MASTER

The design of a decision support tool for allocating capacity to hospital departments taking into account the interdependencies of the outpatient and the surgical department

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Award date:
2018

Eindhoven, November 2018

The design of a decision support tool for allocating capacity to hospital departments taking into account the interdependencies of the outpatient and the surgical department

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BSc Industrial Engineering and Management Sciences
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in partial fulfillment of the requirements for the degree of

Master of Science
in Operations Management and Logistics

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TUE. School of Industrial Engineering
Series Master Theses Operations Management and Logistics

Subject headings: Integral planning, integrated demand forecasting, integrated capacity allocation, decision support tool, fluctuating waiting times, long waiting times, outpatient department, surgical department, care processes, healthcare

Management Summary

This research was conducted at ChipSoft, a company that provides information systems for hospitals. ChipSoft sees the opportunity to support hospitals with planning tools to improve capacity management. Interviews with hospital's capacity managers revealed that hospitals do not plan integrally and do not have insight into the capacity required by new patients and their subsequent treatments, since demand patterns are unknown. A literature study of integrated planning in hospitals revealed that minimal research has been conducted on this subject in the healthcare sector. In particular, the relation between the outpatient department (OPD) and the surgical department (SD) is under-researched in the literature. It is hypothesized that overlooking the interdependencies at the OPD and SD is the main cause of long and fluctuating waiting times at the OPD and the SD. Long and fluctuating waiting times are waiting times that are outside the waiting time norms and where the waiting times' coefficient of variation is high. Therefore, this study focuses on the mitigation of such long and fluctuating waiting times by taking into account the interdependencies at the OPD and SD so that the proportion of patients who experience waiting times outside the norms can be reduced. This led to the following research assignment:

Develop a decision support tool that integrates the OPD and the SD and that would support a capacity manager with tactical decision-making about capacity allocation in order to reduce the proportion of patients experiencing waiting times outside the waiting time norms.

Detailed Analysis

In order to design a decision support tool that reduces fluctuating waiting times, a detailed analysis was conducted to determine the interdependencies of the OPD and the SD and the main causes of the fluctuations. The analysis revealed that three main interdependencies exist at the OPD and the SD.

1. Interdependency of care processes: most patients arriving at the hospital visit the hospital more than once for the same diagnosis. The complete path of a patient through the hospital in the course of providing care on the basis of his/her diagnosis is referred to as the patient's care process. Data analysis revealed that a wide variety of care processes exists (within the same diagnosis). A care process comprises treatments at both the OPD and the SD. This makes the departments mutually dependent since demand at the OPD is caused by demand at the SD, and vice versa.
2. Interdependence of treatments: when a treatment is postponed, the subsequent treatment (at another department) will also be postponed. This principle is known in the literature as *backorder demand* and creates an interdependence of treatments.
3. Interdependency of resources: Each specialism includes a number of specialists. These specialists perform treatments at both the OPD and at the SD. This makes the departments interdependent as they share these specialists. Furthermore, specialisms share the operating theatre, which also makes the departments interdependent.

The main cause of the long and fluctuating waiting times is a mismatch between capacity supply (number of patients a specialist can treat) and capacity demand (number of patients that demand care). This mismatch is caused by fluctuations in patient arrival, fluctuations in resource availability, overlooked interdependences, and a lack of insight when planning for future demand.

Model design

The model aims to match capacity supply with capacity demand in order to reduce the long and fluctuating waiting times. What is required is that the proportion of patients experiencing a waiting time outside the waiting time norm is reduced and that capacity is utilized to as great an extent as possible. The proportion of patients experiencing a waiting time outside the waiting time norms is the performance measure for this model. In order to match capacity supply with capacity demand, these first need to be determined.

Capacity supply

Based on (average) norm processing times, the capacity supply is expressed as the number of patients that a specialist can treat in a time period and is allocated to a department as sessions of specialists' time as the specialist is a shared resource within a specialism, and thus constitutes an interdependency of the hospital departments.

Capacity demand

Based on (average) norm processing times, capacity demand is expressed in the number of patients requesting care. In order to take into account the interdependence of treatments, the capacity demand is based on care processes. Second, capacity demand is determined by the minimum waiting time norm and the maximum waiting time norm in order to include the waiting time requirement in the model. The determination of capacity demand is undertaken in three parts.

1. New patients: new patients visit the hospital for the first time for a specific diagnosis and are the start of the care process.
2. Known patients: these patients are already known to the hospital as they have already been diagnosed. Known patients are divided into two subgroups: (1) planned patients have requested or planned a treatment and are currently awaiting their treatment and (2) historically known patients have already had one or more treatments and will probably require another treatment, which is not yet requested, in the future.
3. Subsequent treatments: subsequent treatments are the remaining treatments of a new or known patient's care process and can be determined by means of data patterns. Transition probabilities, which indicate the probability of a patient being transferred from one stage in the care process to another, were determined.

Combining these three elements creates the total capacity demand at a time period.

Capacity supply vs. capacity demand

A graphic cumulative overview was created based on the capacity demand with a minimum waiting time norm, the capacity demand with a maximum waiting time norm, and the capacity supply per department. In this overview, three scenarios are possible per department:

1. Overcapacity: more capacity is allocated to the department than demanded. The waiting time is higher than the maximum waiting time norm
2. Capacity shortage: more capacity is demanded at the department than allocated. The waiting time is lower than the minimum waiting time norm, or capacity is left unused
3. Slack capacity: Enough capacity is allocated to the department to treat the capacity demand. The waiting times are within the waiting time norms.

The aim of the model is to mitigate waiting time fluctuations that are outside than the norms. The model reallocates specialists across the departments in order to mitigate capacity shortages and surpluses so that, as far as possible, exceeding the waiting time norms is reduced in all departments. The balanced capacity allocation is used as capacity supply per department to allocate patients to a time period and determine their waiting time.

Results

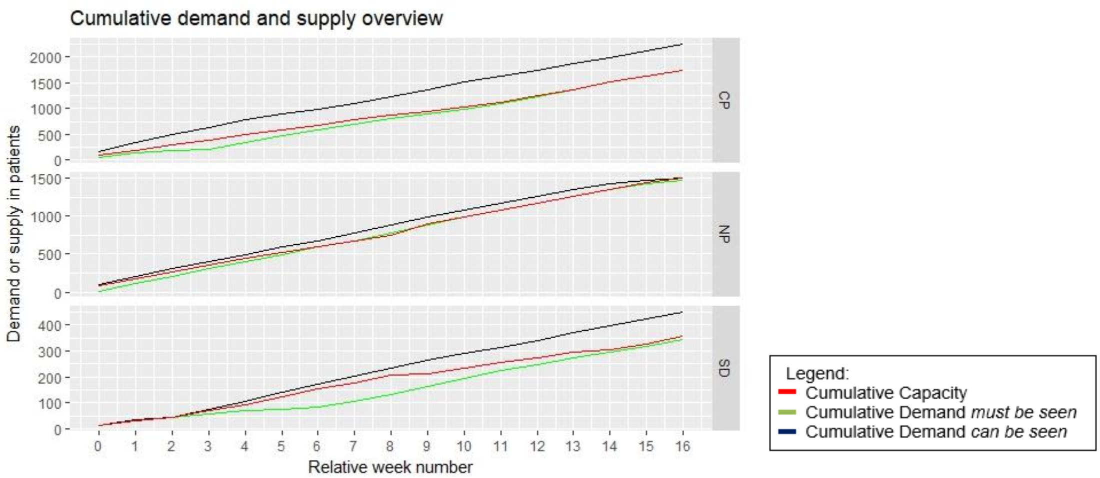

Figure 0.1: Cumulative demand and supply overview after capacity balancing

The model balances the waiting times at the OPD and the SD by determining the capacity that should be allocated to each department. The results of the capacity balancing are presented in Figure 0.1. Second, the model correctly allocates patients to a time slot according to the determined capacity supply. The patient allocation results in a proportion of 1.9 percent of patients experiencing a waiting time outside the norms. Additionally, the three interdependencies of the OPD and the SD are taken into account in the model and a decision support tool that includes the model is designed in order for hospitals to use the model. Insights can be gained of the effect on a department's waiting time of allocating capacity to that department. Therefore, the model is able to support hospitals to optimize the allocation of capacity to the OPD and the SD at a tactical level.

Implementation

The main user of the decision support tool is the hospital's capacity manager. Five steps have been identified for the capacity manager to use the tool.

1. Fill in the specialists' time available for the specialism and the OT time allocated to it.
2. Let the decision support tool determine capacity demand and capacity supply.
3. Assess the graphic cumulative overview and determine whether reallocation of capacity supply is necessary. When capacity reallocation is necessary, determine whether the reallocation should be done by the model or by trial-and-error, or both. Perform the capacity reallocation. Proceed to the next step when the result achieves a positive assessment.
4. Allocate the patient groups to a time period by means of one of the patient decision rules.
5. Assess whether the result is satisfactory. Otherwise, restart the capacity reallocation process.
6. Perform monthly maintenance to the tool to update the patient groups and demand forecast

Recommendations for the hospital

The case hospital is advised to implement the decision support tool in collaboration with ChipSoft. The capacity demand forecast needs to be optimized with hospital-specific characteristics. Additionally, it needs to be optimized by incorporating patient- or diagnosis-specific interarrival times between treatments, and patients' preferred treatment dates. In collaboration with ChipSoft, the decision support tool can be extended to include more hospital departments, more resources, and more decision-making levels. Furthermore, it is advised the fixed time periods in the time horizon be minimized. This will improve the functioning of the decision support tool since the quality of the capacity demand forecast is reduced as the time horizon extends. Finally, regular meetings with ChipSoft to discuss areas of improvement are advised.

Recommendations for ChipSoft

Since the quality of the model depends on the quality of the demand forecast, and the quality of the demand forecast depends on the quality of the data registration, improvements of data registration in the hospital by creating new data variables, for example, the patient's preferred treatment date, medically advised treatment date, the date the demand arose, the date that the patient's treatment got planned, and the like, is recommended. Furthermore, investigating whether hospital planners could be encouraged to better register data is recommended. In order to further improve the demand forecast, including the capacity managers of hospitals in the demand forecast process is recommended. In this manner, hospital-dependent factors can be taken into account in the demand forecast, for example, internal reorganization, reduction of resources, and the like. Furthermore, the hospital can provide more insight into the user's experience of the decision support tool and how it should be designed to make it more intuitive for the end user. In conclusion, maintaining relationships with capacity managers of hospitals in order to improve the tool is recommended. Moreover, it is recommended that ChipSoft further develops the decision support tool. Possible extensions are the incorporation of strategic and operational optimizations, the incorporation of more hospital departments and the incorporation of emergent patients.

Preface

When I was younger, I knew exactly what I wanted to do for living; I wanted to help others. Not knowing how I wanted to help others and knowing that I liked mathematics, I choose *Industrial Engineering* as study program. With this Master's thesis, I ended this study program and I am convinced that the result of this thesis will help others, for example, patients, specialists, hospital's capacity managers, and planners.

Luckily, other people also helped and supported me during my Master's Thesis process, and I am very grateful for that. First, I want to thank my academic supervisor, Henny van Ooijen, for guiding me through the process. His critical questions and research suggestions increased the quality of this thesis. He helped me take a step back in the process when I tended to pass some important research elements. Furthermore, I would like to him for the quick responses on my emails (even during holiday) and the availability to plan meetings. Second, I want to thank Nico Dellaert, as my second academic supervisor, for sharing his great knowledge about the healthcare industry.

Next to the academic support, I am also very thankful for the practical support I received at ChipSoft. I would like to thank Victor Teunissen for the numerous brainstorm sessions we had throughout the process, his help when I struggled with programming, and his explanations about complex healthcare subjects. I also want to thank Yke van Dijk for her practical view on my thesis and sharing her great experience in the healthcare industry. Next to my supervisors, I would like to thank the members of the capacity management team. Everybody was always available for a discussion or a brainstorm about my research topic.

Finally, I want to thank my family and friends for their support during the project. They supported and encouraged me in every possible way, which I am really grateful of. They gave me the energy to create this Masters' thesis, and last but not least, they made me believe in myself.

I hope you enjoy reading my Master's thesis.

Eveline Blikslager,

Eindhoven, November 2018

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List of Abbreviations

General

CP	Check-up patient
DTC	Diagnosis treatment combination
EDD	Earliest due date
EHR	Electronic health record
FCFS	First come first serve
GP	General practitioner
HiX	Healthcare information exchange
LCFS	Last come first serve
LPT	Longest processing time
MSS	Master surgery schedule
MDP	Markov decision process
NP	New patient
OP	Outpatient treatment room
OPD	Outpatient department
OT	Operating theatre
PIOC	Planned input-output controlled
PP	Planned patients
PFW	Acceptance based on actual and future work load
SD	Surgical department
SPT	Shortest processing time
SRO	Slack per remaining operations
VNS	Variable neighborhood search
WLC	Workload control

Specialisms

DEN	Dentistry
ENT	Ear nose throat
GYN	Gynecology
NEU	Neurosurgery
OPH	Ophthalmology
ORT	Orthopedics
PLA	Plastic surgery
SUR	Surgery
URO	Urology

Glossary

Balancing waiting times	Creating waiting times which are within the waiting time norms. Important to notice is that both waiting times longer than the maximum waiting time norm and waiting times shorter than the minimum waiting time norm are mitigated as far as possible.
Capacity demand	Based on norm (average) processing times for each step in a care process, the capacity demand is the number of patients per stage of a care process per patient group and per week of the time horizon and is determined for the minimum and maximum waiting time norm.
Capacity supply	The capacity supply is the number of patients a specialist can treat in a time period and is allocated to a department in sessions.
Care process	A care process is the complete path of a patient group through the hospital
Fluctuating waiting times	Waiting times at a hospital department which are changing periodically. Fluctuating waiting times are waiting times where the standard deviation of the weekly average waiting time is close to its mean.
High waiting times	Waiting times at a hospital department which exceed the maximum waiting time norm
Hospital department	In this study hospital department is a collective noun for the OPD, the SD, the inpatient department, the diagnostic department, and the therapeutic department
Specialists' time	The amount of time (e.g. hours, minutes) a specialist can perform patient-related activities (treatments) at the hospital departments
Treatment	In this study, this term is used as a collective noun to define a surgery, a CP visit, and an NP visit
Visit	In this study, this term is used as a collective noun to define a CP visit and an NP visit
Waiting time	The time period between the moment that the demand for a treatment emerges and moment of the treatment.

1. Introduction

This master's thesis involves a study of the development of a decision support tool to facilitate the allocation of capacity to a hospital outpatient department (OPD) and surgical department (SD). The tool is validated for the case hospital located in the Netherlands.

Section 1.1 discusses the research area, the healthcare industry. Section 1.2 and Section 1.3 introduce the company and the case hospital, respectively. Subsequently, the problem faced by numerous hospitals is described in Section 1.4 and, finally, the thesis outline is presented in Section 1.5.

1.1 Trends in the healthcare industry

The healthcare sector is experiencing increasing pressure (Vissers & Beech, 2005a). On the one hand, demand for and expenditure on healthcare (Figure 1.1) are rising due to people living longer (Figure 1.2) and higher service expectations. On the other hand, healthcare institutions, that is, hospitals, are experiencing capacity and budget reductions per patient (Vissers & Beech, 2005a). Hospitals are expected to deliver high-quality care with a limited number of resources (Pan, Song, & Zhang, 2017). Therefore, hospitals are increasingly focusing on using resources more intensively and efficiently. The literature also focuses on increasing resource intensiveness and efficiency by means of integrated decision making (Adan, Bekkers, Dellaert, Jeunet, & Vissers, 2011; Hulshof, Boucherie, Hans, & Hurink, 2013).

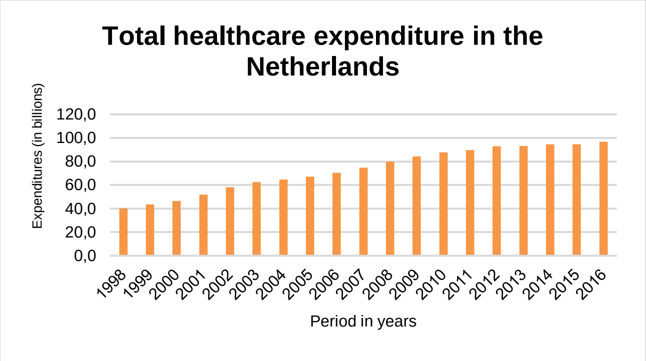


Figure 1.1: Total healthcare expenditure in the Netherlands per year, 1998–2016 (CBS Statistics Netherlands, 2017)

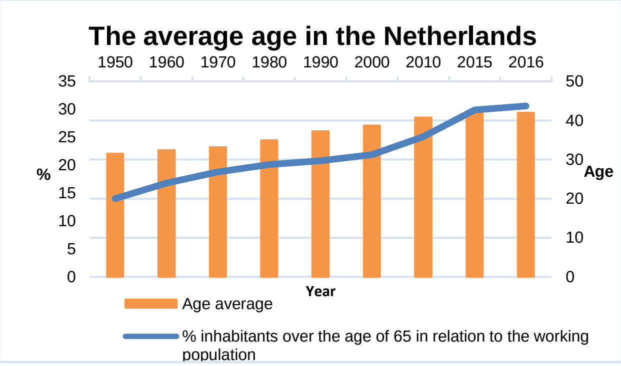


Figure 1.2: The average age of the inhabitants of the Netherlands,1950–2016 (CBS Statistics Netherlands, 2017)

1.2 The company

This research was conducted at ChipSoft, a company that provides a unique information system for hospitals, which was initiated as billing software. Since 1994, the system has been expanded with the implementation of the electronic health record (EHR) in hospitals. The information system is called the Healthcare Information Exchange (HiX). Approximately 70 percent of the Dutch hospitals use HiX as their main information system. Nationwide, hospitals experience difficulties with the integrated planning of resources. ChipSoft sees the opportunity to support hospitals with planning tools in order to manage capacity. Since ChipSoft has access to the data patterns of 70 percent of the hospitals, it can generate generic planning tools to support planners and capacity managers in making capacity-related decisions. ChipSoft aims to provide insight into the processes and the effects of integrated capacity allocation. The goal of this study is in line with the aims of ChipSoft.

1.3 The case hospital

This research focuses on one hospital that has implemented HiX as its primary information system and assumes that many hospitals experience a similar situation with regard to capacity management (Capacity manager of Hospital, 2018; ChipSoft capacity management specialist, 2018). Throughout this study, this hospital is referred to as the *case hospital*. The hospital comprises 22 medical specialisms and 13 supporting departments (e.g. intensive care, first aid, pharmacy) served by more than 1,000 employees (Jaarverslag case hospital, 2016). The different specialties and the structure of the hospital are shown in the organogram in Figure A.1 in Appendix A. The hospital has a progressive vision of serving patients with high quality and high safety levels of care. In the recent past, the level of quality of the care at the hospital has been assessed as being “very good” by the Dutch Institute for Accreditation in Healthcare (Nederlands Instituut voor Accreditatie in de Zorg, 2017).

The case hospital is also experiencing increasing pressure to reduce costs per patient, as explained above. Furthermore, it recognizes that managing processes in a more efficient manner is one possibility for helping more patients (i.e. better performance) with a stable amount of money and resources. In the last two years, the case hospital has conducted multiple projects in order to increase performance. One example of such a project is the implementation of the EHR. The implementation raised some questions, such as “What tasks have disappeared with the implementation of the EHR?” and “How can we save capacity as a result of this?” Another example is the integration of decision-making regarding capacity allocation within the OPDs, SDs, and inpatient departments across multiple specialisms. The term “capacity allocation” in this study is used to refer to the allocation of available resources (e.g. specialists, nurses, operating theatres (OTs), and equipment) to the care of patients who require them. The project resulted in three separate decision-making strategies for capacity allocation (one strategy per department).

1.4 Problem description

The capacity manager at the case hospital set up the project of integrated decision-making to optimize resource utilization. Currently, capacity is allocated to hospital departments and specialisms based on only a hypothetical sense of what the demand for capacity will be in the near future (ChipSoft capacity management specialist, 2018). Patients move through the hospital departments without the capacity manager having insight into the extent of capacity they will require over time. An ad hoc working approach appears to be used to allocate unexpected demand (i.e. emergent demand and demand originating from another department) to capacity, which leads to a lack of visibility of the consequences of the measures implemented (ChipSoft capacity management specialist, 2018). One cause of unexpected demand is that the departments in the hospital operate independently of one another and no coordination exists between them. This leads to optimal resource allocation in one department, while the second department is overloaded with too many patients or receives too few patients. Hospital departments are in fact dependent on one another as a result of care processes (Hulshof et al., 2013; Hulshof, Mes, Boucherie, & Hans, 2016). Care processes are defined as “the complete path of a patient group through the hospital” (Hulshof et al., 2016, p. 1). Since the departments currently operate independently from one another, care processes are seen as independent treatments. Thus, ignorance of the interdependency of the hospital departments results in a lack of insight into the effect of accepting new patients for subsequent treatments. This lack of insight leads to a lack of knowledge of demand patterns, which causes the amount of capacity required to be unknown in advance. This mismatch between capacity and demand leads to inefficient overall capacity allocation, which leads to fluctuating waiting times and resource utilization (Hulshof et al., 2013). The lack of integrated planning is not only causing problems in the case hospital. Most Dutch hospitals do not plan across multiple departments and experience similar problems (Capacity manager of Hospital, 2018). A more detailed analysis of the relationship between the departments can be found in Section 3.4.

Long and fluctuating waiting times affect the performance of hospitals in four ways, namely, negative financial consequences, decreased patient satisfaction, negative hospital image, and unmet national waiting time regulations. First, “uncontrolled access times can be costly, as resources have already been invested, but revenues are still to come” (Hulshof et al., 2013, p. 152). Second, patient satisfaction, which many hospitals identify as a core value, will decrease.

As a consequence, patients could decide to obtain treatment elsewhere, which causes a reduction in demand. This reduces the competitive position of the hospital. Third, long and fluctuating waiting times are a sign that the care system is inefficient (Garg, McClean, Meenan, & Millard, 2010), which negatively affects the hospital's image. The final measure of low and stable waiting times are the national regulations set for waiting times. In the Netherlands, the maximum waiting times are regulated by law (Ministerie van Volksgezondheid, 2003). The maximum acceptable waiting time (or access time) to be seen by a specialist at an OPD is set at 4 weeks. The maximum acceptable waiting time for a clinical treatment is set at 7 weeks. The waiting times of the OPD and the SD aim to be within this range of time. In this study, the waiting times of patients entering the case hospital were computed based on historical data from 2016. Waiting time is measured as the difference in time between the date of requesting care and the date of receiving care. In the case hospital, elective patients for one specialism experience an average waiting time of 2.6 weeks before being seen by a specialist in the OPD (with a standard deviation of 1.9 weeks), and an average waiting time of 6.5 weeks for surgery in the SD (with a standard deviation of 5.6 weeks) in 2016. Since 27 percent of outpatient visits and 29 percent of surgeries do not occur by the target date, the waiting times are relatively long. Furthermore, the standard deviations are nearly as high as the means, which is equal to a high coefficient of variation, which illustrates the fluctuations in the waiting times. Even though no sanctions are imposed for breaking the maximum waiting time regulations, it is a motivation for hospitals to minimize waiting times. An illustration of the weekly fluctuations in 2016 at the OPD and SD for one specialism is given in Figure 1.3 and Figure 1.4, respectively. The figures show the mean waiting time per week in 2016 of patients requesting surgery or a visit. The standard deviation of the waiting time is computed per week and has been used to construct the pink surface in both figures.

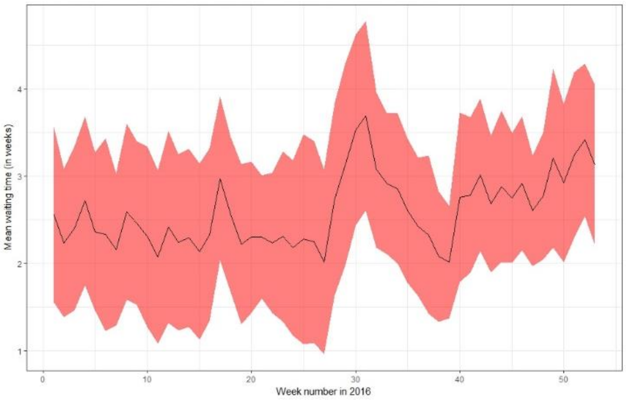


Figure 1.3: Fluctuations in waiting time for a treatment at the OPD in 2016, where waiting time is the time between requesting care and receiving care at the moment of the request

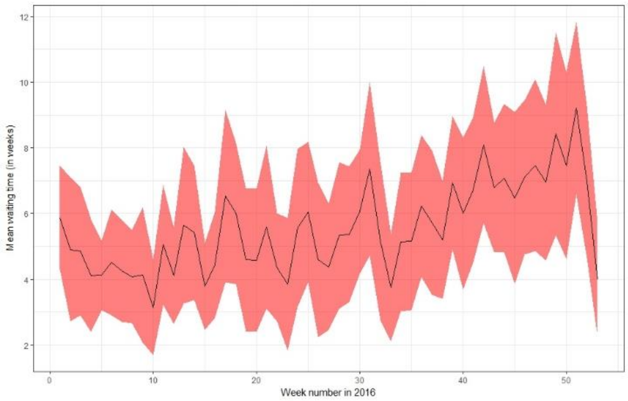


Figure 1.4: Fluctuations in the waiting time for treatment at the SD in 2016, where waiting time is the time between requesting care and receiving care at the moment of the request

Next to long and fluctuating waiting times, fluctuation in resource allocation is an important consequence of the separate management of hospital departments. Resources are extremely expensive and scarce, which makes it ideal to have constant, high resource utilization in order to control costs at the hospital. Capacity demand does not always fit with current capacity allocation. Generally speaking, when capacity demand is relatively high compared to the available capacity, resource utilization will increase. Additionally, when capacity demand is relatively low compared to the available capacity, resource utilization will decrease. In Figure 1.5 and Figure 1.6, resource fluctuations are displayed together with the resource utilization in one OT and the number of treatments performed by one specialist. The figures show the average number of surgeries performed per week in an OT and treatments performed by a specialist (the term *treatments* is used throughout this study to refer to both surgeries and OPD visits). The weekly standard deviation in the number of surgeries is added to the figures in order to obtain an impression of resource utilization fluctuations. Summarized over the year, in OT 1, an average of 15.4 surgeries are performed per week, with a standard deviation of

8.5 surgeries. Concerning the treatments, the specialist performed an average of 54.2 treatments per week, with a standard deviation of 21.3 treatments.

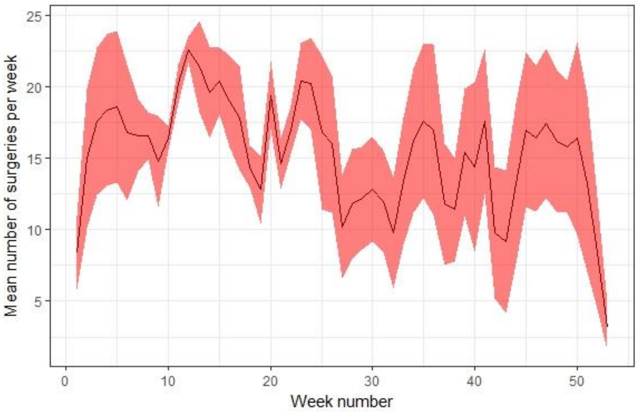


Figure 1.5: Fluctuations in the resource utilization of an OT in mean number of surgeries performed per week and standard deviation over 2013-2016

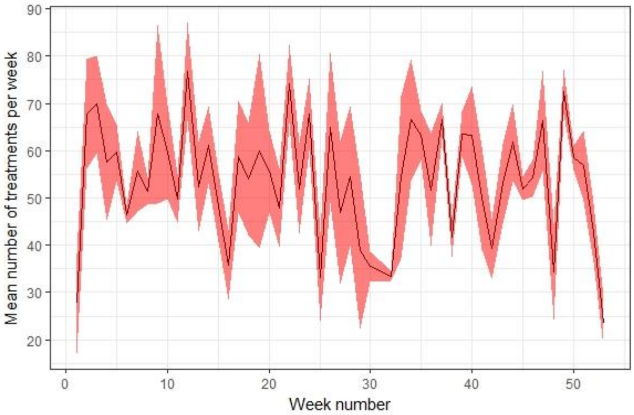


Figure 1.6: Fluctuations in the resource utilization of a specialist in mean number of treatments performed per week and standard deviation over 2013-2016

A third consequence of the separate management of the hospital departments is difficulty in meeting production targets. The production target is aimed to agree upon with the health insurer at the beginning of a year. At this point, it is difficult to set a target as there can be no accurate prediction of what treatment patients might need. In order to cope with this uncertainty, last year's production output is used as a basis for the new target, to which a small percentage of extra demand is added. Furthermore, at the beginning of the year, hospitals do not yet have a good overview of what percentage of the production target has already been achieved in the course of the year (Capacity manager of Hospital, 2018). In such circumstances, no advice can be given to specialists about whether they need to perform more surgeries and undertake fewer visits to the OPD, or vice versa. Reaching the production target without any insight into the progress made is becomes difficult.

Another consequence of the separate management of hospital departments is organizational rumor (ChipSoft capacity management specialist, 2018). Since no interaction occurs between the different departments as regards their planning, last minute changes to specialists' schedules are unavoidable. Last minute changes or ad hoc work methods create organizational rumors as many employees spend much time revising the planning and rescheduling of patients in order for the planning to be successful. Furthermore, specialists are attached to their work schedule. When a certain amount of OT time needs to be given to another specialism, a specialist may be afraid that his or her own specialism will receive less OT time than is required. The specialist will resist and it will be difficult to convince him or her to change working hours. The resistance and conviction of the specialist also create organizational rumor.

In conclusion, insight has been gained into the undesirable situation many hospitals are in. Planners do not integrate multiple hospital departments, which creates inefficient capacity allocation in each department. The main problem investigated in this study is the as yet lack of insight into the required capacity of new patients at the OPD and their subsequent treatments, one that arises due to unknown demand patterns, due to overlooking the interdependency of hospital departments. This problem leads to long and fluctuating waiting times, organizational rumor caused by revising schedules and specialists' times, inefficient resource utilization, and less control over achieving the production target. The causes and effects are presented in the cause and effect tree in Figure 1.7.

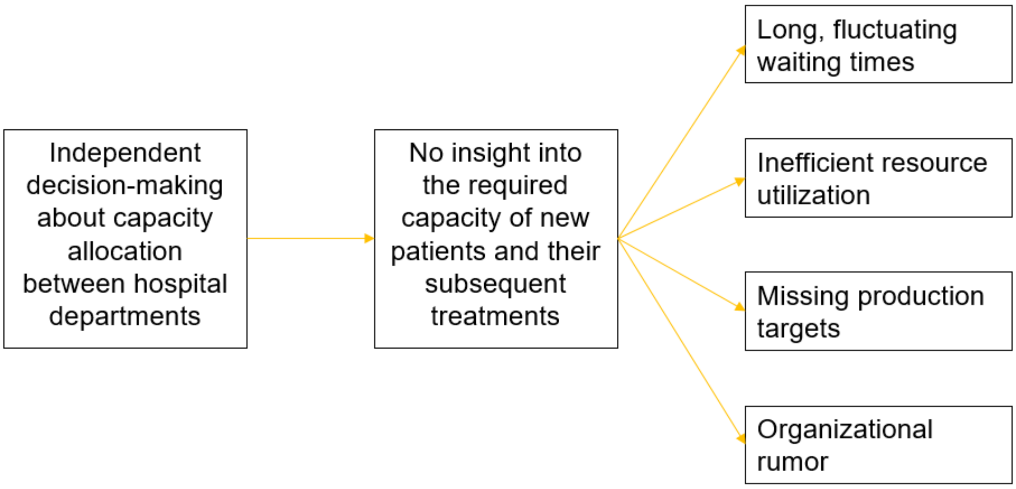


Figure 1.7: Conceptual cause and effect tree related to problem statement

1.5 Thesis outline

The remainder of this report is structured as described in what follows. Chapter 2 presents a literature study on the problem statement discussed above. Additionally, in Chapter 2, the research assignment of this study is determined. A detailed analysis of the problem is provided in Chapter 3, which includes an analysis of the current planning processes and of the interdependencies of hospital departments. In Chapter 4, the conceptual and mathematical models designed for this study are discussed, and a case study that verifies and validates the model is presented in Chapter 5. An implementation strategy for the model is discussed in Chapter 6. Finally, conclusions, recommendations, and suggestions for further research are provided in Chapter 7.

2. Research assignment

The conclusion of the problem statement discussed above is that hospitals face inefficient capacity allocation, which primarily results in long and fluctuating waiting times. The main factor hypothesized as cause for the inefficient capacity allocation is the separate management of the hospital departments. This chapter introduces a solution to this problem hospitals face.

Section 2.1 discusses the relevant literature on the interdependencies of hospital departments. Section 2.2 presents the deliverables of this research. The scope of the project is presented in Section 2.3; and finally, the assignment of the study is presented in Section 2.4.

