Demand forecasting to support optimization of multi-appointment scheduling

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princess máxima center
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Management summary

Background

In the Netherlands, about 600 children per year are diagnosed with cancer. The Princess Máxima Center (the Máxima) is the only national paediatric oncology center, which is established to deliver optimal and centralized care for its patients. Patients require many treatments and to limit travel time to the hospital, the aim is to schedule as many appointments as possible sequentially on one day, which is defined as multi-appointment scheduling.

Objective

Currently, multi-appointment scheduling is not optimal since patients have to wait too long between their appointments, specialists in the Máxima have to change their schedule too often and scheduling of appointments is time-consuming. The main causes are (1) a mismatch between the availability of modalities and specialists and (2) a lack of guidelines for appointment scheduling for different patient types. The research objective is:

'To optimize tactical multi-appointment patient scheduling by designing a method to create a blueprint schedule with time slots for different patient types.'

This research focuses on the patient flow around an ultrasound appointment since this modality has currently the most improvement potential. The utilisation of the ultrasound is not balanced over the weekdays. For example, demand is highest on Tuesday, while capacity is lowest.

Solution approach

To optimize multi-appointment scheduling, we designed a blueprint schedule where the demand for ultrasound is spread over weekdays and time slots are dedicated to patient types.

We first made a distinction between patients from the (1) inpatient clinic and (2) patients from the outpatient clinic or patients who have a day-treatment combined. Inpatients are already in the Máxima and do not have to travel to the Máxima. Therefore, they do not require their appointments sequentially on one day. Patients from the outpatient clinic or who have a day-treatment combined, often have their ultrasound appointment combined with an appointment with the treating physician (91%). The number of patients seen by the treating physician determines the arrival rate of the ultrasound since the treating physicians request the combination appointment. We forecasted the distribution of ultrasound appointments for each weekday, based on discrete convolutions of empirical distributions. Furthermore, we made a distinction in planning terms of the ultrasound requests since operational planning rules are dependent on the planning term. The planning term is defined as the difference between the date of appointment and the date the requester requests the appointment. When the planning term increases, appointments are allowed to deviate more from the requested appointment date. We classified ultrasound requests in the following three planning terms: (2a) emergency, (2b) short-term and (2c) long-term requests. For each planning term, we defined a demand percentile. Emergency patients have to be treated directly, therefore the demand percentile is set high (85%). Hereby, we strive that in 85% of weeks there is sufficient coverage for emergency patients. Long-term requests are allowed to deviate from their requested appointment date and should be spread over weekdays. If demand on a certain day is high, appointments should be scheduled on a day with lower demand. Therefore the demand percentile is set lower (50%). Furthermore, we strive to cover 70th percentile for both the short-term requests and requests from inpatients.

We examined two interventions. The first intervention is the move of the consultation hour from a treating physician who requests many long-term ultrasounds, from Tuesday to Monday. The second intervention is the exchange of appointment blocks on Tuesday and Friday from a treating physician who has their main consultation hour on Tuesday, requests many (long-term) ultrasound requests, and sometimes sees patients on Friday.

Results

Figure 1 shows the performances of the current situation (A) and after the two interventions (B). In the current situation, the total required number of ultrasounds is highest on Tuesday and exceeds capacity. After the interventions, the required number of ultrasounds is lower than capacity for all weekdays for the determined percentiles. Moreover, all weekdays include flexible slots. These flexible slots can be used for new ultrasound requests when the reserved dedicated slots are already utilized for example.

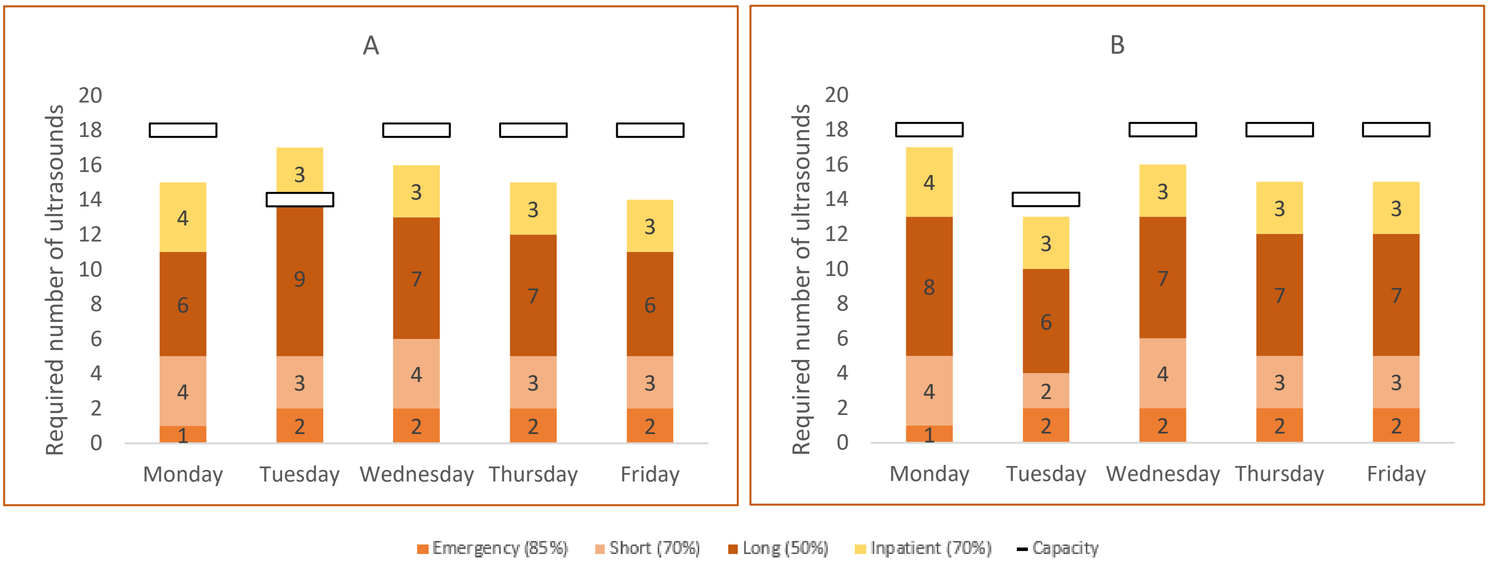

Figure 1: Required number of ultrasounds at current situation (figure 1A) and after interventions (figure 1B) to cover 85th, 70th, 50th, 70th percentile of demand for emergency, short-and long-term requests and inpatients, respectively.

Next, we examined the effect on ultrasound demand for patients from the outpatient clinic or patients with a day-treatment combined, in future scenarios. First, we analysed the effect of a 10% increase in the number of patients hat visit the treating physician. Second, we investigated the effect of a change in a protocol which states that the probability that a patient requires a long-term ultrasound request, increased by 5%. Table 1 shows that as expected, both scenarios resulted in a higher number of required ultrasounds which leads to less flexibility in capacity. This means that less flexible slots are available for other ultrasound requests. This flexibility is for example necessary for requests from inpatients or when the reserved dedicated slots are already utilized. Especially the increase in long-term ultrasound requests leads to less flexible capacity and causes a disbalance in flexibility over weekdays. So, the model still works in both scenarios but the schedules of treating physicians need to be re-evaluated to spread flexibility over weekdays.

Table 1: Flexible ultrasound slots after a 10% increase in the number of patients that visit the treating physicians and a 5% increase in the probability of long-term ultrasound requests, compared to results after changes in the schedules of treating physicians.

	Flexible ultrasound slots		
Weekday	*After interventions*	*+10% patients*	*+5% long-term ultrasound request*
Monday	5	2	1
Tuesday	4	2	1
Wednesday	5	3	2
Thursday	6	5	4
Friday	6	4	4

Conclusion and discussion

This research has a practical contribution to the Máxima since the results of this study show that changes in the schedules of treating physicians lead to a more balanced utilisation of ultrasound. If the required number of ultrasound slots per patient type is implemented in the blueprint schedule, this contributes as a guideline for patient planners to schedule appointments. We strive to have enough slots to schedule emergency requests and we support patient planners to spread long-term requests over weekdays. The described problem solution can be extended to other modalities within the Máxima. Furthermore, with the management, we confirmed that this research creates insights into performance indicators that are important to monitor multi-appointment scheduling within the Máxima. Examples are patients waiting time between multiple appointments, the number of appointments scheduled within the reserved consultation hours of specialists, the planning effort and the utilisation of resources.

The theoretical contribution of this research is that we applied the forecasting model to a patient-centred clinic and evaluated the ultrasound performance as part of the multi-appointment system performance. In literature, this is of interest since optimization in outliers in individual performances might optimize the entire system performance. Furthermore, as mentioned, we implemented that the number of reserved ultrasound slots depends on specific demand percentiles for different types of appointment requests. This percentile is high for emergency requests to be sure enough ultrasound slots are reserved. This percentile is low for long-term requests to support patient planners to spread over weekdays.

Before implementation, we recommend the Máxima to investigate the effects of changes in the schedules of treating physicians on other patient flows. Moreover, the model can be extended by implementing other appointments that are combined with an ultrasound appointment, such as a blood sample test. Furthermore, we recommend to examine the other mentioned performance indicators of multi-appointment scheduling next to utilisation and flexibility of capacity. Last, this model assumes that all weeks are the same. Adapting the model to high and low-demand periods improves the model.

Acknowledgements

Hereby, I present my master thesis: 'Demand forecasting to support optimization of multi-appointment scheduling', as a final step toward finishing my master degree in Industrial Engineering and Management. I was already convinced that I learned many skills during my master, but during this thesis project I developed myself even more on analytical, academic and personal skills. I enjoyed writing my thesis and I do look back on a great time within the Máxima.

I am grateful for my supervisor from the Máxima. Sanne, thank you for all the support and trust you offered me during the whole project. From the start, you guide me through the ins and outs of the hospital and you were always reachable for any kind of help. I appreciate our discussions about the practical aspect of my research. Besides, I want to say thanks to Bianca, who supervised me in the first part of my thesis. You made me feel welcome within the Máxima since our first meeting and helped me a lot with getting to know the 'data environment' of the Máxima. Next, I had the opportunity to work one day a week as a patient planner, and I want to thank my colleagues for the good working atmosphere.

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Next to my supervisors, I am enormously thankful for my family, friends and loved ones who supported me during the whole thesis process. I thank my family who always encouraged and trusted me. Thanks to my friends and roommates, who made me realize that there was also a life next to this project. A special thanks to my boyfriend, Thijs, who even mostly from Mozambique, always supported me. Finally, I want to thank my study friends for interesting discussions about my thesis topic. Most importantly, we enjoyed our group work together and I am proud that we all finish or master soon.

I hope you enjoy reading this master thesis.

Marije Ros

Utrecht, July 2022

Glossary of terms

DES	Discrete Event Simulation
HiX	Healthcare Information eXchange (hospital information system)
HO	Haematology-oncology
ILP	Integer Linear Programming
KPIs	Key Performance Indicators
MPSM	Managerial Problem-Solving Method
NO	Neuro-oncology
OR	Operating Room
SCT	Stem Cell Transplantations
SO	Solid tumour-oncology
The Máxima	Princess Máxima Center
UMCU	University Medical Center Utrecht
WKZ	Wilhelmina Children’s Hospital

Contents

1. Research plan

This research focuses on the improvement of multi-appointment scheduling for the Princess Máxima Center (the Máxima), which is specialized in paediatric oncology. Section 1.1 describes the research context. Section 1.2 establishes the motivation of research. Section 1.3 identifies the problems in the current way of multi-appointment scheduling and Section 1.4 describes the research objective, research scope, and research questions.

1.1. Research context

1.1.1. Princess Máxima Center

About 600 children per year are diagnosed with cancer within the Netherlands and unfortunately, one-fourth of these children still dies. To deliver optimal care for these children, a group of parents and health care professionals took the initiative to establish one national paediatric oncology center, with a close relationship between care and research: the Máxima. The Máxima is a hospital located in Utrecht, the Netherlands, specialized in complex care and research of paediatric oncology. The first patients were admitted to the Máxima on May 18th, 2018. Yearly, around 14,000 patients visit the outpatient clinic, 7,500 patients receive a day-treatment and 2,800 patients have a clinical admission with an average of six days. Furthermore, the Máxima cooperates with various national and international partners, of which the University Medical Center Utrecht (UMCU) and Wilhelmina Children's Hospital (WKZ) are of high importance. These hospitals are located next to each other and connected with the Máxima via a bridge. Projects, programs, and facilities are shared. Moreover, the Máxima has partnerships with other Dutch hospitals, the so-called shared care centers. Although diagnostics, complex treatments, research, and education are within the Máxima, less complex parts of the treatments can be dedicated to one of these shared care centers close to the patients' homes (Prinses Máxima Centrum voor Kinderoncologie B.V., 2020).

1.1.2. Capacity management

The capacity management department of the Máxima investigates and provides insight into the demand and supply of their provided healthcare. Supply is adjusted to demand to offer optimal and efficient care for their patients. The capacity management department is recently merged with the planning department, where patients are planned in line with the availability of modalities, specialists, and patients. Three staff members are mainly responsible for advising this planning process and capacity management. One member is responsible for integral capacity management, with a central role in the organisation and works closely with the heads of health care departments. The second member is for staff planning and data intelligence and the third member specially for patient planning. When decisions are made within the capacity management department, the following perspectives are considered. First, the patient has a central role, which is in line with the vision of the Máxima. Second, the perspective and planning of the specialists and nurses are taken into consideration. Specialists include patients' treating physicians, which are paediatric oncologists and specialised nurses, and other practitioners. Third, the business operations aspect is included.

1.2. Research motivation

The mission of the Máxima is to cure as many children and adolescents as possible with optimal quality of life, and as quickly as possible. To fulfil this goal, both the care process and logistical organization need to be examined, since paediatric oncology is a multidisciplinary process: patients require different treatments from various disciplines. Many patients do not live close to the Máxima and to limit the number of hospital visits, it is desirable to plan as many appointments as possible on the same day. This concept is defined as multi-appointment scheduling, where patients sequentially visit multiple resource types in one day. This is not always reachable and as a result, patients need to visit the hospital more often or have to wait too long between their sequential appointments. Therefore, the current way of multi-appointment patient scheduling needs to be improved. Moreover, requirements for applying multi-appointment scheduling within the Máxima have not been examined before.

1.3. Description of the problem context

To identify the core problem, the Managerial Problem-Solving Method (MPSM) is used (Heerkens et al., 2017). The first step is diagnosing the perceived problem to determine the underlying root causes. After conversations with the experts of the capacity management and planning department and with a paediatric oncologist, the following perceived problem is identified.

