. The other two pillars of the ENT department do not need the extra capacity. For the GYN department, it has to give up virtually all of its capacity because this department rarely has patients who are late. Only the Obstetrics pillar receives additional capacity in the last three weeks. In the URO department, only the NTX and the Functional Pillars are allocated additional capacity. So, it can be concluded that the ENT department gets the most extra capacity and GYN has to give up most.

5.3.2.1 10% Reduction

The new distribution of the 10% reduced capacity is shown in Table 5-9. As with the 5% reduction, most of the capacity has been redistributed to the ENT and URO departments. This is because the GYN also has almost no patients who are late, making it easier to give up capacity.

Table 5-9. The new distribution of capacity with 10% reduction

Week	ENT	GYN	URO
29	0	0	0
30	15.9	0	5
31	11.9	0	8.6
32	15.4	0	6.2
33	8.1	0	12.4
34	6.5	0	15.1
35	10.8	0	9.9
36	12.2	0	9.7
37	11.6	0	8.4
38	10.9	0.7	9.9
39	13.9	3.9	2.2
40	11.7	3	5.9

Looking at the pillar level, Otology especially gets the most extra hours at ENT. At the URO department, the pillars NTX and Functional are assigned the most extra capacity.

5.4 Financial results of the model

This section first discusses the general financial results across all departments taken together and then examines the results for each pillar.

General overview of the financial results of the three departments

The financial data is business-sensitive information that cannot be published. Therefore, Figure 5-8 shows how the financial situation is built up with the 95% capacity and a 5% reduction plan.

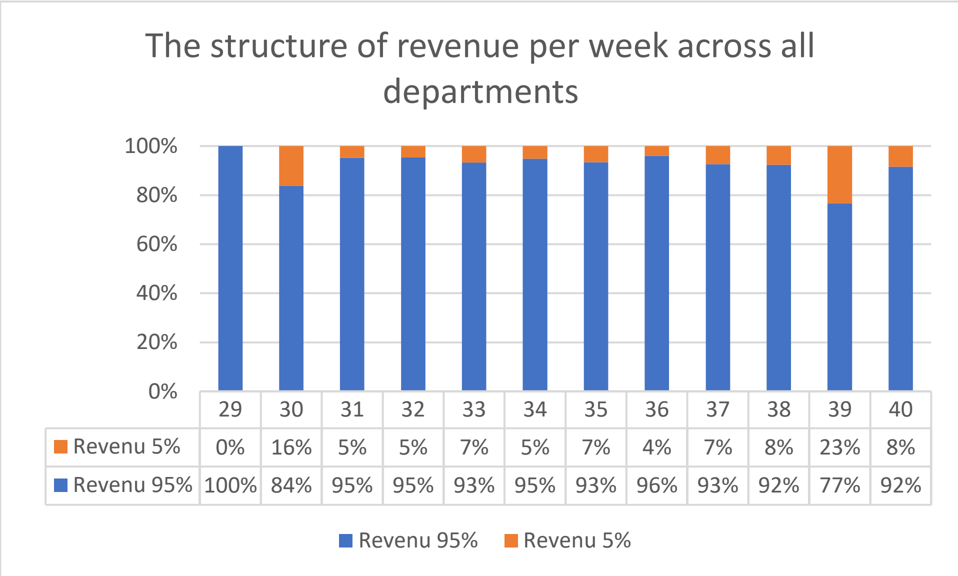


Figure 5-8. The revenue structure per week of all three departments

Figure 5-8 shows that the 5% capacity does have an effect on the financial situation, because in weeks 30 and 39, the 5% capacity accounts for 16% and 23% of the turnover, respectively. Looking at the blueprint and the pillars of the departments in these weeks, it becomes clear that the ENT and URO departments have been allocated extra capacity and that the presumed care products are causing a peak in revenue.

Overview of the financial results of the pillars per department

Considering the pillars of all three departments, it becomes evident that the Otology and Head and Neck Surgery pillars of the ENT department generate the most revenue.