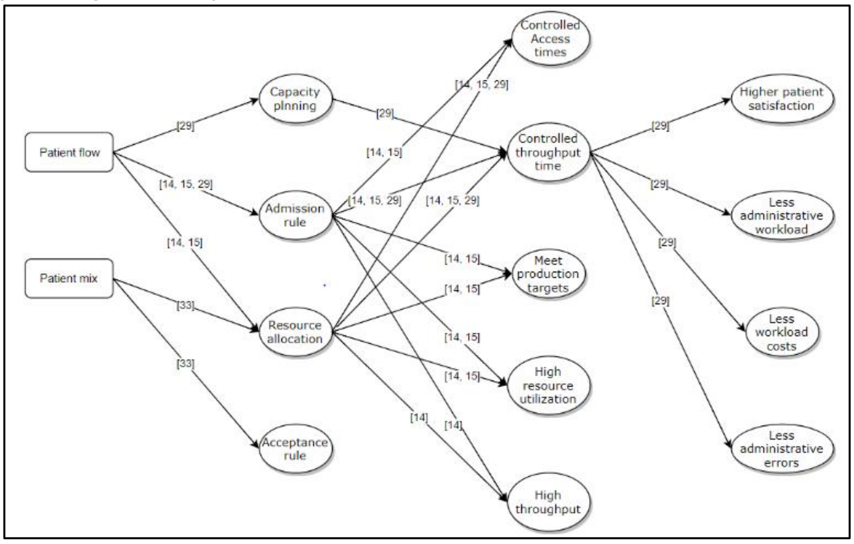
2.1 Related Literature

A literature study of integrated decision-making between hospital departments is undertaken in order to obtain insight into current research on the dependencies between hospital departments and patient acceptance strategies.

Section 2.1 consists of three subsections. The first two concern interdependencies of hospital departments (e.g. the interdependence of the OPD and the SD, and the interdependence of the SD and the inpatient department). The final section covers interdependencies of departments in a job-shop setting in order to supplement the healthcare literature.

2.1.1 Integration of the outpatient and surgical departments

To the best of this researcher's knowledge, Romero et al. (2013) were the first to analyze the integration of resource allocation across outpatient and surgical departments. Their main focus was not the creation of a planning tool, but the improvement of the implementation of a one-stop-shop model. Hulshof et al. (2013) established a method to develop a resource allocation and elective patient admission plan which controls access time to the OPD, production targets, the number of patients served, and the use of resources. Hulshof, Mes, Boucherie, and Hans (2016) conducted follow-up research on Hulshof et al. (2013) in order to improve the capacity plan and create an approximate dynamic programming model. Finally, Vanberkel, Boucherie, Hans, and Hurink (2013) undertook research on the optimal patient mix that leads to an optimal case mix, which functions as a basis for resource allocation. A queuing network model was used to evaluate the impact of accepting new patients of specific groups in the patient mix. Figure 2.1 summarizes the factors that control the relations between the outpatient and surgical departments (Blikslager, 2018).



[29] (Romero et al., 2013) - [15] (Hulshof et al., 2016) - [14] (Hulshof et al., 2013) - [33] (P. T. Vanberkel et al., 2013)

Figure 2.1: Factors controlling the connection between outpatient and surgical departments

2.1.2 Integration of the surgical and inpatient departments

Numerous studies have been conducted on the master surgery schedule (MSS), which takes into account the interdependence of surgical and inpatient departments. Oostrum, Bredenhoff, and Hans (2010) researched the advantages and disadvantages of an MSS and concluded that it has the advantages of both centralized and decentralized planning techniques. In earlier research, Oostrum et al. (2008) proposed an MSS in order to reduce fluctuations in demand at downstream departments, which is the result of unbalanced scheduling of the OT. The article states that the method works well to minimize the number of canceled surgeries and the lead time required for a next treatment. Adan, Bekkers, Dellaert, Vissers, and Yu (2009), Guoxuan and Demeulemeester (2013), and Vissers, Adan, and Bekkers (2005) all researched the MSS in combination with the patient mix. Guoxuan and Demeulemeester (2013) determined the optimal patient mix and volume and used this as the input for the creation of an MSS. A balanced MSS improves the resource utilization and the service level of hospitals. Adan et al. (2009) and Vissers et al. (2005) both aimed to develop an MSS that optimizes resource utilization, throughput, and the resource allocation of a cardiologic thorax center. The difference between both studies was the stochastic and deterministic length of stay used in Adan et al. (2009) and Vissers et al. (2005), respectively. This adaptation decreases the deviations in the resource allocation with more than 40 percent.

Research on the cardiologic thorax center was continued without taking the MSS into account, though still considering the interdependency of the surgical and inpatient care services. Dellaert, Cayiroglu, and Jeunet (2016) changed the focus from optimizing resource utilization to increasing patient satisfaction by reducing waiting times. Slack planning is used to increase patient satisfaction, however, it also decreases hospital efficiency and resource utilization. As it is the hospital that needs to decide which performance indicator is more important, the research does not provide one best result. Follow-up research by Dellaert & Jeunet (2017) aimed to minimize the difference between the expected and target utilization of the OT, beds, and nursing care in relation to the hospital admission plan. By implementing a variable neighborhood search (VNS), the difference between the expected and target utilization was decreased by two to three percent. Nunes, De Carvalho, and Rodrigues (2009) shared the same goal as Dellaert and Jeunet (2017). However, Nunes et al. (2009) are using a Markov decision process (MDP) rather than a VNS to model admission control. The MDP is judged as complex and is not yet easy to implement. In conclusion, Dellaert and Jeunet (2017) is an improvement on the earlier work of Nunes et al. (2009). Another article discussing patient admission is Hof, Fügener, Schoenfelder, and Brunner (2017). They analyze the existing literature concerning case mix planning models in order to set targets for patient admission. The article concludes that there is not much literature available on this subject, so there are many ideas for further research. The last article on the interdependence of the surgical and inpatient departments mentioned here is Adan, Bekkers, Dellaert, Jeunet, and Vissers (2011). Their goal was to increase the benefits of a proposed tactical master plan, such that an operational schedule could be easily created without any last-minute changes.

Van Zon and Kommer (1999) is macro-view based and focuses on undefined integrated activities and undefined integrated waiting lists in the healthcare system. The goal of the article is to describe the outlines of a dynamic linear programming model. The model should be dynamic so that current changes in patient flow and resource allocation can be taken into account in the future. Furthermore, the article takes the central position of the planner into account. The conclusion that can be drawn from the model is that minimizing waiting times does not always lead to greater efficiency or revenue.

2.1.3 Job-shop literature

Much knowledge of integrated capacity planning is produced outside the healthcare literature. Hulshof et al. (2013) suggest taking the environment of a classical job shop into account when analyzing integrated planning between departments in the healthcare sector. The job-shop literature research is focused on integrated planning tools, which are typical of job shops. These planning tools are workload control (WLC), input-output control, order release, and order acceptance. The foundation of capacity planning in job-shop environments is established by Graves (1986). Graves (1986) shows how to change variables in a job-shop environmental model and displays their effects, as well as indicating guidelines that result in a well-functioning job shop.

Ebben, Hans, and Olde Weghuis (2005) aimed to connect the order acceptance method with the WLC method. Newly introduced in this research was the idea of stochastic processing times. Ebben et al. (2005) compared their method with existing methods. Multiple scenarios were tested and results show that a high workload and a little slack can increase the utilization rate by 30 percent. Moreira and Alves (2011) present a new order release rule—the planned input-output controlled (PIOC) rule—and evaluated multiple order acceptance rules and order release decision rules under different due date constraints. The results show that PIOC, in combination with the *acceptance based on actual and future workloads* (PFW), results in optimal values for the performance measures. Thürer, Filho, and Stevenson (2013) and Thürer and Stevenson (2016) both conducted research on the performance of the WLC concept. Thürer and Stevenson (2016) researched the impact of re-entrant flows on job shops. They concluded that the results from articles that ignore re-entrant flows are not comparable with articles that consider re-entrant flows. Thürer et al. (2013) analyzed the impact of controlled order release in the context of finite storage space. Their results show that controlled order release has a positive effect on storage space to achieve a target production rate.

2.1.4 Gaps in the literature

In conclusion, interdependencies of hospital departments are an increasingly important topic in the literature. However, most of the literature on resource and admission planning is still judged to be myopic, is focused decision-making on long-term repeatable plans, or cannot be used in real-life instances (Hulshof et al., 2013). The few articles available that focus on more than one department is often still unusable in hospitals. The literature (Adan et al., 2009; Day, Garfinkel, & Thompson, 2012; Zhang & Rose, 2014) advises to use models that contain impracticalities, such as long running times for simulation models or incorrect assumptions. Furthermore, the models automatically optimize resource utilization or waiting times. Hospitals are not yet ready to implement these automatic systems, as current hospital planners have no insight into the effect of capacity allocation. Therefore, when an automatic system takes over, the planners cannot validate the results. Furthermore, hospital planners have difficulties with interpreting the results of automatic systems and do not have the skills and abilities to run algorithms or rewrite code. This makes hospitals dependent on external parties, or they need to hire professionals. In order to prevent this dependency, non-automatic, user-friendly tools need to be researched and developed. Appreciation could be gained from (hospital) planners if research was conducted on the implementation of models, or on developing easy-to-understand decision tools from algorithms. Moreover, the degree of implementation of decision tools in hospitals would probably increase if they were user-friendly.

An interdependency which has not received much attention is the relation between the OPD and the SD. The departments are connected via the in- and output of patients (e.g. the input of the SD is the output of the OPD, and vice versa). Vanberkel, Bourcherie, and Hans (2010) conclude that even though the effect of the interdependency of the OPD and the SD as regards capacity allocation is known, not much literature is available on this topic.

To summarize, two main aspects have come to the fore in this literature review. First, the independence of hospital departments, especially the OPD and the SD, has not been extensively analyzed. Second, the usability of models focusing on integrating multiple departments is low. These two aspects are the principal focus of this research.

2.2 Deliverables

This research involves two kinds of objectives: the research objective and the business objective.

2.2.1 Research objective

The achieving of the research objective ensures that the literature is complemented by a new insight or methodology. In this study, the literature is complemented by a new methodology for handling inefficient capacity allocation between the OPD and the SD. The primary focus is to develop a decision support tool that provides a reliable prediction of the capacity demanded and provides insight into the capacity requirements of patients' successive treatments.

2.2.2 Business objective

The achieving of the business objective ensures that a solution is developed for the business problem of all hospitals that do not plan the activities of the OPD and the SD in an integrated manner. In this study, the case hospital is used as a pilot hospital; it will receive a decision support tool that assists planners in their decision-making about capacity allocation in hospital departments. The focus is on the usability of the decision support tool. This means that the tool should provide insight into the effect on the waiting time of capacity allocation in the hospital departments. This would enable planners to efficiently allocate capacity across hospital departments. Moreover, a feasible capacity allocation across hospital departments is proposed.

2.3 Scope of Project

Before formulating the research assignment, the project environment needs to be scoped. Hulshof, Kortbeek, Boucherie, Hans, and Bakker (2012) designed a framework for production control in hospitals. The framework comprises four levels that segment decisions about production control into four separate time horizons. The levels are defined by Hulshof et al. (2012) as:

- Strategic planning: at this level, the assortment of services offered by the hospital is defined by the hospital management. Furthermore, decisions are made about the investment of resources, or sharing resources and outsourcing. The time horizon for these decisions is two to five years.
- Tactical planning: at this level, decisions are made about the manner of allocating resources to specialisms and patient groups. Leading shared resources are allocated across specialisms and patient groups. Furthermore, decisions are made about specialists' schedule. The number of patients per time period is determined, including their seasonality. The time horizon for these decisions from weeks to one year.
- Offline operational planning: operational patient planning is established for outpatient visits, admissions, and diagnostic examinations. Patients are allocated to sessions, staff is assigned to shifts and patients, and the equipment necessary for treatment is determined per patient. The time horizon for these decisions is from days to weeks.
- Online operational planning: at this level, current processes are monitored and, if necessary, ad hoc measurements are taken to deal with unplanned events. The time horizon for these decisions is from day to day.

Strategic planning and online operational planning are outside the scope of this research. It is assumed that the strategic decisions mentioned have already been made; they are used as constraints and input values for the model. Tactical planning is the primary focus of this research as this level concerns capacity allocation across hospital departments.

Additionally, this research is limited to the OPD and the SD. As concluded in the literature study, an interdependency exists at the OPD and the SD and has an impact on capacity management; however, this interaction has received minimal attention from researchers. Furthermore, most hospitals have not integrated these departments, though they recognize the need for integration. Therefore, the OPD and the SD are the main focus of this research and the diagnostic and therapeutic departments (e.g. radiology and physiotherapy), and inpatient department are excluded from this research. The department-related scope, based on Vissers & Beech (2005a), is presented in Figure 2.2. All the elements within the orange squares are considered in the scope.

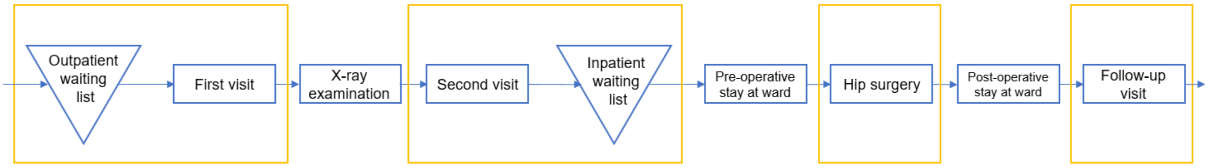


Figure 2.2: Scope presented in terms of an example of a healthcare process by Vissers & Beech (2005a)

Emergency patients are also excluded from this research, since emergency patients are often treated in a separate, reserved OT. Furthermore, as most of the patients in the case hospital are elective, most improvements in hospital planning can be achieved by improving planning for the elective patients.

The research focuses on only one specialism in order to reduce the amount of data and increase the reliability of the data. The desired specialism on which to perform research would be one that contains many routine procedures. Since orthopedics is the specialism in which procedurally routine surgeries are performed, it was selected as the specialism for this research.

2.4 Assignment

The conclusion of the literature study combined with the insights gained from Figure 1.7 provide the problem statement below.

> *Problem statement: separate decision-making about capacity allocation across hospital departments has the result that there is no insight into the required capacity of new patients and their subsequent treatments. This problem causes long and fluctuating waiting times organizational rumors, inefficient resource utilization, and difficulties in meeting the production target.*

The focus of this research is on mitigating the long and fluctuating waiting times at the OPD and SD so that the proportion of patients experiencing waiting times outside the waiting time norms is reduced. This reduction is accomplished by means of integrated planning of resources between the SD and the OPD. Ignorance of the interdependencies of the OPD and the SD are hypothesized as the main cause of the problem and are analyzed and incorporated in the decision support tool.

Given the problem statement, the objectives mentioned in Section 2.2, and the project scope, the assignment for this study is:

> ***Research assignment**: develop a decision support tool that integrates the OPD and the SD and that supports the capacity manager with tactical decision-making about capacity allocation in order to reduce the proportion of patients who experience a waiting time outside the waiting time norms.*

Six sub-assignments are defined which should help to fulfill the research assignment in a structured manner:

1. Identify the current method(s) of capacity allocation in the case hospital.
2. Perform a baseline measurement of performance in the current situation at the case hospital.
3. Determine the interdependencies of the OPD and the SD.

4. Forecast the capacity demand (number of patients that need to be treated by a specialist) for the OPD and the SD.
5. Determine the available capacity supply (number of patients that can be treated by a specialist) for the OPD and the SD.
6. Create a model that allocates capacity supply to capacity demand, which incorporates the interdependencies of the hospital departments and reduces the proportion of patients who experience a waiting time outside the norm.
7. Create a usable decision support tool which incorporates the model.

3. Detailed Analysis

The detailed analysis extends the problem faced by hospitals. In this analysis, the causes of the high proportion of patients experiencing a waiting time outside the norms are analyzed. The detailed analysis is based on information gathered from the literature, interviews, and data analysis. Furthermore, a diagnosis of the current situation at the case hospital is given by means of a baseline measurement.

In Section 3.1, the information sources that function as a basis for the detailed analysis are described. In Section 3.2, an analysis of the current methods of allocating capacity to hospital departments is provided. Performance in the current situation of the case hospital is measured by means of a baseline measurement in Section 3.3. The interdependence of the hospital departments is analyzed in Section 3.4. Finally, in Section 3.5, a summary of the results of the detailed analysis is provided.

3.1 Information sources

The detailed analysis of the current situation of the problem at the case hospital is based mainly on information obtained from interviews and data analysis. The results obtained from the interviews and data analysis are discussed in this chapter.

3.1.1 Interviews

Numerous semi-structured interviews were conducted with the capacity managers or OT planners of different Dutch hospitals to obtain insight into the current manner of allocating capacity to demand. One of the interviews was conducted with the head of the capacity management team at the case hospital. The information collected in this interview was used to identify the current manner of allocating capacity to demand and to explain the patient acceptance process. The semi-structured interview protocol can be found in Appendix B.

3.1.2 Data analysis

The case hospital provided a dataset, including multiple variables, as presented in Table C.1 in 0. The data dates from January 2013 to December 2017 and describes approximately one million outpatient visits, 50,000 surgeries, and 100,000 unique patients. The data includes the treatment number (the visit number at the OPD, or the surgery number at the SD), treatment date, and a scrambled patient number. For orthopedics, the dataset contains information on nearly 60,000 outpatient visits, approximately 7,500 surgeries, and 20,000 unique patients. Most of the data analysis in this chapter is performed on the orthopedics data subset as the decision support tool is designed based on, and tested on, the orthopedics dataset. Insight is gained into the current situation of the orthopedics department at the case hospital.

3.2 Analysis of the current situation at case hospital

In this section, the current situation at the case hospital is analyzed. First, Subsection 3.2.1 discusses the current process of capacity allocation in the hospital as a whole. Second, Subsection 3.2.2 discusses the existing process for accepting patients in the OPD and the SD.

3.2.1 The existing process of capacity allocation

The current manner of allocating capacity to demand is explained in order to provide insight into the process and the origin of the problem faced by many hospitals. The process of capacity allocation at hospitals is initiated in agreements made with health insurance companies. Each year, hospitals agree upon a number of diagnostic treatment combinations (DTCs) with health insurance companies. A DTC is an average package that consists of all the activities used to treat a specific diagnosis (“Handleiding DBC-systematiek,” 2017). An example of the content of a DTC is provided in Table 3.1 ("Independer Zorgverzekeraar", 2018). The board of managers has an annual budget in order to agree upon a certain number of DTCs. In the negotiations with the health insurance companies, the managers attempt to obtain as many

DTCs as possible with the available budget in order to deliver a high level of qualitative and quantitative care for a minimal amount of money, taking into account the current distribution of the budget across the different DTCs. The agreements from the previous year often form a basis for the agreements of the next year. As a result of the negotiations with health insurance companies, the yearly budget is split between a number of DTCs.

Table 3.1: Content of a DTC for treating osteoarthritis of the hip (Source: "Independer zorgverzekeraar", 2018)

Content of the DTC "Treating osteoarthritis of the hip"	Number
Visit to the outpatient department	1 visit
Examination of osteoarthritis in the hip	> 2 investigations
Visits to day treatment or outpatient department	> 2 visits
Installation or removal of plaster or other external fixative material	2 installations or removals
Nursing days in the inpatient department	Max. 5 days
Hip surgery or implanting of a hip prosthesis (including nursing days) in the case of a disorder of skeleton-muscular system or connective tissue.	1 surgery

As shown in Table 3.1, DTCs contain information on the average amount of care required for a patient diagnosed with osteoarthritis of the hip. In other words, the DTC outlines the average care process for a patient diagnosed with osteoarthritis of the hip. The capacity manager of the case hospital converts the content of all DTCs into capacity according to the average duration of the visit, surgery, or admission. The outcome contains information about the capacity that should be allocated to specialisms and departments in order to fulfill the DTCs. These annual amounts are converted into monthly capacity requirements according to the seasonality of patients' treatment patterns. This is referred to as the production plan. Thus, the production plan incorporates multiple treatments per patient. The following subsection provides an illustration of the conversion of an agreed number of DTCs to the monthly capacity allocation.

Example of the conversion from DTCs to capacity allocation

Figure 3.1 shows the process of allocating the available budget for the next year. In this example, in 2016, the hospital managers had a budget of €335 million available for purchasing DTCs. Following negotiations with the insurance companies, the budget is split over a certain number of DTCs. The capacity manager determines the average duration per visit or surgery and converts the DTCs for specialism A into 5,400 and 2,250 hours of visits and surgeries, respectively. Finally, as indicated above, the annual capacity is divided per month based on the seasonality of patient treatment patterns.

Agreed annual budget (DTCs)
€335 million divided over a set DTCs

Average duration per treatment (hours)

\+

DTC content (Table 3.1)

Yearly capacity for specialism A (in hours)	
OPD	5,400
SD	2,250

Seasonality of treatments

The production plan for specialism A (in hours)		
Month	**Capacity OPD (hours)**	**Capacity SD (hours)**
Jan	450	180
Feb	475	185
Mar	420	200
Apr	480	210
May	450	185
Jun	475	200
Jul	420	180
Aug	420	185
Sep	475	200
Oct	410	170
Nov	475	180
Dec	450	175

Figure 3.1: Example of the conversion of DTCs to capacity allocation

Depending on the specialism, seasonality is explained by holiday seasons, flu epidemics, or changes in the weather. Fewer patients are treated during the spring holiday, May holiday, summer holiday, and Christmas and New Year holidays. More patients are treated during flu epidemics or periods with sudden weather changes. The following subsection provides an overview of the patient treatment pattern of the orthopedics specialism in 2016, including seasonality resulting from the holiday seasons.

Patient treatment pattern

Figure 3.2 and Figure 3.3 display the treatment pattern for patients who requested orthopedic surgery or an orthopedic outpatient visit, respectively, in 2016. The figures show the variability in treatments over the course of weeks. In 2016, week numbers 8, 9, 18, 19, 28 to 34, 42, 43, 51, 52, and 53 were holiday seasons in the region of the case hospital. As can be seen in both graphs, the number of patients treated in holiday weeks is lower than in other weeks.

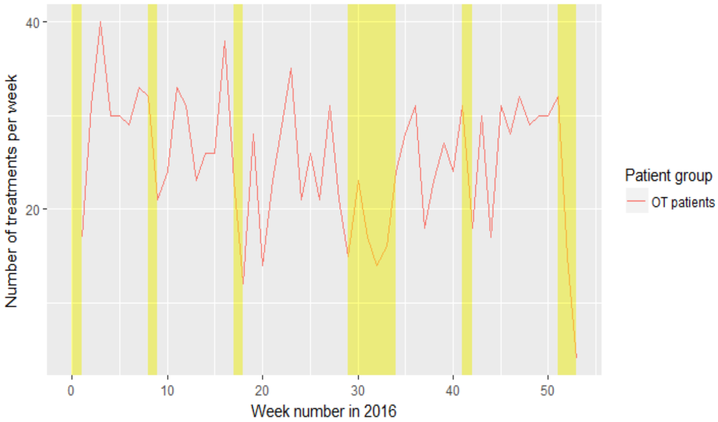


Figure 3.2: The treatment pattern of patients requesting an orthopaedic surgery in 2016 (holiday weeks are marked yellow)

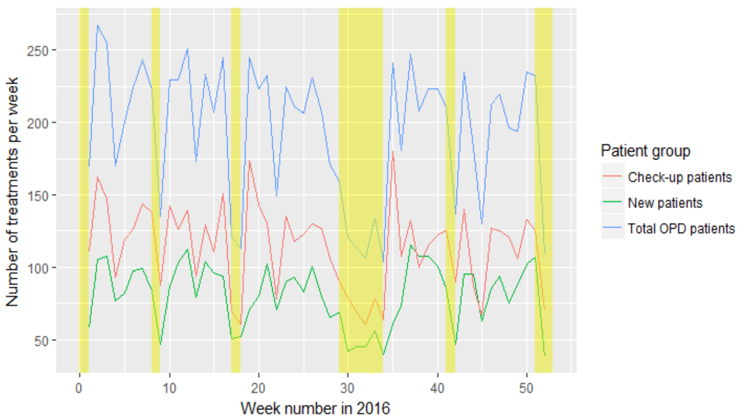


Figure 3.3: The treatment pattern of patients requesting an orthopaedic OPD visit in 2016 (holiday weeks are marked yellow)

The previously mentioned production plan provides each specialism with the number of hours allocated for the SD or the OPD per month, distributed across each week. The number of hours allocated is converted into a number of sessions, taking into account that one session has a standard duration of 240 minutes. An example of a session schedule used in 2016 for the SD is shown in Table 3.2. This session schedule is also known as the previously mentioned MSS.

Master Surgery Schedule

The case hospital has six OTs available to treat elective and emergent patients; these are used daily from 7.45 to 16.15 (excluding weekends, preparation time, and overtime). Table 3.2 shows an MSS for an average week in 2016. As can be seen in the table, all nine specialisms[1] are divided over the available OTs per week. The MSS fluctuates every week due to periodic revisions of the capacity allocation. However, changes are minimal (ignoring the holiday weeks). The black slots are blocked slots that are mainly reserved for emergency patients, as 6.6 percent of the total number of OT patients are emergencies. Emergency patients are defined as patients who need to be treated directly, within 12 hours, within 36 hours, or within one week.

Currently, the MSS for the forthcoming three months is revised on a two-weekly basis. The planned capacity for the following three months is compared to the realized capacity utilization of the previous month. The number of sessions is adapted or retained unchanged according to the result of the comparison of past realizations and the predictions made. No changes are made during the first 8 weeks after the moment of revising as the nurse schedule is already

[1] (The explanation of the used abbreviations for) the specialisms are presented the List of Abbreviations.

created. The revising process of the MSS happens on a rolling horizon, which is shown in Figure 3.4.

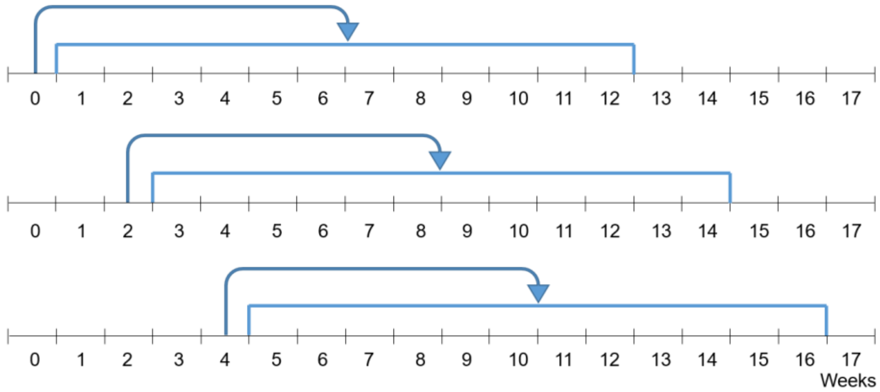


Figure 3.4: Visualization of the revising process of the MSS by means of a rolling horizon

As can be seen in the figure, in week 0, the MSS is revised for week 1 until week 12. Two weeks later, in week 2, the MSS is revised for week 3 until week 14. Two weeks later, in week 4, the MSS is revised for week 5 until week 16. This process repeats continuously.

Table 3.2: Session schedule for the SD

Period \ OT	OT 1	OT 2	OT 3	OT 4	OT 5	OT 6
Mon morning	ORT		SUR	SUR	GYN	
Mon afternoon	ORT	ENT	SUR	SUR	URO	
Tue morning	OPH	SUR	NEU	DEN	URO	
Tue afternoon	ORT	SUR	SUR	DEN		
Wed morning	ORT	SUR	GYN	ENT	ORT	
Wed afternoon	ORT	SUR	OPH	ENT	URO	
Thu morning	ORT	SUR	GYN	GYN	OPH	
Thu afternoon	ORT	SUR	ENT	SUR	OPH	
Fri morning	ORT		SUR	SUR	URO	
Fri afternoon	ORT	GYN	SUR	SUR	URO	

Table 3.3: Session schedule for the OPD

Period \ Room	OP 1	OP 2	OP 3
Mon morning	A	C	D
Mon afternoon	A	C	D
Tue morning	B	C	
Tue afternoon	B	C	E
Wed morning	B		
Wed afternoon	B	D	E
Thu morning	C	D	E
Thu afternoon	A	C	
Fri morning	A		
Fri afternoon	A		

Session schedule for the OPD

The session schedule for the OPD is created per specialism. The sessions are split across the available OPD rooms. Since the OPD rooms are a less critical resource than the OTs, the emphasis lies on the specialist rather than on the room. The character (i.e. A, B, and C) visualized in Table 3.3 represents a specialist. The treatment room (OP) is not registered in the hospital's system *HiX*, so the room numbers mentioned in the headers of Table 3.3 are fictitious.

Work planning for specialists

Currently, the specialism *orthopedics* at the case hospital has four specialists, all of whom perform both visits to the OPD and surgeries in the SD. This resource is a shared resource for both departments, which makes the departments interdependent. Subsection 3.4.3 elaborates on this interdependency. In general, a specialists' 40-hour working week is scheduled with 6 or 7 sessions per week for performing OPD visits and 2 or 3 sessions per week for performing SD surgeries. A session generally comprises 240 minutes.

Finally, the OPD and SD session schedules are revised on a weekly and daily basis. Patient planning is performed on a 6-week planning horizon. This means that patients are only planned to a time slot between now and 6 weeks from now. Patient planning for the next week or days is revised and adapted based on the experiences of the previous week or days. The sequence of patients is adapted or retained unchanged according to the result of the comparison of the past realizations and the predictions made.

3.2.1.1 Resource use

OPD visit duration

A standard value per treatment code is usually used for the duration of an OPD visit. An overview of the different treatment codes and their duration is provided in Table D.1 in Appendix D.

Surgery duration

The duration of surgery is currently derived from the HiX information system. HiX predicts the surgery duration based on the median of the duration of the previous 10 to 15 surgeries involving an equivalent operation and surgeon. The surgery duration is revised by planners numerous times before the surgery. Patient information and other circumstances are taken into account to finalize the prediction for the surgery duration. However, the operation code is not always extracted correctly from the database. Therefore, the diagnosis codes are used to compute the duration of surgeries. The orthopedic diagnoses, along with their average duration and standard deviation can be found in Table E.1 in Appendix E.

3.2.2 Patient acceptance process

In the Netherlands, most orthopedic patients entering the OPD are referred by a general practitioner (GP). The GP examines the patient and if more tests are needed before a patient be diagnosed, the patient is referred to an OPD. At the GP, the patient can already decide on a visit date or obtain a referral without a visit date. When the referral arrives in the hospital system and the visit date has not yet been scheduled, the latter is planned by an OPD planner and the patient is informed of the date by phone or email. From the moment the request for the visit is created, the patient must be seen by a specialist and be diagnosed within 4 weeks (Ministerie van Volksgezondheid, 2003). When a date is assigned to the patient, the availability of the SD for possible follow-up surgery has not yet been checked. Planners do not take this availability into account as it is not yet known whether the patient requires surgery. However, for a patient group, there is always a probability that a proportion of the group requires surgery. This probability is not known to the case hospital. These probabilities are analyzed and computed in Subsection 3.4.1.

When a specialist decides that a patient requires surgery, the specialist submits a request for admission. The request enters the waiting list to have a date assigned. The surgery date can be assigned immediately, or after a few days or weeks. The time of the surgery is only announced between a few days and one week before the surgery date. In most hospitals, the availability of wards is not checked at the time of planning. It is assumed that there is always a bed available as it is more important to utilize the OTs as much as possible. Furthermore, planners do not take into account the availability of a time slot for a check-up visit to the OPD. Patients often require a check-up visit following surgery; however, since this probability is not yet known, the planner only controls the OT planning. These probabilities are also analyzed and computed in Subsection 3.4.1.

3.3 Baseline measurement

In this section, a baseline measurement of the performance of the case hospital is presented to obtain an indication of the current performance of the orthopedics specialism as regards waiting times. Waiting times are used as the performance measure since long and fluctuating waiting times are a sign that the care system is inefficient (Garg et al., 2010). Waiting times are computed for new visits, check-up visits, and surgeries. The baseline measurement is calculated from the orthopedics data subset where patients requested a visit or surgery in 2016.

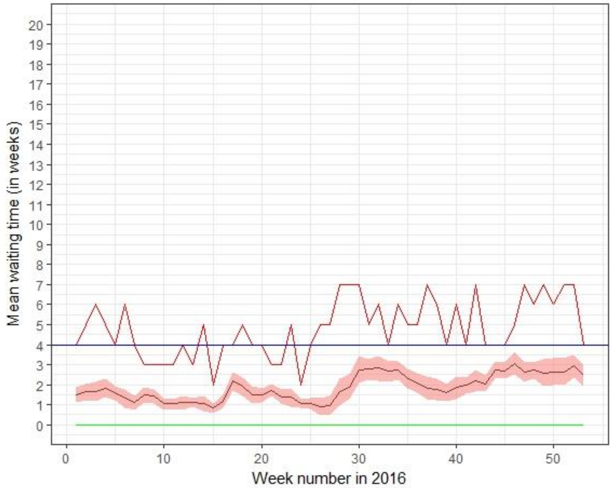
In order to indicate the waiting time, the advantages and disadvantages of a waiting time are investigated. As stated in the introduction, patient satisfaction and demand levels decrease when (long) waiting times exist; these make it more difficult to reach the production target.

Furthermore, the waiting times are compelled to be short by the government. From a patient's point of view, waiting times are not desired. Patients desire to be treated on their preferred date. A wishful scenario would be that all time slots contain an open space, so a patient is free to choose whenever he or she will be treated. Some patients desire immediate care, others desire a few weeks to prepare themselves for the treatment. In either case, a waiting list for the treatment is not wished for. However, from the hospital's point of view, waiting lists may have advantages. Since a waiting list functions as an inventory buffer, sessions at the OPD and the SD could be filled more optimally when a waiting list exists. In such cases, resource utilization is likely to be higher. In conclusion, a trade-off is required in order to fulfill the desires of the hospital and those of the patient.