1.3.1. Perceived problem

When a patient is diagnosed with a certain type of cancer, a treatment plan consisting of multiple appointments is designed by the paediatric oncologist, based on international guidelines. As explained, the Máxima aims to plan as many of these appointments as possible sequentially on the same day. However, this goal is not always fulfilled. As a result, patients have to wait too long between their planned appointments on the same day or patients have to come back to the Máxima on another day. Besides, specialists have to change their schedules to see their patients, and planning of patients becomes more time-consuming for the planning department. Therefore, the action problem is described as follows:

'Multi-appointment scheduling within the Máxima is not optimal, since the waiting time of patients between multiple appointments is too long, specialists have to change their schedule too often and planning of patients is too time consuming'

1.3.2. Causes of the perceived problem

This section describes the causes of the perceived problem. The main cause of the current non-optimal multi-appointment scheduling is the difficulty to match multiple appointments sequentially on one day. The underlying problem is that resources are not efficiently used and demand and supply do not always match. The root causes of the problem are subdivided into two main categories. The first category is the mismatch of availability of modalities and specialists. The second category is the lack of guidelines for appointment scheduling for different patient types. Figure 1-1 shows a problem cluster to visualise the connection between the described causes of the identified problem. The causes of the problem are substantiated in Chapter 2.

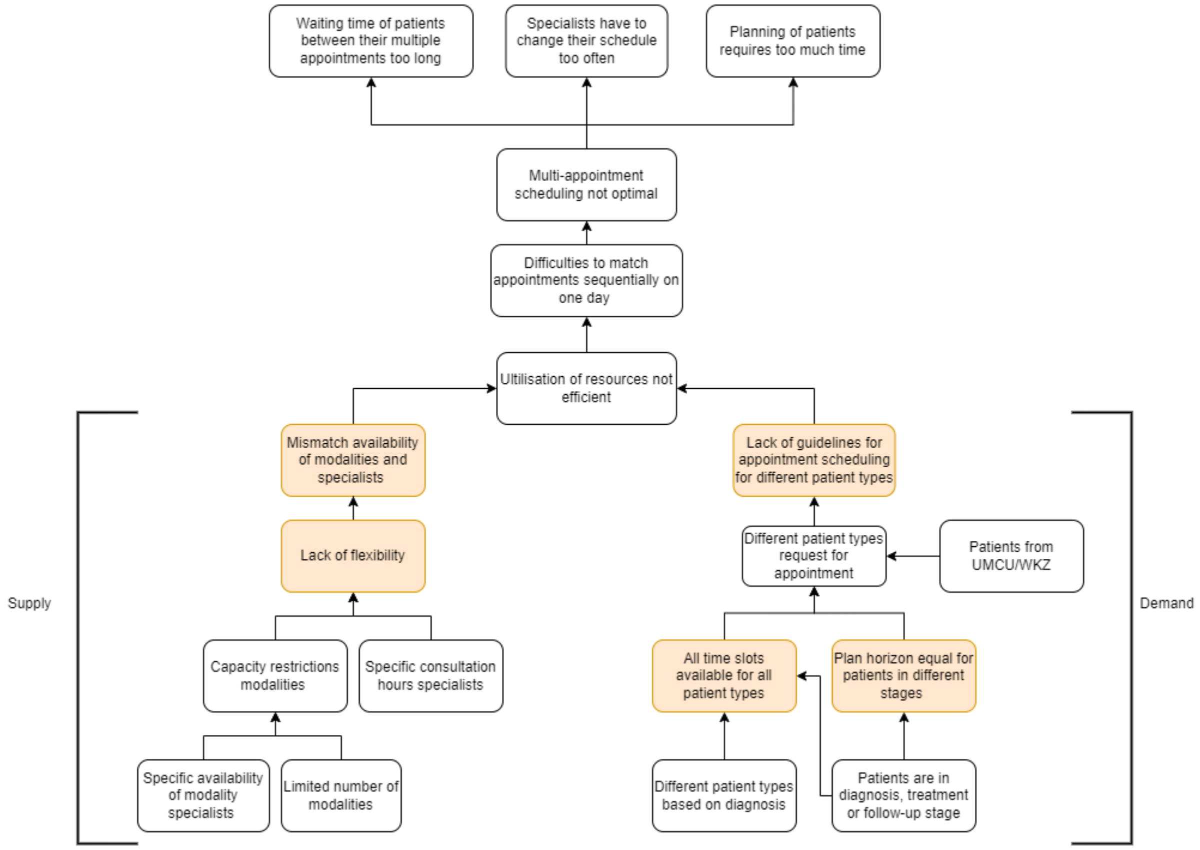

Figure 1-1: Problem cluster

Mismatch availability of modalities and specialists

Patients make use of various specialists and modalities, dependent on their treatment plan. The modalities offered by radiology are MRI, Pet/CT scan, SPECT/CT scan, ultrasound and X-Ray. These modalities have capacity restrictions since the modalities can cover one patient at a time and require specialized staff. Modalities that are currently seen as the largest bottlenecks are the MRI and ultrasound because the MRIs are most of the time fully occupied and the utilisation of ultrasounds is not balanced during the day and week. Furthermore, patients often require an appointment with their treating physician or other specialists to discuss their treatment plan, including the results of the modalities used by the patient. Specialists have multiple tasks and specific consultation hours to see their patients. Therefore, patients need to be planned in line with these consultation hours. For example, when a patient has an ultrasound appointment, the outcome needs to be discussed with their assigned paediatric oncologist. As a result of capacity restrictions and the specific availability of specialists, there is a lack of flexibility. It occurs that there might be time slots in the schedule available for ultrasound, but these slots cannot be combined with the consultation hour of the specialist. Therefore, the utilisation of modalities is not optimally spread during the day and week and appointment scheduling is labour intensive for patient planners.

Lack of guidelines for appointment scheduling for different patient types

Different patient types request for an appointment. These different patient types require different treatment pathways and make use of different modalities. Patients are classified into different subcategories. The first classification is based on the stage of the patients. Patients are in the diagnosis, treatment or follow-up phase. No distinction is made in the planning horizon of these different stages and therefore, all patients are planned at the same time. On average, the planning horizon is short, which makes it hard to adjust capacity to demand. There is currently no advantage to plan on a longer-term. A lack of guidelines for appointment scheduling causes the chance of rework of patient planners when appointments are scheduled on a longer time horizon. Namely, it is difficult to plan patients with a shorter planning horizon between the already planned appointments of for example follow-up patients. The second patient classification is based on the type of cancer diagnosed for the patient, main categories are: haematology-oncology (HO) patients, solid tumour (SO) patients and neuro-oncology (NO) patients. Furthermore, patients from other hospitals request for an appointment. The Máxima closely cooperates with UMCU and WKZ, and these hospitals also request for modalities and specialists. There is a lack of guidelines for appointment scheduling for different patient types because in the current blueprint schedule, all time slots are available for all the above-mentioned patient types.

1.4. Research goal

1.4.1. Research objective and scope of research

The Máxima aims to improve their current multi-appointment scheduling. Since there is a lack of guidelines for appointment scheduling and a mismatch between the availability of resources, this research focuses on tactical resource capacity planning of the hierarchical framework for healthcare planning and control, shown in Figure 1-2 (Hans et al., 2012). Different patient types require different appointment combinations and make use of various resources, depending on their treatment pathway. Since the different patient types are not taken into account in the current blueprint schedule, the following research goal is defined:

'To optimize tactical multi-appointment patient scheduling by designing a method to create a blueprint schedule with time slots for different patient types.'

The blueprint schedule serves as a guideline to schedule different patient types. Different patient types including their treatment pathways and resource use are included in the method to design a blueprint schedule. Therefore, the match between the availability of various resources will be optimized.

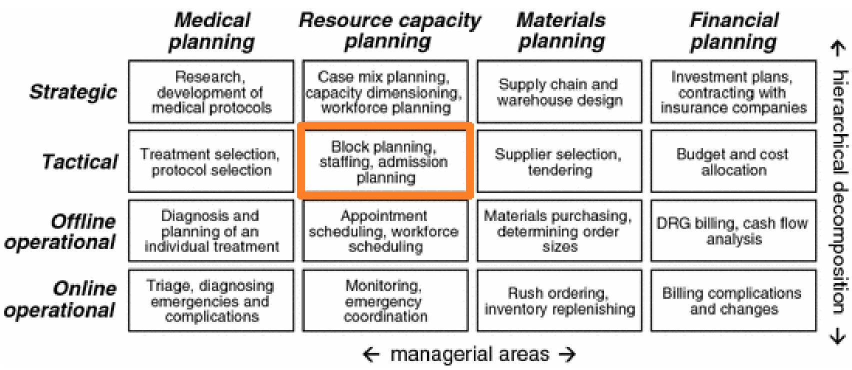

Figure 1-2: Hierarchical framework for healthcare planning and control (Hans et al., 2012).

This research focuses on the combination of ultrasound appointments with other appointments, by examining patient flows around an ultrasound appointment. Ultrasound has currently the most improvement potential and is seen as a bottleneck in scheduling appointments sequentially on one day.

Patients from UMCU or WKZ are excluded from this research since they do not use ultrasound from the Máxima. Next, appointments in shared care centers are excluded from this research.

As explained, patients have a central role in decision-making within the Máxima. Furthermore, the perspective of specialists and the aspect of business operations are considered.

1.4.2. Research questions and methods

To reach the research objective, the following main research question needs to be answered:

'How can the Máxima optimize their current multi-appointment scheduling by using a method to improve their current blueprint schedule?'

To answer the main research question, the following sub-research questions will be answered in the remaining chapters of this report.

1. *'What is the current way of multi-appointment scheduling within the Máxima and what is the current performance?'*

Chapter 2 examines patients that require multiple appointments sequentially on one day and patients that make use of ultrasound. Furthermore, the current multi-appointment scheduling process on both tactical and operational level is described. Next, the combination of an ultrasound appointment with other appointments is investigated. Chapter 2 also selects and analyses performance measurements to investigate the current performance of multi-appointment scheduling. This is necessary to compare further possible solutions with the current situation. Answers in Chapter 2 are obtained from expert opinions and data analysis from available data.

2. *'Which model types can be found in the literature to improve tactical multi-appointment scheduling?'*

Chapter 3 investigates which theories and models are already known in the literature for tactical multi-appointment scheduling.

3. *'What is the design of the selected model to optimize multi-appointment scheduling specific for the Máxima?'*

Chapter 4 describes the most suitable model to optimize multi-appointment scheduling specifically for the Máxima. Answers in Chapter 2 and Chapter 3 are used to answer this question.

4. *'What are the effects of the solution approaches?'*

Chapter 5 analyses the obtained results from the solution model. Furthermore, a sensitivity analysis is performed to investigate the effects of changing input factors on the output.

5. *'Which steps need to be taken to implement the solution in practice?'*

Chapter 6 addresses the implementation plan to implement the designed solution.

2. Context analysis

The goal of this chapter is to answer the following research question: '*What is the current way of multi-appointment scheduling within the Máxima and what is the current performance?*' Section 2.1 describes the current process with a focus on ultrasound and explains multi-appointment patient scheduling. Section 2.2 assesses the performance of the current situation.

2.1. Process description

New patients are referred by a general practitioner or by a specialist from another hospital. Every day a consultant is present who examines the new patients and assigns each patient to one of the following diagnosis group departments. The first department is HO, which are patients with blood cancer, immune system diseases and bone marrow failure. This department also consists of stem cell transplantations (SCT). The second department is SO which includes patients with a tumour in the organs, tissues or the skeleton. The third department is NO. Here, patients with a brain tumour or tumours in the remaining part of the central nervous system are treated. When cancer is diagnosed, the next stage for the patient is the treatment of their specific cancer type and this is followed by a follow-up phase. Diagnosis, treatment and follow-up of the patient are classified as direct care. The patient leaves the hospital when the patient is sent home, moves to another hospital or when the patient dies. Next to direct care, the Máxima has a late effects outpatient clinic for former patients who are cured of cancer. Late effects of cancer treatment are investigated, diagnosed and treated. Patients in this outpatient clinic are defined as LATER. It is possible that patients in the follow-up stage or in LATER care relapse and need to return to the diagnosis or treatment phase. Figure 2-1 summarizes the categorisation of the above-mentioned patient groups.

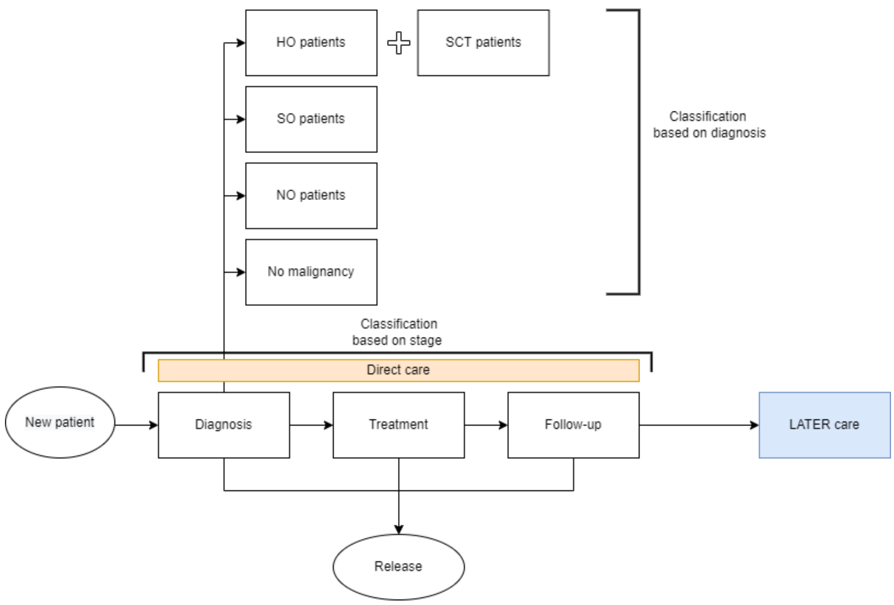

Figure 2-1: Classification types of patients. Orange=Direct care, blue=LATER care

New patients are treated as emergency patients. When they enter the hospital, they have their appointment on the same or the next day. For their treatment, it is important to diagnose and start treatment as soon as possible. Therefore, there is nearly no access time for patients. Furthermore, patients in treatment or follow-up who become seriously ill and need appointments directly, are also classified as emergency patients.