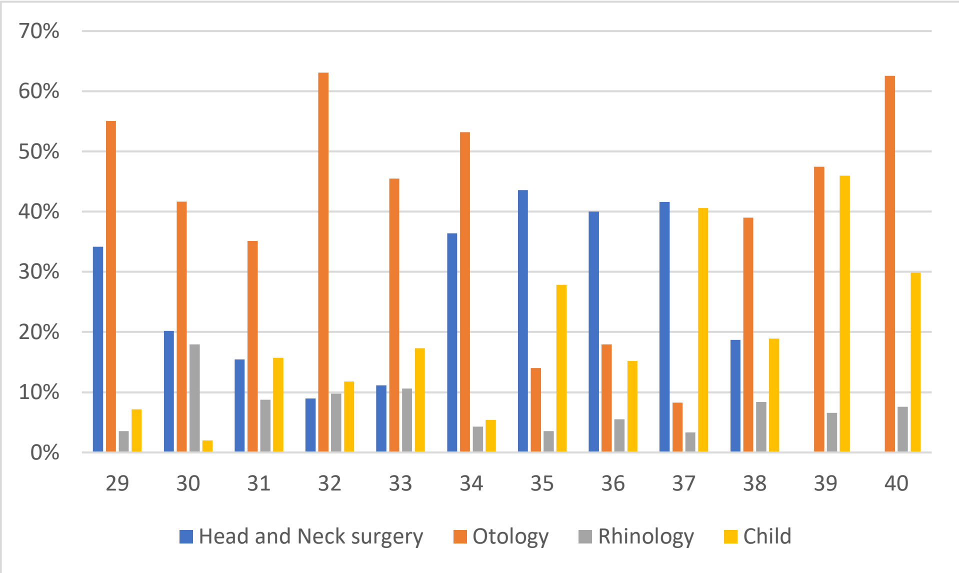


Figure 5-9. The revenue ratio per pillar of the ENT department

Figure 5-9 indicates that these are also the two pillars that generate the most turnover for the ENT department, with an average of 40% of the turnover coming from the Otology pillar and 25% from the Head and Neck Surgery. Here, Otology and Head and Neck Surgery both get one third of the capacity in the master plan used.

For the GYN department, the Genetic pillar creates the most revenue, with 46% of all GYN revenue. For the URO department, pillars Functional and Oncology generate the most revenue, with 27% and 42% by the Oncology pillar.

5.5 Conclusion

This chapter presents the results of the solution model. It can be concluded that the model works well and that the generated blueprint planning is comparable to reality when looking at the number of patients per pillar per week. However, there is still room for improvement in the model, especially in the first step involving prediction of extra patients. This is because the prediction is done using data from the period when there was Covid. For a more reliable prediction, it should be investigated whether there is data available from (several) years prior to Covid.

Furthermore, the results show that reallocating capacity does have advantages, especially in terms of treating patients in a timely manner. In the current situation with the tested waiting list, a 10% reduction per ward is best for assisting all patients. This, however, is not realistic in 2022, as the doctors need to be available, and there is still a Covid-related shortage of staff. Therefore, a 5% reduction is the most realistic one to apply, and in the current situation, 56% of the late patients can still be treated on time.

The financial results of the model match reality well. Thus, the results in terms of the turnover and the profitable pillars are predicted accurately. Furthermore, the 5% reduction capacity is divided among the departments, but also among the pillars. This makes it clear for the relevant departments what the capacity is intended for. However, it should be noted that the redistributed capacity must be converted into whole OR blocks.

6. Implementation and recommendations

Ideas are easy. Implementation is hard – ***Guy Kawasaki****(1954-)*

In this section, the recommendations of this research are discussed. The recommendations are based on the results and assumptions made from the model.

6.1 Recommendations

Although the model has been shown by this study to work well, and the results were found to be good using validation by experts, there is still room for improvement, and in particular, this concerns improvements in the reliability of the presented model. In light of that, the following recommendations are made:

1. To further expand the database of completed patients per urgency level/pillar/week/year to increase forecast reliability.
2. To adjust the waiting list in the database, so that the patients, who indicate that they desire to be assisted later, can change the start week or are temporarily put on a shadow waiting list until they wish to be helped. This should be done so that no patients are scheduled in the blueprint who do not yet desire to be treated.
3. To investigate capacity redistribution within the departments between the pillars to maximize the capacity of an individual department.
4. To make whole OR blocks from the re-allocated capacity, this applies both to hours that must be handed in and to hours that are gained.
5. To analyse the inflow for OR treatments from the patient clinic so that predictions for filling the waiting list are not based on historical data alone.
6. To create a database of the predicted care products per operation. This will reduce the runtime of the model from 4 hours to 1 hour.