The trade-off between the patient's and the hospital's wishes is created by setting a maximum waiting time. The Dutch government determines the maximum waiting times (Ministerie van Volksgezondheid, 2003). *Treeknormen* are defined as "the maximum acceptable waiting time during which the patient should receive care" (Kaljouw, 2017, p. 1). The maximum acceptable waiting time for a patient to see a specialist in the OPD is 4 weeks. The maximum waiting time for clinical treatment (surgery) is 7 weeks. Waiting times for check-up visits are not bound by the *Treeknormen* since check-up visits are planned according to a long, regular time window. However, in order to measure the performance of check-up visits, the *Treeknormen* of the new patient visits are also maintained for the check-up visits.

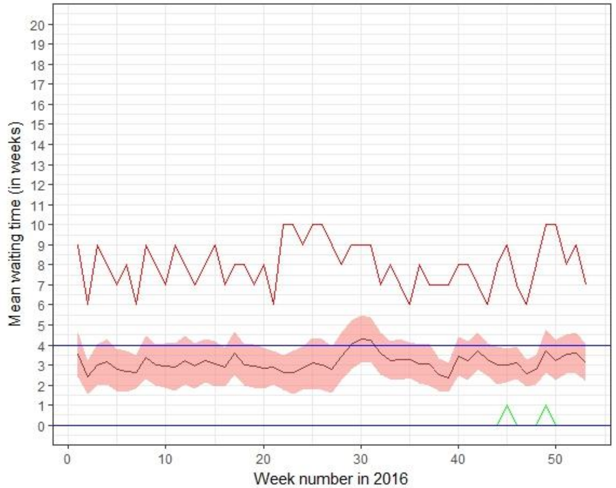
Currently, hospitals are obliged to publish their waiting times (online). In order to determine these waiting times for the OPD, the number of days between the date a patient makes an appointment and the date of the visit is noted (Murray & Berwick, 2003). For measurement reasons, in the agenda schedule, the date of the appointment is the third possible open option for a visit (Murray & Berwick, 2003), in order to publish a more realistic waiting time (patients' preferences and open slots resulting from cancellations are excluded). Since the third possible open option for a visit is not registered in the case hospital's information system, it cannot be used for our baseline measurement. For our baseline measurement, the date of making the appointment is the date of the request that is registered by the planner. For this reason, our computed waiting time is not fully comparable with the published waiting time; however, it provides a good indication of the performance of the system. In the SD, the published waiting time is determined by the number of days between the order date for the surgery and the surgery date (Murray & Berwick, 2003). The dataset contains the order date and the surgery date, which should reflect a realistic scenario. The published waiting times are not used as a baseline measurement since these only review the most recent time period (often a week) and only one average waiting time is published. Since, in this study, fluctuations in the waiting times are the principal problem, one average waiting time over one time period is useless for obtaining information about fluctuations. In order to provide insight into the fluctuations of the waiting times, the waiting times are determined by means of data analysis.

For each type of waiting time (i.e. new visits, check-up visits, and surgeries), the current performance is measured as the proportion of patients who experience a waiting time outside the minimum and maximum waiting time norms. When the proportion of patients with a waiting time outside the waiting time norms is zero, the performance is considered to be positive. The higher the proportion of patients experiencing a waiting time outside the waiting time norms, the worse the performance of the hospital system is. In Figure 3.5, Figure 3.6, and Figure 3.7, four lines are displayed. The black lines with the pink surrounding them represent the mean waiting times per week, plus/minus one standard deviation. The blue lines represent the minimum and maximum waiting time norms (in Figure 3.5, the blue line of the minimum waiting time norm is behind the green line as they are equal). Finally, the green and the red lines represent the minimum and maximum waiting times (excluding the highest waiting times in order to exclude outliers), respectively. The outliers are determined based on the results of Figure F.1 in Appendix F. As can be seen in Figure 3.5, the mean waiting time and standard deviation of the new patients (NP) visits are within the waiting time norms, which is not the case for check-up (CP) and surgical treatments. This can be explained by the fact that NP visits are relatively easy to control. The NP demand is not dependent on the SD, as returning patients to the OPD always create a CP visit. This interdependence is present at the CP and surgical treatments and is likely to cause higher waiting times. This interdependency is analyzed in greater detail in Section 3.4.1. Other possible explanations for the higher waiting times are the patient’s preferences or medical advice from a specialist to wait for a visit or surgery, which could explain the high maximum values of the waiting times for CP and surgical treatments. Since patient’s preferences or medical advice is not registered in the hospitals’ information systems, these long waiting times cannot be identified. Another remarkable observation is the waiting time peaks in the mean waiting times before the summer holiday (for surgeries) and during the summer holiday (for NP and CP visits). Specialists often see many new patients for an NP visit just before the holiday. In this period, the waiting times for NP visits decrease. However, when a specialist diagnoses and refers a patient for a surgery or for a check-up visit, the patient experiences a long waiting time, as fewer specialists are available during the summer holiday. After the summer holiday, waiting times decrease again.



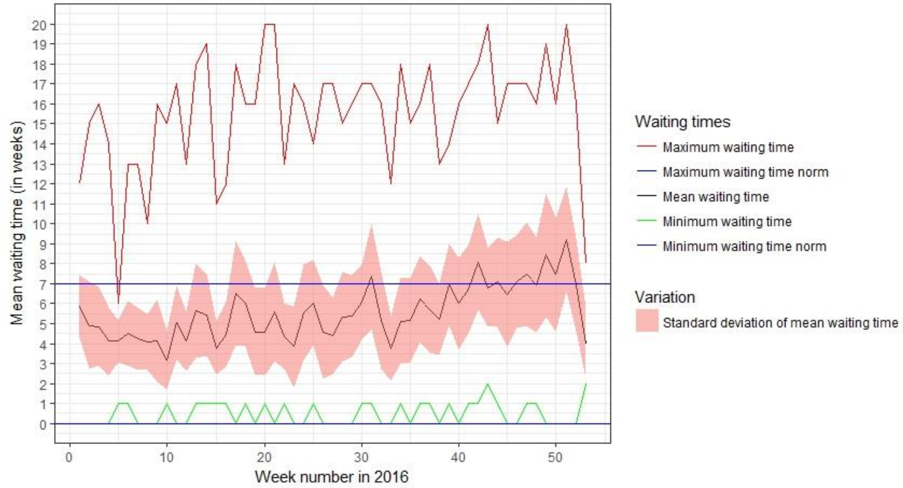
Waiting time NP	# patients	Realized	Target
Exceeding maximum waiting time norm (>4 weeks)	66	1.6%	0%
Within maximum and minimum waiting time (>=0 weeks & <= 4 weeks)	4002	98.4%	100%
Below minimum waiting time norm (<0 weeks)	0	0%	0%
Total	**4068**	**100%**	**100%**

Figure 3.5: Current performance of new visits in terms of waiting time in 2016, including the average, standard deviation, minimum, and maximum waiting time (norm)



Waiting time CP	# patients	Realized	Target
Exceeding maximum waiting time norm (>4 weeks)	1280	25.7%	0%
Within maximum and minimum waiting time norm (>=0 weeks & <= 4 weeks)	3700	74.3%	100%
Below minimum waiting time norm (< 0 weeks)	0	0%	0%
Total	**4980**	**100%**	**100%**

Figure 3.6: Current performance of check-up visits in terms of waiting time in 2016, including the average, standard deviation, minimum, and maximum waiting time (norm)



Waiting time SP	# patients	Realized	Target
Exceeding maximum waiting time norm (>7 weeks)	388	28.4%	0%
Within maximum and minimum waiting time norm (>=0 weeks & <= 7 weeks)	979	71.6%	100%
Below minimum waiting time norm (< 0 weeks)	0	0%	0%
Total	**1367**	**100%**	**100%**

Figure 3.7:Current performance of surgeries in terms of waiting time in 2016, including the average, standard deviation, minimum, and maximum waiting time (norm)

3.4 Analysis of interdependencies within a hospital

To create a decision support tool for capacity allocation for the OPD and the SD, it is necessary to identify all interdependencies of the OPD and the SD. Currently, many hospitals assume that hospital departments are independent of one another. However, departments are interdependent based on multiple factors (i.e. care processes, patient treatments, specialists and treatment rooms). Each subsection below analyzes one of the interdependency factors.

3.4.1 Interdependency of care processes

In analyzing the dataset, it is noticeable that patients visit the hospital more than once for the same diagnosis. Over a period of four years (2013 to 2016), patients went to the hospital 2.4 times on average for visits to the OPD and surgeries in the SD to get treated for the same diagnosis. A mutual interdependency exists at the OPD and the SD, as patients entering the OPD (as new patients) are the patients who also can enter the SD after their first visit. Furthermore, the patients entering the SD again can enter the OPD for control or repetition visits. These interrelations are displayed in Figure 3.8. In order to generate this figure, a process mining-based analysis was undertaken on the total number of treatments performed on orthopedic patients from 2013 to 2016.

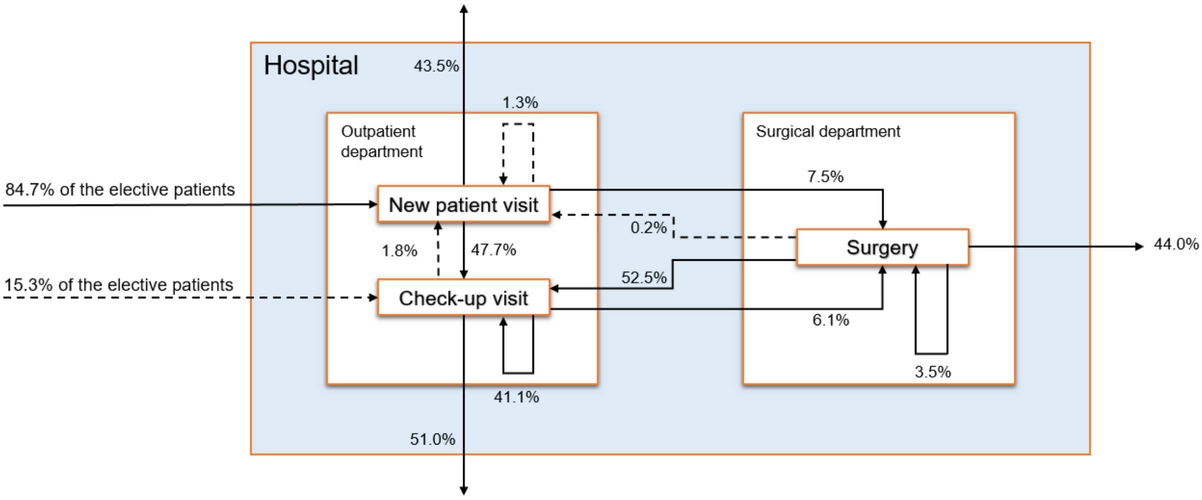


Figure 3.8: A graphic overview of the interdependencies of the OPD and the SD for the orthopedic specialism

Figure 3.8 displays a realistic hospital scenario of orthopedic patients flowing between home, the OPD, and the SD. Figure 3.8 can be interpreted as follows: when elective patients request an orthopedic treatment, they request a first visit to the OPD. Following the visit, patients are either referred to the SD, request a second visit, or go home. In brief, patients can flow through the system in numerous ways. Reviewing this figure, statements can be made about possible registration errors. It is unlikely that patients start their care process with a check-up visit or that they will return from a check-up visit or surgery to a new patient visit. A possible explanation for such registration errors is the often-changing definition of a new patient visit that hospitals use. Furthermore, the different rules for opening and closing care processes have the result that new patients visits are not always the first treatment in a care process. The unlikely patient flows caused by registration errors are indicated by the dotted arrows in Figure 3.8. These registration errors need to be taken into account in the decision support tool. Therefore, it is assumed that all patients start their care process with a new patient visit and that no more than one new patient visit appears in a care process.

Figure 3.8 shows that it is highly likely that a reciprocal pattern exists in the current care processes. This can be derived from the high proportions associated with the arrows from OT back to CP and from CP again to CP. For example, a care process could comprise three surgical treatments and two check-up visits. From the figure above, it cannot be ascertained whether a patient is visiting a stage in the care process (i.e. new patient, check-up patients or surgery) for the first, second, or third time. However, the chances of each scenario occurring would be different. When this difference is ignored, forecast errors will occur in the determination of future capacity demand. Furthermore, the required capacity for each scenario would be different, which also results in forecast errors regarding capacity utilization of the capacity demand. For example, the first surgery in a care process could take longer than a second surgery because the patient's characteristics are already known. The literature confirms this reasoning. Weiss, Cohen, & Hershey (1982) show that a patient's historical care process is relevant to the patient's future care process. In the literature, this concept is referred to as the rejection of the memoryless property (Weiss et al., 1982). An important characteristic of the design of the decision support tool is the non-memoryless characteristic of the different treatments in a care process.

3.4.2 Interdependence of treatments

Related to the interdependency of departments caused by care processes is the interdependence of treatments within care processes. The concept is explained by means of an example. Suppose the demand for the SD in February is 200 hours. Based on the production plan, 15 hours of the SD demand cannot be treated in February and have to be shifted to March. If the next visit to the OPD in the care process for the patients concerned is planned for 4 weeks after the surgery, then the OPD plan for March will also fail. The OPD plan for March then has to be adapted. In the literature, this concept is referred to as backorder demand (Nahmias & Cheng, 2009). An important characteristic of the design of the decision support tool is the inclusion of the backorder demand.

Whether this situation is present in the case hospital is not clear, since no insight could be gained of the consequences of the current capacity allocation in one department at other departments. What important is to provide insight into this interdependency when capacity is allocated to demand. Furthermore, it remains unclear what the period between treatments in the (different) departments is. Ideally, the period between two treatments would be the suggested period set by the specialist. However, due to capacity constraints, this period could be extended if no open space is available for the patient earlier. Moreover, the time could be extended because of patient preferences. The standard period required by specialists, the patient's preferred date, and capacity shortages are not registered in HiX, so extracting the period between two treatments from the dataset is a complex task.

3.4.3 Interdependency of resources

The OPD and the SD have a unique interdependency in the hospital as a result of a shared resource; the specialist. Specialists perform surgeries in the SD and, for the remaining part (excluding administrative paperwork, work in the plaster room, first-aid care, and work in the inpatient department), they undertake visits to the OPD. In the case hospital, there are four orthopedic specialists. Assuming a workweek consists of 40 hours, the case hospital has a total of 160 hours of the specialists' time available. It is challenging to divide the available specialist hours across the two departments.

The first allocation challenge is the fact that the MSS not only shares the specialists with the OPD—it also shares the six available OTs with the other eight specialisms. As a result of this interdependency, the hours available in the OT are first determined per specialism. The allocated OT hours to the specialism require a specialist to perform surgeries. Therefore, in the current situation, part of the 160 hours are first allocated to the OTs, and the remaining hours are allocated to the OPD. This allocation method has a downside since the allocation to the MSS is quite fixed. When a specialist in a particular specialism wants to perform more surgeries, all the other specialisms are required to change their allocations in the OPD and the SD. This means that session schedules can only be allocated weeks in advance and that revising session schedules becomes complicated from a specific point in time.

A second allocation challenge is fluctuating patient arrival at the OPD. All patients requesting a treatment at the OPD need to be seen within four weeks. If many patients request a visit in a week, the demand for surgeries in the near future will also rise. An extra SD session should be opened, which is difficult because of the fixed MSS. Therefore, the waiting time for the SD increases. However, when an extra SD session is opened, more surgeries can be performed and the waiting time at the SD remains stable; however, the demand for check-up visits at the OPD increases. The effect is that another OPD session needs to be opened. This is referred to as the bullwhip effect (Hulshof et al., 2013). On the other hand, when the number of requests for OPD visits decreases, the waiting time for the SD decreases, and an OT session needs to be closed and rescheduled across the other specialisms.

A third allocation challenge is the fluctuating availability of resources. Specialists are allocated to the SD and the OPD schedules two or three months before the schedules are operative. However, specialists, for instance, regularly visit conventions and go on holidays, and this creates a lack of specialists during some time periods.

Rescheduling session schedules in the OPD and the SD does not frequently occur in hospitals. Since rescheduling the MSS may require specialists of a specialism to give their OT time to other specialisms (which is often returned to the specialism another moment in time), specialists resist. The current mindset of many specialists is that the SD is the leading department. If the SD is productive, the hospital as a whole will be productive. This mindset is often false. For example, when the waiting time in the OPD is substantially longer than the waiting time in the SD, it can be more efficient to release one session in the SD to another specialism and use this time to see more patients in the OPD in order to decrease the waiting time in the OPD. This effect of rescheduling has not yet provided valuable insights. Capacity managers of numerous hospitals have indicated in interviews that the effect of reallocating specialists' time from the OPD to the SD, and vice versa, is not yet visible at the length of waiting time in both departments. The effect is not visible since no structured way of rescheduling is used. Ad hoc methods are used for rescheduling purposes, which lead to the effect that numerous factors (e.g. patient arrival, capacity allocation at the OPD or the SD, and available resources) in the process may have an effect on the waiting time.

The interdependencies mentioned may influence the matching of capacity and demand. However, the interdependencies have scarcely been analyzed in the literature. For this reason, each interdependency is incorporated into the decision support tool as a requirement.

3.5 Summary

As a result of the detailed analysis, the main causes of the problem statement have been extended. The results are shown in Figure 3.9.

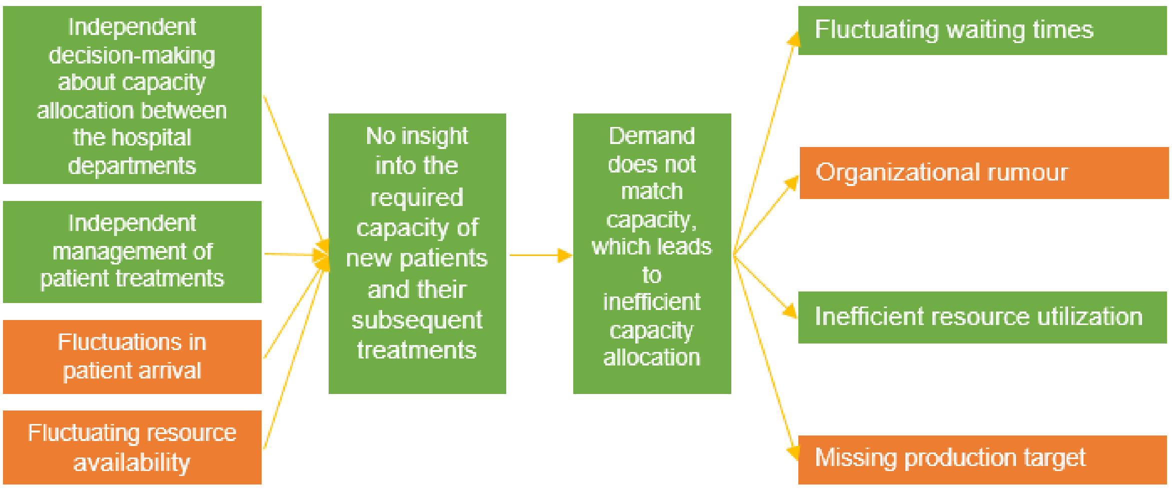


Figure 3.9: Extended cause and effect tree related to problem statement

The focus of this research is creating the match between capacity demand (number of patients that needs to be treated by a specialist) and capacity supply (number of patients that can be treated by a specialist) taking into account the interdependency of the OPD and the SD in order to reduce waiting time fluctuations. Waiting time fluctuations are reduced by reducing the proportion of patients experiencing a waiting time outside the waiting time norms. Since the fluctuations in patient arrival and resource availability are not controlled by capacity management, these causes are not mitigated in this study. Since organizational rumor, inefficient resource utilization, and difficulties in meeting the production target are not measurable using the current information sources of the case hospital, these consequences are not the focus of this research. However, these causes are taken into account in the decision support tool. The focus areas are indicated by the green squares in Figure 3.9. The main goal of the decision support tool is to support planners to make decisions on the allocation of capacity by providing them with a reliable forecast of the capacity demanded and an insight into the effects of capacity allocation on the waiting time. Furthermore, a model is designed that reduces the proportion of patients experiencing a waiting time outside the waiting time norms.

4. Model Design

In this chapter, the design of a conceptual model for allocating specialists to the hospital departments is presented. The model aims to solve the problem described in Chapter 2, which is faced by hospitals. The conceptual model is generalized so that many hospitals can use it. The chapter is divided into two main sections; the conceptual model and the mathematical model. Section 4.1 discusses the conceptual model. Section 4.2 discusses the mathematical model.

4.1 Conceptual model

The central problem investigated in this study is the high proportion of patients who experience a waiting time outside the waiting time norm in a hospital department. As read in Chapter 3, waiting time is referred to as the time between the moment of requesting care and receiving care. The main causes of the problem are addressed in Chapter 3. A detailed analysis of the problem demonstrates that the long, fluctuating waiting times are primarily caused by the mismatch of capacity supply and capacity demand, which is caused by overlooking the interdependencies of hospital departments, and by the variability in patient arrival and resource availability. The model needs to incorporate these interdependencies as required features. Another required feature is the usability of the model for hospital capacity managers.

In order to incorporate the interdependencies in the model, capacity demand is forecasted and based on care processes. As mentioned in the introduction, care processes are defined as "the complete path of a patient group through the hospital" (Hulshof et al., 2016, p. 1). The care processes ensure that the interdependencies of the treatments are incorporated. Furthermore, the shared resource that is "specialist" is incorporated in the model as the critical resource that needs to be divided across the hospital departments in order to satisfy the capacity demand. The specialist as a critical resource incorporates the interdependency of the resources into the model. Consequently, the aim of this model is to divide the specialists across the hospital departments for each time period within the time horizon, so that the forecasted care processes are achieved in the hospital. What is required is that the patients' waiting times in the hospital departments are within the given norms and the specialists' time are utilized as well as possible. The proportion of patients experiencing a waiting time outside the norm is the performance measure of the model.

The proposed model determines per specialism how to allocate specialists across the hospital departments. In order to achieve this, first, the total number of specialists and the amount of specialists' time available for the specialism need to be determined. Second, the number of patients to which the specialists need to be allocated has to be determined. Determination of the capacity supply and the capacity demand is described in subsections 4.1.1 and 4.1.2, respectively.

4.1.1 Capacity Supply

Each specialism has a number of specialists performing treatments in numerous hospital departments. During each time period (e.g. a week), a specialist performs many treatment sessions in a department. During each session, a specialist can treat a number of patients. Hence, based on the (average) norm processing times, the number of patients who can be treated in a time period is determined by counting the available specialists, the number of sessions they can perform, and the number of patients they can treat in a session. The capacity supply is expressed as the number of patients that a specialist can treat in a time period and is allocated to a department as sessions of specialists hours. Specialists' time is referred to as amount of time (e.g. hours, minutes) a specialist can perform patient-related activities (treatments) at the hospital departments.

An initial allocation of sessions to departments is initiated annually by means of the MSS. For each time period of the time horizon, an initial number of sessions have already allocated to the SD from the MSS. The remaining departments initially receive the remaining portion of the specialists' sessions. This creates an initial allocation of capacity supply to the departments, which can be adapted if the waiting time norms of the capacity demand are not met by this allocation. This adaption is explained in Subsection 4.1.4.

4.1.2 Capacity demand

In order to determine the capacity demand, the model requirements need to be incorporated. The model requirements related to demand are the following: (1) the capacity demand has to incorporate the abovementioned interdependencies, (2) the capacity demand has to be treated within the waiting time norms, and (3) all the capacity demand has to be treated in the hospital. As explained above, the first requirement is included in the model since capacity demand is based on the care processes. The second requirement is included in the model by determining the capacity demand with the minimum waiting time norm and the maximum waiting time norm. The capacity demand with a minimum norm is also referred to as the "capacity demand that could be seen". If a patient is not treated within this time period, the patient may be treated in another time period, until the patient has waited the maximum period of time. If the patients wait the maximum period of time (the maximum waiting time norm), it is also referred to as the "capacity demand that must be seen". The third requirement is incorporated by allocating *all* capacity demand to a time period. Capacity demand is determined as described below.

Based on norm (average) processing times for each stage (i.e. NP visit, CP visit, surgery) in a care process, capacity demand is expressed as the number of patients per stage in a care process per patient group and per week of the time horizon and is determined for the minimum and maximum waiting time norms. Capacity demand should be partly forecasted since the specialists are allocated across the hospital departments a number of weeks before patients arrive at the hospital. Capacity demand comprises three components.

1. New patients. New patients visit the hospital for the first time for a specific diagnosis. New patients are the start of each elective orthopedic care process and their arrival pattern could be seen as an external arrival process. The forecast determines the number of new patients arriving at the hospital per patient group per time period within the time horizon. In order to forecast the number of new patients arriving, numerous techniques are proposed in the literature, for example, moving average, linear regression, exponential smoothing, double exponential smoothing, Holt-Winters, and autoregressive integrated moving average. Since the quality of functioning of each forecast technique depends on case-related factors, such as seasonality, trends, and randomness, each hospital and/or specialism should determine their own forecast methodology. At the time of arrival, the new patients have a waiting time of zero. The time period when the forecasted new patients arise is transformed into the time period when the new patients experience the minimum waiting time norm and the maximum waiting time norm.
2. Known patients. These patients are already known to the hospital since they already required a treatment for their diagnosis. The known patients are extracted from the hospital's information system. Known patients are divided into two subgroups:
    1. Planned patients: These patients have requested or planned a treatment and are currently awaiting their treatment.
    2. Historically known patients: These patients have already had one or more treatments and will probably require another treatment, which is not yet requested, in the future. They are not waiting since the demand for the next treatment has not yet emerged. These patients are not relevant to capacity allocation since their treatments have already occurred. However, the subsequent treatments of historically known patients are taken into account.
3. Subsequent treatments of the new or known patients. The subsequent treatments are the remaining treatments of a new or known patients' care process and can be determined by data patterns. The forecasting of the subsequent treatments is based on the concept used

in Figure 3.8. The probabilities mentioned in Figure 3.8 are referred to as *transition probabilities*. With the transition probabilities, which treatments the new or known patients of a patient group are likely to undergo until they are fully recovered from their diagnosed disease can be determined. Since it was determined in Chapter 3 that the memoryless property needs to be abandoned, the transition probabilities of Figure 3.8 have been adapted for the model by taking into account the history of a patient's care process in each stage of a care process. Additionally, the interarrival times between treatments are determined. The interarrival time is the time period between the last treatment date and the date of arising demand of the next treatment. In addition to the interarrival times, the minimum and maximum waiting time norms are included to determine the time period of the next treatment. Combining the number of new patients or known patients, the transition probabilities, the interarrival times, and the waiting time norms generates a patient group's care process. In order to generate an impression of a care process, including the transition probabilities (prob to), historical events (hist), interarrival times (IAT), and waiting time norms (Norm WT), an example of a care process is presented in Figure 4.1. As can be seen in the figure, 100 new patients of a specific patient group are forecasted for the first time period. 25 percent of these new patients require surgery after four weeks; this means that 25 patients require surgery in time period 5. Finally, nine of the 100 new patients require the full care process as presented in Figure 4.1. The remaining 91 patients followed a (partial) different care process. The sum of all the care processes of the different patient groups defines the capacity demand per department and per time period.

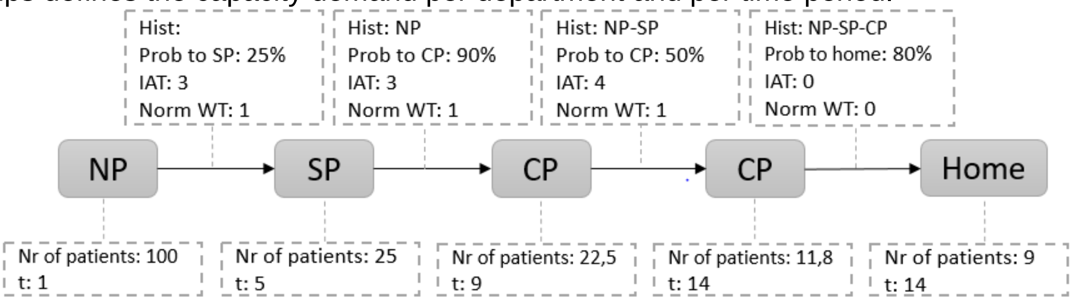
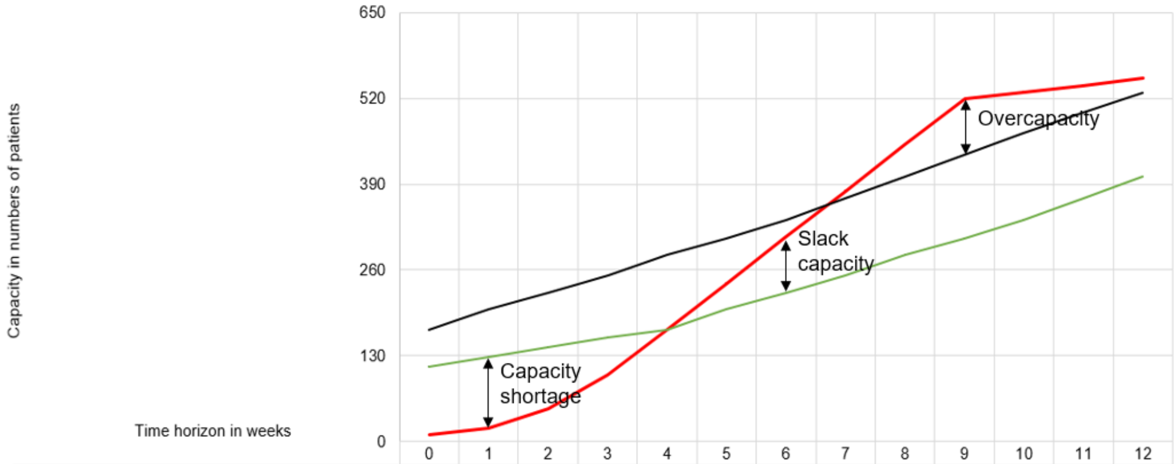


Figure 4.1: Example of a sub-trajectory of a care process, including transition probabilities (prob), historical events (hist), and interarrival times (IAT).

4.1.3 Capacity supply versus capacity demand

Now that capacity demand and the capacity supply per department and per time period have been determined, an overview of capacity demand and capacity supply can be generated in order to assess whether the initial allocation of the specialists' time meets the waiting time requirements. A useful method to create an overview of capacity supply and capacity demand is the cumulative graphical approach. This approach is an element of aggregate planning and is useful as it is intuitively appealing, easy to understand (Çakanyıldırım, 2011) and gives insight in the capacity demand of numerous time periods, which is a requirement for the decision support tool. In the execution of the cumulative graphical approach, the capacity demand that *must be seen*, the capacity demand that *could be seen*, and the capacity supply are cumulated over the time periods of the time horizon. By combining these three elements, an overview of capacity supply and capacity demand per department is generated and displayed. An example of one department is given in Figure 4.2.



	0	1	2	3	4	5	6	7	8	9	10	11	12
Cumulative capacity in number of patients	10	20	50	100	170	240	310	380	450	520	530	540	550
Cumulative demand with maximal norm waiting time in number of patients	113	128	143	158	170	200	226	251	283	308	336	368	401
Cumulative demand with minimal norm waiting time in number of patients	170	200	226	251	283	308	336	368	401	434	468	498	529

Figure 4.2: Overview of capacity and demand at department d

As can be seen in the example in Figure 4.2, a capacity shortage is present from time period 0 to time period 3 as the cumulative capacity supply (red line) is lower than the cumulative capacity demand that *must be seen* (green line). A capacity shortage means that not all patients who *must be seen* can be treated before the maximum waiting time norm is reached, thus creates undesired long waiting times. Furthermore, an overcapacity is present in time periods 7 to 12, as the cumulative capacity supply (red line) is higher than the cumulative capacity demand *could be seen* (black line). Overcapacity means that more patients can be treated than those that *could be seen*. Overcapacity creates possibly undesired brief waiting times. When the minimum waiting time norm is zero, unused capacity supply remains. Thus, overcapacity creates undesired brief waiting times or low utilization of the specialists' sessions. Finally, slack capacity is present from time periods 4 to 6, since the cumulative capacity supply is higher than the cumulative capacity demand that *must be seen* and lower than the cumulative capacity demand that *could be seen*. Slack capacity means that all patients that *must be seen* can be treated and some of the patients that *could be seen* can be treated within the waiting time norms. The waiting times are controlled, hence no undesired high or low waiting times result.

A conclusion of the above reasoning is that cumulative capacity supply should be within the area between the cumulative capacity demand lines in order to satisfy all the patients that *must be seen* and some patients that *could be seen* within the waiting time norms. This means that no overcapacity or capacity shortage is allowable since overcapacity decreases the waiting time more than the minimum waiting time norm and capacity shortages increase the waiting time more than the maximum waiting time norms. When the cumulative capacity supply is not between the cumulative capacity demand lines, measures need to be taken. When the cumulative capacity supply is between the cumulative capacity demand lines, waiting times are balanced and waiting time fluctuations are mitigated. These measures are explained in the next phase of the model, capacity balancing.

4.1.4 Capacity balancing

The result of the cumulative graphical approach is an overview of the cumulative capacity supply combined with the cumulative capacity demand that *must be seen* and that *could be seen* for each department and for each time period in the time horizon. The conclusion is reached that the cumulative capacity supply should be within the area between the cumulative capacity demand lines in order to satisfy all the patients that *must be seen* and some patients that *could be seen* within the waiting time norms. In other words, both capacity shortages and overcapacity are to be mitigated as far as possible in each department so that the waiting times are within the waiting time norms. In the cumulative graphical overview, the mitigation of capacity shortages and overcapacity is accomplished when the cumulative capacity supply (red line) is within the demand range (black and green lines). In conclusion, the aim of the model is to bring the cumulative capacity supply within the demand range lines as far as possible for each department in order to reduce the proportion of patients who experience a waiting time outside the waiting time norms.