As explained, patients make use of various resources of the hospital. Depending on the patients' stage and type of diagnosed cancer, various specialists and modalities are used. The HO, SO, NO and SCT departments have their paediatric oncologists, nurse specialists and nurses. The current number of paediatric oncologists per department is 23, 16, 12 and 8 respectively. However, next to examining their patients, they have multiple side tasks such as research, education or management tasks. Other specialists in the departments are (orthopaedic) surgeons, anaesthetists and internists. Furthermore, the Máxima has psychologists, dieticians, pain specialists and physical therapists to support the care of their patients. The radiology department offers the following modalities: 2 MRIs, 1 Pet/CT scan, 1 SPECT/CT scan, 2 ultrasounds and 1 X-Ray. Lab technicians perform the examinations and radiologists analyse the results of the modalities. However, both the lab technicians and radiologists are employed by UMCU and not by the Máxima. This holds for more specialisms within the hospital and reduces flexibility. Namely, these staff members work on multiple locations and UMCU has to agree with changes in availability. Other important resources are the 5 treatment rooms and 22 outpatient rooms where specialists see their patients.

Depending on the cancer type and the severity of cancer, a patient visits the outpatient or inpatient clinic. The outpatient clinic serves patients that have an appointment in the hospital but do not have a clinical admission. The inpatient clinic is for patients that need to stay for at least one night. The Máxima has 87 rooms available. Besides, patients have day-treatments. These are patients who need for example a bed or chair for chemotherapy for a few hours, but do not visit the inpatient clinic. The Máxima has two day-treatment rooms.

Appointments with different resources are often combined. As explained, especially the modalities MRI and ultrasound are hard to combine with other appointment types. Since this research focuses on ultrasound, ultrasound appointments are analysed in more detail in the following sections.

2.1.1. Ultrasound

All patient types classified in Figure 2-1 make use of ultrasound. 23% of all patients have at least one ultrasound appointment in their pathway. Figure 2-2 shows that the average number of ultrasound appointments per month remained constant over the period January 2019-November 2021, indicated by a moving average window (w) of 6. However, the variation around the mean increased over the years.

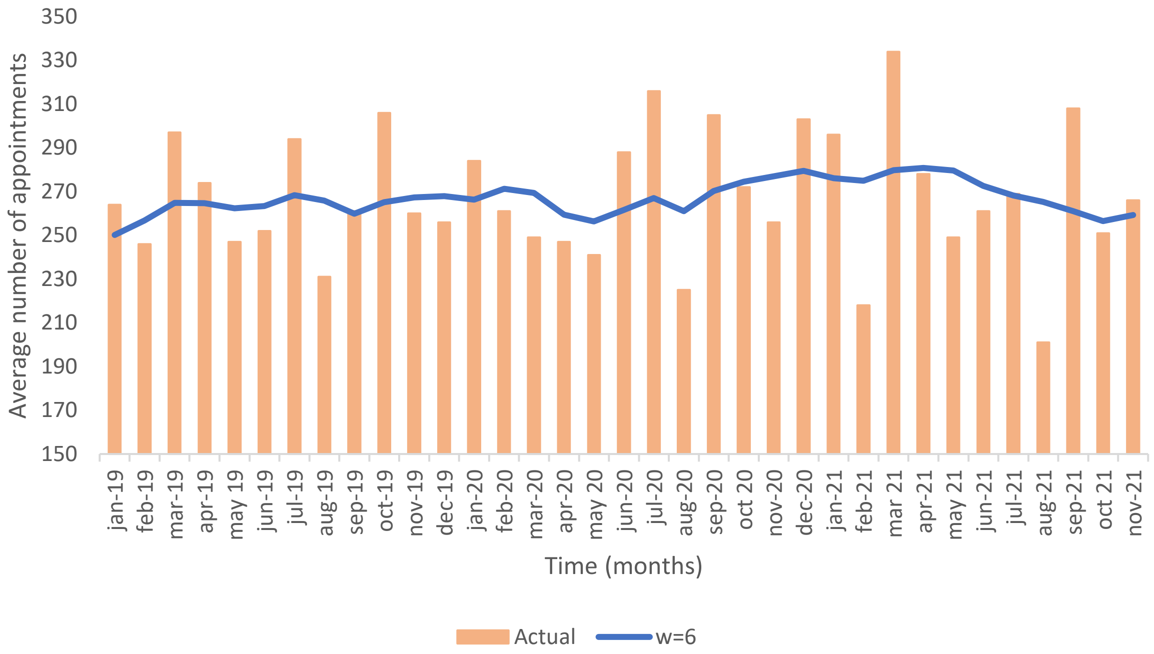

Figure 2-2: Number of ultrasound appointments per month over time. 'w' = moving average window (n=9,366; Data for January 2019 - November 2021, source: HiX).

The weekly averages and the variation around the mean are calculated to support the increase of variation around the mean over time. Table 2-1 shows the average number and the coefficient of variation of weekly number of ultrasound requests for 2019, 2020 and 2021. The coefficient of variation increased over time for the period 2019-2021. There is no clear reason for this increase in variation, but together with the management, we concluded that it might be that during the COVID-19 pandemic, patients cancel or ask for rescheduling their appointments more often. During holidays, the number of appointments is always lower since both patients and specialists are less available. Figure 2-2 shows for example that the number of ultrasound appointments is lower in August, which compensates in September, when the number of appointments increases.

Table 2-1: Average number and coefficient of variation of number of weekly ultrasound requests for 2019, 2020 and 2021 (n=9,366; Data for January 2019 - November 2021, source: HiX)

Year	***Average number of weekly requests***	***Coefficient of variation***
2019	61.08	0.20
2020	61.63	0.21
2021	59.82	0.26

As explained in Section 2.1, patients are classified into diagnosis groups. Figure 2-3 shows that all patient types from different diagnosis groups make use of ultrasound. Half of the requests are from SO patients (50%), followed by HO patients (35%).

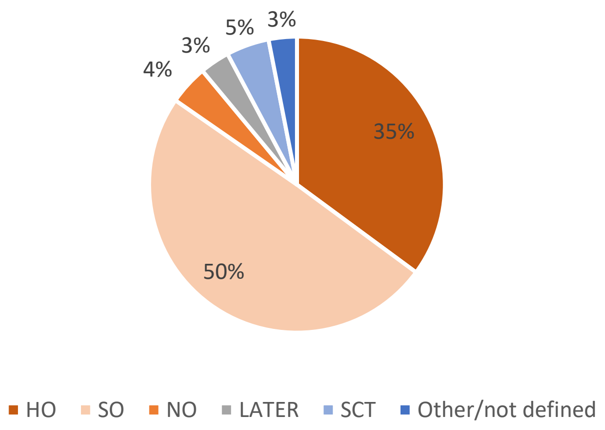

Figure 2-3 Percentage of patient types per diagnosis department (n=6,295, data for January 2020 – December 2021, source: HiX)

The number and percentage of patients in diagnosis, treatment or follow stage are currently not available. Figure 2-4 shows that the majority of patient requests for ultrasound are from the outpatient clinic (71%). After that, patients in the inpatient clinic request most ultrasound appointments (22%) and the rest of the appointments are requested by patients who combine the ultrasound appointment with a day-treatment (7%).

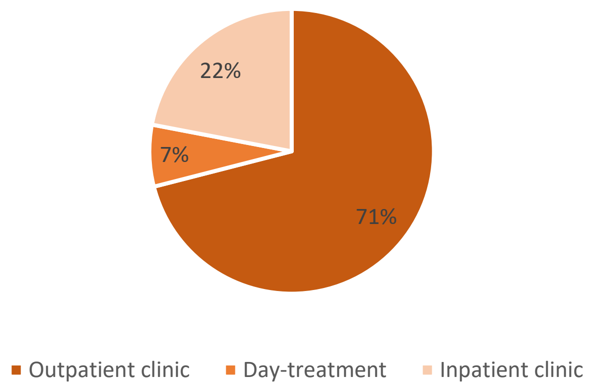

Figure 2-4: Percentage of ultrasound appointments requested from outpatient clinic, day-treatment and inpatient clinic (n=3,192; Data for November 2020- October 2021, source: HiX).

2.1.2. Multi-appointment patient planning process

The planning department is separated in patient planning and staff planning. The patient planning schedules the appointments of the patients, requested by the patients' treating physicians. Patient planners have different roles. One is responsible for HO patients, one for SO patients, one for NO patients, one for SCT patients and one for LATER patients. These planners also check whether the patient needs a day-treatment. Furthermore, one planner is responsible for scheduling clinical admissions for the inpatient clinic, one for Operating Room (OR) appointments, and one for sedation of patients. There are no specific patient planners for modality appointments, except for MRI. Capacity of MRI is scarce and therefore coordinated by a separate planner. Planners experience difficulties with combining an ultrasound appointment with other appointments sequentially on one day.

Tactical patient planning

The Máxima uses Healthcare Information eXchange (HiX) for patient planning. The schedule of the modalities is subdivided into time slots for every day. For ultrasound, all available time slots within the schedule can be reserved for all patient types with the following exception. Each day, there are time slots reserved for emergency patients. These become available one working day before. Emergency time slots on Monday become available on Friday before. The available capacity for ultrasound only adjusts when lab technicians or radiologists are not available or when the ultrasound needs maintenance. In general, the available capacity is not adjusted based on changes in demand. However, for Christmas 2021 for example, one of the two ultrasounds was unavailable on purpose, since the demand was low. Figure 2-5 shows the blueprint schedule of the ultrasound. Both ultrasound machines have the same schedule. The duration of an ultrasound appointment is 45 minutes. The first available block starts at 08:00h and the last at 14:45h. Tuesday is an exception with the last time slot at 13:15h, since radiologists need to be present at the so-called tumor board, where specialists multidisciplinary discuss a patients' treatment protocol. On each day, radiologists have a break between 11:45h and 13:15h with other obligations. The last slot of every day is available for emergency patients, which is every day at 15:30h, and on Tuesday at 14:00h. So, for both ultrasound machines, there are eight time slots available each day, plus an extra slot for emergency patients. On Tuesday there are six time slots plus an emergency slot.

	Monday	Tuesday	Wednesday	Thursday	Friday
08:00	1	1	1	1	1
08:45	2	2	2	2	2
09:30	3	3	3	3	3
10:15	4	4	4	4	4
11:00	5	5	5	5	5
11:45	Break	Break	Break	Break	Break
12:30	Break	Break	Break	Break	Break
13:15	6	6	6	6	6
14:00	7	7	7	7	7
14:45	8	Tumor board	8	8	8
15:30	9		9	9	9

Available for all patient types
Break/Tumor board
Emergency: Available one day before

Figure 2-5: Blueprint schedule ultrasound

Operational patient planning

Patient planners receive multiple orders from different specialists. The requester of the order requests an exact date. When no exact date is desirable, the requester asks for an appointment in a certain term. The patient planners schedule the patients via their patient work list, specific for their role. There is no waiting list for patients, since orders are planned on the requested date, or orders with a requested period are planned within the corresponding margins:

- One week — Requested date +/- one day
- Two weeks — Requested date +/- two days
- Three weeks — Requested date +/- three days
- One month — Requested date +/- one week
- Two months — Requested date +/- two weeks
- Three months — Requested date +/- three weeks
- ≥ Four months — Requested date +/- four weeks

Orders with the closest requested appointment date are planned first. No distinction is made in scheduling patients in different stages. Many patients are in the diagnosis or treatment stage which results in many orders that need to be scheduled within the short term. Therefore, patient planners do not have time to plan orders for follow-up patients, who often have requested orders with a longer term. For example, when an order is requested in three months, the order remains on the patient work list until the patients' planners reach the requested appointment data minus the current planning horizon. Moreover, if many appointments of one patient are on the working list, not all of these appointments are scheduled since when appointments are scheduled over a long-time horizon, the chance of rework is high. Emergency patients are planned on online operational level. This means that the order is requested, but the requester also calls the patient planning department, and the appointment is scheduled immediately.

When patients visit the outpatient clinic, the goal is to combine multiple appointments sequentially on one day. Planners need to combine the schedules of the requested appointments. Sometimes appointments in the Máxima are combined with appointments in UMCU/WKZ. The planners also try to plan the combination with these appointments sequentially on one day. When it is not possible to plan multiple appointments on one day, the following steps are taken. The patient visits another colleague, specialists meet the patient outside consultation hours, appointments are scheduled on multiple days or other patients' appointments are rescheduled. Since difficulties are experienced with combining ultrasound appointments with other appointments, these combinations are investigated.

Combination of ultrasound with other appointments

Patients that are in the inpatient clinic are excluded from these analyses, because these patients are already in the hospital and do not necessarily need multiple appointments sequentially on one day. Next to patients that visit the outpatient clinic, patients who receive a day-treatment need multiple appointments scheduled sequentially on one day, since the goal is to combine the day-treatment with other appointments. These two patient groups are examined separately since different appointment types are combined for these groups. Ultrasound appointments are often combined with one or multiple other appointment types.

Table 2-2 shows the number and percentage of common combinations of an ultrasound appointment with other appointments for both the outpatient clinic and the combination with a day-treatment. Since patients might have more than two appointments on one day, subtotal percentages might be higher than the sum of the corresponding subcategories. For the outpatient clinic, 3% of ultrasound appointments are not combined with any other appointment on one day. For patients with a day-treatment combined, 7% of ultrasound appointments are not combined with another appointment. For both outpatient clinic and day-treatment, most ultrasound appointments (92% and 79% respectively) are combined with at least an appointment with the patients' treating physician. Furthermore, when an ultrasound appointment is scheduled on a day for the outpatient clinic, this is often combined with at least an X-Ray appointment (46%). Another frequent combination is an ultrasound appointment combined with a blood sample test (45%). An ultrasound appointment including a day-treatment is often combined with an appointment in the treatment room (72%) or a MRI scan (26%). An example of an appointment in the treating room is the puncturing of the port-a-cath, which is used to draw blood or to give a treatment.