6.2 Implementation of the new blueprint schedule model

The designed blueprint schedule is static and created reflecting the current circumstances. The blueprint schedule can be implemented if the steps from Figure 6-1 are followed. A brief discussion of each step is offered below.

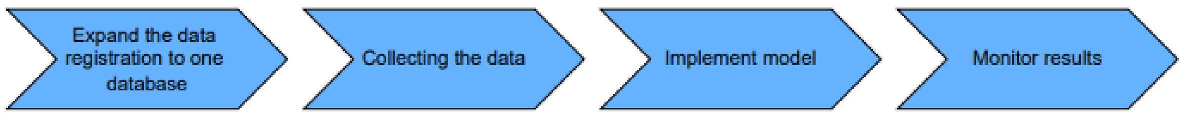


Figure 6-1. General overview of the implementation process

Expanding data registration

For the first step of the model (*forecast*), a new database should be created using the current database for the number of treatments performed as an input. This new database should track the number of treatments performed per year, per week number, per urgency level. The second step (*predicted care product*), is to expanded the database for the waitlist. This way the model needs to run for less time, and only one database is needed instead of three. Furthermore, a second database needs to be created, where care products per operation have already been predicted. This can be made because the care product in question that has the highest probability of surgery is always chosen, and this data is already known. The new database will allow the second step of the model to be executed faster and will reduce the runtime of this step from 4 hours to 1 hour. When the second database is created, costs and turnover can also be determined per healthcare product, with the Logex database.

The department responsible for expanding and adding databases is BIA. BIA is Radboud's data processing department that also builds the models. Furthermore, this has to be done in collaboration with PVI, as they consult with the departments and are responsible for tactical planning.

The biggest obstacle for expanding data registration is that there has to be a demand in the Radboud UMC to start using the developed tactical plan model. This is not the case at present, because first, this study had to be carried out to assess how much benefit a tactical plan model is likely to deliver. When the demand from the Radboud UMC emerges, then the biggest challenge will be the time and availability of the BIA department.

Data collection
For the model to work properly, the data described above must be tracked and collected. The necessary data falls into the following categories:

1. The number of patients per week per treatment urgency level
2. The current waitlist
3. Cost and revenue per care product
4. Care product database per surgery
5. Master plan and seasonality of the available capacity.

This data should be reviewed for from present to future to enable tactical planning. Furthermore, historical data should also be retrieved as far back as possible, in order to create an optimal plan at the tactical level in the present. After all the data is collected, the model can be run, and a tactical blueprint plan can be created.

Data collection should be done by the expanded database and monitored by the responsible person from PVI, because PVI is responsible for conducting and supervising the TPOs. Furthermore, it is advised to review the blueprint every three weeks for every TPO and to run the model every three weeks to compare the results. This because the circumstances can change every week, especially with Covid.

Model implementation
To effectively implement the model, in addition to expanding the database and collecting the right data, several other steps need to be carried out, and namely:

1. Collecting the necessary data
2. Running the model designed in this study
3. Presenting the results to doctors and accompanying staff
4. Running a pilot with the three hospital departments
5. Assigning the responsibility for the TPO to an employee with the required knowledge and skills and trusted by the doctors
6. Further expanding and testing the model across other departments within Radboud UMC
7. Establishing a standardized tactical plan process withing the Radboud UMC.

First, as mentioned earlier, the right data must be collected to create a realistic waiting list. Then, the model described in chapter 4 should be run. After that, the results of the model and those of this research should be presented to the doctors, planners, department heads, and PVI. Based on the results of this study, the aforementioned people should be convinced that the tactical plan model is definitely a toehold to the current way of working. It is expected that The resistance to this will mainly come from the doctors and heads of departments, as none of them want to give up capacity in the first place. This is also where the biggest challenge will lie with implementing the model. However, using the results of chapter 5, it can be shown that tactical planning can have many benefits even in a department alone by redistributing capacity across the pillars. Therefore, if there is a lot of resistance, a pilot could first be conducted per department on its own, in which the current capacity of the departments is redistributed among the pillars. This reallocation of capacity is already happening ad-hoc in the departments , but with the tactical plan model this could be done beforehand which creates calm and clarity within a department.