When the cumulative capacity supply is above or below the cumulative capacity demand lines, such as in the example of Figure 4.2, measures need to be taken. Two main measures exist: the capacity demand could be changed, and the capacity supply could be changed. Two measures exist to change the capacity demand: (1) postpone the capacity demand to a later time period, or (2) transfer the capacity demand to another hospital. In postponing the capacity demand that *must be seen* to a time period later than the time of a maximum waiting time norm, the maximum waiting time norms are no longer reached and, thus, fluctuations are caused. This is undesirable and against the main aim of this study. Therefore, further postponement of capacity demand is not desired. Second, some of the capacity demand could be moved to other hospitals for their treatment. This is also undesirable since it is the aim of the study to treat all the care processes within the hospital. Hence, measures need to be taken with regard to capacity supply. A number of measures could be taken: (1) more specialists could be hired, (2) temporary specialists could be hired, or (3) specialists' working schedules could be changed by reallocating specialists to other departments. When hiring more specialists, more time slots for patients to be treated are created. However, since the specialists' time is currently not utilized as much as possible (as presented in Figure 1.6), the utilization of specialists will decrease while the utilization fluctuations remain. When flex-working specialists are hired for busy times, the waiting time fluctuations may be reduced. However, specialists are too expensive a resource for them to do flex-working. Furthermore, the OT is also a bottleneck resource that is not available at the last minute. A capacity supply measure needs to be taken that mitigates the waiting time fluctuations and the resource utilization fluctuations at a point at which it is still possible to reallocate OT time. This could be accomplished by reallocating specialists to (other) hospital departments. When overcapacity occurs in one department and a capacity shortage exists in another department, the specialists' time that causes the overcapacity in one department can be exchanged with the department with a capacity shortage. In this way, both the capacity shortage and the overcapacity are mitigated. The exchange of specialists can be effected when the time unit duration used is equal, for example, minutes or hours, or sessions with equal duration, or dayparts (e.g. morning or afternoon). When one overcapacity or shortage is larger than the other, the specialists' time is transferred proportionally to the size of the overcapacity or capacity shortage. Furthermore, slack capacity can be reduced in one or more departments to assist with decreasing the capacity shortage in other departments. Slack capacity can also be increased in one or more departments to decrease the overcapacity in other departments.

The principle of the reallocation of specialists' time at time period t is presented in Figure 4.3 and Figure 4.4. An example is present with three departments at time period t. Department 1 has no overcapacity or capacity shortage at time period t though slack capacity occurs. The slack capacity at time period t is indicated by the green double arrow. Department 2 has a capacity shortage at time period t, which is indicated by the red double arrow. Department 3 experiences overcapacity at time period t, which is indicated by the blue double arrow.

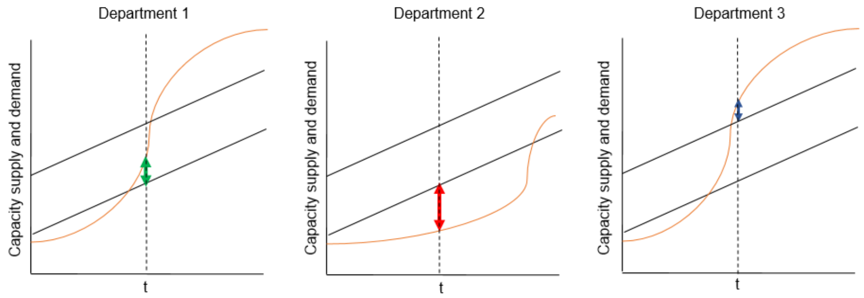


Figure 4.3: Example of an overview of cumulative capacity supply and capacity demand at three departments at time period t

Assuming that the time units in each department are equal so that the specialists' time can be exchanged on a one-to-one basis, the capacity shortage (red arrow) is filled by the specialists' time that causes the overcapacity (blue arrow) and by the specialists' time that causes slack capacity (green arrow). Simultaneously, the overcapacity is resolved by the capacity shortage (red arrow) and the slack capacity (green arrow) is decreased to zero in order to fill the capacity shortage in Department 2. This balancing of allocated specialists' time is presented in Figure 4.4. In this example, the capacity shortage is equal to the specialists' time that causes overcapacity and slack capacity, so the specialists' time could be exchanged one to one. However, many situations exist in which the exchange is not as perfect as in this example. When one capacity shortage or overcapacity is larger than another, the capacity shortage or overcapacity is resolved to a ratio in order to balance the waiting time. Furthermore, when both capacity shortage and overcapacity exist, the overcapacity is first exchanged before the slack capacity is exchanged. This is effected as overcapacity creates undesired waiting time fluctuations, while slack capacity does not.

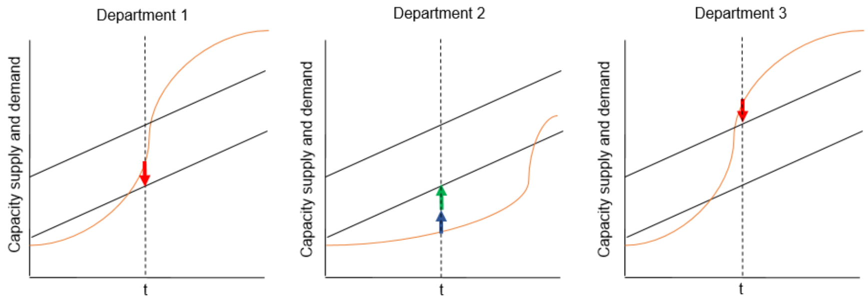


Figure 4.4: An example of the functioning of capacity balancing

The model is able to assess each department and each time period as regards capacity shortage and overcapacity. Additionally, the model reallocates the specialists' time per time period by means of the steps described below.

1. The model determines which departments have a capacity shortage, which departments have overcapacity, and which departments have no overcapacity or capacity shortage in the time period analyzed.
2. For each department, the model determines what the capacity shortage or overcapacity is expressed in specialists' time in equal time unit (e.g. sessions, dayparts, minutes or hours). The model determines the total capacity shortage expressed in specialists' time in an equal time unit and the total overcapacity in equal time unit in all departments in the time period analyzed.
3. The model assesses the situation in all departments in the time period and performs the handling according to the following scenarios:
    a. None of the departments contains a capacity shortage or overcapacity. In this case, no measures need to be taken and the next time period can be analyzed.
    b. The total shortage of all departments is equal to the total overcapacity of all departments. In this case, the specialists' time that create overcapacity is reallocated to the departments with a capacity shortage. Both overcapacity and the capacity shortage are resolved.

c. The total capacity shortage in all departments is larger than the total overcapacity of all departments. In this case, the following situations are possible:
   i. There are no other departments (without a capacity shortage): in this case, no reallocation of specialists' time can be effected.
   ii. There are no departments with overcapacity: in this case, there is no overcapacity that can be reallocated to a department with a capacity shortage—there are only departments without a capacity shortage or an overcapacity. The capacity shortage can (partly) be solved by slack capacity. The specialists' time causing slack capacity is reallocated to the departments with a capacity shortage until the capacity shortage is solved or the specialists' time causing slack capacity is zero. The departments with the highest capacity shortage receive the most specialists' time from other departments in order to balance the waiting times.
   iii. The total overcapacity is not enough to solve the total capacity shortage: in this case, all of the specialists' time causing overcapacity is reallocated to the capacity shortage. The departments with the highest capacity shortage receive most of the specialists' time in order to balance the waiting times. Slack capacity is used to solve the remaining capacity shortage. All the specialists' time causing the overcapacity and slack capacity are reallocated to the departments with a capacity shortage until the capacity shortage is solved or the specialists' time causing the slack capacity is zero. The departments with the highest capacity shortage receive the most specialists' time from other departments in order to balance the waiting times.

d. The total capacity shortage of all departments is smaller than the total overcapacity of all departments. In this case, the following situations are possible:
   i. There are no other departments (without overcapacity): in this case, no reallocation of specialists' time can be effected.
   ii. There are no departments with a capacity shortage: in this case, there is no capacity shortage that can be filled by the specialists' time that causes department's overcapacity—there are only departments without a capacity shortage or overcapacity. When overcapacity cannot be resolved by a capacity shortage, it is assumed that the overcapacity can be (partly) solved by the remaining slack capacity. All of the remaining slack capacity is filled with specialists' time from the departments with an overcapacity until the overcapacity is resolved or the remaining overcapacity is zero. The departments with the highest overcapacity reallocate the most specialists' time to other departments in order to balance the waiting times.
   iii. The total capacity shortage is not enough to resolve the total overcapacity: in this case, all of the capacity shortage is filled by the overcapacity. The departments with the highest overcapacity reallocate most of the specialists' time causing the overcapacity to the capacity shortage in order to balance the waiting times. The remaining slack capacity is used to reallocate the specialists' time remaining overcapacity. All of the capacity shortage and the remaining slack capacity are filled by the specialists' time causing overcapacity until the overcapacity is resolved or the remaining slack capacity is zero. The departments with the highest overcapacity receive the most specialist's time from other departments in order to balance the waiting times.

When overcapacity and capacity shortages for each department are reduced as far as possible, the cumulative capacity supply is updated by means of the balanced capacity allocation of the time period analyzed. Subsequently, this capacity balancing is repeated for each time period within the time horizon, except for the time periods where no changes to the session schedule are allowed. In the first time periods of the time horizon, the session schedule of the SD is fixed since the nurses have already received their working schedule. Furthermore, patients require a treatment date for a visit or for surgery a specific time in advance. When overcapacity exists in the fixed time period, the overcapacity is removed, since lost specialists' time cannot be used in the next time period. For the time periods where no changes can be made to the session schedule, the waiting times cannot be controlled by capacity balancing. However, since the model will be continuously utilized by the end-user, the session schedule will be continuously revised, which could prevent such uncontrolled waiting times.

4.1.5 Patient Allocation

The output of the capacity balancing is the allocated capacity supply for each department. Patient allocation uses the allocated capacity supply as input to allocate the capacity demand to a time period. At first, all the patients are scheduled for an initial time period. The planned patients who already have planned a treatment date are scheduled for the period planned. New patients and the subsequent treatments can initially be planned by means of forward or backward scheduling (Reid & Sanders, 2005). Forward scheduling determines the start and end time of each treatment in a care process by assigning the patient to the earliest available time period, while backward scheduling assigns the patient to the latest available time period. Forward scheduling is used to treat patients as soon as possible and minimizes the lead times, while backward scheduling minimizes the inventory of finished goods (Reid & Sanders, 2005). Since hospitals provide a service, no inventory of finished goods is present. Therefore, the used initial allocation methodology is forward scheduling.

The model allocates all patient groups to an initial time period and assesses whether all patient groups fit in the time periods allocated. When all patient groups fit in their initially allocated time period, all patients' waiting times will be zero. However, if some time slots are overutilized, patient groups will need to be shifted to the next time period so that the specialists' time allocated is not overutilized. This shifting causes a longer waiting time of one week. Shifting the patients one week ahead can be done by means of one of the relevant decision rules described below (Reid & Sanders, 2005). The six most relevant decision rules for patient allocation are:

1. Earliest due date (EDD): the patient group with the earliest due date (the lowest maximum waiting time) has priority over other patient groups. This methodology is used when patient groups or departments have different maximum waiting time norms. EDD improves customer service since few treatments are performed after the due date.
2. First come first serve (FCFS): the patient group requesting the treatment first has priority over other patient groups. This methodology is fair to customers; however, patient characteristics are not taken into account, which negatively affects throughput time or the resource utilization of the process.
3. Last come first serve (LCFS): the patient group requesting the treatment last has priority over other patient groups. This methodology is used to give priority to the last patients entering a queue. The underlying thought is that patients do not arrive too early and wait too long in the queue. LCFS reduces the average waiting time in the queue.
4. Shortest processing time (SPT): the patient group with the shortest processing time has priority over other patient groups. This methodology minimizes the average waiting time in the queue and maximizes resource utilization.
5. Longest processing time (LPT): The patient group with the longest processing time has priority over other patient groups. This methodology is used to ensure that at the end of a time period, no long processing times remain in the planning and create long overtime for the last treatment.
6. Slack per remaining operations (SRO): The patient group that requires the most remaining treatments relative to the remaining slack time (the remaining waiting time until the maximum waiting time for the treatment) in their care processes have priority over other patient groups. This methodology proves to be useful when a high proportion of the patients need to be treated within the due date. However, the average throughput time is high.

Based on these decision rules, it can be determined which patient group has to be transferred entirely to the next or previous time period (1), which patient group has to be transferred to the next or previous time period according to a ratio (2), and which patient group is allowed to remain in the initial allocated time period (3).

After shifting the patients at time period t according to the selected decision rule(s) described above, the remaining time periods need to be analyzed for overutilization. The model has to be repeated for each subsequent time period with an overutilization in the time horizon. When all remaining time periods of time horizon have been analyzed, no further overutilization is present. Furthermore, each time period has an average waiting time since all patients are allocated to a time period. The average waiting time per time period functions as evaluation of capacity balancing. Since the output of the capacity balancing (the allocated capacity supply) is based on the minimum and maximum waiting time norms, the waiting time should not be outside the waiting time norms, unless capacity balancing has already shown an underutilization that could not be prevented by the capacity shortage.

4.2 Mathematical model

The conceptual model as described in Section 4.1 can be translated into a mathematical model. First of all, the variables used as input parameters are discussed in Subsection 4.2.1. Second, the formulas for the determination of the available capacity supply are discussed in Subsection 4.2.2. Third, the formulas for the determination of capacity demand are discussed in Subsection 4.2.3. Finally, capacity balancing and patient allocation are expressed in formulas in Subsection 4.2.4 and Subsection 4.2.5, respectively.

4.2.1 Input parameters

$d \in D$	Set of departments
$c \in C$	Set of care processes
$n \in N$	Set of steps in the care process c
$s \in S$	Set of stages in a care process
$S(c,n)$	The stage of the n^{th} step of the care process c
$s \in d$	Set of stages in a care process with an equal resource requirement
$g \in G$	Set of patient groups
$t \in T$	Time horizon ($t = 0, \dots, T$)
t_0	The first time period of the time horizon
t_{fixed}	Last time period when the capacity schedule and/or patient planning is fixed, when no capacity reallocation occur
$SP(t)$	Number of available specialists at time period t
$SE(t)$	Equal time unit during which a specialist can perform treatments in each department at time period t, e.g. sessions, dayparts, minutes, hours
P_d	Number of patients who can be seen during one time period of specialists' time in the department d
$MSS_{SPEC}(t)$	Initially allocated sessions of specialists' time in the SD for specialism $SPEC$ at time period t
$WT_{norm}(s)$	(minimum or maximum) Waiting time norm for stage s
$q_{g,c,n}(t - WT_{norm}(s))$	Number of new patients ($n = 1$) or patients' successive treatments ($n > 1$) of patient group g at time period t who are in the n^{th} step of care process c and are already awaiting $WTnorm(s)$ time periods
$q_{g,c,n}(t)$	Number of planned patients of patient group g who are in the n^{th} step of care process c , and who already have a planned treatment date at time period t
$p_{g,c,(n \to n+1)}$	Transition probability that patient group g transfers from the nth step to the $n + 1^{st}$ step of the care process c
$x_{c,n \to n+1}(s)$	The time period between arising of the capacity demand at the n^{th} step of care process c until the $n + 1^{st}$ step of care process c (including average waiting time for stage s)

4.2.2 Capacity supply

The capacity supply $C(t)$ (specialists' time) is expressed in the equal time unit (sessions, dayparts, hours, or minutes), in time period t, and is determined by the following formula:

$$C(t) = SP(t) * SE(t) \tag{1}$$

Second, based on the average processing times, the initial allocation of specialists' time $IC_d(t)$, expressed as the number of patients who can be treated, for the SD and remaining departments in time period t is determined by Formula (2).

$$IC_d(t) = \begin{cases} \dfrac{C(t) - MSS_{SPEC}(t)}{m-1} * P_d & ,\forall d \neq SD \\ MSS_{SPEC}(t) * P_d & ,\forall d = SD \end{cases} \tag{2}$$

The cumulative sum of the initial allocated specialists' time $ICC_d(t)$, expressed as the number of patients that can be treated, at department d at time period t is determined by the following formula:

$$ICC_d(t) = \sum_{p=0}^{t} IC_d(p) \qquad ,\forall t \in T \tag{3}$$

4.2.3 Capacity demand

Based on the (average) norm processing times, the capacity demand $D_{s,g}(t)$ is the number of patients in patient group g requiring a treatment at stage s at time period t. The capacity demand is constructed in three steps. First, the new patient demand of patient group g arising at time period $t - WT_{norm}(s)$ is forecast as the first step $(n = 1)$ of care process c. Second, the subsequent treatments of patient group g arising at time period $t - WT_{norm}(s)$ are forecasted as the subsequent steps $(n > 1)$ of care process c. Third, the planned patient demand of patient group g which is planned in time period t is extracted as the n^{th} step of care process c. Capacity demand $D_{s,g}(t)$ is expressed in Formula (4):

$$D_{s,g}(t) = \sum_{\{\forall n \forall c | S(c,n)=s\}} q_{g,c,n}\big(t - WT_{norm}(s)\big) + q_{g,c,n}(t) \tag{4}$$

Where,

$q_{g,c,n}(t)$ — Number of planned patients of patient group g who are in the n^{th} step of care process c , and who already have a planned treatment date at time period t.

$q_{g,c,n}\big(t - WT_{norm}(s)\big)$ — Number of new patients $(n = 1)$ or patients' subsequent treatments $(n > 1)$ of patient group g at time period t who are in the n^{th} step of care process c and are already awaiting $WTnorm(s)$ time periods.

The number of patients forecasted in their subsequent treatments $(n > 1)$ is determined by means of transition probabilities by the following formula:

$$q_{g,c,n}\big(t - WT_{norm}(s)\big) = q_{g,c,n-1}\big(t - WT_{norm}(s) - x_{c,(n-1)\to n}(s)\big) * p_{g,c,(n-1)\to n}, \quad for\ n > 1 \tag{5}$$

Where,

$q_{g,c,(n-1)}\big(t - WT_{norm}(s) - x_{c,(n-1)\to n}\big)$
is the number of patients in patient group g with a subsequent treatment in the n^{th} step of care process c, at time period $t - WT_{norm}(s) - x_{c,(n-1)\to n}$. Time period $t - WT_{norm}(s) - x_{c,(n-1)\to n}$ is the time period during which the number of patients at stage s are present minus the interarrival time between the moment that the capacity demand arises at stage s and the moment of treatment at stage s.

$$p_{g,c,(n-1)\to n} = P\{X(t - WT_{norm}(s)) = S(c,n) \,|X\big(t - WT_{norm}(s) - x_{c,(n-1)\to n}\big) = S(c,n-1)\} \tag{6}$$

is the probability of being treated in stage s at time period $t - WT_{norm}(s)$, knowing that at time period $t - WT_{norm}(s) - x_{c,(n-1)\rightarrow n}$ the patients were treated in the n^{th} step of care process c.

Now that the capacity demand per stage and per patient group at time period t is known $(D_{s,g}(t))$, the total capacity demand per time period t can be determined. Furthermore, the total capacity demand that *must be seen* and that *could be seen* can be determined.

$$D_d(t) = \sum_{g\in G}\sum_{s\in d} D_{s,g}(t)\,, when\ WT_{norm}(s) = 0 \tag{7}$$

$$DM_d(t) = \sum_{g\in G}\sum_{s\in d} D_{s,g}(t)\,, when\ WT_{norm}(s) = WT_{max}(s) \tag{8}$$

$$DC_d(t) = \sum_{g\in G}\sum_{s\in d} D_{s,g}(t)\,, when\ WT_{norm}(s) = WT_{min}(s) \tag{9}$$

In order to compute the cumulative graphical overview, the cumulative capacity demand that *must be seen* $CDM_d(t)$ and the cumulative capacity demand that *could be seen* $CDC_d(t)$ are determined by cumulating the capacity demand that *must be seen* and the capacity demand that *could be seen* over time periods within the time horizon, respectively.

$$CDM_d(t) = \sum_{p=1}^{p=t} DM_d(p)\,, \qquad \forall t \in T \tag{10}$$

$$CDC_d(t) = \sum_{p=1}^{p=t} DC_d(p)\,, \qquad \forall t \in T \tag{11}$$

4.2.4 Capacity balancing

Before commencing the capacity balancing, the model reduces the unused capacity supply of the departments for the time periods in the fixed time period in order to prevent cumulative lost capacity. This is achieved by means of the following formula:

For $t_0\ until\ t_{fixed}$ and for each department determine the capacity allocation $CC_d(t)$ by taking the minimum of the cumulative capacity demand that *could be seen* $CDC_d(t)$ and the initial allocated capacity $ICC_d(t)$.

$$CC_d(t) = (CDC_d(t), ICC_d(t))^- \tag{12}$$

For $t_0 + t_{fixed}\ until\ T$ and for each department:

1. Determine the departments with a capacity shortage D^- or overcapacity D^+ or without overcapacity or a capacity shortage $D^{+/-}$.

$$D^+ = \{d \in D | ICC_d(t) > CDC_d(t)\} \tag{13}$$

$$D^- = \{d \in D | ICC_d(t) < CDM_d(t)\} \tag{14}$$

$$D^{+/-} = \{d \in D | (CDM_d(t) \le ICC_d(t) \le CDC_d(t))\} \tag{15}$$

2. Determine the capacity shortage $SH_d(t)$ and overcapacity $OC_d(t)$ per department and the total capacity shortage $SH(t)$ and overcapacity $OC(t)$ across all departments.

$$SH_d(t) = \left(\frac{\lfloor CMC_d(t) - ICC_d(t)\rfloor}{P_d}\right)^+ \tag{16}$$

$$SH(t) = \sum_{d\in D} (SH_d(t)) \tag{17}$$

$$OC_d(t) = \left(\frac{\lfloor ICC_d(t) - CDC_d(t)\rfloor}{P_d}\right)^+ \tag{18}$$

$$OC(t) = \sum_{d\in D} (SU_d(t)) \tag{19}$$

3. Assess the scenario.
   a. $If\ (SH(t) = 0\ and\ OC(t) = 0)\ than:$

$$BCC_d(t) = ICC_d(t)$$

   b. Determine the balanced cumulative capacity $BCC_d(t)$ allocation in cases where the capacity shortage is equal to the overcapacity and perform the associated measures.

      $Else\ if\ (SH(t) = SU(t))\ than:$

$$BCC_d(t) = \begin{cases} ICC_d(t) + (SH_d(t) * P_d, & \forall d \in D^- \\ ICC_d(t) - OC_d(t) * P_d, & \forall d \in D^+ \end{cases} \quad (20)$$

c. Determine whether the capacity shortage is greater than the overcapacity and perform the associated measures in order to determine the balanced cumulative capacity $BCC_d(t)$ allocation.

$Else\ if\ (SH(t)\ >\ OC(t))\ than:$

i. $If\ (D \setminus D^- = \emptyset)\ than:$

$$BCC_d(t) = ICC_d(t) \quad (21)$$

ii. $Else\ if\ \left(D\ =\ \{D^- \cup D^{+/-}\}\right) than:$

$Determine\ the\ slack\ capacity\ per\ department\ SC_d(t)\ and\ the\ total\ slack\ capacity\ SC(t).$

$$SC_d(t)\ = \left(\frac{\lfloor ICC_d(t) - CDM_d(t) \rfloor}{P_d}\right)^+ \quad (22)$$

$$SC(t)\ = \sum_{d \in D} (SC_d(t)) \quad (23)$$

$If\ SH(t) = SC(t)\ than:$

$$BCC_d(t) = \begin{cases} ICC_d(t) + SH_d(t) * P_d, & \forall d \in D^- \\ ICC_d(t) - SC_d(t) * P_d, & \forall d \in D^{+/-} \end{cases} \quad (24)$$

$Else\ if\ SH(t) > SC(t)\ than:$

$$BCC_d(t) = \begin{cases} ICC_d(t) + \dfrac{SH_d(t)}{SH(t)} * SC_d(t) * P_d, & \forall d \in D^- \\ ICC_d(t) - \dfrac{SH_d(t)}{SH(t)} * SC_d(t) * P_d, & \forall d \in D^{+/-} \end{cases} \quad (25)$$

$Else\ if\ SH(t) < SC(t)\ than:$

$$BCC_d(t) = \begin{cases} ICC_d(t) + \dfrac{SC_d(t)}{SC(t)} * SH_d(t) * P_d, & \forall d \in D^- \\ ICC_d(t) - \dfrac{SC_d(t)}{SC(t)} * SH_d(t) * P_d, & \forall d \in D^{+/-} \end{cases} \quad (26)$$

iii. $If\ D\ =\ \{D^- \cup D^{+/-} \cup\ D^+\}\ than:$

$$BCC_d(t) = \begin{cases} ICC_d(t) + \dfrac{SH_d(t)}{SH(t)} * OC_d(t) * P_d, & \forall d \in D^- \\ ICC_d(t) - \dfrac{SH_d(t)}{SH(t)} * OC_d(t) * P_d, & \forall d \in D^+ \end{cases} \quad (27)$$

Recalculate the shortage per department and total shortage and repeat Step 3.c.iii.

d. Determine whether the capacity shortage is greater than the overcapacity and perform the associated measures in order to determine the balanced cumulative capacity allocation $BCC_d(t)$.

$If\ \left(SH(t) < OC(t)\right)\ than:$

i. $If\ (D \setminus D^+ = \emptyset)\ than:$

$$BCC_d(t) = ICC_d(t) \quad (28)$$

ii. $Else\ if\ (D\ =\ \{D^+ \cup D^{+/-}\})\ than:$

$Determine\ the\ remaining\ slack\ capacity\ per\ department\ RSC_d(t) and\ the\ total\ remaining\ overcapacity\ RSC(t).$

$$RSC_d(t) = \left(0, \frac{\lfloor CDC_d(t) - ICC_d(t) \rfloor}{P_d}\right)^+ \quad (29)$$

$$RSC(t)\ =\ \textstyle\sum_{d \in D} (RSC_d(t)) \quad (30)$$

$If\ OC(t) = RSC(t)\ than:$

$$BCC_d(t) = \begin{cases} ICC_d(t) - OC_d(t) * P_d, & \forall d \in D^+ \\ ICC_d(t) + RSC_d(t) * P_d, & \forall d \in D^{+/-} \end{cases} \quad (31)$$

$Else\ if\ OC(t) > RSC(t)\ than$:

$$BCC_d(t) = \begin{cases} ICC_d(t) - \dfrac{OC_d(t)}{OC(t)} * RSC_d(t) * P_d, & \forall d \in D^+ \\ ICC_d(t) + \dfrac{OC_d(t)}{OC(t)} * RSC_d(t) * P_d, & \forall d \in D^{+/-} \end{cases} \quad (32)$$

$Else\ if\ OC(t) < RSC(t)\ than$:

$$BCC_d(t) = \begin{cases} ICC_d(t) - \frac{RSC_d(t)}{RSC(t)} * OC_d(t) * P_d, \ \forall d \in D^+ \\ ICC_d(t) + \frac{ROC_d(t)}{ROC(t)} * OC_d(t) * P_d, \ \forall d \in D^{+/-} \end{cases} \quad (33)$$

iii. $Else\ if\ (D = \{D^- \cup D^{+/-} \cup D^+\}\ than$:

$$BCC_d(t) = \begin{cases} ICC_d(t) - \frac{OC_d(t)}{OC(t)} * SH_d(t) * P_d, \ \forall d \in D^+ \\ ICC_d(t) + \frac{OC_d(t)}{OC(t)} * SH_d(t) * P_d, \ \forall d \in D^- \end{cases} \quad (34)$$

Recalculate the capacity shortage per department and the total capacity shortage. Repeat Step 3.d.iii.

4. $t = t + 1$, until $t = T$ and go back to Step 2 if $t \neq T + 1$.

4.2.5 Patient Allocation

1. Schedule the capacity demand per time period t and per department d with a waiting time of zero $(D_d(t))$.
2. Compare the allocated capacity demand $(D_d(t))$ in each time period and each department with the balanced capacity supply $(BC_d(t))$ allocation.

$$BC_d(t) = \begin{cases} BCC_d(t), & \forall\ t = 0 \\ BCC_d(t) - BCC_d(t-1), & \forall\ t \neq 0 \end{cases} \quad (35)$$

3. Determine if time periods exist where the allocated capacity demand in a department $D_d(t)$ is larger than the allocated capacity supply $C_d(t)$.

$$T^- = \{t \in T | D_d(t) > C_d(t)\} \quad (36)$$

   a. If $T^- = \emptyset$: Stop: all patients are planned without exceeding the allocated capacity supply in each time period and each department.
   b. If $T^- \neq \emptyset$:
      i. Determine the minimum time period with a capacity shortage.

$$t^* = \min\{t | t \in T^-\} \quad (37)$$

      ii. Determine the capacity shortage for patients for t^*.

$$SH_d(t^*) = D_d(t^*) > C_d(t^*). \quad (38)$$

      iii. Based on one of the decision rules mentioned in Subsection 4.1.5, determine which patient group:
         1. Has to be transferred entirely to time period $t + 1$.
         2. Has to be transferred to time period $t + 1$ according to a ratio.
         3. Is allowed to stay in time period t.
      iv. Remove the patients who are required to shift one time period at time period t.
      v. Remove the subsequent treatments of the patients who are required to shift one time period in their time period t.
      vi. Place the shifted patients and their subsequent treatments at time period $t + 1$.
      vii. The overutilization is resolved at t^*. Go back to Step 3 to check whether other time periods still have a capacity shortage.

The determination of the new and known patients and their subsequent treatments is accomplished following the methodology explained in Section 4.1 and which is further explained in the case study, since the methodologies are case dependent.

5. Case Study

In this chapter, the designed model is validated and verified by means of a case study performed at the case hospital. Furthermore, a decision support tool is designed in order for hospitals to use the model. Screenshots of the decision support tool are shown in Appendix G. The results of the model specified for orthopedics are discussed in this chapter. The chapter is structured as follows: in Section 5.1, the input parameters for the model are determined according to the current organization of the case hospital. In Section 5.2, the results of the model are discussed. In Section 5.3, the model's performance is discussed and compared to the baseline measurement.

5.1 Determination of input parameters

In this section, the values of the input parameters of the model are determined. All the input parameters discussed in the mathematical model are determined in the forthcoming subsections. First, the planning horizon is determined in Subsection 5.1.1. Second, the relevant departments for the specialism discussed are determined in Subsection 5.1.2. In Subsection 5.1.3, the relevant stages in the care process are determined. In Subsection 5.1.4, the patient groups are determined. Subsection 5.1.5, 5.1.6, 5.1.7, 5.1.8, 5.1.9, and 5.1.10 discuss the available specialists' time, the available OT time, the waiting time norms, the number of new patients, the number of known patients, and the subsequent treatments, respectively.

5.1.1 Determination of the planning horizon

An input parameter of the model is the time horizon over which the capacity supply is allocated to the capacity demand. As stated by Vissers & Beech (2005a), the time horizon for resource planning is three months to one year. Additionally stated is the time horizon for patient group planning, which is from some weeks to three months. The designed model combines resource planning with patient group planning in two steps; capacity balancing and patient allocation. Capacity balancing focuses on resource planning and patient allocation focuses on patient group planning. Since the model includes both resource planning and patient planning, the time horizon should be around three months.

In order to determine the exact length of the planning horizon, the total planning horizon can be divided into two subsections; the demand time fence and the planning time fence (Çakanyıldırım, 2011). The demand time fence of the time horizon is known as *the fixed time period*. The planning time fence of the time horizon is known as *the open time period*. An example of the two time periods in the time horizon is presented in Figure 5.1.

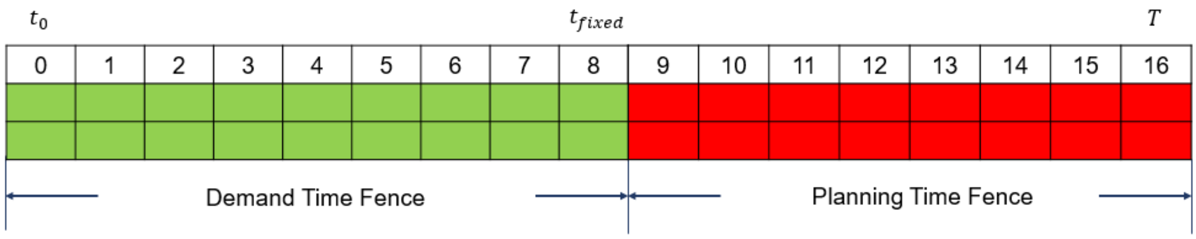


Figure 5.1: Relevant phases in the time horizon of the model (Çakanyıldırım, 2011).

The demand time fence is characterized by a fixed nurse schedule. In this time period, the session schedule for the SD is published and, thus, fixed. The nurse schedules need to be published 8 weeks in advance, which sets the fixed time period of the time horizon to 8 weeks (Anonymous orthopaedist, 2018).

The planning time fence begins 8 weeks after the start of the time horizon. In the open time period, the specialists' time is reallocated between departments and specialisms in order to reduce the proportion of patients experiencing waiting times outside the waiting time norms.