*Table 2-2: Percentage and number of ultrasound appointments combined with other appointments for outpatient clinic and ultrasound appointments combined with a day-treatment. *Includes treatment rooms, but also functional rooms where for example blood samples are conducted. (n=2,240 for outpatient clinic and n=226 for combination with day-treatment; Data for November 2020- October 2021, source: HiX).*

Combined with	***Category***	***Subcategory***	***Outpatient clinic number (%) (n=2,240)***	***Day-treatment number (%) (n=226)***
No other appointment			75 (3%)	15 (7%)
At least an appointment with	Treating physician	Paediatric oncologists and specialized nurses	2052 (92%)	179 (79%)
	Treatment room (general) *	*Subtotal*	*1412 (63%)*	*162 (72%)*
		Treatment room	331 (15%)	152 (67%)
		Ultrasound heart	131 (6%)	16 (7%)
		Blood sample	1025 (45%)	10 (4%)
	Radiology	*Subtotal*	*1074 (52%)*	*112 (50%)*
		Ultrasound	10 (0%)	2 (1%)
		X-Ray	1031 (46%)	35 (15%)
		Pet/CT-scan	19 (1%)	9 (4%)
		MRI-scan	88 (4%)	58 (26%)
		Nuclear research	7 (0%)	8 (4%)
	Paramedical	*Subtotal*	*56 (3%)*	*13 (6%)*
		Dietician	22 (1%)	4 (2%)
		Physiotherapist	35 (2%)	10 (4%)

2.2. Performance of the current patient planning

The goal of this research is to optimize multi-appointment scheduling. To measure the current performance of multi-appointment scheduling, Key Performance Indicators (KPIs) are defined. The perspective of the patient, staff and management are included. From the patients' perspective, as many of patients' appointments as possible should be scheduled on one day, while the waiting time, defined as the scheduled time (in minutes) between sequential appointments, should be as low as possible. Therefore, the number of appointments and the scheduled time between sequential appointments including an ultrasound appointment on one day are analysed. From a staff's perspective, the aim is to have as many appointments as possible scheduled within the scheduled consultation hours of the specialists. Moreover, the aim is to reduce the effort for patient planners to schedule appointments. From a management perspective, the utilisation of modalities is analysed. From all perspectives, it is of relevance to examine the number of rescheduled appointments. The KPIs are explained in more detail in the following subsections.

2.2.1. Number of appointments on one day

From the patients' perspective, the number of appointments on one day and the waiting time between their multiple appointments are of importance. Figure 2-6 shows the percentage of the number of appointments scheduled when also an ultrasound appointment is scheduled for the outpatient clinic and when an ultrasound appointment is combined with a day-treatment. For the outpatient clinic, most of the time (34%), a total of four appointments are scheduled on a day when an ultrasound appointment is scheduled. On average, 3.3 appointments are scheduled when an ultrasound appointment is scheduled on a day. For ultrasound appointments combined with a day-treatment, there are most of the time three appointments scheduled. This means that an ultrasound appointment is scheduled with two other appointments, plus a day-treatment. On average, 3.5 appointments are scheduled when an ultrasound appointment and a day-treatment are scheduled. We discussed that the goal is to schedule as many of patients' appointments as possible on one day, but with current information it is not possible to set a norm. It is not known how many appointments are desired to be scheduled for one day for a patient. All patients have unique treatment pathways with a unique number of appointments. When the total number of appointments for a patient is known, a suggestion would be to determine the percentage of appointments that are scheduled together on one day out of the total number of appointments that could be scheduled together on one day.

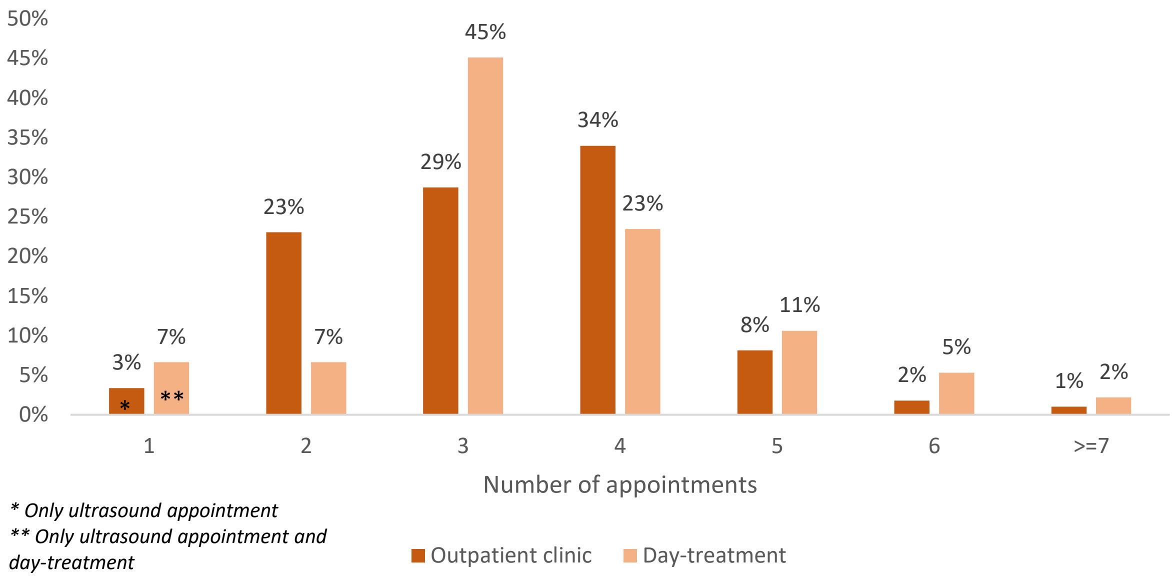

Figure 2-6: Number of appointments scheduled when an ultrasound appointment is planned for outpatient clinic and when ultrasound appointment is combined with day-treatment (n=2,240 for outpatient clinic, n=226 for combination with day-treatment; Data for November 2020 - October 2021, source: HiX).

2.2.2. Waiting time between multiple appointments

By combining multiple appointments on one day, patients might have to wait between their appointments. Here, waiting time is defined as the scheduled time (in minutes) between sequential appointments. Figure 2-7 shows the average waiting time between multiple appointments on one day, when an ultrasound appointment is scheduled for the outpatient clinic. The average scheduled waiting time between sequential appointments is 25 minutes. There are some side notes. Sometimes a minimum time is reserved between two appointments, since this is in the medical protocol. Since these reserved times are not documented for all appointment combinations, no distinction is made in waiting times and reserved waiting times. Second, there is no strict norm for the waiting time between appointments. We discussed that this should be around 15 to 30 minutes. Namely, a waiting time of zero minutes is also not desirable since this might result in overdue appointments when patients arrive too late. Patients require time to move between their multiple appointments. Next, a more ideal performance indicator would be the actual waiting time between appointments. However, this data is not available. Therefore, the scheduled waiting time between appointments is considered as waiting time in this research.

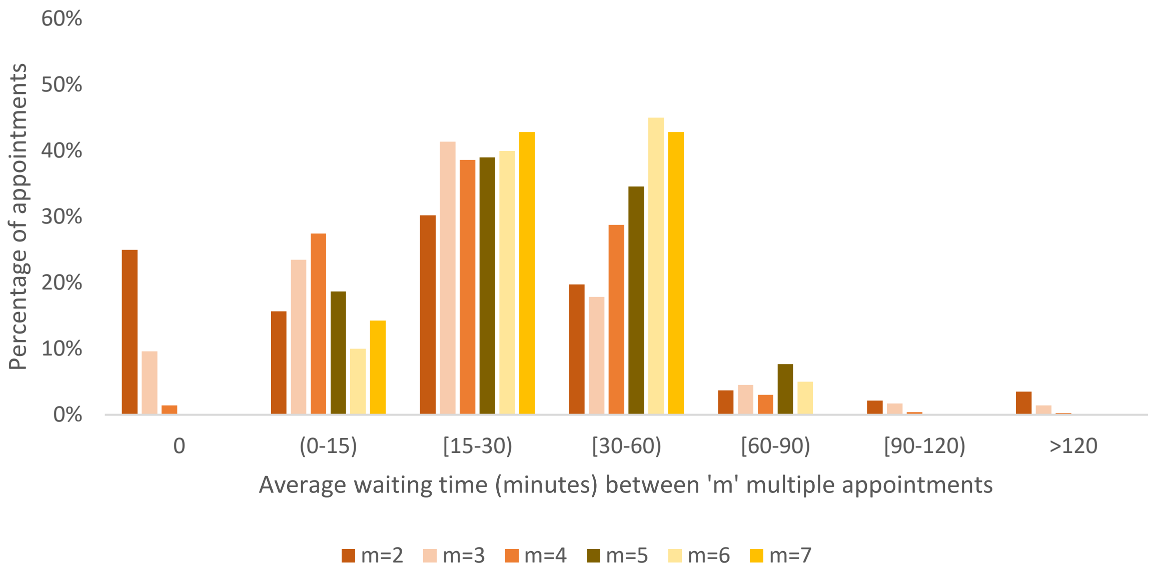

Figure 2-7: Average waiting time between multiple appointments when ultrasound appointment is scheduled on a day when number of appointments (m) > 1 (n=2,165; Data for November 2020- October 2021, source: HiX).

Figure 2-8 shows the average waiting time for ultrasound appointments combined with a day-treatment. The average waiting time is 53 minutes and therefore higher than for the outpatient clinic (25 minutes). We discussed that this average waiting time is higher than the norm.

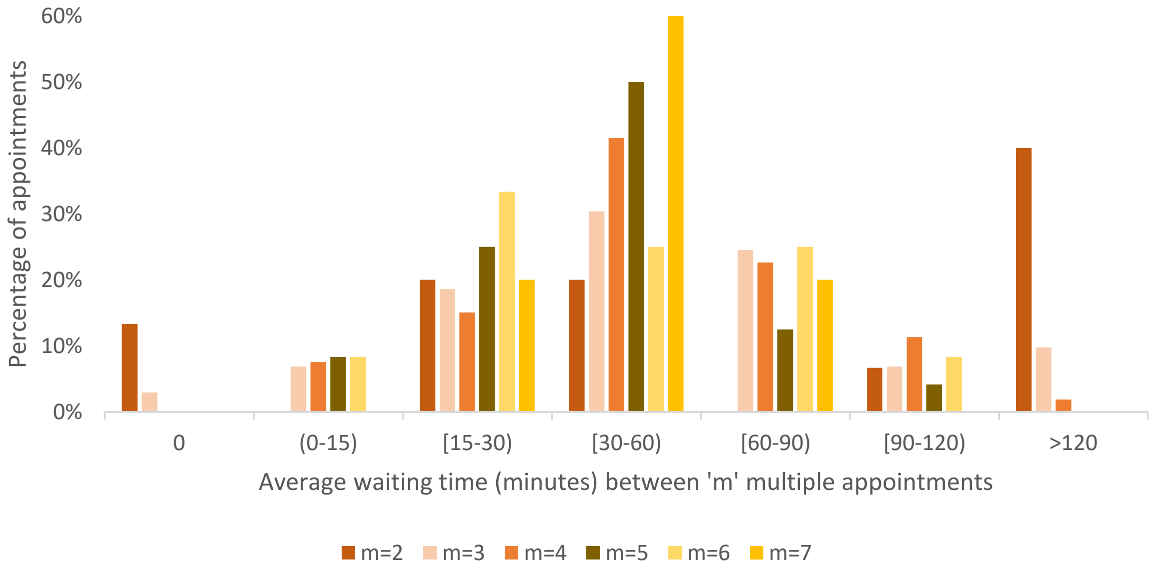

Figure 2-8: Average waiting time between multiple appointments when ultrasound appointment is combined with a day-treatment when number of appointments (m) > 1 (n=211; Data for November 2020- October 2021, source: HiX).

The maximum waiting time is also examined. Therefore, the highest waiting times (>120 minutes) between sequential appointments are investigated, when appointments are combined with an ultrasound appointment. For the outpatient clinic, most of the appointment combinations with a scheduled waiting time > 120 minutes between sequential appointments are the combination between an ultrasound appointment and an appointment with the treating physician (22%). Next, the combination between an ultrasound appointment and an appointment in a treating room (8%), and an X-ray appointment with an appointment with the treating physician (8%) lead to high waiting times. However, the X-ray appointment has a short duration (~10 minutes) and enough capacity, which is therefore not seen as a bottleneck. The long waiting times are probably caused by other appointments on the day, such as the ultrasound appointment. Furthermore, most of the appointment combinations with a waiting time >120 minutes are on Tuesday (27%) and least on Thursday (13%). This indicates that the waiting time between appointments differs per weekday.

For an ultrasound appointment combined with a day-treatment, the appointment combinations with the highest waiting times are between an ultrasound appointment and an appointment with the treating physician (24%), between an ultrasound appointment and an appointment in a treating room (8%) and the combination between an MRI-scan and an appointment with a treating physician (10%). Most of the appointment combinations with a waiting time >120 minutes are on Friday (24%) and least on Monday (11%), which again indicates a difference in waiting time per weekday.

2.2.3. Appointments scheduled within the reserved consultation hours of specialists

From a staff's perspective, the following KPI is defined: the percentage of appointments scheduled within the reserved consultation hours of specialists. Specialists want to plan as many appointments as possible in the reserved time slots during their consultation hour, especially because specialists have more activities next to seeing their patients. However, in practice, this is not always reachable since multiple appointments and therefore, multiple schedules, need to be combined.

Table 2-3 shows the number and average percentage of appointments scheduled within the consultation hours of specialists, when the appointment is combined with an ultrasound appointment. Specialists for LATER patients have most patients scheduled within their consultation hours (94%). Specialists of NO patients have the least scheduled patients within specialists' consultation hours (52%). The number of appointments scheduled within the consultation hours of specialists for HO, SO and SCT patients is 78%, 79% and 75%, respectively. The average percentage of appointments within consultation hours over all specialist types is 76%. We discussed that this percentage is low, since in an ideal situation, all appointments are scheduled within the defined consultation hours.

*Table 2-3: Number and average percentage of appointments scheduled within consultation hours of specialists when appointment is combined with ultrasound appointment. *Specialists are only included when at least five appointments were scheduled in one year and specialists without reserved appointment time slots are excluded. (n=2,057 appointments; Data for January 2021-December 2021, source: HiX.)*

Specialists type with n appointments scheduled	***Number of specialists included***	***Number and average percentage of appointments scheduled within consultation hours of specialists****
HO (n=750)	19	587 (78%)
SO (n=1,134)	19	898 (79%)
NO (n=91)	10	48 (52%)
SCT (n=12)	1	9 (75%)
LATER (n=70)	7	70 (94%)

Furthermore, we analysed the average utilisation of consultation hours of the included specialists. Namely, if the consultation hours are fully utilized, it is not possible to schedule more appointments within the reserved consultation hours. If there is idle time in the consultation hours, more appointments could be scheduled within the consultation hours, based on the utilisation of consultation hours. Equation 2.1 shows the formula to calculate the average utilisation of consultation hours per specialist type. Table 2-4 shows the outcomes of the average utilisation of consultation hours. The duration of a consultation hour and the duration of individual appointments differ per specialist and appointment type. Therefore, we cannot determine the exact number of appointments that could have been scheduled within the consultation hours. However, we determined the average duration of a consultation hour and appointment for each specialist type. Equation 2.2 shows the formula which calculates the average of empty slots per specialist type. Equation 2.2a and 2.2b substantiate Equation 2.2. Table 2-4 shows the calculated average empty slots per specialist type. Since all specialist types show that there are on average empty slots available for appointments, we assume that it is possible to schedule more appointments within the consultation hours with the current low utilisation rates of the consultation hours.