If the pilots per department are a success and the doctors and department heads are enthusiastic, a pilot can be conducted for all three departments together, as was done in the experiments in this study. After the pilot with the three departments is successful and the majority of the key actors are convinced, an employee should be appointed within PVI, as this department is responsible for the TPOs, who will be responsible for tactical scheduling every three weeks. The employee should have the knowledge and skills required to run the tactical plan model and manage the results with the departments. The employee also needs to have knowledge about different forecasting models to be able to adjust these for the first step of the model in case of a hiccup or if a change in design is necessary. This is important because the first step ensures that the waiting list is as realistic as possible and the best possible tactical plan can be made. This employee should also responsible for ensuring that the OR planners adhere to the blueprint planning as much as possible in terms of the number of people to be scheduled per week.

When tactical planning goes well within the three departments, the model can be extended to other departments. The new departments must first be analyzed, and the databases expanded for that purpose. When all tactical planning goes well, it can be made as standard within Radboud UMC. Standardisation will come fairly naturally as more and more departments get involved in the tactical plan model and it is implemented regularly, every three weeks. Furthermore, when other departments see that tactical planning adds value to the departments already using it, the new departments will be more quickly convinced to apply it.

Timeline
Currently, it is quite difficult to predict a timeline for implementing the proposed model as there is still some expectation of Covid disrupting normal workflow. Furthermore, it is also extremely difficult to predict accurately how much time it will take to convince the doctors and department heads to adopt the model. In addition, expanding the database depends on the availability of the BIA department, which must first have time to create it, and it’s still unknown when this time will be available. Finally, to implement the model, the official request must first be issued by Radboud UMC to make the model, as PVI may not start implementing the model on its own.

7. Conclusion

*Simplicity is the ultimate sophistication – **Leonardo da Vinci**(1452-1519)*

7.1 Conclusion

This research was undertaken to investigate the possibility and effects of creating a blueprint for a tactical-level operating room planning and control model for Urology, Gynaecology, and ENT departments, so that OR and ward capacities can be specifically distributed over the next 2-3 months and the budget goals are met. To our knowledge, this issue has not been explored before. Therefore, this research has contributed to theory by creating a model that realises such a blueprint.

As shown by the present study, the model works properly and the effects from higher or lower reductions in capacity can be successfully experimented with. Furthermore, there is an option for applying the model to one or more departments at a time. Thus, when used for only one department, the model will reallocate the capacity among the pillars of the department. In addition, the model is easy to apply, and, if the right data is available, it could also be applied to other hospitals.

The analysis shows that the model can clearly reallocate capacity between the relevant departments and that the number of patients per pillar planned per week is realistic. Furthermore, the financial results are reliable and make it clear what effects can be achieved from a 5% reduction on the financial results in one week. It also shows how reallocating 5% capacity per department can have an effect on patients who would otherwise be late but can now be treated on time. For example, the GYN department has only 3% of patients late with the current capacity, and the ENT and URO departments have 55% and 41% respectively. This is why GYN has to give up the most capacity in all weeks, because the focus is first on patients who are otherwise late.

In addition, the results show that reallocating capacity does have advantages for elective care, especially for treating patients on time. In the current situation with the tested waiting list, a 10% reduction per ward is best to ensure that all patients are helped. However, this is not realistic in 2022 because the relevant doctors also need to be available, and the hospital still experiences Covid-related staff shortages. Therefore, a 5% reduction is the most realistic one to apply, and in the current situation, 56% of the late patients can still be treated on time. By using the tactical plan model to make the necessary adjustments, the uncertainties in strategic planning become less serious because they are anticipated during the care year.

Support must also be created within the department for proper application of the blueprint, since it is unlikely that a given department will gladly give up capacity to another department. Therefore, a good first step is to create a blueprint for a single department and reallocate capacity across the pillars of that department, to demonstrate that the model and the blueprint are well-suited for its goals.

The results of the research provide quantitative data that prove that a tactical blueprint plan that reallocates the OR capacity can benefit a hospital to help more patients effectively and help reach its financial goals.

This research adds to the science in that it integrates capacity management with financial goals of a hospital. Furthermore, proposed theory (model) is applicable to other hospitals and/or hospital departments. It is important that the right (input) data is available or that a start is made to record the right data. Without the right data, the theory cannot be used.