The length of the open time period is set at 8 weeks. This choice is based on the following reasoning:

- When the time horizon lengthens, a forecast of the far future will be less accurate (Nahmias & Cheng, 2009). Hence, the time horizon needs to be minimized.
- When the time horizon becomes shorter, the planned time fence becomes shorter while, in this time period, the model performs at its greatest strength. Furthermore, there is a risk that not all the last treatments in a care process are outside the time horizon, which could cause unexpected peaks of capacity demand (Çakanyıldırım, 2011). Hence, the time horizon needs to be maximized.

A trade-off is necessary to determine the length of the open time period. Since the capacity manager is advised to check the session schedule every other week (ChipSoft capacity management specialist, 2018), the open time period needs to be a minimum of 2 weeks. In order to correct or edit the capacity planning once more during the next session planning, the open time period is set to 8 weeks.

Summarizing, a planning horizon of 16 weeks is selected for this model. Note that other hospitals could maintain other divisions of the time horizon.

The start date of the model was selected as 05-09-2016. This date was selected because the dataset provided is complete until 31-12-2016. This means that the time period analyzed is the most recent time period.

Since the planning horizon comprises 16 weeks, the dimension of time selected is weeks. One disadvantage of a time dimension of weeks instead of days is that the waiting times are not as precise as desired. However, analyzing the model per week reduces variability and provides a clear overview for the capacity manager.

5.1.2 Relevant departments

An input parameter is the relevant departments across which the specialists need to be divided. Since this study is scoped on orthopedics and specialists only perform patient-related activities at the OPD and the SD, these are the relevant departments in this case study.

5.1.3 Stages in care processes

The SD knows one main stage to be in: surgery. The OPD knows two main stages for a patient to be in: NP and CP. Combining the OPD and the SD, three main stages for a care process in this case study are NP, CP, and surgery.

5.1.4 Determination of patient groups

In order to create a realistic demand forecast, capacity demand is forecast per patient group. As seen in Chapter 3, DTCs contain average care processes and could be interesting for grouping patients in order to determine their care processes. However, DTCs are mainly intended for financial purposes, rather than logistics. This has the result that the DTC is not directly registered at the first visit of a patient. Furthermore, more than 4,000 different DTCs exist (Nederlandse Zorgautoriteit, 2017). Since the DTCs are not registered at the first visit of a patient, another classification of patients is required. A code similar to the DTC code, though at a higher level, is the diagnosis code. The diagnosis code is part of the derivation of the DTC code and is often registered at the first visit of a patient. Around 2,500 diagnosis codes exist (Ministerie van Volksgezondheid, 2016). The diagnosis codes are used as a basis for the creation of patient groups.

To divide patients into patient groups, orthopedic patients are classified by their diagnosis code. However, since 2,500 diagnosis codes exist, some patient groups are very small. For forecasting accuracy purposes, small patient groups are not desired, since fewer observations are present. In order to increase the number of patients per patient group, diagnosis codes are grouped into a patient group. Patients may be classified according to the similarities in their care processes. One similarity in care processes is the need for resources, for example, the need for an OT. Patients with the same diagnosis code and an equal surgical duration are clustered in the same patient group. Since the k-means algorithm is a fast, well-known, and easily understood method, it is used as the clustering technique to find the optimal composition of diagnosis codes within k number of clusters. The data points are clustered based on a similarity (Hartigan, 1989). In this case, surgery duration is the variable of similarity. In order for the k-means algorithm to work, the surgery durations of each diagnosis type need to be normally distributed. Strum, May, and Vargas (2000) conducted research on a large and diverse dataset of surgery times and concluded that "procedure times (surgical time and total time) fit the log-normal distribution significantly better than they do the normal" (Strum et al., 2000, p. 1167). Based on these results, the log-normal surgery durations are transformed so that they follow the normal distribution.

The k-means algorithm assumes a number of k clusters. In order to determine k, the k-means algorithm is performed for each k between zero and twenty. The performance of the k-means algorithm is registered for each k. The k number of clusters is chosen by the increase in the performance of the algorithm. When the performance of an extra cluster does not improve by more than 5 percent, no extra cluster is added. This threshold value is determined by means of the elbow methodology, which is displayed in Figure H.1 in Appendix H. The elbow methodology helps to determine what the optimal number of clusters should be by means of a trade-off between the increase in performance and the increase in clusters (Bholowalia & Kumar, 2014). The elbow methodology is not always clear, for example, when multiple "elbows" appear. In this case, the smallest "elbow" value is chosen in order to maximize the number of patients per patient group. In this study, the smallest "elbow" value is six patient groups. A seventh patient group is added, which consists of diagnosis codes where no surgery appears in the care processes. The care processes with these diagnosis codes only contain OPD visits and perhaps a diagnostic visit or a clinical admission. However, since these latter departments are out of the scope of this study only the OPD visits are included. The final patient groups are presented in Table 5.1. The execution of the clustering method, including which diagnosis code belongs to which patient group, can be found in Table H.1 and Table H.2 in Appendix H.

Table 5.1: Patient groups determination

Patient group	Mean surgery duration (minutes)	Average number of NP per week (% of total)	Average number of CP per week (% of total)	Average number of SD per week (% of total)
1	60.50	19 (22%)	22 (21%)	4 (16%)
2	34.23	10 (12%)	5 (5%)	1 (4%)
3	85.63	20 (24%)	31 (30%)	7 (28%)
4	16.44	1 (12%)	1 (1%)	0 (0%)
5	120.97	8 (9%)	15 (14%)	4 (16%)
6	45.04	22 (26%)	25 (24%)	9 (36%)
7	0	5 (6%)	6 (6%)	0 (0%)

5.1.5 Determination of the available specialists' time for OPD and SD

An input parameter for this model is the total available specialists' time per specialism per time period. In order to determine this input parameter, the number of available specialists per specialism per time period $SP(t)$ and the number of time slots (sessions, dayparts, hours, minutes etc.) $SE(t)$ a specialist can fill per time period needs to be determined. Additionally, the number of patients P_d who can be seen by one specialist in one time slot needs to be determined per department.

The available specialists' time for the OPD and the SD combined can be determined by the number of specialists available. As indicated in Chapter 3, the case hospital has four orthopedic specialists. Each specialist can perform 10 patient-related dayparts each week for 44 weeks a year (Federatie Medisch Specialisten, 2017). Converting this number to a year of 52 weeks, around 8.5 patient-related dayparts each week can be fulfilled. For orthopedics, patient-related activities consist of visits to the OPD and surgeries in the SD, for both elective and emergency treatments. Excluding the emergency patient-related activities, 6.7 patient-related dayparts can be filled each week. For this case study, this means that, each week, a maximum of 27 dayparts can be allocated across both departments.

Also shown in Chapter 3 is the fact that both the OPD session schedule and the SD schedule are based on one session per daypart. In other words, one daypart could contain one OPD or SD session per specialist. Therefore, sessions can be exchanged one by one in the capacity balancing. One session in the OPD can be exchanged with one session in the SD and the other way around since both fit within one daypart and no more than one session is planned within a daypart. Based on average processing times, the average number of patients treated in each session in a department is determined according to the procedure described below.

The number of patients a specialist can see in an SD and OPD daypart depends on the duration of the treatment. In the case hospital, a fixed amount of time per visit is planned. For an NP visit, 10 minutes is scheduled and for a CP visit, 5 minutes is scheduled. Furthermore, it is known that the ratio of NP:CP used in an OPD session is around 1:1. Taking into account that an OPD session also contains other visit types (Appendix D), which covers 10 percent of the demand, 10 percent of the OPD sessions are reserved for other visit types and a break. The data analysis reveals that an average of five NP patients and five CP patients can be seen in an OPD session. In an SD session, an average of three patients can be seen. This number is based on the total number of historical elective orthopedic treatments divided by the total number of historical orthopedic elective sessions at the case hospital in 2016.

The initial capacity supply per department is determined by dividing the available specialists' time across the relevant hospital departments. In this case study, the relevant hospital departments are the OPD and the SD. The SD is initially allocated the specialists' time from the MSS allocated to orthopedics. The OPD is allocated the remaining specialists' time. Since the case hospital works with NP and CP slots in the OPD sessions, the specialists' time is separately allocated to these stages. It is important to provide insight into the effect of accepting a new patient on the number of subsequent CP visits and surgeries in the SD. For these reasons, the OPD is separated into two sub-departments. In the remainder of this case study, the relevant hospital departments are NP, CP, and SD.

The remaining specialists' time needs to be allocated across NP and CP. The allocated specialists' time is computed by means of Formula (2). An extra restriction is added since the NP and CP work with time slots within sessions. To make the sessions one-to-one exchangeable, separate sessions are created for NP and CP. Since the duration of an NP visit is twice the duration of a CP visit, the 1:1 patient ratio is not maintained when the sessions are allocated 1:1 across the sub-departments. Therefore, the ratio 2:1 is used in order to reflect a realistic starting scenario. The initial allocation of the remaining specialists' time to the NP and CP in sessions and in patients is shown in Table J.1 and Table J.2, respectively.

5.1.6 Determination of available OT time from the MSS

In addition to the specialists' time, the initial allocated OT time (in sessions) per specialism and per time period $MSS_{SPEC}(t)$ should be an input parameter for the model. The initial allocated OT time per specialism is determined from the annually created MSS. The initial SD allocation is shown in Table J.1 in Appendix J.

5.1.7 Determination of waiting times norms

An input parameter is the target range the waiting times are aimed to occur within. The target waiting time range can differ per stage in the care process. The waiting times are required to be within the range determined by the *Treeknormen*. As indicated above, the *Treeknormen* are as follows: in the SD, a maximum waiting time $(WTmax_{OK})$ of 7 weeks is allowed and no minimum waiting time norm is provided. In the OPD, a maximum access time $(WTmax_{NP})$ of 4 weeks is allowed and a maximum waiting time $(WTmax_{CP})$ of 4 weeks is allowed. However, in this case study, the waiting time norms for the SD and the access times are slightly adapted for the following reasoning: the minimum waiting times norms for each department at the OPD $(WTmin_{CP}\ and\ WTmin_{NP})$ are set at zero.

The waiting time for surgery often (80.6 percent of all surgery requests from 2013 to 2016) begins on the day of the previous treatment, since the request for surgery is made directly at the end of the visit. In order to maintain the *Treeknormen*, patients need to be seen at least 7 weeks after the surgery request date; however, the patient can only be treated 3 weeks after the request date (Anonymous orthopaedist, 2018). This means that the minimum waiting time norm for the SD is set at 3 weeks and the maximum waiting time norm remains 7 weeks. Second, based on the knowledge gained from an anonymous orthopedist (2018), the maximum access time norm for NPs is adapted to 1 week. Competitive private institutions can provide an access time of 1 week or less and take away patients who desire early access. Hospitals need to maintain a maximum access time of 1 week in order to prevent demand loss.

5.1.8 Determination of new patients

New patients are the start of each elective orthopedic care process. The arrival pattern of new patients can be seen as an external arrival process. As mentioned in Section 4.1.2, numerous techniques exist to forecast an external arrival process. Since the external arrival process of the case hospital includes seasonality and a trend, Holt-Winters is selected as the forecast methodology. The methodology, presentation of the external arrival process and the forecast, the results, and the evaluation are discussed in Appendix I.

New patient demand is transformed into the new patient demand that *must be seen* and the new patient demand that *could be seen* by the determined waiting time norms. Since the Holt-Winters methodology forecast the date that the demand arises, the demand that *could be seen* (DC_{new}) is equal to the result of the Holt-Winters forecast. The demand that *must be seen* (DM_{new}) is equal to the result of the Holt-Winters forecast when all patients wait 1 week. The patients *that must be seen* in week 0 are planned patients (PP) and are forecast in the following subsection. The new patient demand that *must be seen* and *could be seen* are presented in Table 5.2. PP represents the planned patients that causes the capacity demand that *must be seen* in week 0.

Table 5.2: Result of the new patient demand that must be seen and could be seen

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
DC_{new}	99	94	95	92	95	98	81	103	110	97	91	96	87	94	82	42	34
DM_{new}	PP	99	94	95	92	95	98	81	103	110	97	91	96	87	94	82	42

5.1.9 Extraction of known patients

As mentioned in Subsection 5.1.1, the start date of the model is 05-09-2016. Patients who went to the hospital with their care demand before the start date have thus already started their care process. Two data extractions have been performed in order to gather the planned patients and the historically known patients.

The first data extraction performed gathered all the historically known patients who already started their care process before the start date. Only the last treatment of the open care process, which occurred before the start date, is taken into account. This last treatment functions as the basis for the forecast of the remainder of the care process. Since the treatments of the historically known patients are already in the past, these patients no longer require capacity. However, the remainder of their care processes does require capacity in the future. The remaining treatments of their care processes are referred to as subsequent treatments and are determined in Subsection 5.1.10.

The second data extraction performed gathered all the patients who already have requested a treatment, though the treatment date is after the start date of the model. These patients have requested a treatment before the start date and still waiting to receive a treatment date, or they may already have planned a treatment date. Since this difference is not retraceable in the dataset, it is assumed that these patients already have planned a treatment date, which is fixed. This means that the planned treatment is seen as both demand that *could be seen* and demand that *must be seen*. Table 5.3 shows the number of treatments of the planned patients in each time period of the time horizon. A notable observation is that at the beginning of the time period, many patients are planned and, at a certain time, the number of planned patients is low. This sudden decrease is probably caused by the planning horizon of the department.

Table 5.3: The result of the planned patient extraction per time period in the number of patients

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	3	10	5	0	3	1	1	1	0	0	0	0	0	0	0	0	0
CP	48	91	41	27	28	27	3	1	0	0	0	0	0	0	0	0	0
SD	13	21	11	12	12	7	6	5	10	4	6	2	1	0	0	2	3

5.1.10 Determination of subsequent treatments

Subsequent treatments are based on the new and the known patients. By means of transition probabilities and interarrival times, the subsequent treatments can be determined. The determination of transition probabilities and the interarrival times are accomplished in the subsections that follow. Finally, the result of the subsequent treatments forecast is provided.

5.1.10.1 Determination of transition probabilities

The transition probabilities indicate the probability of a patient group transferring from stage i to stage j. The transition probabilities are determined from the dataset provided by the case hospital. All orthopedic-related treatments a patient has had at the OPD and the SD are collected. In this overview, it is unknown whether all the treatments that cure the same diagnosis belong to the same care process. By means of the DTC code, the treatments of a patient can be linked to a care process identifier. This link provides a dataset that shows all the treatments for all the care processes performed for orthopedics. From this dataset, each transition, including its historical stages, can be determined..

5.1.10.2 Determination of interarrival times

The transition probabilities indicate the probability of a patient group transferring from stage i to stage j. However, it is also crucial to know *when* the subsequent treatments occur. The interarrival times need to be determined in order to make the transition probabilities meaningful. The interarrival times are defined as the time between the last treatment date and the date of the arising of the capacity demand for the next treatment. There are two ways to determine the interarrival times:

1. Extraction from historical data: From the dataset, the time between the last treatment and the subsequent treatment in a care process could be extracted. However, this interarrival time does not fit with the abovementioned definition of interarrival times. The important difference between these dates is that an unknown period of waiting time is included in the realized interarrival times. For example, a patient could request a treatment date earlier or later than the moment the demand is expected to arise, because of patient preferences. Another possibility is the extension of the waiting time due to a lack of capacity. This creates a bias in the registered interarrival times. For this reason, it was decided not to extract the interarrival times from the dataset.

2. Set deterministic interarrival times: In order to set realistic interarrival times, the interarrival times are deterministically determined in consultation with an orthopedist. The prewritten, deterministic interarrival times as a result of the consultation are presented in Table 5.4.

Table 5.4: Medically preferred interarrival times set by an orthopedist

Transition	Interarrival times
NP → CP	8 (due to the diagnostic department or physiotherapy)
NP → SD	3 (due to pre-surgical activities)
CP → CP	8 (due to medicine or physiotherapy)
CP → SD	3 (due to pre-surgical activities)
SD → SD	2 (repair surgery)
SD → CP	8 (due to wound healing/infection)

5.1.10.3 Results of the subsequent treatment forecast

The combination of the known patients, new patients that *must be seen* and new patients that *could be seen*, the transition probabilities, and the interarrival times create the subsequent treatments. The result of the subsequent treatments that *could be seen* and *must be seen* is presented in Table 5.5 and Table 5.6, respectively.

Table 5.5: Result of the subsequent treatments that could be seen *(in the number of patients)*

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
CP	107	98	111	105	119	91	97	97	140	133	144	116	126	113	115	131	150
SD	PP	PP	PP	18	18	29	25	26	24	24	22	21	25	30	26	25	26

Table 5.6: Result of the subsequent treatments that must be seen *(in the number of patients)*

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
CP	PP	PP	PP	PP	107	98	111	105	119	91	97	97	140	133	144	166	126
SD	PP	PP	PP	PP	PP	PP	PP	18	18	29	25	26	24	24	22	21	25

5.2 Model results

This section presents the results of entering the determined parameters into the model. The performance measure of interest is the proportion of allocated patients experiencing a waiting time outside the waiting time norms. The output of the capacity balancing is the amount of specialists' time allocated to each hospital department, and the output of the patient allocation is the allocation of patients to each time period and their corresponding waiting time. The following subsections provide an overview of the results of each step of the model. Subsection 5.2.1 provides an overview of the results of capacity balancing. Subsection 5.2.2 provides an overview of the results of patient allocation.

5.2.1 Results of capacity balancing

Based on the determined input parameters, an overview of the cumulative demand *that must be seen*, cumulative demand that *could be seen,* and cumulative capacity supply is generated. The detailed computation of capacity demand, capacity supply, and the cumulative graphical overview, including explanation of the overview, is presented in Appendix J. Next, before the capacity balancing is undertaken, the overcapacity in the time periods with a fixed nurse schedule is removed. The start scenario of the capacity balancing is presented in Figure 5.6. As indicated by the blue surface in the figure, overcapacity was present in the SD in the fixed time horizon. This overcapacity is removed by removing specialists' time allocated to the SD. The number of sessions of specialists' time removed per time period is shown in Table 5.7 and indicated by the number in parentheses. As can be seen in the table, the total number of sessions decreases during these time periods.

Table 5.7: The result of the initial capacity allocation across the relevant departments in sessions of specialists' time

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	12	13	13	12	13	11	11	12	11	12	11	11	11	11	11	11	11
CP	6	7	7	6	7	6	6	7	6	7	6	6	6	6	6	6	6
SD	4 (-4)	7	4 (-3)	9	7	10	10	8	10	8	10	10	10	10	10	10	10
Tot.	**23 (-4)**	**27**	**24 (-3)**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**

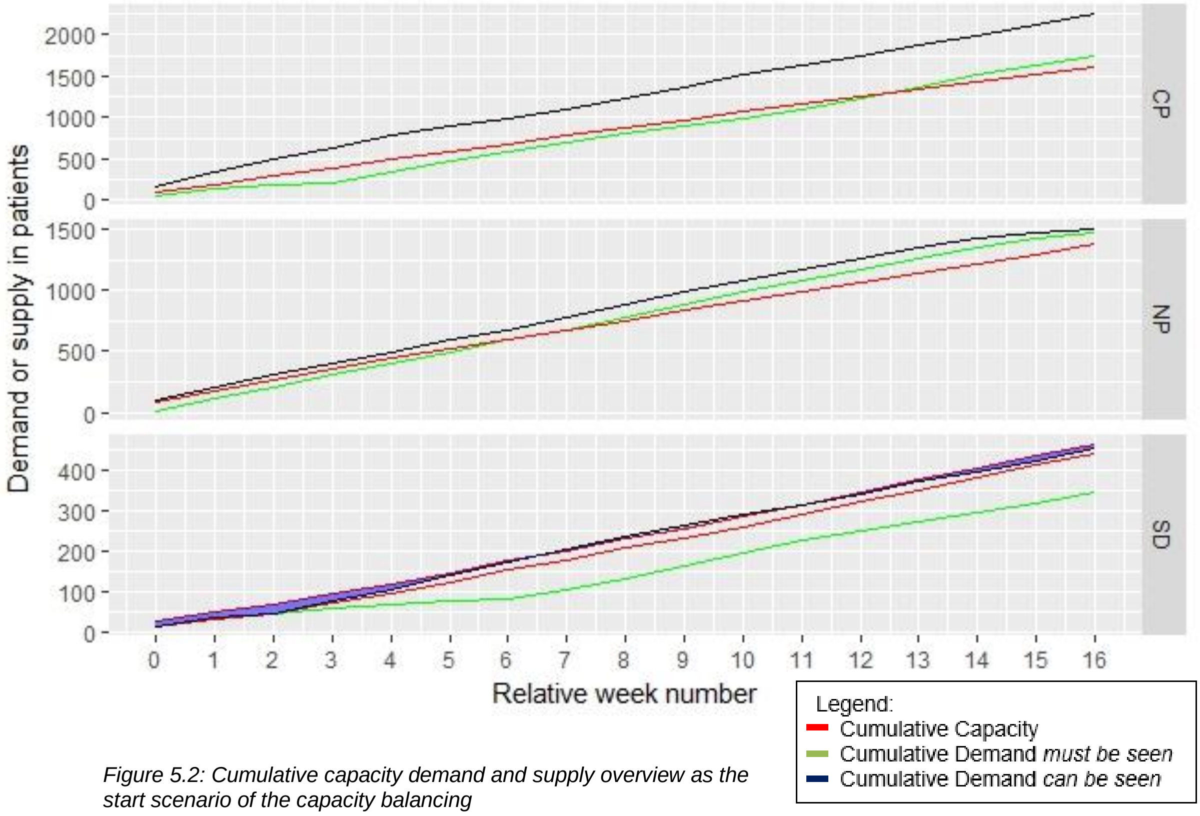


Figure 5.2: Cumulative capacity demand and supply overview as the start scenario of the capacity balancing

With this overview, the capacity balancing has been conducted. Figure 5.3 shows the result of the capacity balancing for the open time period. The figure provides an overview of cumulative demand and supply after the reallocation of capacity in the open time period. As can be seen, the cumulative capacity fits within the cumulative demand range, except for time period 8 in the NP sub-department. Unfortunately, no capacity could be added to this part of the time horizon since the nurse schedule had already been released. The maximum waiting times are exceeded. However, since this model would be used continuously every two weeks, exceeding the waiting time can be prevented in the future.

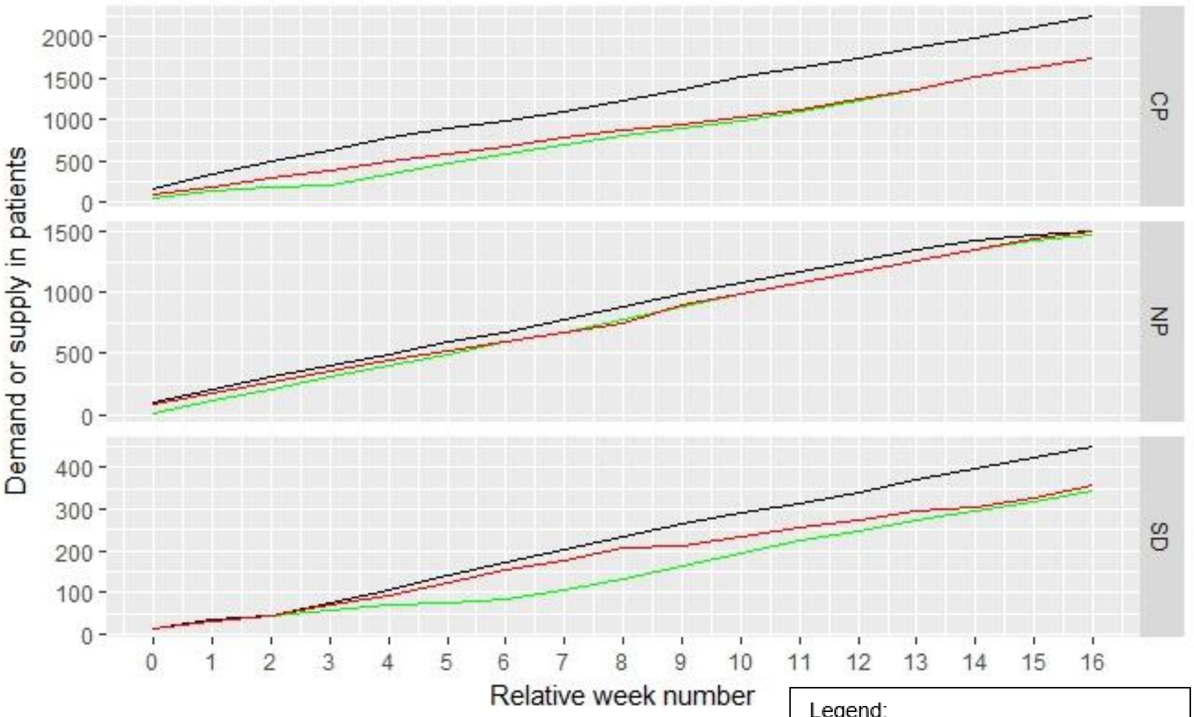


Figure 5.3: Cumulative capacity demand and supply overview as the result of the capacity balancing

The final balanced capacity allocation in sessions is presented in Table 5.8. As can be seen in the table, the distribution of the sessions across the departments has changed. The session adaptations are indicated by the numbers in parentheses per time period. It can be noted that the sum of the session adaptations is zero in each time period. This causes the total allocated capacity to remain 27 in the open time period, from which can be concluded that all the specialists' time is utilized.

Table 5.8: The balanced capacity allocation to each relevant department per open time period

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	12	13	13	12	13	11	11	12	11	20 *(+8)*	14 *(+3)*	13 *(+2)*	13 *(+2)*	13 *(+2)*	13 *(+2)*	12 *(+1)*	10 *(-1)*
CP	6	7	7	6	7	6	6	7	6	5 *(-2)*	6	6	8 *(+2)*	8 *(+2)*	10 *(+4)*	8 *(+2)*	7 *(+1)*
SD	4 *(-4)*	7	4 *(-3)*	9	7	10	10	8	10	2 *(-6)*	7 *(-3)*	8 *(-2)*	4 *(-4)*	6 *(-4)*	4 *(-6)*	7 *(-3)*	10
Tot.	**23 *(-4)***	**27**	**24 *(-3)***	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**

The capacity allocation in sessions is also determined per department (OPD and SD) for each time period. The number of sessions allocated to both departments in each time period is shown in Table 5.9.

Table 5.9: The balanced capacity allocation for the OPD and SD per open time period

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	18	20	20	18	20	17	17	19	17	25	20	19	21	21	23	20	17
SD	3	7	4	9	7	10	10	8	10	2	7	8	4	6	4	7	10
Tot.	**23**	**27**	**24**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**

Since the OPD sessions consist of NP and CP time slots, the number of NP and CP time slots per session needs to be determined. This is achieved by means of the NP:CP ratio. The ratio of NP:CP visits per OPD session can be determined by the sessions allocated to the NP and CP is shown in Table 5.8. The resulting NP:CP ratio is shown in Table 5.10.

Table 5.10: The balanced NP:CP ratio within the allocated OPD session per time period

	9	10	11	12	13	14	15	16
NP:CP	4:1	7:3	13:6	13:8	13:8	13:10	3:2	10:7

The proposed capacity allocation for each department is a feasible solution, though not the optimal solution. Capacity managers are free to decide about other feasible solutions. This decision-making is enabled by the decision support tool.

5.2.2 Results of patient allocation

In the patient allocation, the patients requesting treatment in the OPD or in the SD are allocated to an initial time period according to the forward scheduling methodology. Furthermore, the patients are shifted to a later time period when the time period is overutilized. This shifting is accomplished by means of one of the decision rules mentioned in Subsection 4.2.5. The decision rule selected for this case study to shift patients to another time period are FCFS and EDD. This decision is based on the following reasoning:

1. Since this decision support tool supports decision-making at a tactical level, processing times per stage are assumed to be an average processing time, which is equal for all patient groups. No difference or priority as regards a patient group can be indicated by means of processing time. In conclusion, the SPT and the LPT are not useful in this case study as allocation methodologies.
2. Since the aim to balance the waiting times, LCFS is not a useful methodology to use to allocate patients to a time period. Patients experiencing a long waiting time will get a longer waiting time and patients with a short waiting time will be seen immediately. Furthermore, since a hospital provides a service to patients, patients could experience that it is unfair or feel that they are being ignored. For this reason, LCFS was not selected as a patient allocation decision rule.
3. Since SRO balances the waiting times per patient instead of the waiting times per department, this decision rules was not selected as patient decision rule.
4. Since all patient groups are elective, no distinction is made between the due dates of patient groups in each department. Each patient group has the same maximum waiting time for each stage in the care process and for each department, and thus, the same due date. Therefore, the EDD is equal to the FCFS, since the earliest request has the earliest due date. This methodology is used to allocate patients to a time slot.

In conclusion, EDD and FCFS are used as a decision rule to allocate patients to a time period. This means that patients with a long waiting time have priority over patients with a brief waiting time. However, a hospital is free to choose (an)other decision rule(s), when another optimization is the aim.

In addition to the selected decision rule, priority is given to patients who have already received a treatment date. Ideally, this date is no longer changed after the patient has been informed of it. These patients have the highest priority level.

When patients have the same waiting time and are the same patient type (planned treatment or no planned treatment) and the time slot is full, the patient groups are shifted to the proportion of the overcapacity and allocated to the subsequent time slot.

The model performed patient allocation based on the selected decision rules. Table K.1 in Appendix K shows the number of patients treated per department per week with their waiting times as a result of patient allocation.

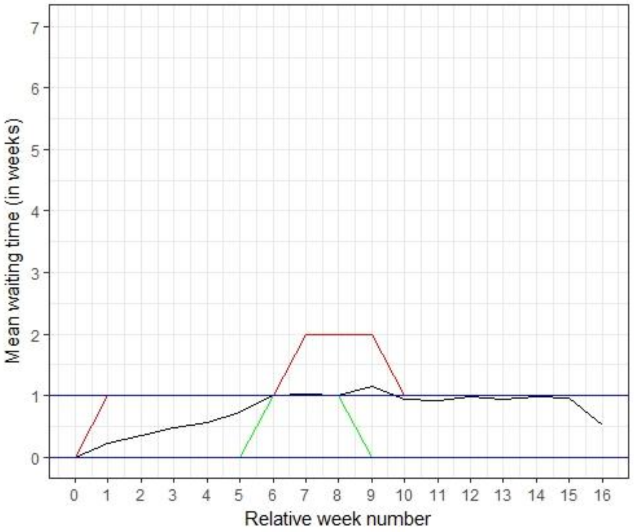
5.3 Model performance

The resulting average waiting times for NP visits, CP visits, and surgeries are presented in Figure 5.4, Figure 5.5, and Figure 5.6, respectively. As in the baseline measurement in Section 3.3, five lines are displayed to present the waiting times: the average waiting time, the minimum and maximum waiting times, and the minimum and maximum waiting time norms. When part of a line is not displayed, the line is underneath another line and follows the same pattern. For this performance measure, planned patients are excluded, since these patients already had a treatment date before the model was used. These waiting times are not influenced by the model.

As can be seen in Figure 5.4, the average waiting time for NP visits at the beginning of the time horizon is close to zero, since the cumulative capacity was nearly equal to the demand that *could be seen*. When the cumulative capacity approaches the demand that *must be seen,* the waiting time increases to just above 1 week in time periods 7 and 9. In these time periods, a capacity shortage remains, which indicates the waiting time peaks. The remaining overcapacity in the other departments in time period 7 is caused by the fixed time period. No capacity reallocation could be accomplished during this time period. The remaining capacity shortage in time period 9 is a consequence of the capacity shortage in time period 7 since the capacity that *must be seen* exceeds the maximum waiting time norm in time period 7. This means that the demand that *must be seen* in the subsequent time periods is higher than the demand shown that *must be seen* line, since unforeseen patients must be seen in later time periods. Furthermore, the high maximum waiting time values are remarkable. The average waiting times of CP visits and surgeries are balanced between the minimum and maximum waiting times norms.

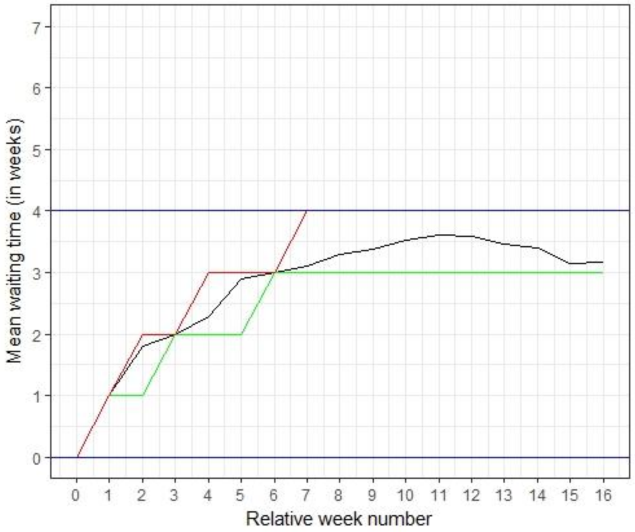
Comparing the results of the decision support tool with the results of the baseline measurement, waiting time performance is improved. The proportion of patients who experience a waiting time outside the waiting time norms is lower. Furthermore, the minimum and maximum waiting times are closer to each other, which means that the waiting times are more reliable. However, the results generated are probably more positive than could be generated in realistic hospital scenarios, for a number of reasons. All patients are seen following the EDD decision rule, while in realistic scenarios, patients are planned according to their surgery operation (in Dutch: verrichtingen “straatje”) or patient preference for a later treatment date. These scenarios could cause waiting time fluctuations; however, they are not taken into account in this result.