Equation 2.1

$$Average\ \%\ utilisation\ of\ consultation\ hours = \frac{100\%}{N} \sum_{n=1}^{N} \frac{\sum Duration\ of\ appointments\ within\ consultation\ hour}{Total\ duration\ of\ consultation\ hour}$$

Equation 2.2

$$Average\ empty\ slots = \frac{100\%}{N} \sum_{n=1}^{N} Total\ slots\ within\ consultation\ hour\ * \frac{Average\ \%\ idle\ time\ of\ consultation\ hour}{100}$$

Where N is the total number of unique consultation hours per specialist type.

Equation 2.2a

$$Total\ slots\ within\ consultation\ hour = \frac{Total\ duration\ of\ consultation\ hour}{Average\ appointment\ duration\ within\ consultation\ hour}$$

Equation 2.2b

$$Average\ \%\ idle\ time\ of\ consultation\ hour = 100 - Average\ \%\ utilisation\ of\ consultation\ hours$$

Table 2-4: Average utilisation of consultation hours per specialist type (n=6,340 unique consultation hours, Data for January 2021-December 2021, source: HiX.)

Specialists type	***Number of specialists included***	***Average % utilisation of consultation hours***	***Average duration of consultation hour (minutes)***	***Average duration of appointments (minutes)***	***Average empty slots***
HO (N=2,730)	19	29.2	127.0	22.7	3.5
SO (N=1,549)	19	17.8	173.2	21.9	7.7
NO (N=1,111)	10	24.6	128.1	32.1	3.5
SCT (N=52)	1	41.9	229.6	21.2	5.6
LATER (N=898)	7	38.7	175.0	31.7	3.6

2.2.4. Effort patient planners

Patient planners experience difficulties with scheduling ultrasound appointments combined with other appointments. The combination of an ultrasound appointment with an appointment with a patients' treating physician requires the most effort. Next, combining an ultrasound appointment with another scarce modality, mainly the MRI-scan, requires effort. Patient planners estimate that such appointment combinations require about five minutes, which is double from scheduling an appointment combination without obstacles.

2.2.5. Utilisation

The goal is not to maximize utilisation, but to efficiently spread utilisation over the weekdays, reflecting patients' demand. Figure 2-9 shows the average number of ultrasound appointments for Monday to Friday. Saturday and Sunday are excluded since ultrasound appointments on these days are rare. All patient types are included. Noticeable is that on Tuesday the capacity (14.0) is lower than on the other weekdays (18.0), while the average number of appointments is second highest on Tuesday (12.8), after Wednesday (13.4). Therefore, capacity is especially limited on Tuesday and this is also experienced by patient planners. As explained in Section 2.1, most ultrasound appointment requests are from SO patients. Paediatric oncologists of SO patients have most of their consultation hours on Tuesday, and the paediatric oncologists of HO patients on Wednesday. Since ultrasound appointments are often combined with an appointment with the paediatric oncologist, it is indeed expected that most ultrasound appointments take place on Tuesday and Wednesday. Appendix A shows the division of used ultrasound capacity per patients' diagnosis group.

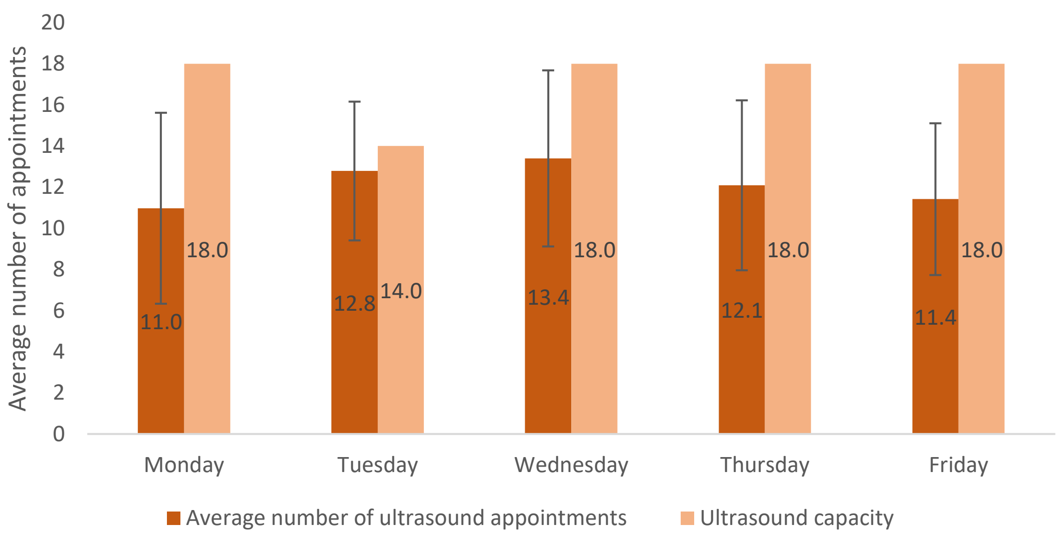

Figure 2-9: Average number of scheduled ultrasound appointments for each weekday, including standard deviation, next to ultrasound capacity (n=6,331, data for December 2019 – November 2021, source: HiX)

Equation 2.3 shows the formula to calculate the corresponding utilisation rates. Table 2-5 shows the utilisation per weekday. As expected, and corresponding to Figure 2-9, the highest average utilisation is on Tuesday and the least on Monday and Friday. Therefore, capacity is scarce on Tuesday, while other weekdays show there is flexibility in the capacity to schedule appointments. Appendix A shows the average utilisation per weekday per time slot of the ultrasound. The earliest time slot and last time slot on the day are on average least utilized, while the time slots in the middle of the day are most utilized. Lab technicians experience that the average treatment time to perform the ultrasound depends on the body part that is to be examined. An ultrasound of the abdomen takes more treatment time than an ultrasound of the neck for example.

$$Average\ ultrasound\ utlisation = \frac{100\%}{T} \sum_{t=1}^{T} \frac{\sum Number\ of\ ultrasound\ appointments}{Ultrasound\ capacity} \qquad \textit{Equation 2.3}$$

Where $T$is the total number of days in the included data set.

Table 2-5: Utilisation of ultrasound per weekday (T=522 days, with total n=6,331 ultrasounds, data for December 2019 – November 2021, source: HiX)

Weekday	***Average utilisation***
Monday (T=105)	61%
Tuesday (T=105)	91%
Wednesday (T=104)	74%
Thursday (T=104)	67%
Friday (T=104)	63%

2.2.6. Rescheduled appointments

Patient planners spend a lot of time on rescheduling patients, to make sure that most patients have multiple appointments sequentially on one day. Therefore, from a staff's perspective, the number of reschedules of appointments needs to be as low as possible, to have more time to actually plan patients. Moreover, for patients it is frustrating when their appointments are rescheduled. Also, for management it is more efficient if patients are not rescheduled. Data on rescheduling is currently not available.

No-show rates

The no-show rate of ultrasound appointments is low (<1%). Appointments are cancelled, but most of the time these appointments are rebooked for another patient such that the slot is still scheduled.

2.3. Conclusion

The average number of ultrasound appointments remained constant over time over the period January 2019-November 2021. However, the variation around the mean has increased during the years. All patient types make use of ultrasound appointments and most requests are from SO and HO patients that visit the outpatient clinic.

In the current blueprint schedule, neither a distinction is made in time slots for different patient types based on diagnosis, nor the stage of patients' disease, nor whether the patient visits the inpatient clinic, outpatient clinic or receives a day-treatment, nor the patient flows regarding multi-appointment scheduling.

Patients have a central role in decision-making within the Máxima, and are therefore important to consider in optimizing multi-appointment scheduling. From a patients' perspective, as many appointments as possible should be combined in one day and the waiting time between multiple appointments should be minimized. However, we concluded that these KPIs should be optimized in the future by gathering more information to set a norm for the number of combined appointments and to determine the actual waiting time instead of the scheduled waiting time. We concluded that the average scheduled waiting time between multiple-appointments is within the norm for the outpatient clinic, but above the norm for patients with a day-treatment combined. We examined that most ultrasound appointments are combined with an appointment with the patients' treating physician for both the outpatient clinic and for day-treatment. Moreover, the highest waiting times (>120 minutes) between appointments were found for this combination. Next, an ultrasound appointment in the outpatient clinic is commonly combined with a blood sample test or with an X-Ray. For patients with a day-treatment, the combination of an ultrasound appointment with an appointment in the treatment room or with an MRI-scan is common.

From a staff's perspective, patient planners experience difficulties with scheduling the combination of an ultrasound appointment with an appointment with the patients' treating physician or with another scarce modality. As a result, specialists see their patients often outside consultation hours.

From a management perspective, the utilisation of ultrasound is not balanced, since for example on Tuesday, capacity is lowest, while demand is second highest of all weekdays. This is especially caused by a high number of ultrasound requests from SO patients since many SO treating physicians have their consultation hours on Tuesday.

To conclude, especially scheduling the combination of an ultrasound appointment with an appointment with the treating physician requires improvement.

3. Literature review

Chapter 2 described current multi-appointment patient planning including perceived and observed obstacles. This chapter examines the literature and answers the research question: *'Which model types can be found in the literature to improve tactical multi-appointment scheduling?'*. Appendix B shows the approach for the literature review to find relevant papers to answer the research question. Section 3.1 explains three multi-appointment systems. Section 3.2 describes the decision levels in multi-appointment scheduling. Section 3.3 shows the possible solution approaches within tactical resource capacity planning. Section 3.4 discusses methods used in tactical multi-appointment scheduling. Section 3.5 investigates which aspects should be included when designing a blueprint schedule and Section 3.6 describes which methods are used to design a blueprint schedule. Section 3.7 summarizes this chapter and concludes which literature is used for which purpose.

3.1. Multi-appointment systems

This research focuses on multi-appointment scheduling where patients have multiple appointments on multiple resource types. The main challenge is to maximize the number of appointments on a day, with minimum waiting times between appointments. From a mathematical view, multi-appointment scheduling requires more constraints in comparison to single appointment scheduling. Precedence relations between appointments and the availability of resources from involved disciplines need to be considered (Leeftink et al., 2020). To include the constraints, multi-appointment scheduling is often modelled as a job shop scheduling problem (Pham & Klinkert, 2008). A job shop problem schedules jobs on a machine without overlapping on the machines. The goal is to minimize the makespan (time at which all jobs are completed) (Schutten, 1998). Resources used in a healthcare setting can be considered as such a machine. According to Leeftink et al., (2020), there are three multi-disciplinary systems known in the literature to include the precedence and resource constraints and consider the problem as a job shop problem: flow-shop, open-shop and mixed-shop. Flow-shop is also known as a one-stop-shop and carousal (Brucker, 1999). Figure 3-1 shows these three multi-disciplinary systems: the flow-shop, open-shop and mixed-shop.

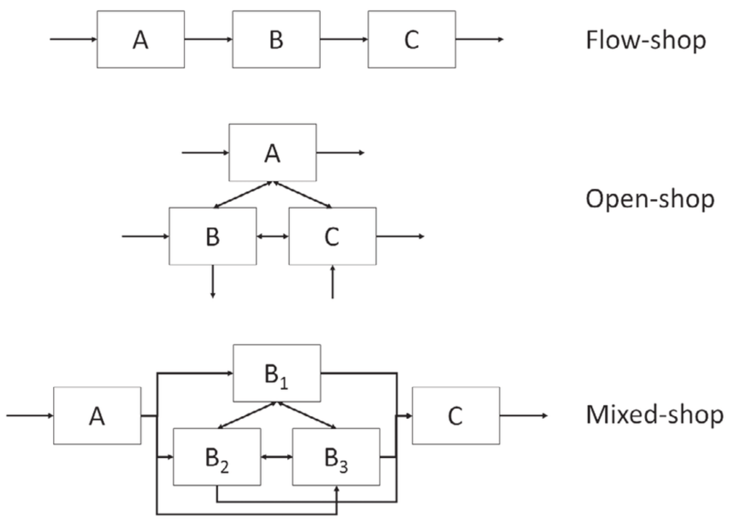

Figure 3-1: multi-disciplinary systems: Flow-shop, Open-shop and Mixed-shop (Leeftink et al., 2020)

A flow-shop is a system where patients have a predefined sequence of appointments at multiple facilities (Leeftink et al., 2020). An example is found for scheduling medical tourists who travel to destination medical centers, since patients have to undergo a fixed number of stages, before the patients finish their treatment (Rezaeiahari & Khasawneh, 2020).

In an open-shop, the sequence of appointments is not strict and results in flexibility in the order of appointments (Leeftink et al., 2020). An example is patient scheduling in the pathology laboratory, since there is no predefined sequence for tests at the laboratory for each patient (Azadeh et al., 2014).

A mixed-shop is a combination of a flow-shop and an open-shop. Some appointments have precedence constraints. However, there is some flexibility in the sequence of a mixed-shop system. Some appointments have precedence constraints, but there is some flexibility in a subset of all appointments. For example, the sequence of consultation-examinations-consultation is fixed, but the order of examinations might be variable (Leeftink et al., 2018). An example of a mixed-shop is described in the article of Morrice et al., (2020), where some resources need to be scheduled in a sequence, such as surgeons and physical therapists, while for example rooms need to be scheduled simultaneously. Moreover, the sequence in which patients see other healthcare providers is not important.

Furthermore, the bullwhip effect is common in multi-appointment scheduling. Multi-appointment scheduling often influences multiple disciplines. The interrelatedness of appointments might cause that delays in one appointment, result in enlarged delays in further downstream appointments. Since variability in appointment duration in an early stage of a patient might impact a later stage, it is important to consider this variability to avoid large bullwhip effects (Leeftink et al., 2020).

3.2. Decision level of multi-appointment scheduling

Figure 1-2 in Section 1.4 shows the hierarchical framework for healthcare planning and control of Hans et al. (2012). The framework subdivides decisions in healthcare into the following managerial areas: decisions based on medical planning, resource capacity planning, materials planning, and financial planning. This research focuses on resource capacity planning which is defined as: 'resource capacity planning and control addresses the dimensioning, planning, scheduling, monitoring and control of renewable resources'. The four hierarchical levels in the framework are strategic, tactical, offline operational and online operational. Strategic planning is defined as structural decision making, while offline and online operational planning focuses on short-term decision-making. To reach an optimum on the operational level, optimization needs to start at the strategic level (Marynissen & Demeulemeester, 2019). Tactical planning is in between strategic and operational planning. At the tactical level, decisions are made to facilitate the conversion of strategic to operational decision-making. A general note to be aware of is that there is an interrelation between the multiple managerial areas and within the described hierarchal levels (Hans et al., 2012).