7.2 Limitations

The research presented in this thesis is subject to several limitations, most of which are centred around a lack of data or uncertainty in the data regarding the waiting list or the financial data of the patient.

The first limitation is that the costs for the care products are assumed to be normally distributed and the mean with the standard deviation is used. Using the mean can distort the financial results. Therefore, it would be better to use the cost per insurance per patient. Another limitation is that there is despite the fact that the financial results are good, the distribution of healthcare products should also be considered , so that the turnover and costs become more accurate. This results in the fact that the financial picture cannot be shown to be completely accurate. However, during the validation, the results of the model were in good agreement with reality, and choosing the right distribution per care product will make the financial prediction even more accurate.

The second limitation is that the operation codes are used for forecasting, which provides 80% of the demand for a department. However, these may change in the future and must be taken into account. In addition, a probability per care product can be calculated and used for predicting an surgery for a predicted patient. This is not a major limitation, but if a probability per care product is determined, a more realistic picture may emerge in the forecast.

The third limitation concerns assessment of the reliability of data used for forecasting(the first step of the model), because if this is not done properly, the blueprint will not deliver optimal results. For instance, too few patients are predicted than who actually arrive at the hospital. When more reliable data is collected, this limitation can be fixed. The data has a big impact on the final result of the forecast, as data from during Covid does not give a realistic picture of a normal healthcare year. Indeed, all three departments at Radboud UMC had to sacrifice capacity and so were not able to treat the number of patients comparable to that of a normal care year.

The fourth limitation is that it is assumed that all patients on the waiting list are cleared for surgery. In practice, the patients on the waiting list still have to go through a number of steps prior to surgery (such as anaesthesia). The impact of this is that in the model, patients are now proposed to be scheduled in week X, but in practice are not ready for surgery at all because not all steps have been completed yet.

The last limitation is that the model makes no distinction between outpatients and inpatients. This factor can be added to the model when needed. To implement this, the waiting list must indicate whether a person is an inpatient or outpatient and the capacity of a possible inpatient OR must be specified per pillar per department in the master plan.

7.3 Future research

We recommend future research to focus on another way of forecasting the pillar and urgency levels using a model that is dependent either on other types of data or has more reliable data. This is the first step to improve the model and make it more reliable.

Furthermore, it should be investigated whether the waiting list can be adjusted so that only those patients who are, in fact, ready for surgery are scheduled, and that a distinction is made between in- and outpatients.

Another question that needs further investigation is whether the proposed blueprint can be made dynamic, so that it can respond more effectively to another patient mix than that predicted by the forecast. This study generated a static blueprint schedule, which should be regularly reviewed (e. g., three weeks for every TPO). However, dynamic blueprint schedules would make this unnecessary. Therefore, further research could investigate how capacity can be dynamically adapted when the patient mix changes.

Finally, the creation of patient groups, which has been discussed extensively in the literature, can be examined to see whether it would also have an effect on the outcome of the model designed in this study.