In conclusion, the model balances the waiting times in both the SD and the OPD by determining what capacity should be allocated to each department. Furthermore, the model correctly allocates patients to a time slot. In addition, the three interdependencies of the OPD and SD are taken into account by the model and the model is graphically supported to ensure that hospital capacity managers can insert the model in their hospital environment. Insights into the effect of allocating capacity to a department based on a department’s average waiting time could be gained. Therefore, the model is able to support hospitals in optimizing the allocation of capacity to the OPD and the SD at a tactical level.



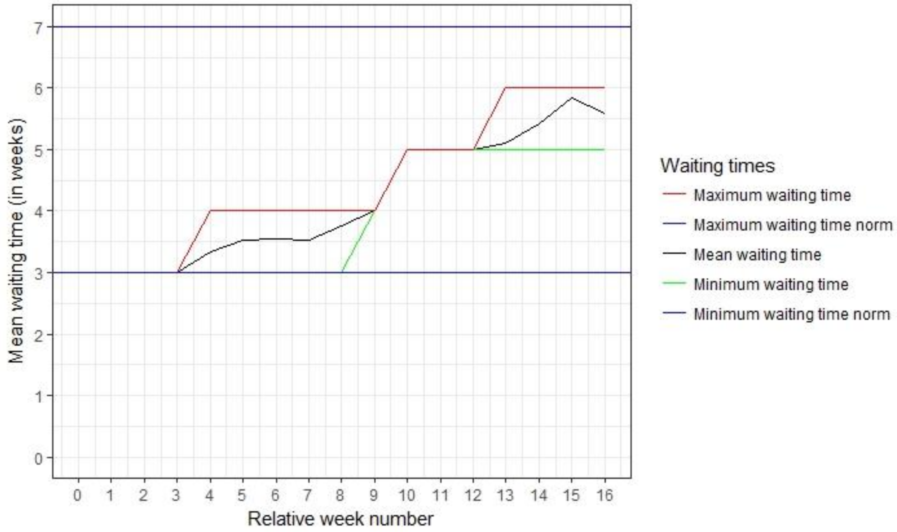
Waiting time NP	# patients	Realized	Target
Exceeding maximum waiting time norm (>1weeks)	28	1.9%	0%
Within maximum and minimum waiting time norm (>=0 weeks & <= 1 weeks)	1460	98.1%	100%
Below minimum waiting time norm (< 0 weeks)	0	0%	0%
Total	**1488**	**100%**	**100%**

Figure 5.4: Model performance of new visits in terms of waiting time in 2016, including the average, standard deviation, minimum, and maximum waiting time (norm)



Waiting time CP	# patients	Realized	Target
Exceeding maximum waiting time norm (>4 weeks)	0	0%	0%
Within maximum and minimum waiting time norm (>=0 weeks & <= 4 weeks)	1474	100%	100%
Below minimum waiting time norm (< 0 weeks)	0	0%	0%
Total	**1474**	**100%**	**100%**

Figure 5.5: Model performance of check-up visits in terms of waiting time in 2016, including the average, standard deviation, minimum, and maximum waiting time (norm)



Waiting time SP	# patients	Realized	Target
Exceeding maximum waiting time norm (>7 weeks)	0	0%	0%
Within maximum and minimum waiting time norm (>=3 weeks & <= 7 weeks)	242	100%	100%
Below minimum waiting time norm (< 3 weeks)	0	0%	0%
Total	**242**	**100%**	**100%**

Figure 5.6: Model performance of surgeries in terms of waiting time in 2016, including the average, standard deviation, minimum, and maximum waiting time (norm)

6. Implementation

In this chapter, how the capacity managers and planners should use the decision support tool and its output are described. The decision support tool's main users are the capacity managers. The use of the decision support tool by capacity managers is explained in Section 6.1. The output of the decision support tool is used by the planners. The use of the output of the decision support tool by the planners is explained in Section 6.2. Finally, the maintenance protocol of the decision support tool is explained in Section 6.3.

6.1 Use of the decision support tool by capacity managers

Capacity managers are the main users of the decision support tool. By means of this tool, a capacity manager can determine what amount of capacity should be allocated to each relevant hospital department in order to reduce the proportion of patients experiencing a waiting time outside the waiting time norms. The capacity manager is advised to use the allocation tool once every two weeks. Each time the capacity manager uses the decision support tool, the following steps need to be executed:

1. The capacity manager needs to fill in the number of specialists available per week within the time horizon and the number of sessions the specialists are available. In addition, the sessions allocated from the MSS need to be added to the decision tool.
2. The decision support tool determines the initial capacity allocation for each department and performs a demand forecast. Alternatively, the capacity manager could determine the initial capacity allocation based on experience.
3. The decision support tool provides an overview of cumulative capacity and the cumulative demand that *must be seen* and *could be seen*. The capacity manager needs to assess this overview. When the overview is assessed as being positive, the initial capacity allocation to the departments is used for patient allocation. When the overview is assessed negatively, the capacity manager needs to change the capacity allocation by means of one of the following options:
    a. The capacity manager could change the capacity allocation by means of the model.
    b. The capacity manager could change the capacity allocation by him- or herself by trial and error.
    c. The capacity manager could change the capacity allocation by means of the model and by him- or herself by trial and error.
4. The capacity manager should choose a decision rule to allocate patients to a time period according to the performance measure of interest. The model will then perform the patient allocation. As a result, for each time period in the time horizon, the expected average waiting times are provided.
5. The capacity manager needs to assess the resulting waiting times. When the capacity manager assesses these as being positive, the capacity allocation can be transferred to the OPD and SD planners. When the capacity manager assesses the resulting waiting times as being negative, the capacity allocation process needs to be repeated.

6.2 Use of output of the decision support tool by planners

The output of the decision support tool are the sessions and OPD time slots allocated to each department. Planners receive the proposed session schedule for the fixed time period. Planners can allocate patients to these sessions. Planners have the task of filling the sessions and OPD time slots with arriving patients and patients on the waiting list. If there is a waiting list exists, the abovementioned decision rules could be used to allocate the patients to a session or a time slot in a session. Furthermore, medical and patients preferences need to be taken into account, but it is important to plan patients according to their waiting time.

6.3 Maintenance protocol

In order for the tool to be operational on the long-term, periodic maintenance is required. First, the dataset that the capacity demand forecast is based on, needs to be updated with recent patient treatments. The set of existing care processes can be extended and transition probabilities will be updated. By updating the dataset, the patient groups also need to be revised. It is recommended that the data be updated monthly. This updating can be implemented in the software so that each month the dataset is updated during the night.

Second, when capacity supply changes (e.g. an extra specialist is hired or an extra OT is opened), the tool should be able to forecast the demand change caused by the capacity supply change. The demand forecast needs to be adapted in order to take into account the demand change.

7. Conclusion and recommendations

The aim of this study has been to allocate specialists across hospital departments in order to reduce the proportion of patients experiencing a waiting time outside the waiting time norms. The decision support tool developed supports capacity managers in hospitals to make decisions about the allocation of specialists across the hospital departments. Section 7.1 evaluates the research assignment. Furthermore, Section 7.2 and Section 7.3 discuss the theoretical and practical contributions, respectively. Section 7.4 discusses the recommendations for ChipSoft. Finally, the limitations and further research directions of this study are discussed in Section 7.5.

7.1 Conclusion

The research assignment of this study was to develop a decision support tool that integrates the OPD and the SD and which supports the capacity manager of a hospital with the tactical decision-making about capacity allocation in order to reduce the proportion of patients experiencing a waiting time outside the waiting time norms. In order to develop this decision support tool, a detailed analysis was performed on the current methodology of capacity allocation and the main causes of the waiting time fluctuations.

Detailed analysis revealed that current capacity allocation is mainly based on the capacity allocation of the previous year and that no (integrated) insights into the effects of capacity allocation on the waiting time are available. Second, the analysis revealed that multiple interdependencies exist at the OPD and the SD. However, these interdependencies are not taken into account in the current methodology of capacity allocation. These factors, in combination with the fluctuating arrival of new patients and the fluctuating resource availability, were identified as the main causes of the long and fluctuating waiting times. Therefore, providing insight into the effect of capacity allocation on the waiting time and taking into account the interdependencies between the OPD and the SD were indicated as the main requirements of the decision support tool.

To reduce waiting time fluctuations, a model was developed that matches capacity demand and capacity supply. First, capacity demand that *must be seen*, capacity demand that *could be seen* for each department, and the specialists' time available for the SD and the OPD were determined. The model displays these three elements per department and determines whether overcapacities or shortages exist. The model reallocates the specialist across the relevant departments in order to mitigate the overcapacities and shortages and, thereby, the long and fluctuating waiting times. Following the capacity reallocation, the patients are allocated to a time period and an average waiting time per time period is created. The results of a case study revealed that the average waiting times of the determined capacity demand are mainly within the waiting time norms.

This study developed a support decision tool that integrates the OPD and the SD and that supports the capacity manager with the tactical decision-making about capacity allocation in order to reduce the proportion of patients experiencing a waiting time outside the waiting time norms. However, it can be concluded that the performance of the model is strongly dependent on the quality of the demand forecast. When the demand forecast is not comparable with actual patient demand, the capacity is allocated to the wrong departments in the wrong time periods. The quality of the demand forecast depends on the quality of the data registration. For the performance of the model, it is crucial that the data registering is performed correctly.

7.2 Theoretical contributions

This study has contributed to the literature in several ways. First, research has been conducted to the interdependencies of the OPD and the SD, which was an area that has been minimally studied in the literature (Vanberkel et al., 2010). Second, an decision support tool was developed which mitigates long and fluctuating waiting times by taking into account the interdependencies discussed. Additionally, the decision support tool was validated and verified by means of a case study. Therefore, this study supplements the current literature on integrated capacity management in hospitals.

7.3 Practical contributions and recommendations

This study has contributed to hospitals in several ways. First, this study provides a method that gives insight into the capacity required by new patients and their subsequent treatments, and therefore, gives insight into the effect of capacity allocation on capacity demand and the waiting times in different departments. For a hospital, it is important to know what interdependencies exist at hospital departments and how they influence capacity demand and waiting times. This study revealed that the OPD and the SD interact with each other in three ways: both departments create each other's demand, the capacity demand will be backordered, and both departments share the same resources. Second, this study provides a method to allocate capacity to capacity demand in the OPD and the SD, which mitigates waiting time fluctuations. Additionally, a method to allocate patients to hospital departments within a specific time period has been provided. Additionally, this study revealed a useful methodology to forecast capacity demand, consisting of new patient arrivals and subsequent treatments, which could be used to forecast capacity demand hospital-wide.

This study has provided the hospital with a useful tool to control waiting time and capacity use in the relevant hospital departments. The tool allows greater understanding of the origin of long and fluctuating waiting times and how to mitigate them. Grounded decisions about capacity allocation to the OPD and the SD can be made since the effect of capacity allocation to departments on capacity demand and waiting times is visualized and supported by quantitative research. It can be allowed that the utilization of the SD is not always required to be 100 percent if the OPD requires more specialists' time. Furthermore, the support decision tool is an instrument that requires the capacity manager to continuously revise the capacity allocation planning. In this way, fewer ad hoc mutations are required at the operational level. This generates more structure and less organizational rumor in the organization. Furthermore, costs can be reduced since fewer planners are required to repair the damage to planning caused by unplanned events. A final contribution of the tool is that the progress of production can be monitored and compared with the production agreements made with insurance companies. Capacity managers can anticipate the amount of specialists' time to be allocated to a department by means of this insight.

It is recommended that the case hospital implement the decision support tool in collaboration with ChipSoft. The capacity demand forecast needs to be optimized with hospital-specific characteristics. Additionally, the capacity demand forecast needs to be optimized by incorporating patient or diagnosis-specific interarrival times and patient's preferred treatment dates. In collaboration with ChipSoft, the decision support tool can be extended to include more hospital departments, more resources and more levels of decision-making. Furthermore, it is advised that the fixed time periods in the time horizon be optimized. This will improve the functioning of the tool since the quality of the capacity demand forecast is reduced as the time horizon becomes longer. Finally, regular meetings with ChipSoft to discuss areas of improvement are recommended.

7.4 Recommendations for ChipSoft

Since the quality of the model depends on the quality of the capacity demand forecast, and the quality of the capacity demand forecast depends on the quality of the data registration, it is recommended data registration in the hospital is improved by creating new data variables, for example, patient's preferred treatment dates, medically preferred treatment dates, the arise date of the capacity demand, the date that a patient was planned, and the like. Furthermore, an investigation of whether hospital planners could be encouraged to register data correctly is recommended. In order to further improve the demand forecast, it is recommended that the capacity managers of hospitals are included in the demand forecast process. In this manner, hospital-dependent factors can be taken into account in the capacity demand forecast, for example, internal reorganization, reduction of resources, and the like. In addition, the hospital can provide further insight into users' experience of the support decision tool and how it should be designed in order to make it more intuitive for the end user. In conclusion, maintaining the relationship with capacity managers of hospitals in order to improve the tool is recommended. Moreover, it is recommended that ChipSoft develop the decision support tool further. Possible extensions are the incorporation of strategic and operational optimization. Additionally, the further research directions discussed in the following section could be incorporated into the decision support tool.

7.5 Limitations and further research directions

- The results of this study are limited to the orthopedics specialism at the case hospital. The conclusions are based on a model that includes assumptions and is therefore a simplification of the real situation.
- In this study, the orthopedics specialism is considered to be independent of the other specialisms, while in the SD they co-occur. The MSS allocates capacity to all specialisms. When balancing capacity, other specialisms should be taken into account in order to overcome suboptimal solutions. In this study, a possibility exists that all the specialists of orthopedics would be allocated to the SD. This leaves the remaining specialisms with very few remaining time slots in the MSS. A possible solution would be to set a maximum number of SD time slots to allocate to orthopedics. The desired situation would be to include all specialisms in the decision support tool so that an optimal allocation of MSS time slots can be generated for all the specialisms.
- The study excludes the arrival of emergency patients in the model. In the future, the model could be elaborated to include emergency patients.
- Furthermore, the model does not incorporate the diagnostic, therapeutic, and inpatient departments, since the focus of the study was on the interdependencies at the OPD and the SD. Diagnostic departments currently have long waiting times and do not meet the *Treeknormen* (Anonymous orthopaedist, 2018). These long waiting times cause the long interarrival times between an NP visit and a CP visit. Therefore, the inclusion of the diagnostic department could have a positive effect on the performance of the OPD. The model is already able to include numerous departments in the decision support tool. However, since the model only allocates specialists as a resource, and the diagnostic, therapeutic, and inpatient departments do not require specialists for every specialism, more resources that need to be allocated across the departments need to be added to the model.
- Due to time limitations, optimal planning is not implemented in a real-life scenario by capacity managers. This means that the effect of the continuous revising of the capacity allocation every two weeks has not yet been tested. When this is tested, the time horizon and the distribution of the open and fixed time periods can be optimized.
- The quality of the model depends considerably on the quality of the demand forecast. Since the demand forecast depends on the data and the manner of registration, these need to be revised. Currently, it is not known when the demand for a visit or surgery arose, when a patient wants to wait longer, or when a patient is forced to wait longer for medical reasons or for capacity constraints. A circular pattern exists. In the model, deterministic (not related to the stage in the care process, though this should be the case) interarrival times are used, which cause unrealistic scenarios. The demand arise date should be properly registered by hospitals. With this improvement, realistic interarrival times could be extracted from the data, which would improve the capacity demand forecast quality. Another disadvantage of the demand forecast based on the data is that only known or previously occurred care processes are forecasted. Unknown care processes do not contain a transition probability and do not appear. The model

should learn from these new patients and extend/revise the transition probabilities. Another disadvantage of basing the demand forecast on historical data is that one care process may contain numerous diagnosis codes. The patient groups are based on the diagnosis codes of the first new patient visit since this is the code that is known at that time. However, when the diagnosis code changes in the care process, the forecast will change; however, this is not taken into account. Another disadvantage is the miscommunication regarding the definition of a new patient. It is not only the start of a care process that is seen as a new patient visit; sometimes a patient is registered as a new patient after being a check-up patient. Future research could be conducted to improvements of data registration and capacity demand forecast improvements.

- Since the time horizon is modeled per week, the waiting times could be longer than the waiting time mentioned. For example, when a patient requests surgery on Monday in week 1 and the patient is treated on Friday in week 8, the patient has experienced a waiting time of 7 weeks and 4 days, which is longer than 7 weeks. The model judges this as being within the waiting time norms. Further research could be conducted to other segmentations of the time horizon.
- The model assumes that all patients can be seen by all specialists. This is not always the case. Furthermore, it is often desired that a patient be treated by the same specialist throughout the entire care process. Further research could be conducted on capacity allocation, waiting time, and the capacity utilization when this assumption is rejected.
- In this study, the capacity demand of surgery patients is based on the average processing time of all the surgeries performed. Further research could be conducted to forecast the duration of surgery for a patient or patient group.
- In this study, the capacity allocation was determined based on a graphical cumulative overview. This overview works when the capacity allocated to each department remains within the demand range. When this is not the case, the waiting time norms are not met and thus the subsequent treatments will shift more than is shown in the overview. Future research could be conducted to design a mechanism that responds directly to the allocated capacity.
- A limitation of this study is the fact that capacity balancing can only be undertaken in the open time periods. For the fixed time periods, no capacity reallocation is possible. Further research can be conducted to decrease the required number of fixed time periods or to include flexible sessions in the fixed time periods. Another possibility is to divide the time horizon into three parts: one fixed, one semi-fixed, and one open. A further possibility is to create department-specific time horizons portions. Among some departments, capacity reallocation can be undertaken during the entire time horizon; while between two other departments it can only be undertaken in the final weeks of the time horizon.

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Appendix A. Organizational Structure

This appendix presents the organizational structure of the case hospital.

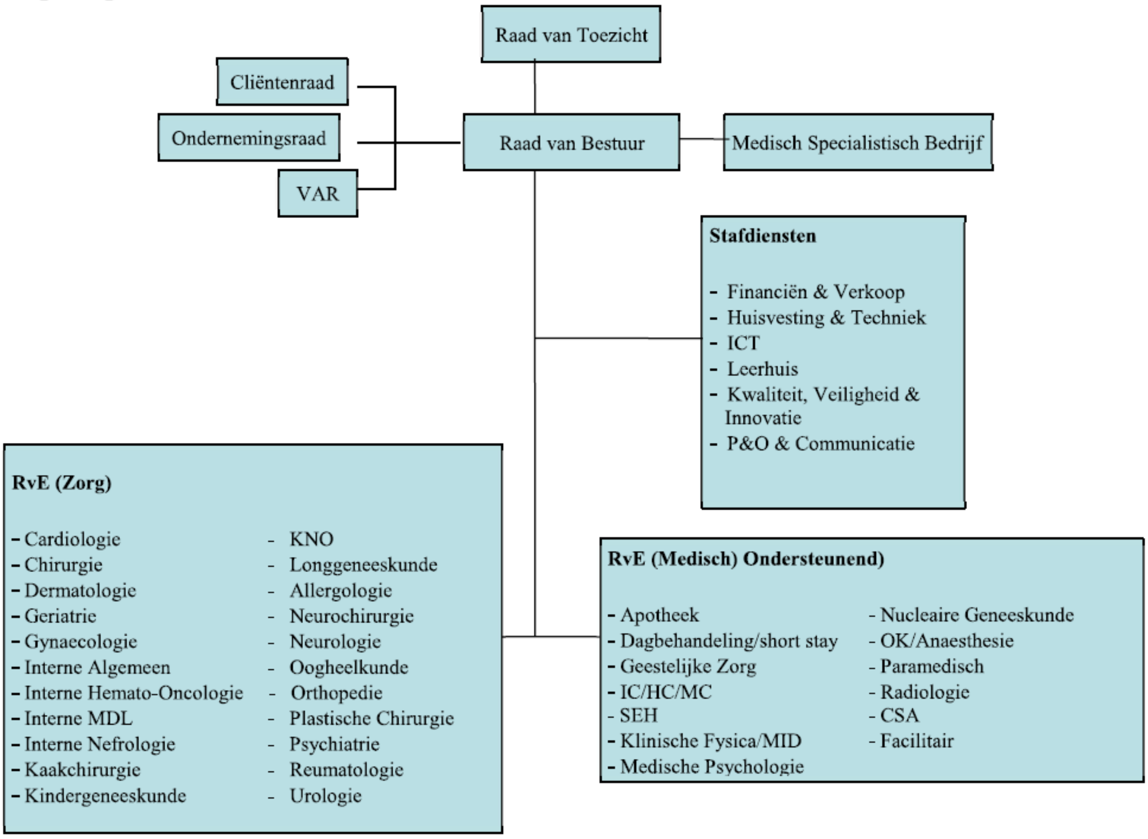


Figure A.1: Organizational structure of the case hospital

Appendix B. Interview protocol

The following interview questions are used for the semi-structured interviews which are held to five capacity managers (or similar/related functions) in five different Dutch hospitals.

Interview questions

1. What is the current process of converting production agreements with the health insurances to the capacity allocation over hospital departments?
2. What are the benefits of the current planning process?
3. What is the input of the tactical planning?
4. Which resource causes are a limiting resource?
5. Is the planning process centralized in the hospital?
6. Which problems arise since planning processes are not integrated?
7. Where would you start integrating planning processes?
8. How do you think the integration policy will help meeting the production goals?
9. How do you determine the patient flows through the hospital? Where do you start analyzing a patient flow?
10. What is the patient acceptance policy at the outpatient department? Is every patient accepted (immediately)?
11. What is the time horizon for tactical decision making at the outpatient department and the surgical department?
12. Which insights are necessary to improve the decision making about capacity allocation over the hospital departments?
13. How should resistance from planners or specialists be handled?

Appendix C. Available data

This appendix presents the available data registered at the case hospital.

Table C.1: Available data registered in the case hospital

Variable	Table	Data field
Query 1: Outpatient department		
Visit number	AGENDA_AFSPRAAK	AFSPRAAKNR
Visit date	AGENDA_AFSPRAAK	DATUM
Patient number	AGENDA_AFSPRAAK	PATIENTNR
Registration date of visit	AGENDA_AFSPRAAK	INVOERDAT, TERMIJN
(planned) visit duration	AGENDA_AFSPRAAK	DUUR, AANKOMST, OPROEP, VERTREK
Visit code and description	AGENDA_AFSPRAAK AGENDA_AFSPCODE	CODE, AFSPTYPE, EPB OMSCHR
Location of the visit	AGENDA_AFSPRAAK AGENDA_BEHLOC	BEHLOC OMSCHR
Location in hospital	AGENDA_AFSPRAAK AGENDA_AGENLOC	LOKATIE OMSCHR
Specialism	CSZISLIB_ARTS	SPECIALISM
Specialist performing the visit	AGENDA_AFSPRAAK	UITVOERDER, HOOFDBEHID,DOORWIE
Type of doctor	CSZISLIB_ARTS CSZISLIB_ARTSTYPE	ARTSTYPE OMSCHR
Start date of specialist	CSZISLIB_ARTS	BEGINDAT
End date of specialist	CSZISLIB_ARTS	EINDEDAT
Visit status	AGENDA_AFSPRAAK	VOLDAAN, STATUS
Session number	AGENDA_AFSPRAAK	VIADAGDEELID, TIJD + AGENDA + SUBAGENDA
Query 2: Surgical department		
Surgery number	OK_OKINFO	OPERATIENR
Date of surgery	OK_OKINFO	OPERATIE_D, GP_DATUM
Patient number	OK_OKINFO	ZKH_NR
Request date of surgery	OK_OKINFO	AANVRAAG_D, VOORKEUR, ANNULEERDA

(Planned) duration of surgery	OK_OKINFO	GP_DUUR, VERW_DUUR, SNIJTIJD, BT_OK, ET_OK, BT_OPERATI, ET_OPERATI, BT_ANAEST, T_RECOVERY T_VOORBER, ET_INLEIDI BT_UITLEID, ET_ANAEST, GP_VAN
Surgery operation and description	OK_OKINFO OK_VERCODES	HOOFDVER, COTGCODE, CODE, OMSCHR
Operating theatre	OK_OKINFO OK_OKKAMERS	OKKAMER, GP_OKKAMER OMSCHR
Location in hospital	OK_OKINFO CSZISLIB_LOCCODE	ZKHLOCCODE LOCOMSCH
Specialism	OK_OKINFO	SPECIALISM
Specialist performing the surgery	OK_OKINFO	SNIJD_SPEC
Type of doctor performing the surgery	CSZISLIB_ARTS CSZISLIB_ARTSTYPE	ARTSTYPE OMSCHR
Start date of specialist	CSZISLIB_ARTS	BEGINDAT
End date of specialist	CSZISLIB_ARTS	EINDEDAT
Surgery status	OK_OKINFO	STATUS
Priority of the surgery	OK_OKINFO OK_PRIORITE	PRIORITEIT CODE, OMSCHR
Session number	OK_OKINFO	GP_SESSIENR
DTC and care processes		
DTC number	AGENDA_AFSPRAAK OK_OKINFO EPISODE_DBCPER	EPISODE EPISODENR DBCNUMMER
Start date of DTC	EPISODE_DBCPER	BEGINDAT
End date of DTC	EPISODE_DBCPER, EPISODE_EPISODE	EINDDAT, EINDDATDBC
Care process number	EPISODE_EPISODE, EPISODE_DBCPER	EPISODE, EPISODE
Start date of care process	EPISODE_EPISODE	BEGINDAT
End date of care process	EPISODE_EPISODE	EINDDAT
Diagnosis DTC and description	EPISODE_EPISODE EPISODE_DBCPER EPISODE_DIAG	HOOFDDIAG, VERWDIAG HOOFDDIAG, SAMENDIAG OMSCHRIJV
Type of care	EPISODE_DBCPER	ZORGTYPE LANDELIJK OMSCHRIJV
Session schedule – Outpatient department		
Agenda number	AGENDA_AFSPRAAK AGENDA_RASTER	AGENDA AGENDA

	AGENDA_DAGDEEL	AGENDA
Daypart number	AGENDA_AFSPRAAK AGENDA_RASTER AGENDA_DAGDEEL	VIADAGDEELID DAGDEELID DAGDEELID
Daypart type and description	AGENDA_DAGDEEL AGENDA_DAGDEEL	DDCODE, TYPE, OMSCHR
Session duration	AGENDA_RASTER AGENDA_DAGDEEL	BLOKDUUR, BEGINTIJD, EINDETIJD BEGINTIJD, TSDUUR
Session date	AGENDA_RASTER	DATUM
Location of session	AGENDA_RASTER AGENDA_DAGDEEL	KAMER BEHLOC
Specialist of the session	AGENDA_RASTER	UITVOERDER
Occupied duration of session	AGENDA_RASTER	BEZETDUUR
Session schedule – Surgical department		
Session number	OK_OKINFO OK_LOGSESS	GP_SESSIENR SESSIENR
Session type and description	OK_LOGSESS SES_SESSIE	SESSIE OMSCHR
Session duration	OK_LOGSESS	START, STOP
Session date	OK_LOGSESS	DATUM
Location of session	OK_LOGSESS OK_OKKAMERS OK_OKKAMERS	OK WERKLOCATI OMSCHR
Specialism of the session	OK_SESSIES	SPECIALISM
Number of surgeries per session	OK_LOGSESS	AANTALOPER
Time of switching sessions	OK_LOGSESS	WISSELTIJD
Occupied duration in a session	OK_LOGSESS	BEZET
Session cancelled or not	OK_LOGSESS	AFWEZIG

Appendix D. Outpatient visit codes

This appendix presents all the outpatient visit codes present in the dataset of the case hospital. Furthermore, the duration of each visit code, the frequency of the visit code appears in the dataset, and the percentage the visit codes appears in the dataset relative to all the visit codes is shown. As can be seen in Table D.1, over 90 percent of the outpatient visits is a new patient visit or a check-up visit.

Table D.1: Description, duration, and frequency of the outpatient visit codes.

Outpatient code	Description	Duration	Percentage in dataset	Frequency in dataset
BL	Appointment via phone	5	2.5%	1511
CP	Check-up patient	5	55.7%	33,563
IARTINJ	Intra-articular injection by orthopedics	10	0.2%	137
ICC	Intercollegial vizitation	5	0%	29
INGR	Intervention	15	2.1%	1,261
KLPAT	Clinical patient	5	0%	5
MARCA	Marcanizations	15	0.6%	377
MB	Co-treatment	5	0%	1
MDO	Multidisciplinary visitation	5	0%	5
NP	New patient	10	37.7%	22,695
SEH	Control patient after visiting the emergency department	10	1.1%	656
SPCON	Emergency visit	10	0%	24
TOTAL	**-**	**-**	**99.9%**	**60,264**

The duration of the codes is often fixed per code. The few times the code contains multiple different planned durations, the median of the duration is taken. Furthermore, the total percentage is not 100% because of rounding errors.

Appendix E. Surgery duration

In the table below, the diagnosis codes and the groups based on the codes are explained. The groups are based on Dutch Diagnosis list from the CBS (CBS, 2017). Furthermore, the average surgery duration and the standard deviation per diagnosis group is computed.

Table E.1: Surgery duration based on diagnosis group

Diagnosis group	Diagnosis code	Number in 2013 – 2016 (%)	Mean surgery duration in minutes (standard deviation)
Total general and/or systemic	1010, 1020, 1030, 1040, 1050, 1099	0 (0.00)	0 (0.0)
Total bones and weak parts tumors	1110, 1120, 1130, 1140, 1150,1199	41 (0.71)	56.1 (5.6)
Total cervical spine	1201, 1202, 1203, 1210, 1220, 1240, 1240, 1250, 1260, 1296, 1297, 1298, 1299	1 (0.02)	75 (0.0)
Total thoracic/lumbar spine	1301, 1302, 1330, 1340, 1350, 1360, 1365, 1370, 1380, 1390, 1392, 1394, 1395, 1396, 1397, 1398, 1399	4 (0.07)	47.8 (0)
Total shoulder girdle/upper arm	1401, 1402, 1404, 1450, 1460, 1470, 1480, 1495, 1496, 1497, 1498	481 (8.36)	80.2 (9.1)
Total elbow / fore arm	1501, 1502, 1503, 1504, 1550, 1560, 1596, 1597, 1598, 1599	63 (1.09)	48.5 (6.4)
Total hand / wrist	1601, 1602, 1603, 1604, 1620, 1630, 1640, 1650, 1660, 1670, 1680, 1695, 1696, 1697, 1698, 1699	179 (3.11)	43.3 (6.7)
Total pelvis / hip / upper leg	1701, 1702, 1703, 1704, 1710, 1730,	966 (16.78)	87.1 (11.3)

	1740, 1760, 1796, 1798		
Total knee	1801, 1802, 1803, 1804, 1805, 1810, 1820, 1830, 1840, 1850, 1860, 1870, 1880, 1890, 1898, 1899	3241 (56.30)	59.12 (8.6)
Total lower leg / ankle / foot	1910, 1920, 1960, 1996, 1997, 1998, 1999, 2001, 2002, 2003, 2004, 2006, 2010, 2015, 2020, 2030, 2035, 2040, 2045, 2050, 2055, 2060, 2064, 2070, 2075, 2095, 2096, 2097, 2098, 2099	444 (7.71)	49.4 (7.6)
Total fractures	3001, 3002, 3003, 3004, 3005, 3006, 3007, 3007, 3008, 3009, 3010, 3011, 3012, 3013, 3014, 3015, 3016, 3017, 3018, 3019, 3020, 3021, 3022, 3023, 3024, 3025, 3026, 3027, 3028, 3029, 3030	94 (1.63)	70.1 (9.1)
Total sprains	3101, 3102, 3103	19 (0.33)	62.6 (9.4)
Total luxations	3201, 3202, 3203, 3204, 3205, 3206, 3207, 3208, 3209, 3210, 3211	18 (0.31)	89.68 (8.9)
Total bruises	3301, 3302	4 (0.07)	62.3 (6.9)
Total capsule / tendon / muscle rupture	3401, 3402, 3403, 3404, 3409	27 (0.47	59.6 (7.6)

Total other orthopedics	2110, 2120, 2130, 2140, 2150, 3501, 3502, 3601, 3602, 3603, 3701, 3702, 3703, 3801, 3803, 3901, 4101, 4102, 4103, 4104, 4105	175 (3.04)	93.7 (10.6)
Total	-	8087 (100.0)	-

Appendix F. Outlier removal

This appendix shows the waiting time in weeks of patients requesting a treatment in 2016 per week. Outliers are removed in order to analyze realistic waiting times.