3.3. Tactical resource capacity planning

Tactical resource capacity planning is used to reach fair access times and treatment duration for patients, to treat a strategically defined number of patients, and to maximize resource utilisation and balance workload (Hulshof et al., 2013). In tactical resource capacity planning, three strategies are often used to divide resource capacity to specialities, patient types or time slots:

- Designing a blueprint schedule. A blueprint schedule is a template of the appointment slots in an agenda. This template can be used to allocate capacity to specific patient types or process stages in operational planning. Within multi-appointment scheduling, the aim is to combine consultations on one day or to minimize waiting time on a day (Leeftink et al., 2020). Furthermore, objectives in research are to reduce access time or throughput time (Bikker et al., 2015; Dharmadhikari & Zhang, 2011; Liang et al., 2015).
- Patient admission planning. Patient admission planning describes the design of an admission policy (Leeftink et al., 2020). The aim is to offer equitable access and treatment duration for patient groups to serve the targeted number of patients and maximize resource utilisation and balance the workload (Hulshof et al., 2013).
- Temporary capacity changes. Temporary capacity changes are described as an increase or decrease in capacity allocation, adjusted to changes in patient demand (Leeftink et al., 2020). Temporary capacity changes are applied to balance access time and resource utilisation (Hulshof et al., 2013).

3.4. Methods for tactical multi-appointment scheduling

Different methods are used in the literature to optimize tactical multi-appointment scheduling (Leeftink et al., 2020). From a theoretical perspective, exact methods are preferred to find optimal solutions. Exact methods give the best possible solution. A disadvantage of an exact method is that uncertainty is not included. From a practical perspective, an evaluation study is beneficial. An evaluation study is relatively easy to understand compared to an exact method. Besides, an evaluation model supports the researcher to investigate several interventions and scenarios. (Zonderland et al., 2021).

An example of an exact method is the research of Apergi et al., (2020). They developed an integer programming for an outpatient cardiology department, where patients need to go through the necessary procedures within a defined time frame. Furthermore, capacity availability is included in the model. The aim was to minimize the number of times that the patients have to go to the hospital and the waiting time in the hospital. Since multi-appointment systems are complex through precedence constraints, heuristics are often used in research instead of exact methods. Heuristics find an approximate solution to an optimization problem. Furthermore, simulation is also a commonly used approximation technique to evaluate multi-appointment scheduling. With simulation, the performances of multiple scenarios are examined and compared (Leeftink et al., 2019). Discrete Event Simulation (DES) is commonly used to examine patient flow problems at outpatient clinics. This model needs detailed input information and is therefore time consuming. Another common method for modelling patient flow is queuing theory which requires less detailed information (Zonderland et al., 2021). Queuing theory models the arrival and departure processes of queues, to analyse the number of resources required to provide a certain service (Wolff, 1989). However, queuing models require other skills from the researcher, and is therefore less commonly used in practice. A disadvantage of a queuing model is the requirement of a trail-and-error approach to find the optimal solution (Zonderland et al., 2021). Depending on the research question and skills, a modelling tactic is selected. Queuing models are commonly used to evaluate access times. Van de Vrugt et al., (2017) used for example a discrete-time queuing model to evaluate the access time distribution of new patients for a breast cancer center with multi-disciplinary meetings. Furthermore, queuing theory is used for demand modelling. For example, Vanberkel et al., (2011) investigated the expected arrival rate to the hospital wards based on an operating room block, from a queuing theory perspective.

3.5. Key decisions in designing a blueprint schedule

Blueprint schedules provide specific times and dates for patient consultations. The aim of designing a blueprint schedule is often minimizing patient waiting time, maximizing resource utilisation and minimizing resource idle time. A trade-off is to balance patient waiting time and resource idle time. Therefore, the following key decisions need to be made before designing a blueprint schedule (Hulshof et al., 2012; Zonderland et al., 2021).

- Number of patients per consultation session. This number controls patient access and waiting times. A high number of patients per consultation session reduces access times but increases patient waiting time and provider overtime (Hulshof et al., 2012).
- Patient overbooking. Patient overbooking is beneficial if the no-show rate of appointments is high. Namely, booking more patients into a consultation session compensates for no-shows (Hulshof et al., 2012).
- Length of the appointment interval. The length of the appointment interval influences resource utilisation and patient waiting time. Reducing the length results in a decrease in resource idle time but increases patient waiting time. Moreover, a distinction can be made among patient groups, when the expected consultation time is different between patient groups. This might result in lower waiting time and resource idle time (Hulshof et al., 2012)
- Number of patients per appointment slot. Scheduling all patients in the first appointment slot minimizes resource idle time but increases patient waiting time. Distribution of patients over the consultation session balances resource idle time and patients waiting time (Hulshof et al., 2012).
- Sequence of appointments. Based on patient groups or expected variance of appointment duration, the sequence of appointments can be determined. This influences the waiting times and resource utilisation. When there is variation in consultation duration between patient groups, patient waiting time and resource idle time might be minimized by sequencing patients by increasing variance. (Hulshof et al., 2012)
- Queue discipline in the waiting room. The queue discipline in the waiting room influences patient waiting time since the higher the priority, the lower patients' waiting time. The first-come-first-serve (FCFS) principle is a common queue discipline. When emergency patients are involved, the highest priority is given to this patient group. When walk-in patients are included, these patients have the lowest priority. Another strategy is to give the highest priority to patients who need the most resources in one day (Hulshof et al., 2012).
- Anticipation for unscheduled patients. When a facility includes unexpected patient groups such as emergency patients and walk-in patients, an appointment scheduling approach which anticipates on these unexpected changes is required. A strategy is to reserve slack capacity, by for example leaving appointment slots open for these patient groups. Another strategy is to increase the length of the appointment interval. Reserving insufficient capacity for the unexpected patients results in overcrowded facilities, while reserving too much capacity leads to increased resource idle time (Hulshof et al., 2012).

3.6. Methods to design a blueprint schedule

Common methods used to design a blueprint schedule are mathematical programming or heuristics. This is often combined with robust optimisation or computer simulation to enhance robustness. Moreover, stochastic programming is used to include variability in patient arrivals, appointment durations, resource capacity and care pathways (Leeftink et al., 2020). This section discusses methods used in designing a blueprint schedule, specific for multi-appointment scheduling settings.

Liang et al., (2015) investigated operational performances in an oncology clinic by a DES. Thereafter, schedules for oncologist visits and chemotherapy treatment were generated by a mathematical programming model. Patients' waiting time and total working time for both the outpatient oncology and the infusion clinic were reduced. Furthermore, more balanced resource utilisation was achieved.

Radiotherapy is a common application area for examining multi-appointment scheduling. Radiotherapy is limited in capacity and a multidisciplinary group of specialists with multiple tasks and restricted availability is involved (Vieira et al., 2016). This is comparable to a centralized and specialized cancer center. Bikker et al., (2015) designed a blueprint doctors' scheme for the radiotherapy care process where multiple resources are involved by an integer linear programming (ILP) model. The outcomes are evaluated by a DES. The aim was to minimize expected access times of all patients and to match the number of slots with demand, while maintaining efficient resource utilisation.

Otten et al., (2021) designed a blueprint schedule for both a rheumatology clinic and a medical oncology & haematology clinic with multi-appointment patient trajectories. Restrictions on the number of patients simultaneously in the waiting room, and the effect of early arrival and bridging times are included. Bridging times are defined as the obligatory time between two sequential appointments to analyse blood samples, for example. An ILP schedule is created and used as a blueprint schedule, where early arrival times and appointment durations are deterministic. The quality of the ILP schedule is examined under randomness by using a Monte Carlo Simulation.

Kortbeek et al., (2017) presented an ILP which selects patients that are invited for a treatment day and schedules a combination of appointments on one day for a children's muscle center. Precedence constraints were included. Results from the ILP are used to determine the capacity of the center by a simulation. The objectives were to maximize the number of patients with a (complete) visit and to maximize the treatment time of scheduled patients. Moreover, idle time in the schedules of staff and patients was tried to be minimized.

3.6.1. Methods including variability

Wiesche et al., (2017) included flexible capacity to deal with variation in arrival rates. They determined optimal capacity allocation by a mixed integer linear model which is evaluated by a stochastic simulation. In general, to allocate capacity, the ratio between fixed and flexible capacity needs to be determined. Typically, 20-40% of capacity is used flexibly to cover fluctuations in patient demand (Zonderland et al., 2021).

Leeftink et al., (2019) optimized multi-disciplinary patient scheduling with a stochastic optimization model. Scheduling decisions include variability in time intervals and patient routing is stochastic. They designed a blueprint schedule including open access requirements for a multi-disciplinary cancer clinic. Hur et al., (2021) developed a stochastic optimization model to construct an appointment template for a special form of the outpatient clinic: an integrated practice unit. This is a patient-centred approach where a multidisciplinary team of providers in a single facility take care of the full cycle care of patients. They included variability in service time and handoff and documentation time between patients within their model.

To design a blueprint schedule with dedicated slots for specific patient types, the demand distribution of these patient types requires to be examined (Ahmadi-Javid et al., 2016). (Vanberkel et al., 2011) describes an analytical approach to predict the workload distribution for downstream departments of the operating room. The demand for elective inpatient care beds is examined as a function of the schedules of surgeries within the operating room. Discrete convolutions are used to determine the total number of patients in recovery on a certain day and include demand uncertainty. The model is an evaluation model where workload balance is examined. The model shows that changes in the schedules of surgeries resulted in a balanced workload of recovering patients.

3.7. Conclusion

Chapter 3 answers the research question *'Which model types can be found in the literature to improve tactical multi-appointment scheduling?'*. Tactical multi-appointment scheduling is commonly optimized by designing a blueprint schedule, patient admission planning or temporary capacity changes.

Multi-appointment scheduling requires more constraints compared to single-appointment scheduling, since restrictions on precedence relations and availability of multiple resources should be included. For multi-disciplinary systems, three systems exist: flow-shop, open-shop and mixed-shop. Within the Máxima, the aim is to schedule the ultrasound appointment before the appointment of the treating physician and therefore considered as a flow-shop. If another modality, next to the ultrasound, is scheduled for a patient on the same day, the sequence of the modalities is flexible and the system is analysed as a mixed-shop.

Mathematical programming is often used to design a blueprint schedule but requires a limited scope to be solvable and requires robust optimization or simulation to incorporate uncertainty. Moreover, the analytical approach of Vanberkel et al., (2011) incorporates uncertainty of demand and serves as an evaluation model. As explained, several interventions and scenarios can be investigated with an evaluation model.

As mentioned in Chapter 1, the root causes of the current non-optimal multi-appointment scheduling are the 1) mismatch between the availability of modalities and specialists and 2) the lack of guidelines for appointment scheduling for different patient types. As a first step in optimizing multi-appointment scheduling, we optimize the current blueprint schedule of the ultrasound. The blueprint schedule in this research works as a guideline for patient planners since capacity is reserved for different patient types. We distinguish different patient types which we explain further in Chapter 4.

Recap from Chapter 2, especially the combination of an ultrasound appointment with an appointment with the treating physician requires optimization. We predict the expected arrival rate of different patient types for the ultrasound as in the article of Vanberkel et al., (2011), where the arrival rate to hospital wards was computed based on operating room blocks. As most ultrasound appointments are combined with an appointment with the treating physician, and this combination appointment requires most improvement, we forecast the ultrasound demand based on the schedules of treating physicians. With this demand forecast, we can determine the required capacity for the patient types.

4. Model design

This chapter answers the research question: *'What is the design of the selected model to optimize multi-appointment scheduling specific for the Máxima?'*. Section 4.1 describes the selected forecasting model. Section 4.2 gives the model assumptions and Section 4.3 indicates suggestions to improve current schedules.

4.1. Forecasting model

The goal of this research is to optimize tactical multi-appointment patient scheduling by designing a method to create a blueprint schedule with time slots for different patient types. Since this research focuses on ultrasound, the first step is to determine the demand for ultrasound requests. In the current blueprint schedule of the ultrasound, appointment slots are not dedicated to patient type requests, except for emergency requests. Another classification within the Máxima is that patients are divided into the following three classes:

- Patients from the outpatient clinic
- Patients that have their appointments combined with a day-treatment
- Patients from the inpatient clinic

For multi-appointment scheduling, a focus is on the first two classifications, since for these patients the aim is to combine as many appointments as possible, with minimum waiting times between appointments. As concluded in Chapter 1 and 2, these patients have their ultrasound appointment often combined with an appointment with their treating physician (91%). We analysed that this combination appointment is the bottleneck in current multi-appointment scheduling and therefore tried to optimize in this study.

To model the demand for ultrasound requests for patients from the outpatient clinic or patients that have a day-treatment, we create a forecasting model based on the research of Vanberkel et al., (2011). This model is an analytical approach to determine the workload for downstream departments, based on the master surgery schedule, from queuing theory perspective. In the case study used in the model, the master surgery schedule states which patients have their surgery on which day. When this schedule is known, the aggregate number of patients in each ward is computed. Furthermore, probability distributions for daily admission and discharges can be computed.

In this research, the appointment with the treating physician and ultrasound are connected since the treating physician requests the combination with an ultrasound appointment. Therefore, the number of patients seen by the treating physician causes the arrival rate of ultrasound requests. The schedule of the treating physician is cyclic, which means that the schedule is repeated every week. By knowing these schedules, arrivals for the ultrasound can be forecasted. The forecasting model consists of three steps. Figure 4-1 shows these steps.

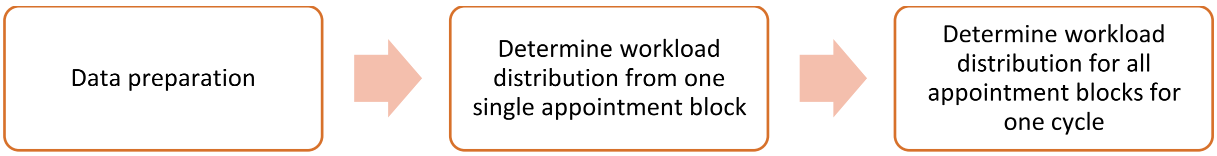

Figure 4-1: Steps in the forecasting model

4.1.1. Data preparation

The first step of the forecasting model is to prepare the data. Appointments with patients' treating physician and ultrasound appointments from patients from the outpatient clinic and patients with a day-treatment are included. Appointments with the treating physician are specified to:

- Treating physician s ($s \in \{1,2,..,S\}$), where S is the number of treating physicians, which is 86 in this forecasting model.
- Weekday t ($t \in \{1,2,..,T\}$), where T is the number of days in one cycle, which is 5 in this forecasting model (1=Monday, 2=Tuesday, 3=Wednesday, 4=Thursday, 5=Friday).
- Time block i ($i \in \{1,2,\dots,I\}$), where I is the number of time blocks, which is 6 in this forecasting model (1=<A, 2=A, 3=B, 4=C, 5=D, 6=D>).