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Appendix A

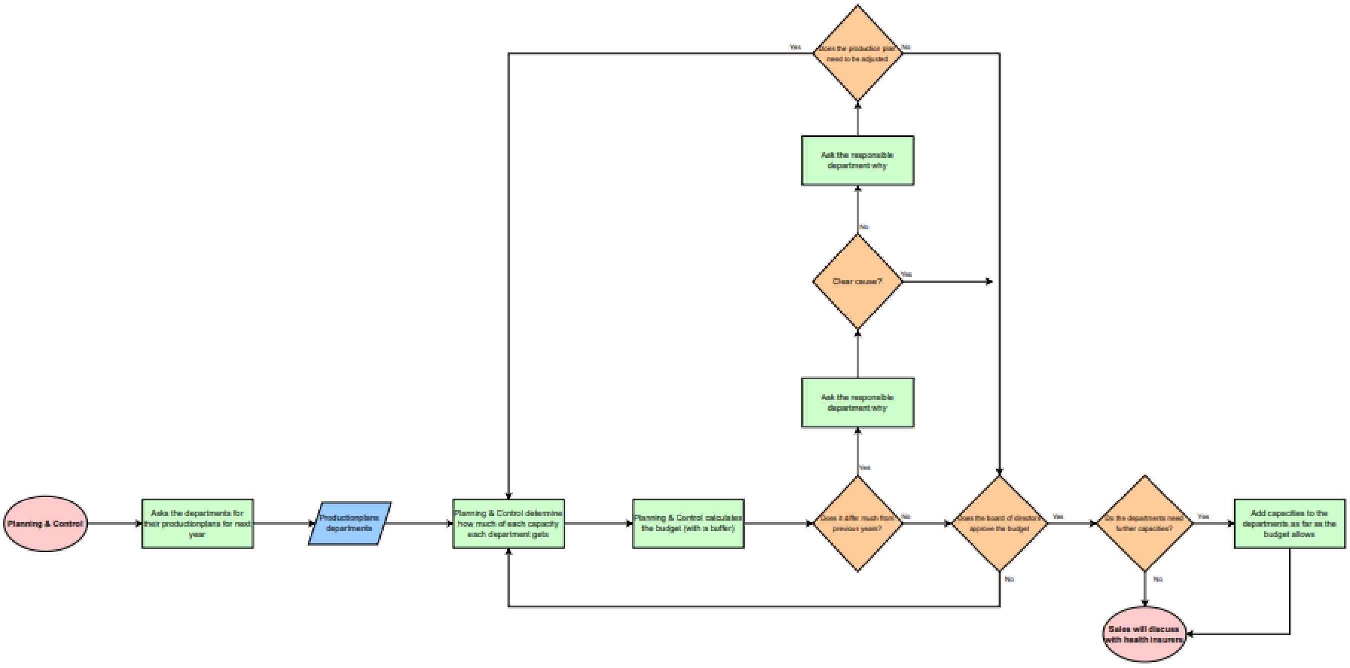

Figure 0-1. Flowchart of all the steps and decision moments necessary for determining the budget.

Appendix B. Systematic literature review

To identify the literature that answers the knowledge questions, two databases, PubMed and Google Scholar, are used. Some searches are carried out to acquire common knowledge about the topic. Other searches are systematically performed to find all the literature regarding that topic.

To gather the literature, the following keywords are gathered and used:

1. Tactical planning in hospitals
2. Tactical planning in ORs *OR* clinic *OR* capacities
3. Budget Tactical planning *OR* Budget monitoring
4. Tactical Budget *AND* Patient planning
5. Tactical planning in ORs *AND* Bed capacity *AND* budget

These keywords are used in different combinations to find the literature necessary for answering the main research question and sub-questions.

Appendix C. The number of extra patients added per week per urgency level

Specialicme	Year	WeekNr	Urg2	Urg4	Urg6	Urg12	Urg53
GYN	2022	24	6	0	0	2	0
GYN	2022	25	7	0	0	2	0
GYN	2022	26	9	0	7	2	0
GYN	2022	27	10	0	9	3	0
GYN	2022	28	10	0	7	4	0
GYN	2022	29	10	0	6	4	0
GYN	2022	30	10	0	5	2	0
GYN	2022	31	10	0	4	5	0
GYN	2022	32	10	0	8	3	0
GYN	2022	33	10	0	9	3	0
GYN	2022	34	10	0	9	4	0
GYN	2022	35	9	0	8	5	0
GYN	2022	36	9	0	11	6	0
KNO	2022	24	2	2	1	0	0
KNO	2022	25	2	0	4	0	0
KNO	2022	26	5	4	1	0	0
KNO	2022	27	5	3	4	0	0
KNO	2022	28	6	5	5	0	0
KNO	2022	29	6	3	3	0	0
KNO	2022	30	6	5	5	0	0
KNO	2022	31	6	5	5	0	0
KNO	2022	32	6	3	3	0	0
KNO	2022	33	6	2	2	0	0
KNO	2022	34	6	3	3	0	0
KNO	2022	35	6	3	3	0	0
KNO	2022	36	6	2	2	0	0
URO	2022	24	0	0	0	0	0
URO	2022	25	2	0	0	0	0
URO	2022	26	2	0	0	0	0
URO	2022	27	3	0	6	0	0
URO	2022	28	3	0	7	2	0
URO	2022	29	3	0	7	0	0
URO	2022	30	3	0	1	0	0
URO	2022	31	3	0	6	0	0
URO	2022	32	3	0	5	0	0
URO	2022	33	2	0	4	0	0
URO	2022	34	2	0	7	0	0
URO	2022	35	2	0	8	0	0
URO	2022	36	2	0	8	0	0