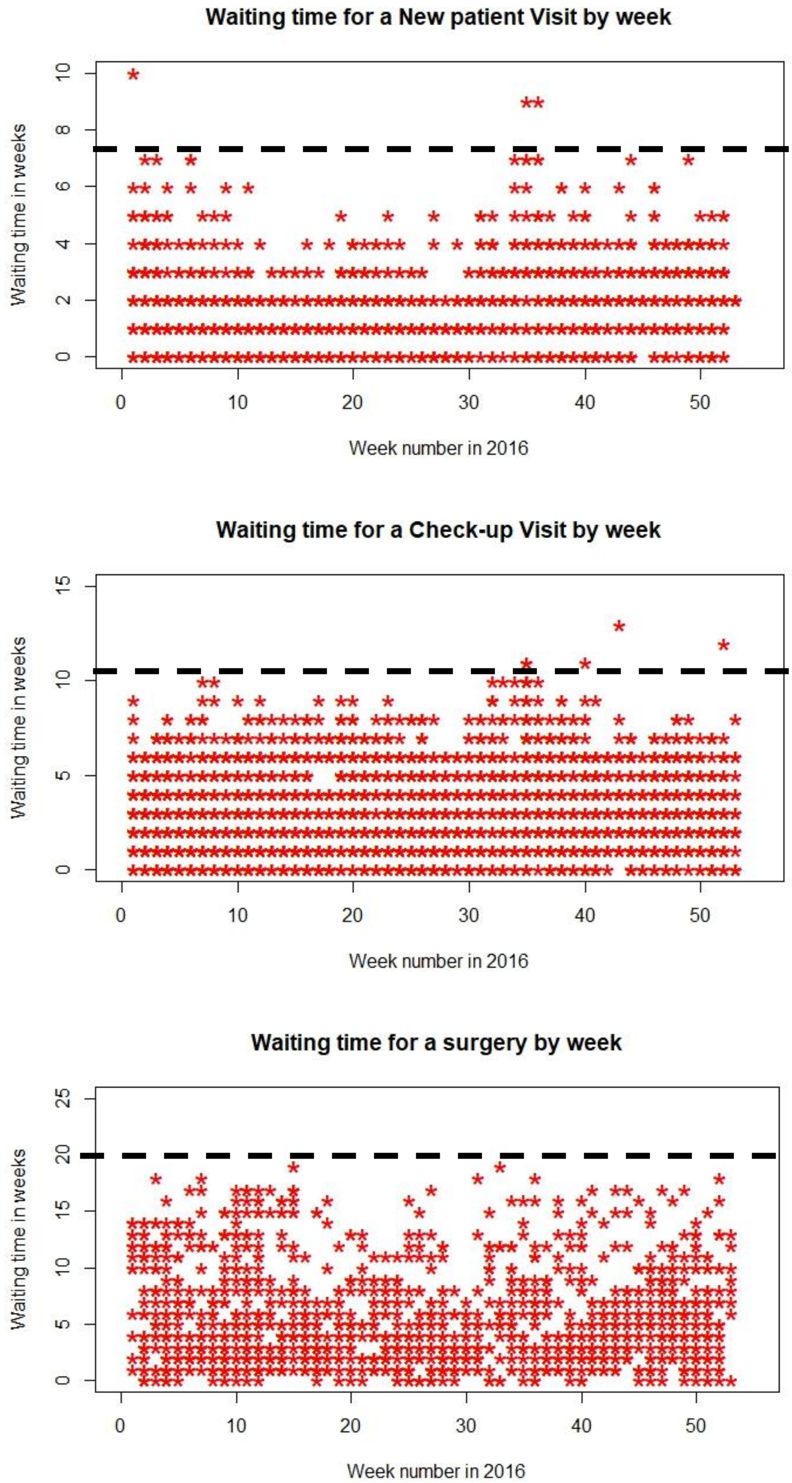
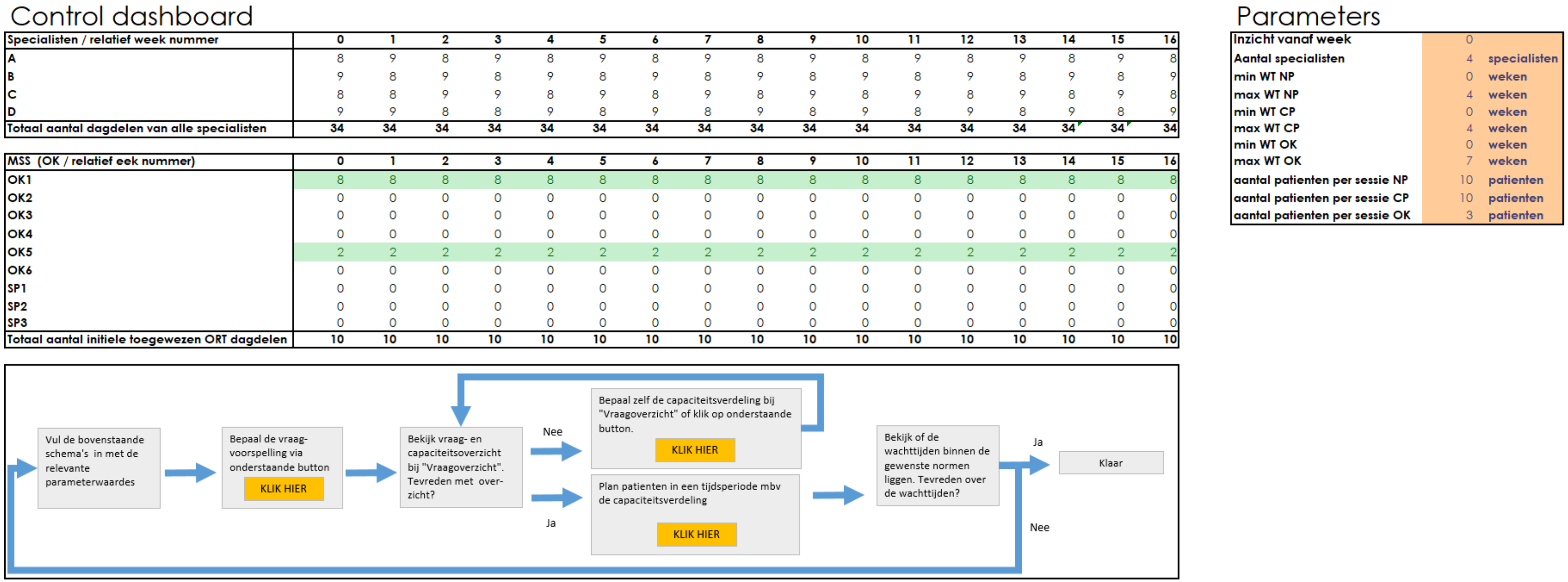


Figure F.1: Determination of outlying waiting times at NP visits, CP visits and surgeries

Appendix G. Decision support tool

This appendix presents the designed decision support tool. The decision support tool consists of two main screens. In this first screen, the control dashboard is presented where end-users can edit input parameters and follow the flow chart to optimize the capacity allocation. In the second screen, the graphical overview of capacity supply and capacity demand is visualized and the effect on the waiting time is shown. The first screen is presented in Figure G.1 and the second screen is presented in Figure G.2.



Control dashboard

Specialisten / relatief week nummer	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
A	8	9	8	9	8	9	8	9	8	9	8	9	8	9	8	9	8
B	9	8	9	8	9	8	9	8	9	8	9	8	9	8	9	8	9
C	8	8	9	9	8	9	8	9	8	9	8	9	8	9	8	9	8
D	9	9	8	8	9	8	9	8	9	8	9	8	9	8	9	8	9
Totaal aantal dagdelen van alle specialisten	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34

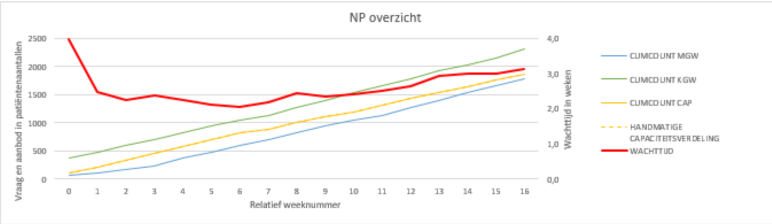
MSS (OK / relatief eek nummer)	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
OK1	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
OK2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OK3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OK4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OK5	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
OK6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Totaal aantal initiele toegewezen ORT dagdelen	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10

Parameters

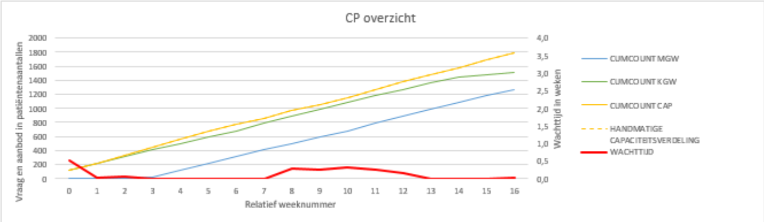
Inzicht vanaf week	0	
Aantal specialisten	4	specialisten
min WT NP	0	weken
max WT NP	4	weken
min WT CP	0	weken
max WT CP	4	weken
min WT OK	0	weken
max WT OK	7	weken
aantal patienten per sessie NP	10	patienten
aantal patienten per sessie CP	10	patienten
aantal patienten per sessie OK	3	patienten

Figure G.1: The first screen of the decision support tool: the control dashboard

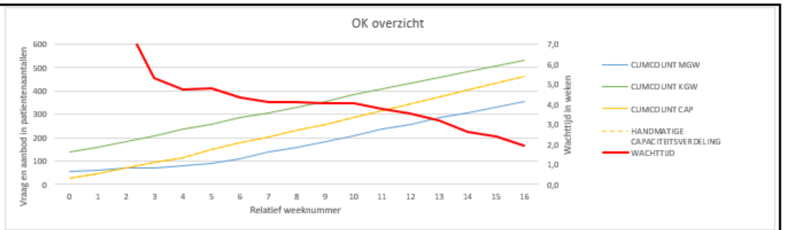
Overzicht vraag en capaciteit



CP sessies oud/vast	12	9	13	11	13	12	12	7	12	9	9	12	12	11	11	11	11
CP sessies nieuw/ aanpast	12	9	13	11	13	12	12	7	12	9	9	12	12	11	11	11	11
CP Cum nieuw	120	210	##	##	##	##	##	##	###	###	1190	1310	1430	1540	1650	1760	1870

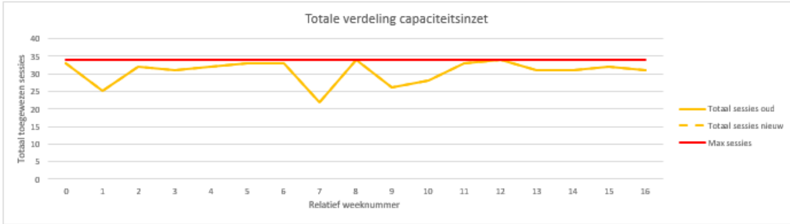


NP sessies oud/vast	12	9	12	11	12	11	11	7	12	9	9	11	12	10	10	11	10
NP sessies nieuw/ aanpast	12	9	12	11	12	11	11	7	12	9	9	11	12	10	10	11	10
NP Cum nieuw	120	210	##	##	##	##	##	##	970	###	1150	1260	1380	1480	1580	1690	1790



OK sessies oud/vast	9	7	7	9	7	10	10	8	10	8	10	10	10	10	10	10	10
OK sessies nieuw/ aanpast	9	7	7	9	7	10	10	8	10	8	10	10	10	10	10	10	10
OK Cum nieuw	27	48	69	96	117	147	177	201	231	255	285	315	345	375	405	435	465

Overzicht totale capaciteitsinzet



Totaal sessies oud	33	25	32	31	32	33	33	22	34	26	28	33	34	31	31	32	31
Totaal sessies nieuw	33	25	32	31	32	33	33	22	34	26	28	33	34	31	31	32	31
max	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34

Figure G.2: The second screen of the decision support tool; Graphical cumulative overview of capacity demand and capacity supply, and the average waiting time per week

Appendix H. Patient group clustering

This appendix presents the clustering methodology to determine the patient groups. Table H.1 presents the results of the k-means algorithm, where k ranges between zero and twenty. The number of clusters chosen is indicated by the orange highlighted row with a threshold value of the performance increase of 0.05. The determination of the threshold value is based on the Elbow methodology. The threshold value is indicated with the dotted line visualized in Figure H.1. Finally, the patient groups and their diagnosis number are presented in Table H.2.

Table H.1: The result of the k-means algorithm in terms of performance

Number of clusters	Increase of number of clusters	Performance of clustering	Performance increase
2	1	2.125	1
3	0.5	1.182	0.444
4	0.333	0.598	0.275
5	0.25	0.408	0.089
6	0.2	0.248	0.075
7	0.167	0.196	0.0246
8	0.143	0.163	0.0156
9	0.125	0.116	0.0220
10	0.111	0.101	0.0069
11	0.1	0.093	0.00400
12	0.091	0.089	0.00169
13	0.083	0.087	0.00095
14	0.077	0.087	0.00035
15	0.071	0.075	0.00546
16	0.067	0.071	0.00189
17	0.063	0.069	0.00073
18	0.059	0.067	0.00102
19	0.056	0.037	0.01428
20	0.053	0.034	0.00132

←Threshold value = 0.05

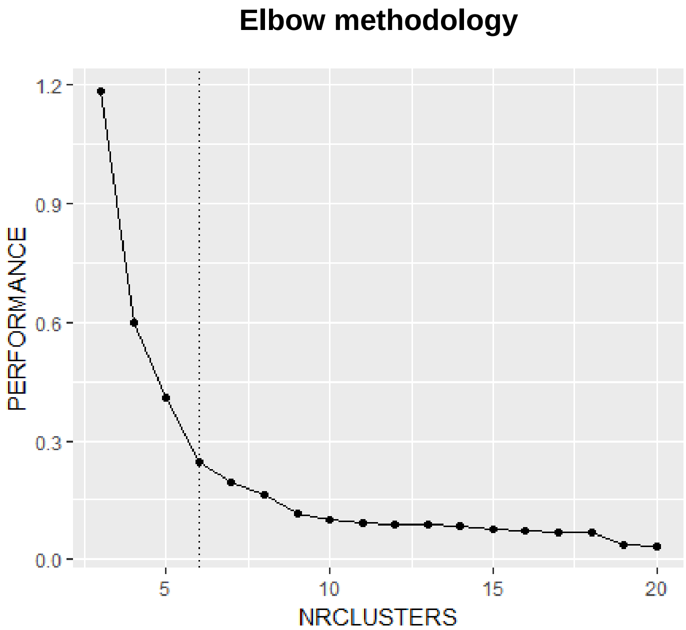


Figure H.1: Result of the Elbow methodology where the dotted line indicates the threshold value for the performance increase of the k-means algorithm

Table H.2: The determined patient groups and their diagnosis codes

Patient group	Diagnosis codes
1	1450, 1460, 3403, 1402, 1802, 1840, 2001, 2050, 3010,3012, 2097, 1796, 3023, 1860, 2096, 1480, 2020, 1680, 2055, 1695, 1710, 3409, 3202, 1740, 1810, 3025, 3301, 3302, 1340, 1501, 1396, 3103, 1910, 1967, 1754, 2092, 2095, 1498
2	1630, 1560, 1130, 2015, 2070, 3009, 2045, 1696, 3011, 1870, 3016, 3015, 2026, 1604, 2081, 1692, 2099, 1890 3030, 1568, 3014, 1370, 1099, 1807
3	1801, 1601, 1702, 1495, 3008, 2150, 1820, 3006, 1301, 1110, 1401, 3021, 1960, 1496, 1360, 1798, 1395, 3013, 1730, 1490, 1771, 3022, 1203, 1350
4	2025, 1965, 1765, 3026, 2098
5	1701, 1803, 3019, 1404, 1703, 3201, 1704, 3207, 1302, 3017, 1140, 3020, 1201, 1998
6	1805, 3404, 2060, 4105, 1650, 2002, 2030, 2010, 1896, 1880, 1804, 1850, 4104, 1602 , 1504, 1120, 2130, 3029, 1898, 3209, 1470, 1550, 1502, 1596, 3211, 1620, 2075, 2006, 3024, 1892, 3004, 2031, 1875, 2090, 2004, 1891, 1899, 1830, 2057
7	1030, 1760, 1750, 258, 1392, 1720, 1210, 1220, 3206, 1897, 3205, 2140, 1996, 1397, 1202, 3401, 1297, 3203, 3204, 207, 1394, 1390, 2065, 3007, 1797, 1150, 1296, 1380, 1670, 1598, 1398, 1697, 1799, 1920, 1050, 1403, 1040, 2035, 2110, 1330, 1640, 1199, 3102, 1089, 1399, 302, 3703, 1698, 3402, 1365, 1999, 1751, 1997, 2120, 3027, 3028, 1260, 3003, 3208, 3210, 401, 3702, 1383, 1753, 2021, 1930, 2082, 2076, 1563, 2135, 1566, 1970, 2079, 1685, 1382, 1567, 1381, 4102, 1054, 1806, 2083, 1031, 1565, 3901, 1485, 1660, 1391, 1693, 4002, 3018, 2080, 1599, 1298, 1741, 1240, 1484, 1487, 1931, 1876, 1499, 1772, 2040, 1742, 2003, 1971, 3701, 1569, 1299, 044

Appendix I. NP arrival pattern and forecast

This appendix presents the methodology and the result of the forecast of the new patients' arrival pattern. The arrival pattern of new patients from patient group 1 is visualized in Figure I.2. As can be noticed, the arrival pattern of each patient group contains an additive[2] seasonal pattern, a trend and some randomness. The arrival pattern of new patients for the remaining patient groups is visualized at the end of this appendix. In Figure I.1, a decomposition of the trend, seasonal and random patterns is visualized. Since the Holt-Winters forecast methodology is able to forecast additive seasonal patterns and trends, this method is chosen to forecast the weekly new patient arrivals. The Holt-Winters methodology, results and evaluation of the results are discussed in the next subsections.

Methodology

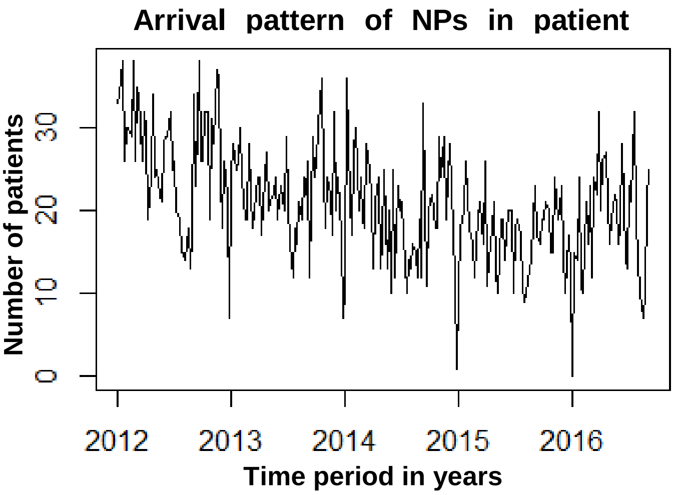


Figure I.2: Arrival pattern of new patients in patient group 1 and its decomposition into seasonal, trend and random patterns

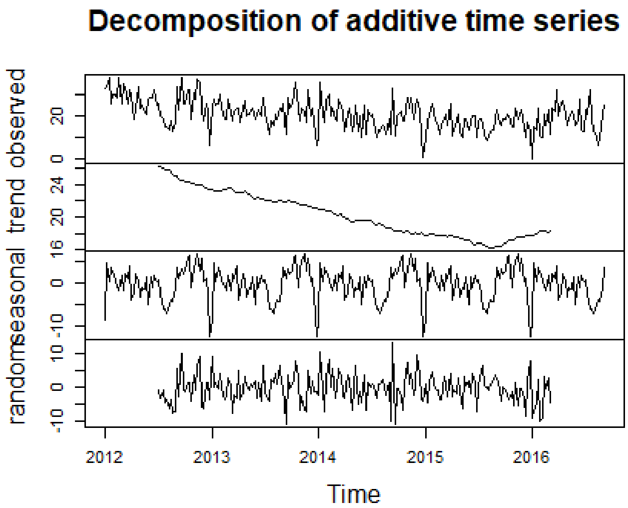


Figure I.1: Decomposition of the arrival pattern of new patients in patient group 1 into seasonal, trend and random patterns

For each patient group, the weekly arrival pattern is forecasted with the following formulas (Nahmias & Cheng, 2009).

Holt-Winters forecast	$F_{t+m} = ((S_t + mb_t)I_{t-L+m})$ $where,$	(39)
Overall Smoothing	$S_t = \alpha \dfrac{y_t}{I_{t-L}} + (1-\alpha)(S_{t-1} + b_{t-1})$	(40)
Trend Smoothing	$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1}$	(41)
Seasonal Smoothing	$I_t = \beta \dfrac{y_t}{S_t} + (1-\beta)I_{t-L}$	(42)

Variables

y	Observation	α	Overall smoothing constant
t	Time period	β	Seasonal constant
L	Periods per season	γ	Trend constant
m	Number of time periods ahead		

Results

The Holt-Winters methodology is performed in Rstudio. Firstly, the smoothing constant, the seasonal constant and the trend constant are optimized by means of the test dataset. The test dataset contains nearly 5 years of data (2012 until start date (05-09-2016)). 2012 is used as the initial period, and 2013 until the start date are used to fit the model and update the

[2] A dataset could contain an additive or multiplicative seasonal pattern. Additive seasonal patterns are characterised by returning demand peaks of equal amplitudes. Multiplicative seasonal patterns are characterised by returning demand peaks which is the same proportion higher as the last peak in the returning period (Nahmias & Cheng, 2009).

constants. Secondly, a forecast is performed over the test dataset. The forecast for the test period of new patients in patient group 1 is visualized in Figure I.4. Finally, a forecast of the arrival pattern of new patients in patient group 1 is performed over the determined time horizon. This forecast is visualized in Figure I.3. The forecast over the test dataset of the new patient arrival pattern for the remaining patient groups is visualized in Figure I.5 until Figure I.16. The final forecast of new patients arriving per patient group per week is presented in Table I.2.

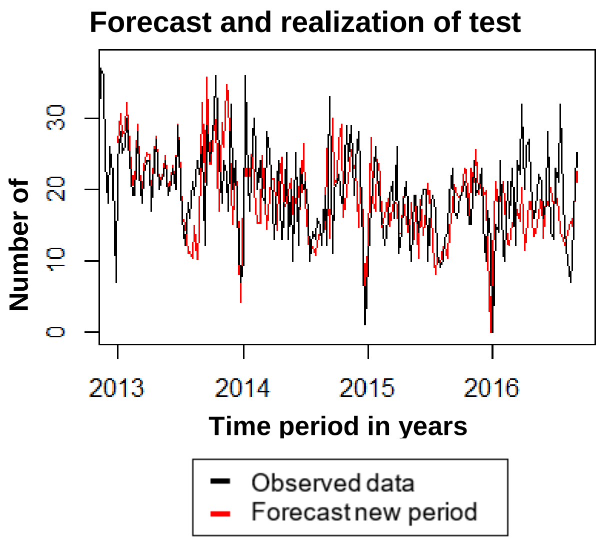


Figure I.4: Comparison of demand forecast and realized demand of patient group 1 in test period

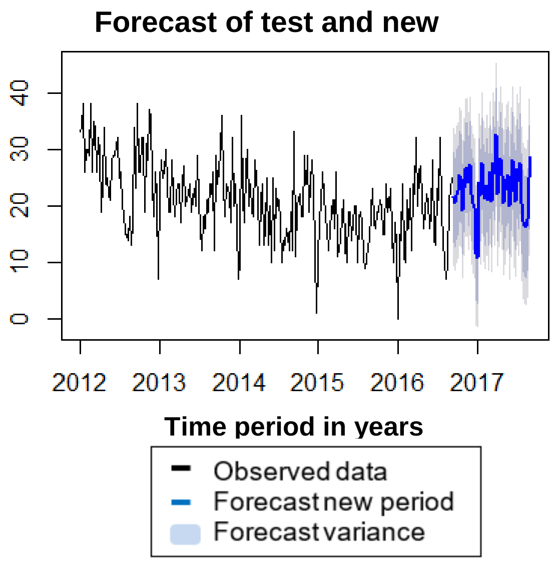


Figure I.3:NP forecast of patient group 1 over the test period and new period

Evaluation

As read in the previous subsection, the obtained result of the forecast is a number of new patients per patient group arriving each week of the time horizon. Since a forecast is never 100% accurate (Nahmias & Cheng, 2009), the forecast is evaluated on its error with the actual arrival pattern. In this evaluation is determined what the difference is between the forecasted number of patients and the actual number of patients arriving per week.

Multiple measures exist to evaluate a demand forecast. The most commonly used evaluation measures are the Mean Squared Error (MSE), the Mean Absolute Deviation (MAD), and the Mean Absolute Percentage Error (MAPE) (Nahmias & Cheng, 2009). Since the MAPE cannot be used when the forecast contains a period with zero demand (dividing by zero), the MAD or MSE should be used as an evaluation measure. The MAD is often preferred above the MSE because the MAD does not require squaring (Nahmias & Cheng, 2009). However, the MSE gives a higher error value to the relatively high deviation, so both are evaluated in this study. The closer the MAD and the MSE are to zero, the more accurate the forecast is.

The result of the evaluation by means of the MAD and the MSE is given in Table I.1.The MAD shows the mean deviation of the forecast compared to the actual number of patients over the total time period. The MSE squares the individual deviations and calculates the mean of the squared errors over the total time period. The MAD and the MSE are calculated for each patient group.

Table I.1: Evaluation of NP forecast by means of the MSE and MAD per patient group

Patient group	1	2	3	4	5	6	7
MAD	4.6	2.8	4.3	1.0	2.8	5.0	1.9
MSE	36.5	14.5	33.7	1.8	14.0	47.7	6.9

Visualization of results of patient group 2:

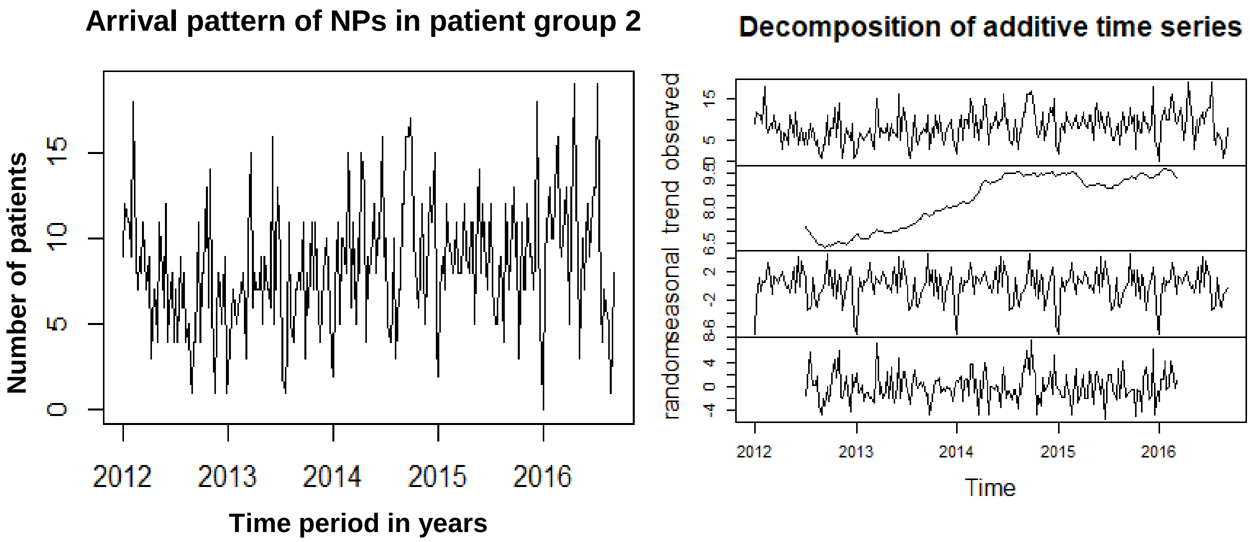


Figure I.5a+b: Arrival pattern of new patients in patient group 2 and its decomposition into seasonal, trend and random patterns

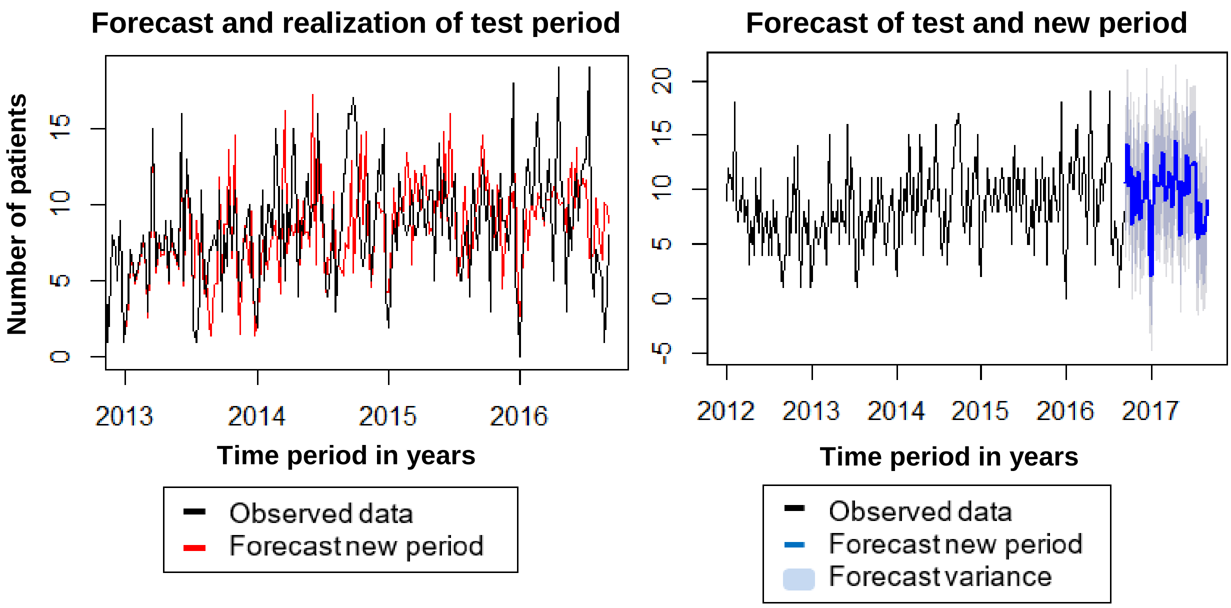


Figure I.6a+b:NP forecast of patient group 2 over the test period and new period

Visualization of results of patient group 3

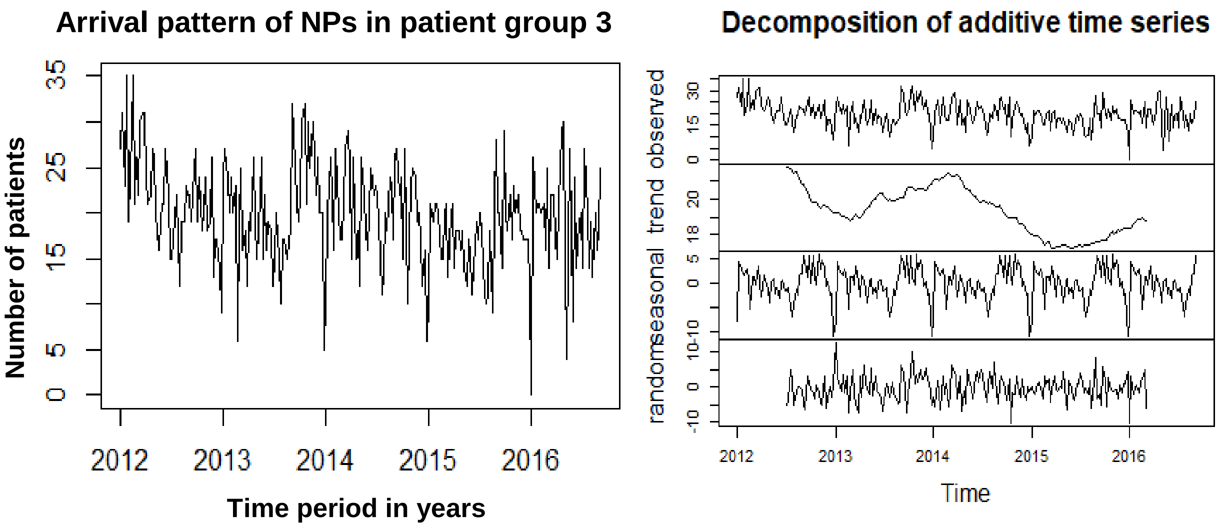


Figure I.7a+b: Arrival pattern of new patients in patient group 3 and its decomposition into seasonal, trend and random patterns

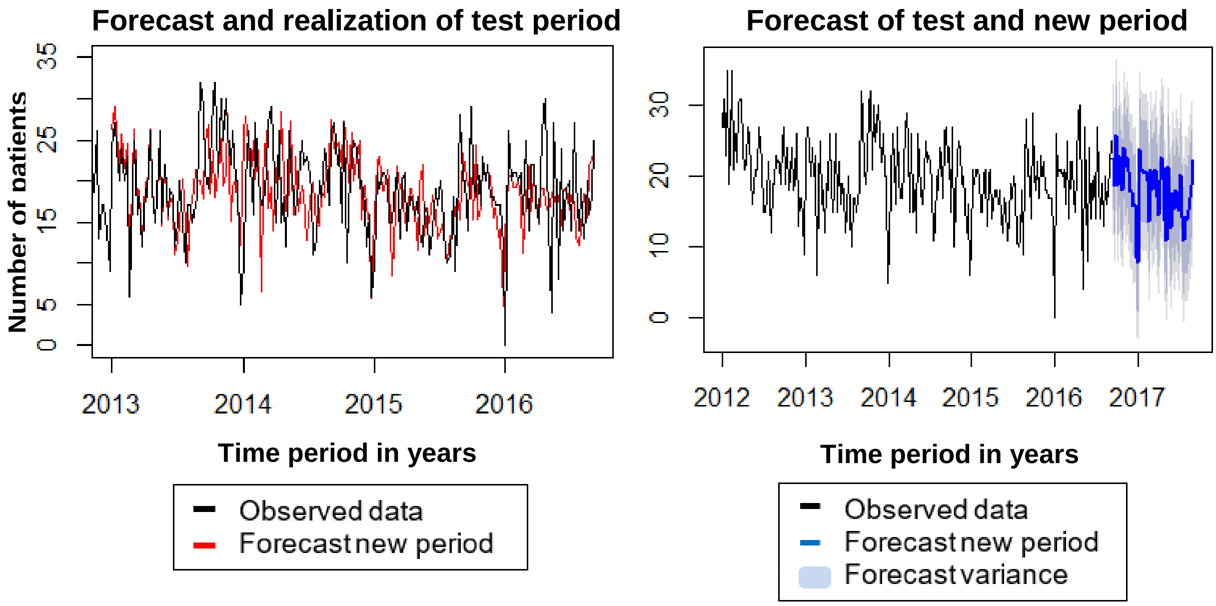


Figure I.8a+b: NP forecast of patient group 3 over the test period and new period