Table 4-1 shows the classification of the above-mentioned time blocks. These time blocks are selected since most consultation hours of treating physicians are in line with these hours. Furthermore, as resulted from Chapter 2, treating physicians often see their patients outside consultation hours. Therefore, a broader range than just consultation hours of treating physicians is included to derive valid workload distributions.

Table 4-1: Classification of time blocks for consultation hours of treating physicians

Block	Daypart	Time window
<A	<Morning	[00:00 - 09:00)
A	Morning	[09:00 - 10:30)
B	Morning	[10:30 - 12.30)
C	Afternoon	[12:30 - 14.20)
D	Afternoon	[14:20 - 16:00)
D>	>Afternoon	[16:00 - 00:00)

Empirical discrete distributions of patients visiting treating physician

To determine the probability of *k* patients ($c_{sti}(k)$) seen for each treating physician *s*, weekday *t*, and time block *i,* we first derive empirical discrete distributions of the number of patients seen. Therefore, we determined how many times *k* patients were seen by treating physician *s*, on weekday *t*, and time Block *i* ($k \in \{0,1,\dots,K\}$) in one-year data (November 2020 – October 2021), where *K* is the maximum number of patients that can visit the treating physician within the specific block. Public holidays and leave of absence days of treating physicians are excluded since these days are known in advance and this model states: when the treating physician is present, what is the chance *k* patients are seen. This data is not available for all treating physicians. If this data is not known, an average of leave of absence of the treating physicians for which this data is known, is assumed per weekday. Appendix C shows these averages. In queuing systems, the arrival process of patients is often modelled as a Poisson process (Law & Kelton, 2007). To test whether this distribution fits the arrival data of patients who visit the treating physician in this model, a chi-square test is performed for each empirical discrete distribution. Chapter 5 elaborates on this. The arrival of patients in each block is independent since patients do not interfere.

Derive probability of ultrasound appointment

To determine the workload distribution of ultrasound appointments, patients are modelled as patients who have an appointment with their treating physician combined with an ultrasound appointment or without an ultrasound appointment.

The probability that a patient has an appointment with their treating physician combined with an ultrasound appointment, is dependent on the treating physician, weekday and time block. Therefore, the probability that a patient who visits the treating physician *s*, on weekday *t*, and time block *i*, also has an ultrasound appointment on day *t* is calculated by Equation 4.1.

Equation 4.1

$$d_{sti} = \sum_{week1}^{52} \frac{\substack{Number\ of appointments\ combined\ with\ an\ ultrasound\ appointment\ on\ day\ t \\ for\ treating\ physician\ s, day\ t, and\ block\ i}}{Number\ of\ patients\ seen\ by\ treating\ physician\ s, day\ t, and\ block\ i} \quad \forall sti$$

4.1.2. Determine workload distribution from one single appointment block

The first step of the convolution model is to compute the distribution of ultrasound appointments for a single Block. So, for one treating physician, one weekday and one time block. Equation 4.2 shows the formula to calculate the distributions. Table 4-2 explains Equation 4.2.

$$h_{sti}(x) = \sum_{k=x}^{C} \binom{k}{x} {d_{sti}}^{k} c_{sti}(k)(1 - d_{sti})^{k-x} \qquad \forall sti \qquad \textit{Equation 4.2}$$

For example: $h_{111}(2) = 0.15$ means that the probability that two ultrasounds require to be combined with the appointment block of specialist 1, on Monday, in the first-time block, is 15 percent.

Table 4-2: Explanation of Equation 4.2

Notation	***Explanation***
$h_{sti}(x)$	The probability of x ultrasound requests from patients for treating physician *s,* day *t,* block *i*
C	Maximum number of patients in a specific block
$\binom{k}{x}$	All combinations x from k
${d_{sti}}^{k}$	*k* patients who visit the treating physician *s*, on weekday *t*, and block *i*, also have an ultrasound appointment on day *t*
$c_{sti}(k)$	The probability of *k* patients visiting treating physician *s*, on weekday *t*, and block *i*
$(1 - d_{sti})^{k-x}$	*k-x* patients who visit the treating physician *s*, on weekday *t*, and block *i*, do not have an ultrasound appointment on day *t*

4.1.3. Aggregate workload distribution for all appointment blocks for one week

The second step of the forecasting model is to derive the workload distribution resulting from all single appointment blocks in one week. The computed distributions of ultrasounds appointments for one single block from the first step are used as input for this second step. Namely, all single blocks might have patients who need an appointment combination with an ultrasound. Patients are independent of each other and therefore the aggregate number of patients for which an ultrasound appointment is requested can be calculated by discrete convolutions. Equation 4.3 shows the equation for discrete convolutions.

$$C(x) = \sum_{k=0}^{\tau} A(k)(x-k) = A * B \qquad \textit{Equation 4.3}$$

Where A and B are independent discrete convolutions, τ is the largest x which can result from $A * B$, and * indicates a convolution.

For this convolution model, $H_t(x)$ is the probability of x ultrasounds on day *t* for all treating physicians and time blocks. Equation 4.4 shows the formula to calculate this probability by using discrete convolutions.

Equation 4.4

$$H_t(x) = h_t^{treating\ physician\ 1, block\ 1} * h_t^{treating\ physician\ 1, block\ 2} * h_t^{treating\ physician\ 1, block\ 3} * \dots \quad \forall t$$

Next to calculating the workload distributions for each weekday t, the workload distributions are calculated for each daypart per weekday. Ideally, ultrasound appointments should be scheduled about 15 minutes before the appointment with the treating physician. In this sequence, the outcomes of the ultrasound appointment and other appointments can be discussed with the treating physician. If a patient has another appointment combined, which is often a blood sample test, this sequence is still valid. Since there should be a reserved time between the blood sample test and the appointment with the treating physician, the ultrasound appointment needs to be scheduled in between to obtain the lowest waiting time between appointments for the patient. By forecasting the distribution of ultrasounds that require to be combined with the appointment block of the specialist for a daypart, it can be derived whether the ultrasound should take place in the morning or afternoon. The dayparts morning and afternoon are defined as:

- Morning ($i \in \{1,2,3\}$)
- Afternoon ($i \in \{4,5,6\}$)

For example: the workload distribution of ultrasound requests on Monday morning are calculated by Equation 4.5.

Equation 4.5

$$H_{i=1+i=2+i=3, t=1}(x) = h_{1,1}^{treating\ physician\ 1} * h_{1,1}^{treating\ physician\ 2} * h_{1,1}^{treating\ physician\ 3} * \dots$$

Next, the forecasted mean and corresponding utilisation rates are calculated per weekday. Equation 4.6 shows the formula to calculate the mean of the forecasted distribution. Equation 4.7 indicates the formula to calculate the ultrasound utilisation.

$$\mu = \sum_{x=0}^{X} H_t(x) * x \qquad \textit{Equation 4.6}$$

$$ultrasound\ utlisation = \frac{\mu}{Ultrasound\ capacity} \qquad \textit{Equation 4.7}$$

Furthermore, the cumulative probability ($\boldsymbol{H}_t(x)$) is calculated, which is the probability that indicates that the value is within a given range. For example: if management decides that 60% of the weeks there are enough ultrasound slots reserved, they strive to cover the 60th percentile of demand. With the cumulative probability, the minimum x is calculated for which the 60th percentile of ultrasound demand is covered. So: $\boldsymbol{H}_t(x) \geq 0.6$.

4.2. Model Assumptions

- Total demand for ultrasound is determined, not specified for one of the two ultrasound machines available in the Máxima.
- Seasonality is not included. For example, during holiday periods demand for ultrasound requests is lower.
- Consultation hours of treating physicians are generalized to appointment blocks, which might deviate for some physicians.
- If demand is more than the available slots in the ultrasound blueprint, lab technicians and radiologists work overtime or help the patient in between other ultrasound appointments. Otherwise, patients will make use of ultrasound in WKZ.

4.3. Changes to current schedules

With the solution model, we forecast the required number of ultrasounds for patients who have their appointment combined with an appointment with their treating physician. Section 4.4.1. describes the experiment where time slots in the blueprint schedule are assigned to these patients and other types of patients. Section 4.4.2. describes the examination of changes in the schedules of the treating physicians. Since ultrasound appointments are the downstream of the schedules of the physicians, this might influence the required number of ultrasounds. Chapter 5 shows the results of both experiments.

4.3.1. Dedicate patient types to blueprint schedule ultrasound

The goal of this research is to optimize the current blueprint schedule by assigning slots to different patient types. We examined two scenarios. The first one is a division in time slots for inpatients and patients with a combination appointment with their treating physician. The second one is the division of the ultrasound appointments based on their planning term. Both scenarios are explained in more detail in the following paragraphs.

Inpatients and patients with combination appointment

With the model, we forecasted the ultrasound appointments for patients who have an appointment with their treating physician combined with an ultrasound appointment. With these outcomes, we can assign the number of required appointment slots to these patient types in the blueprint schedule of the ultrasound. However, the forecast is only performed for patients from the outpatient clinic and patients who have a day-treatment combined. We also analyse the required number of ultrasounds for the inpatient clinic. It is important to analyse the difference in requests from patients from the inpatient clinic with patients with combined appointments, since the inpatient clinic requests are more flexible. Inpatients can use the slots with the least utilisation. Appendix D shows that these patients are rarely combined with an appointment with the treating physician and it is not a requirement to combine the appointments for this patient type. We fit a Poisson distribution on the requested ultrasounds for patients from the inpatient clinic. Next, the cumulative distribution is obtained to determine the minimum number of ultrasound slots to fulfil demand.

Planning terms for patients with combination appointment

Ultrasound requests are requested by the treating physician with different planning terms. Planning term is defined as the difference between the date of appointment and the date the requester request the appointment. As explained, patients are in the diagnosis, treatment or follow-up phase. If a patient is in the diagnosis phase, the patient requires an ultrasound appointment in a short term, while a patient in the follow up stage needs it mostly later. Recap from Chapter 2, planning rules for the patient planning department, depend on the planning term. When the planning term increases, the patient planner is allowed to deviate more days from the requested date. This is explained in the following two examples. Appointments with the following planning terms need to be scheduled within the corresponding margins:

- One week		Requested date +/- one day
- Two months		Requested date +/- two weeks

So, flexibility in appointment dates increases when the planning term increases. In the forecasting model, the required number of ultrasound slots to fulfil demand depends on the selected demand percentile. With the cumulative probability, the minimum required number of ultrasound is calculated that covers the selected demand percentile. The percentile indicates a ratio between fulfilling demand versus vacancy slots. If a percentile is set high, more demand is covered, but the risk of vacant slots is higher. To determine a threshold value for the percentiles, we decided to make a distinction in planning terms. The current blueprint schedule only makes a distinction between regular and emergency requests. In the forecast of ultrasound appointments, this distinction is still included. Furthermore, we separated the regular requests into short- and long-term requests. So, the following definitions are determined: emergency, short- and long-term requests. Table 4-3 shows the corresponding planning terms. We decided to set the distinction between short- and long-term requests at 28 days (4 weeks), since these four weeks allow the patient planners to schedule the appointments with a margin of +- 4 days, which allows to spread the appointment over weekdays.

Table 4-3: Defined planning terms for ultrasound requests

Definition ultrasound requests	***Planning term***
Emergency	[0,2) days
Short	[2,28) days
Long	[28, …)

The planning terms are incorporated in the model by specifying the probability that a patient has an ultrasound combined with their appointment with the treating physician to a planning term p ($p \in \{1,2,..,P\}$), where P is the number of planning terms, which is 3 in this forecasting model (1=emergency, 2=short-term, 3=long-term). So, for every single appointment block of the treating physicians, there is a probability that the physician request for a combination with an ultrasound appointment with a planning term p. Equation 4.8 shows these adjustments to equation 4.1. Chapter 5 shows the result of this model extension where we specify the probability that a patient has an ultrasound combined with their appointment with the treating physician to a planning term p.

Equation 4.8

$$d_{sti}^{p} = \sum_{week1}^{52} \frac{\substack{Number\ of appointments\ combined\ with\ an\ ultrasound\ appointment\ with\ plan\ term\ p, on\ day\ t \\ for\ treating\ physician\ s, day\ t, and\ block\ i}}{Number\ of\ patients\ seen\ by\ treating\ physician\ s, day\ t, and\ block\ i} \quad \forall stip$$

4.3.2. Changes in the schedule of treating physicians

A change in the schedules of the treating physicians will lead to a change in the demand for ultrasound requests, since ultrasound appointment requests are a downstream of an appointment with a treating physician. Therefore, we examined the effect of these changes on the required number of ultrasound slots per weekday. Chapter 5 shows the results of this experiment.

5. Numerical model outcomes

Chapter 5 answers the research question *'What are the effects of the solution approaches?'*. Section 5.1 describes the model input distributions. Section 5.2 shows the output from the forecasting model. Section 5.3 indicates the verification and forecast accuracy steps. Section 5.4 assesses the outcomes of the changes to current schedules. Section 5.5 shows the sensitivity analysis and Section 5.6 concludes this chapter.

Model preparation and the first step of the forecasting model are performed in Excel and Visual Basic for Application. The convolutions are implemented in RStudio.

5.1. Input distributions

As mentioned in Chapter 4, the number of patients who visit a specific treating physician, weekday, and time block, is modelled as a Poisson process. This means that we fit a Poisson distribution to the empirical discrete distribution for each unique combination of specialist, weekday, and time block. Figure 5-1 shows the fitted Poisson distribution and the historical data for one specific specialist, weekday, and time block combination. To test whether this Poisson distribution is the right distribution, a Chi-square test is performed with $\alpha = 0.05$ and degrees of freedom is 12. The outcome of the Chi-square test ($p=0.93$) indicates that it is not significantly proven that the Poisson distribution differs from the historical data. This holds for each unique combination of specialist, weekday, and time block. Therefore, we can model the arrival of patients as a Poisson process.