Visualization of results of patient group 4:

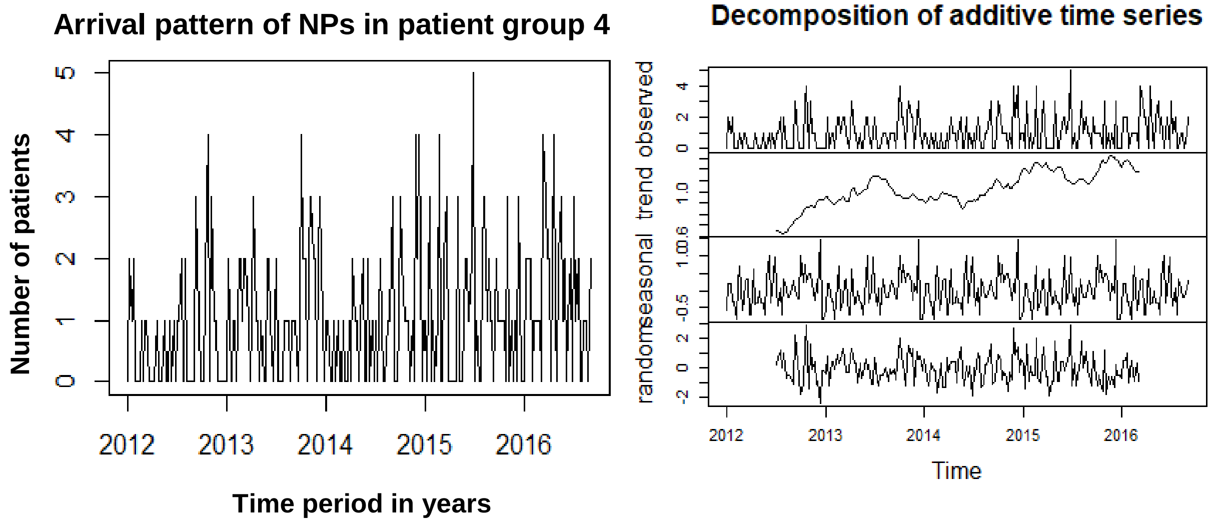


Figure I.9a+b: Arrival pattern of new patients in patient group 4 and its decomposition into seasonal, trend and random patterns

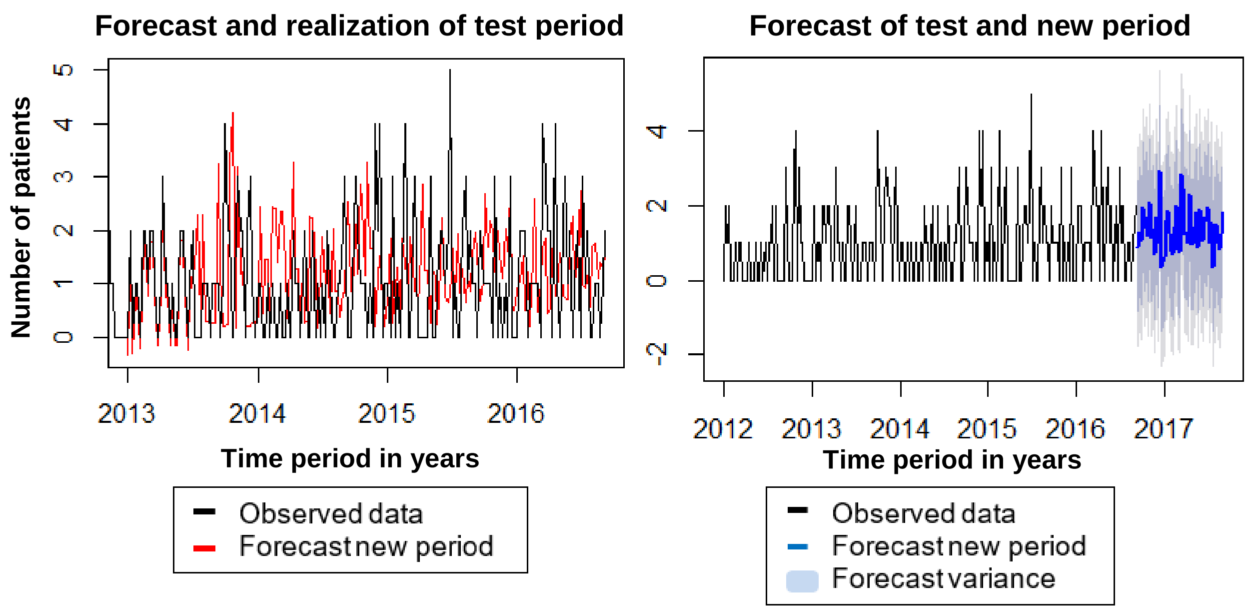


Figure I.10a+b: NP forecast of patient group 4 over the test period and new period

Visualization of results of patient group 5:

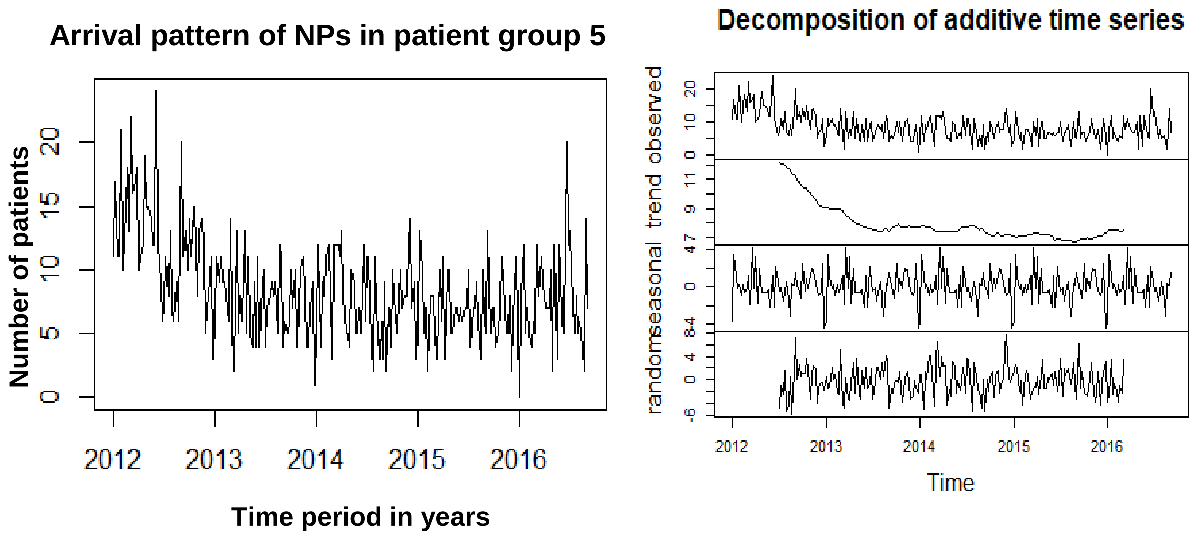


Figure I.11a+b: Arrival pattern of new patients in patient group 5 and its decomposition into seasonal, trend and random patterns

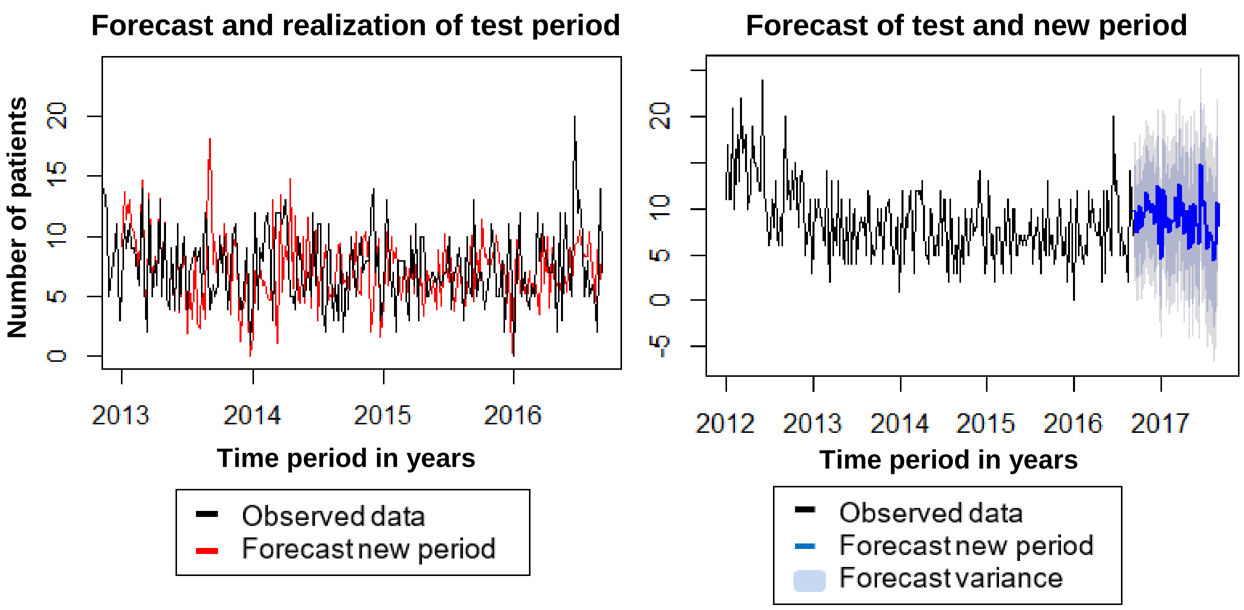


Figure I.12a+b: NP forecast of patient group 5 over the test period and new period

Visualization of results of patient group 6:

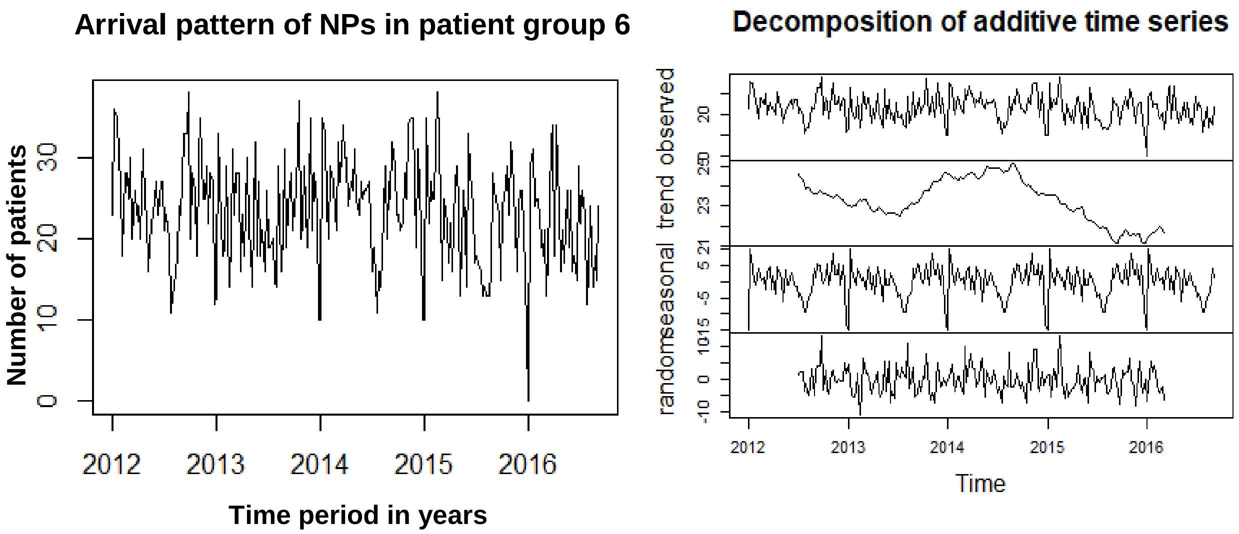


Figure I.13a+b: Arrival pattern of new patients in patient group 6 and its decomposition into seasonal, trend and random patterns

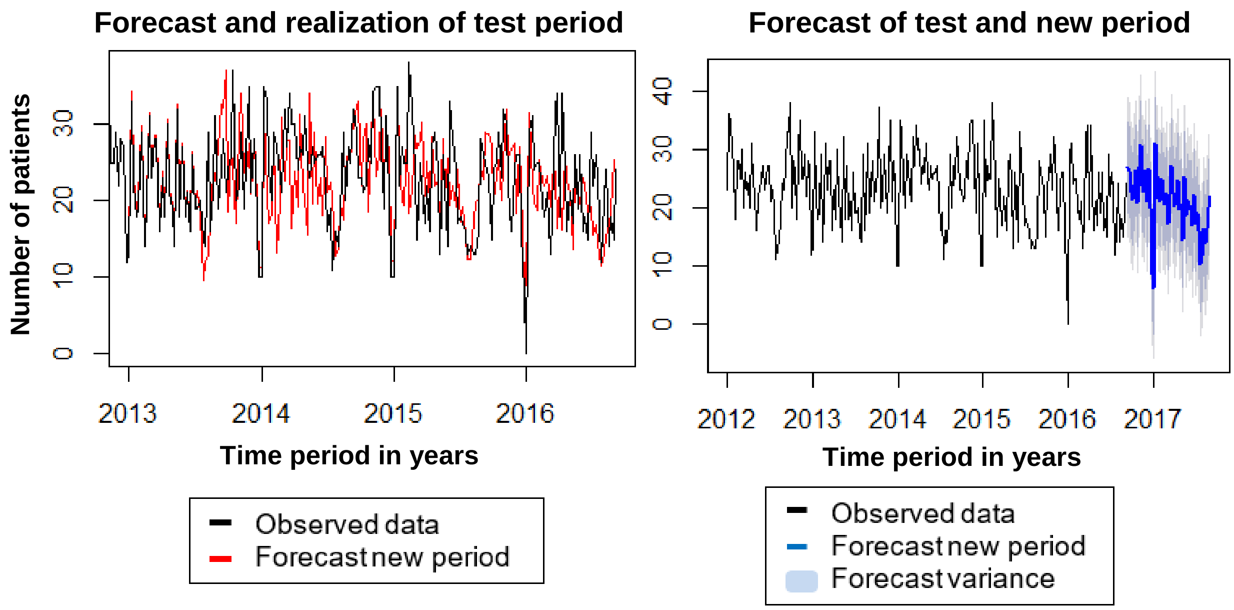


Figure I.14a+b: NP forecast of patient group 6 over the test period and new period

Visualization of results of patient group 7:

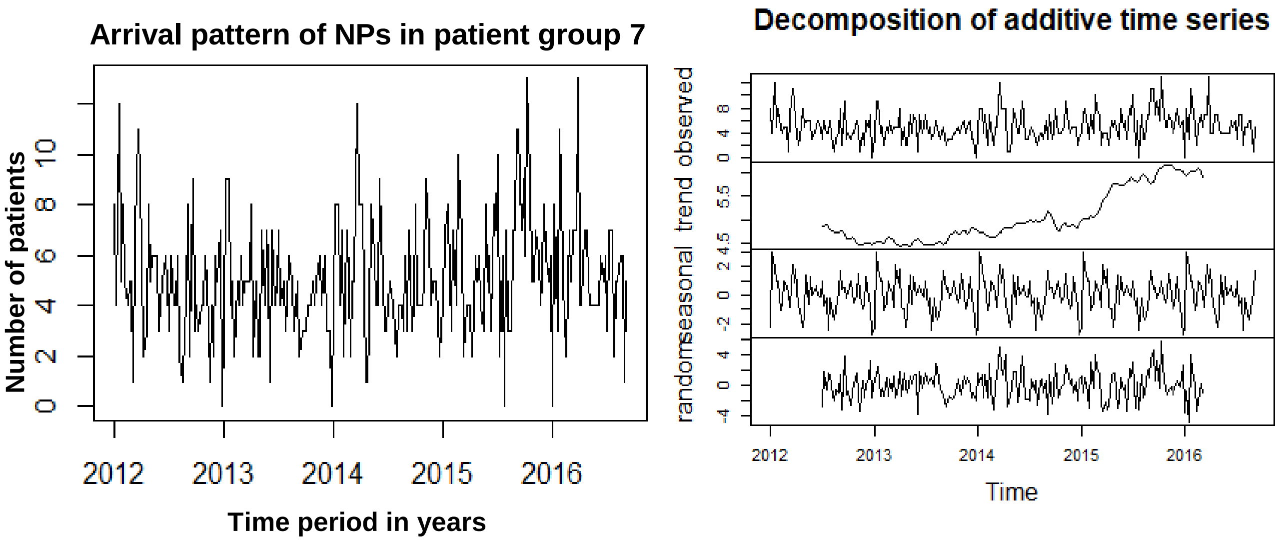


Figure I.15a+b: Arrival pattern of new patients in patient group 7 and its decomposition into seasonal, trend and random patterns

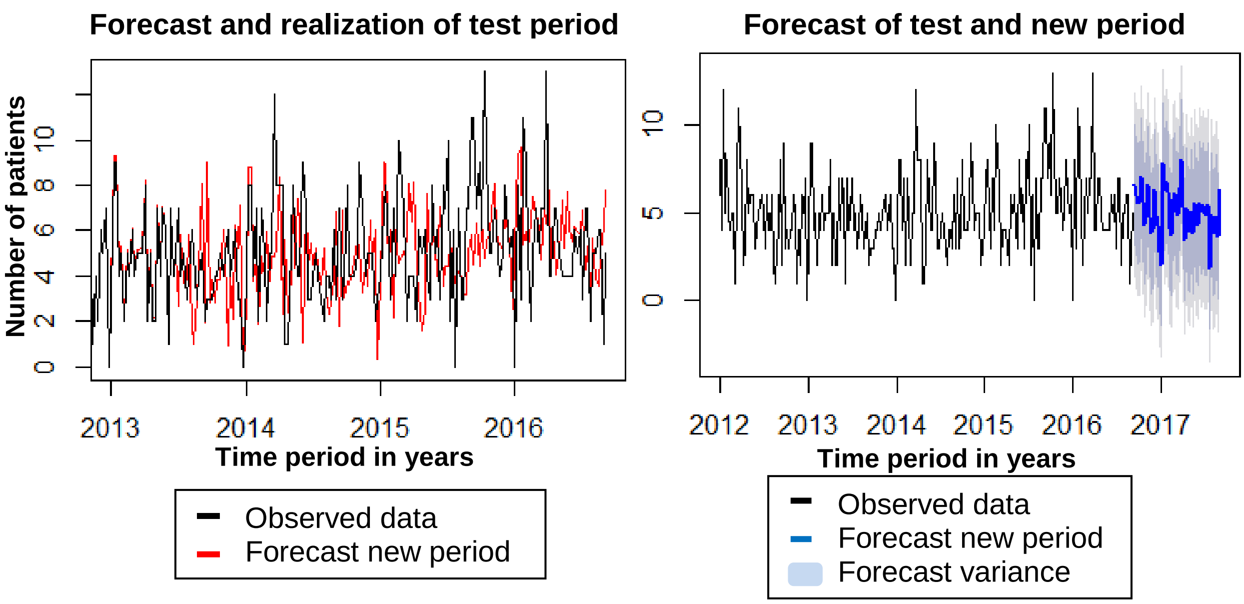


Figure I.16a+b: NP forecast of patient group 7 over the test period and new period

Final NP forecast per patient group and per time period in the time horizon

Table I.2: Final NP forecast per patient group and per time period in the time horizon

Week Patient group	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	15	22	21	22	23	25	25	19	23	27	27	24	27	22	20	20	11
2	10	11	14	10	12	7	11	8	10	12	7	9	9	11	14	9	4
3	22	22	19	26	19	23	20	18	24	21	23	21	18	18	16	16	8
4	1	1	1	1	2	1	2	1	2	1	1	1	2	1	3	0	0
5	9	10	7	8	10	8	9	10	12	11	10	10	10	8	9	12	6
6	19	27	26	23	21	24	26	21	27	31	24	23	26	21	26	20	9
7	5	7	6	6	6	7	6	4	5	7	5	4	4	6	5	4	3

Appendix J. Capacity demand and capacity supply

In this appendix, the capacity demand and the capacity supply are determined. The methodology as described in Section 4.1 is used.

Capacity supply

The capacity supply per department is determined by dividing the available specialists' time over the relevant hospital departments. In this case study, the relevant hospital departments are the OPD and the SD. The SD will be initially allocated with the specialists' time from the MSS allocated to orthopedics. The initial SD allocation is shown in Table J.1. The OPD will be allocated with the remaining specialists' time. Since the case hospital is working with NP and CP slots within the OPD sessions, the specialists' time is separately allocated to these stages. An important fact is providing insight into the effect of accepting a new patient on the number of succeeding CP visits and surgeries at the SD. For these reasons, the OPD is separated into two sub-departments. The remainder of this case study, the relevant hospital departments are NP, CP, and SD.

The remaining specialists' time needs to be allocated over NP and CP. The allocated specialists' time is computed by Formula (2). An extra restriction is added since the NP and CP are working with time slots within sessions. To make the sessions one by one interchangeable, separate sessions are created for NP and CP. Since the duration of an NP visit is twice the time of a CP visit, the 1:1 patient ratio is not maintained when the sessions are allocated 1:1 over both sub-departments. Therefore, the ratio 2:1 is used in order to reflect a realistic start scenario. The initial allocation of the remaining specialists' time over the NP and CP in sessions and in patients is shown in Table J.1 and Table J.2, respectively.

Table J.1: The result of the initial capacity allocation over the relevant departments in sessions

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	12	13	13	12	13	11	11	12	11	12	11	11	11	11	11	11	11
CP	6	7	7	6	7	6	6	7	6	7	6	6	6	6	6	6	6
SD	9	7	7	9	7	10	10	8	10	8	10	10	10	10	10	10	10
Tot.	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**	**27**

Table J.2: The result of the initial capacity allocation over the relevant departments in patients

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	84	91	91	84	91	77	77	84	77	84	77	77	77	77	77	77	77
CP	90	105	105	90	105	90	90	105	90	105	90	90	90	90	90	90	90
SD	27	21	21	27	21	30	30	24	30	24	30	30	30	30	30	30	30
Tot.	**201**	**217**	**217**	**201**	**217**	**197**	**197**	**213**	**197**	**213**	**197**	**197**	**197**	**197**	**197**	**197**	**197**

Capacity demand

The capacity demand consists of three parts; the forecast of new patients, the extraction of known patients, and the successive demand of new and known patients. For each element of the capacity demand, the forecasting strategy is explained in the Sections 5.1.8, 5.1.9, and 5.1.10. The total capacity demand is obtained by combining the new patients, known patients and their successive demand. Depending on the minimum or maximum waiting time norm, the total capacity demand that *could be seen* or the total demand that *must be seen* is determined. The total capacity demand that *could be seen* and *must be seen* per time period and per department are shown in Table J.3. An explanation of the result will be given in the next section.

Table J.3: The capacity demand that could be seen per time period in each relevant department

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	102	104	100	92	98	99	82	104	109	97	91	96	87	94	82	42	34
CP	155	189	152	132	147	118	100	98	140	133	144	116	126	113	115	131	150
SD	13	21	11	30	30	36	31	31	34	28	28	23	26	30	26	27	29
Tot.	**270**	**314**	**263**	**254**	**275**	**253**	**213**	**233**	**283**	**258**	**263**	**235**	**239**	**237**	**223**	**200**	**213**

Table J.4: The capacity demand that must be seen per time period in each relevant department

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	3	109	99	95	95	96	99	82	104	109	97	91	96	87	94	82	42
CP	48	91	41	27	135	125	114	106	119	91	97	97	140	133	144	117	127
SD	13	21	11	12	12	7	6	23	28	33	31	28	25	24	22	23	28
Tot.	**64**	**221**	**151**	**134**	**242**	**228**	**219**	**211**	**250**	**233**	**225**	**216**	**261**	**244**	**260**	**222**	**197**

These values are cumulated over each time period, in order to determine the cumulative demand that *must be seen* and that *could be seen*. Both the cumulative demand that *must be seen* and that *could be seen* are evaluated in the next subsection.

Evaluation

Since the capacity demand is based on two forecasts (new demand forecast and a successive demand forecast), a forecast evaluation is necessary to determine the forecast error. However, the forecast error is hard to determine, because the successive demand is created with deterministic interarrival times. This means that the forecasted capacity demand per period is probably different from the actual capacity demand per period. In order to overcome this problem, the forecast is evaluated cumulatively over the total time horizon.

Table J.5: Evaluation of total cumulative new patient forecast with the actual new capacity demand

	Demand that must be seen at t = T	Demand that could be seen at t = T	Actual new capacity demand at t = T
NP	1479	1513	1535
CP	1751	2261	1536
SD	346	452	391

The number of patients who are actually been treated should be around the demand that *must be seen* and *could be seen* in order to be a good forecast. As can be seen in the new capacity demand evaluation, is that both NP forecasts are slightly lower than the actual new capacity demand. The forecast of surgical patients is slightly higher than the actual capacity demand. The CP forecast is a lot more than the actual capacity demand. Two plausible explanations for this difference exists. First of all, the number of check-up visits in a care process is decreased by specialists. In 2012, new technologies and determined care processes require a patient to come back less often for a check-up after a treatment (Anonymous orthopaedist, 2018). The transition probabilities for the successive demand are based on data from 2012 until 2016, which could mean that the transition probabilities to get a check-up visit are higher than the actual transition probabilities since relative old data is included. A second explanation is that the deterministic interarrival time to get a check-up visit is too short. This would cause many more check-up visits in the time horizon instead of being outside the time horizon. However, the increase of the interarrival times to get a check-up visit would also affect the number of surgeries, since the whole care process will be affected by this change.

Capacity demand vs capacity supply

The initial cumulative overview of the capacity demand and the capacity supply is created and visualized in Figure J.1. The figure shows the overview of the cumulative demand that *could be seen* and *must be seen*, together with the cumulative capacity per department and can be interpreted as follows. The first notable observation is the particular shape of some of the demand lines. The first weeks of the cumulative demand line are increasing slowly, while the remaining of the lines rises increasingly. This phenomenon is caused by the waiting time norms. In the periods before the minimum or maximum waiting time value, the only patients demanding care that *must be seen* are the known patients. These patients already have requested a treatment in the past and planned a treatment date in the future. The fact that planned patients *must be seen* and *could be seen* at the same period explains that the demand that *must be seen* is equal to the demand that could be seen at the beginning of the time horizon at the SD. Another notable fact is the reduced increase in the demand that *could be seen* at the end of the time horizon of NP visits. Since week 16 contains a Christmas break and many patients wishes not to be treated during or just before Christmas, the demand is decreasing in these periods. Finally, it can be remarked that the SD mostly knows an overcapacity or overcapacity, while both NP and CP experience a decreasing overcapacity which results in a capacity shortage at the end of the time horizon. Based on this knowledge, the Capacity Balancing is performed in the next step of the model.

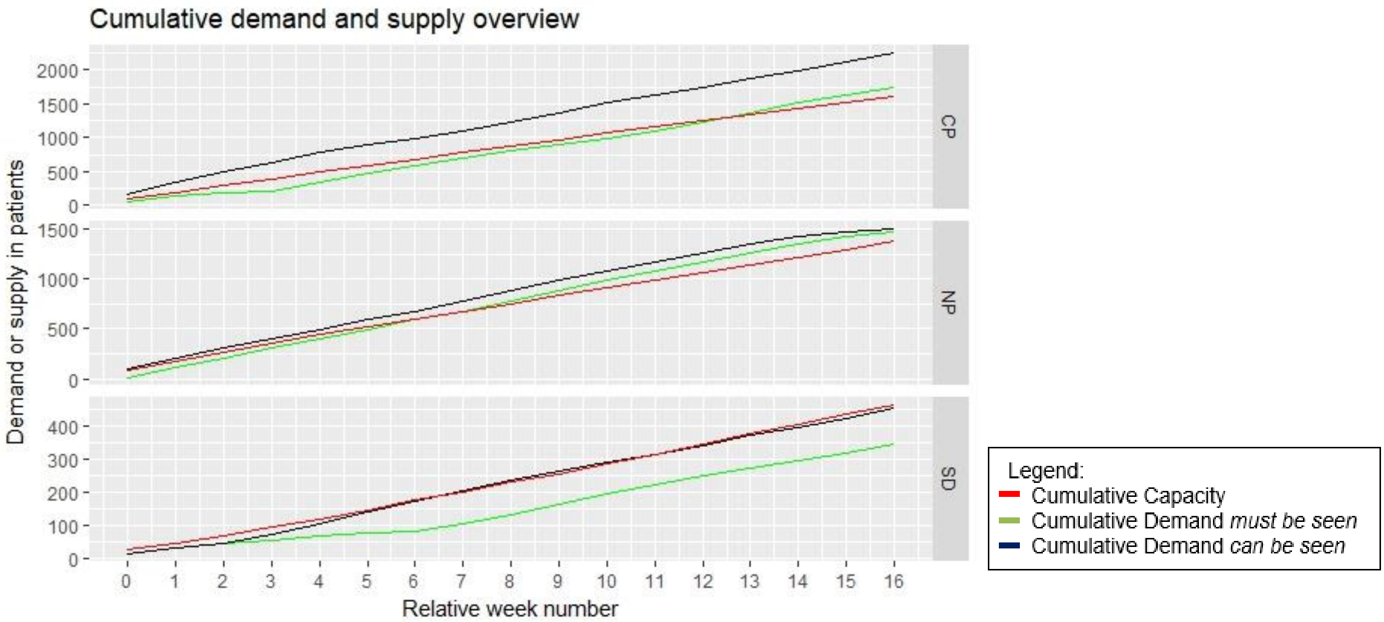


Figure J.1: Cumulative demand and supply overview

Appendix K. Result of patient allocation

This appendix presents the result of the patient allocation. Per week of the time horizon and per department the number of patients treated is determined and which waiting times the patients have experienced. PP indicates the number of planned patients who got treated in the department and week.

Table K.1: Patient allocation to NP, CP, and SD per week including their realized waiting time

	Week 0		Week 1		Week 2		Week 3		Week 4		Week 5		Week 6		Week 7	
	Patients	WT	Patients	WT	Patients	WT	Patients	WT	Patients	WT	Patients	WT	Patients	WT	Patients	WT
CP	48	PP	91	PP	41	PP	27	PP	28	PP	27	PP	3	PP	1	PP
	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
			14	1	13	1	0	1	0	1	0	1	0	1	0	1
					51	2	63	2	55	2	7	2	0	2	0	2
									22	3	56	3	87	3	93	3
															11	4
NP	48	PP	10	PP	5	PP	0	PP	3	PP	1	PP	1	PP	1	PP
	81	0	63	0	55	0	44	0	39	0	20	0	0	0	0	0
			18	1	31	1	40	1	49	1	56	1	76	1	81	1
SD	13	PP	21	PP	11	PP	12	PP	12	PP	7	PP	6	PP	5	PP
							0	0	0	0	0	0	0	0	0	0
							0	1	0	1	0	1	0	1	0	1
							0	2	0	2	0	2	0	2	0	2
							15	3	6	3	11	3	11	3	9	3
									3	4	12	4	13	4	10	4

	Week 8		Week 9		Week 10		Week 11		Week 12		Week 13		Week 14		Week 15	
	Patients	WT	Patients	WT	Patients	WT	Patients	WT	Patients	WT	Patients	WT	Patients	WT	Patients	WT
CP	3	PP	0	PP	0	PP	0	PP	0	PP	0	PP	0	PP	0	PP
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
	0	2	0	2	0	2	0	2	0	2	0	2	0	2	0	2
	63	3	47	3	42	3	36	3	50	3	65	3	90	3	102	3
	27	4	28	4	48	4	54	4	70	4	55	4	60	4	18	4

NP	0	PP	0	PP	0	PP	0	PP	0	PP	0	PP	0	PP	0	PP
	0	0	5	0	6	0	7	0	1	0	5	0	2	0	4	0
	77	1	109	1	92	1	84	1	90	1	86	1	89	1	80	1
			26	2												
SD	10	PP	4	PP	6	PP	2	PP	1	PP	0	PP	0	PP	2	PP
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
	0	2	0	2	0	2	0	2	0	2	0	2	0	2	0	2
	5	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3
	15	4	2	4	0	4	0	4	0	4	0	4	0	4	0	4
					15	5	22	5	17	5	16	5	7	5	3	5
											2	6	5	6	16	6

	Week 16	
	Patients	**WT**
CP	0	PP
	0	0
	0	1
	0	2
	88	3
	17	4
NP	0	PP
	33	0
	37	1
SD	3	PP
	0	0
	0	1
	0	2
	0	3
	0	4
	11	5
	16	6

Table K.2: Total number of allocated patients per department per week

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	84	91	91	84	91	77	77	83	77	140	98	91	91	91	91	84	70
CP	90	105	105	90	105	90	90	105	90	75	90	90	120	120	150	120	105
SD	13	21	11	27	21	30	30	24	30	6	21	24	18	18	12	21	30

Table K.3: Filled sessions with the allocated patients per department per week

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
NP	12	13	13	12	13	11	11	12	11	20	14	13	13	13	13	12	10
CP	6	7	7	6	7	6	6	7	6	5	6	6	8	8	10	8	7
SD	4.3	7	3.7	9	7	10	10	8	10	2	7	8	6	6	4	7	10