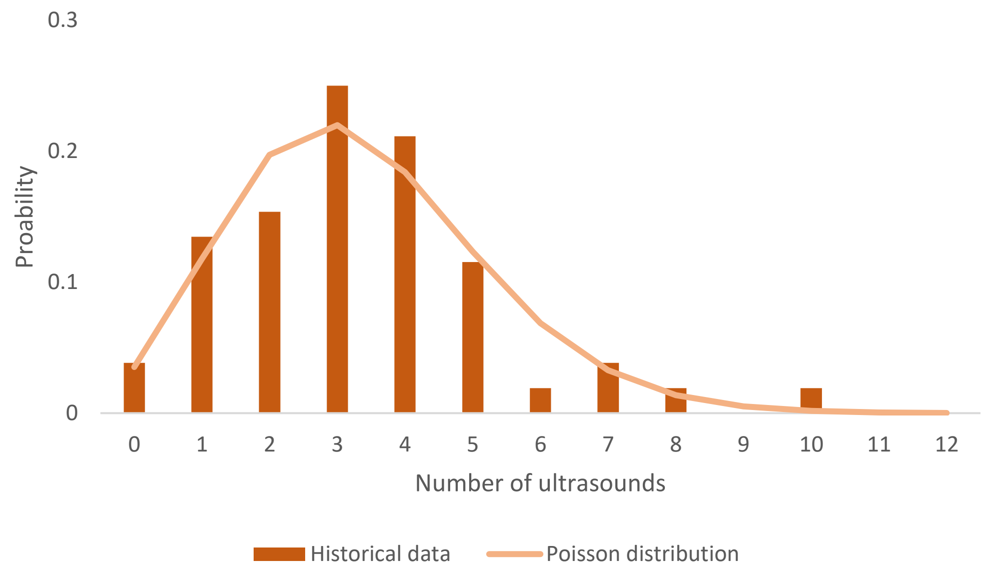

Figure 5-1: Poisson distribution for the number of patients seen by a specific specialist, weekday, and time block (n=52 weeks, data for November 2020–October 2021, source: HiX)

5.2. Output from the forecasting model

The workload distribution of ultrasound requests is first calculated for each weekday for patients from the outpatient clinic or patients with a day-treatment followed from an appointment with their treating physician. Furthermore, the ultrasound demand is derived for both the morning and afternoon of each weekday. The outcomes are visualised by showing the forecasted mean. Furthermore, we visualise the 50th percentile to indicate the required number of ultrasound slots on a weekday to cover

50th percentile of demand. Figure 5-2 shows the forecasted mean per weekday. Noticeable is that on Tuesday most demand is forecasted, while capacity is lowest on this weekday. This result is in line with the expectation since this result was also concluded from Chapter 2. Figure 5-3 shows the forecasted mean of ultrasound demand as a result from appointments with treating physicians in the morning and afternoon for each weekday. The figure shows that the disbalance in demand over weekdays is especially in the morning, where demand is highest on Tuesday and lowest on Monday. The demand in the afternoon seems equally divided over the weekdays. However, the reduction in capacity on Tuesday, is in the afternoon because of the tumour board and therefore demand on Tuesday afternoon is desired to be lower compared to other weekdays. Therefore, the aim of the experiments should be to lower demand on Tuesday, to balance demand over weekdays. Appendix E shows the mean number of ultrasounds versus the mean number of patients seen by the specialists for each weekday.

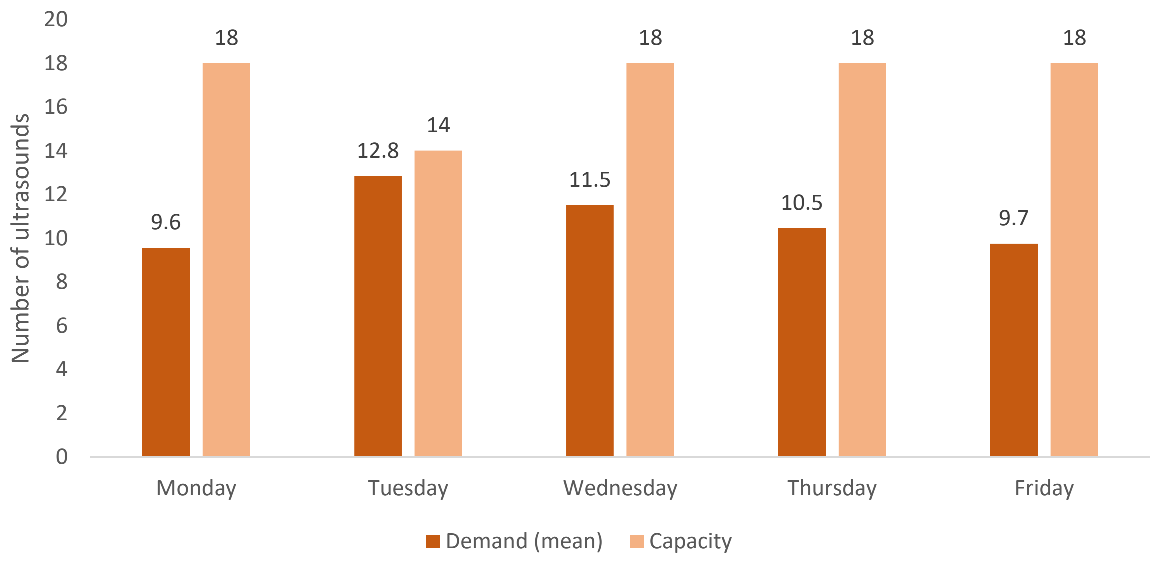

Figure 5-2: Forecasted mean of ultrasound demand per weekday for outpatients and patients with a day-treatment with an appointment with the treating physician

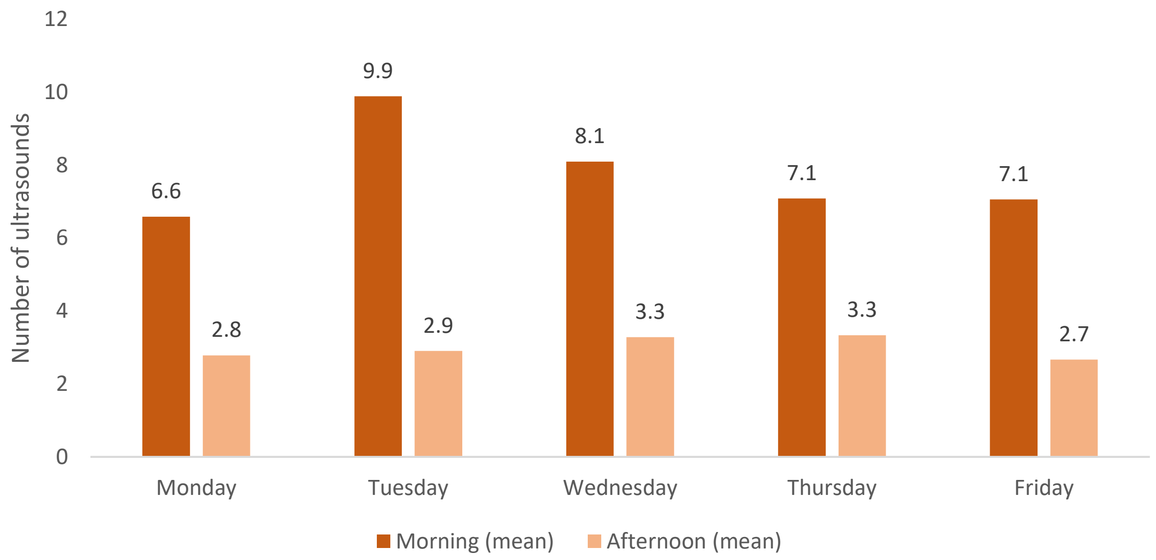

Figure 5-3: Forecasted mean of ultrasound demand of ultrasounds requests combined with a morning or afternoon appointment with treating physician for outpatients and patients including day-treatment

Figure 5-4 shows the 50th percentile of demand for each weekday. So, the numbers show the required number of ultrasound slots for which at least 50% of the weeks there are enough ultrasound slots reserved to fulfil demand. As expected, the required number of ultrasounds shows the same workload distribution over weekdays as the forecasted mean.

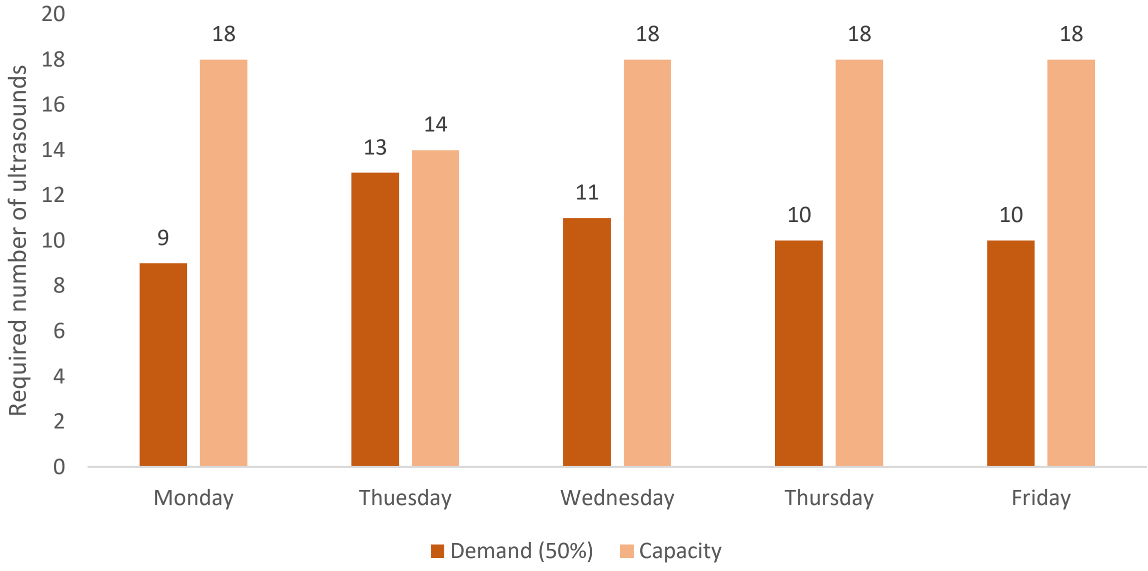

Figure 5-4: 50th percentile of ultrasound requests per weekday for outpatients and patients with a day-treatment with an appointment with the treating physician

5.3. Verification and forecast accuracy

5.3.1. Verification

Verification is the extent to which the model performs according to initial modelling assumptions (Law & Kelton, 2007). First, the coding is divided into subparts to check the model on mathematics and coding. After a subpart of the code works correctly, which is controlled by debugging the code, it is combined with the previous subparts. Second, the sum of the probabilities should be equal to 1 for each combination of treating physician, weekday, and time block in step 1 of the forecasting model. Equation 5.1 shows this statement. Besides, the convolution probabilities in step 2 of the forecasting model should be equal to 1. Equation 5.2 shows the formula to verify whether this statement holds.

$$\sum_{x=0}^{C} h_{sti}(x) = 1 \ \forall sti \qquad \textit{Equation 5.1}$$

$$\sum_{x=0}^{C} H_t(x) = 1 \ \forall t \qquad \textit{Equation 5.2}$$

Where C is the maximum number of ultrasounds.

5.3.2. Forecast accuracy

Forecast accuracy shows the accuracy of the forecasted demand by comparing the forecasted demand with the actual demand. Therefore, forecast accuracy is required to confirm whether the model output reflects the real data. The forecast accuracy is determined in two steps.

1) The outcomes of the forecasting model are discussed together with the stakeholders
2) The outcomes of the forecasting model are compared with the actual values, retrieved from data

The first step is performed and the model is considered valid. For the second step, data is separated into a training and test data set. The training data is the historical data (November 2020 to October 2021) used to fit the forecasting model. The test data (November 2021 to April 2022) is used to evaluate the performance of the forecasting model. It is important to analyse multiple forecast error measurements, as each measurement has disadvantages. Here, three forecast error measurements are analysed to determine the forecast accuracy. First, the bias of the forecasting model is calculated to analyse whether the forecast predicts on average too high or too low. Equation 5.3 shows the formula to calculate the bias. Furthermore, to measure how close the forecast outcomes are to the actual realisations, the mean absolute error (MAE) and the mean absolute percentage error (MAPE) are calculated, as in the article of (Kortbeek et al., 2015). The target values for MAE and MAPE are 0 and 0% respectively. Equation 5.4 and 5.5 show the formulas of these measurements. Where a_n is the actual value and y_n the predicted value of the number of ultrasounds, which is the forecasted mean. Appendix F shows the formula and values of the mean predicted value. N is the number of weeks in the test data set. We calculated these measures for each weekday, since we forecasted each weekday separately.

$$Bias = \frac{1}{N} \sum_{n=1}^{N} a_n - y_n \qquad \textit{Equation 5.3}$$

$$MAE = \frac{1}{N} \sum_{n=1}^{N} |a_n - y_n| \qquad \textit{Equation 5.4}$$

$$MAPE = \frac{100\%}{N} \sum_{n=1}^{N} \frac{|a_n - y_n|}{a_n} \qquad \textit{Equation 5.5}$$

Table 5-1 shows the outcomes of the measurements. A positive bias means that the forecasting model overestimates the number of ultrasounds, while a negative bias shows an underestimation of the number of ultrasounds. On Monday, the bias is close to zero. This means that on average, over and under estimation is equally balanced over the weeks of the test data. On Tuesday, Thursday, and Friday, the forecast overestimates the number of ultrasounds, while on Wednesday the forecast underestimates the number of ultrasounds. The MAE is constant over weekdays, but higher on Friday. For example, on Monday, the average absolute error is 2.5. According to Lewis (1982), a MAPE value between 20-50 can be interpreted as reasonable forecasting, which holds for Monday to Thursday. A MAPE >50 is seen as inaccurate forecasting, which is valid for Friday. However, the formula of MAPE shows that each error is individually divided by its demand. So, when the actual demand on a certain weekday is low and the error is high, this will have a high impact on the MAPE value. If the actual demand on Friday is for example 5, the individual MAPE value is already 96% ($MAPE = \frac{100\%}{1} * \frac{|5-9.8|}{5}$). Since we examined low demand periods in the test data, we consider the MAPE values reasonable.

Table 5-1: Forecast error measures and outcome values (n=126 weekdays, data for November 2021 – April 2022, source: HiX)

Weekday	***Forecast error measurements***			
	Forecasted mean	*Bias*	*MAE*	*MAPE*
Monday (N=25)	9.6	-0.05	2.5	40%
Tuesday (N=26)	12.8	1.9	2.5	37%
Wednesday (N=25)	11.5	-0.4	2.8	41%
Thursday (N=26)	10.5	0.9	2.5	33%
Friday (N=24)	9.8	0.7	3.5	52%

Next, we compared the predicted ultrasound percentiles from the model (α) with the percentiles related to the test data set to test the accuracy of the forecasting model. Equation 5.6 shows the formula to calculate the actual percentile.

$$Actual\ (\alpha) = \frac{1}{N} \sum_{n=1}^{N} Actual\ demand\ \leq D\ (\alpha) \qquad \textit{Equation 5.6}$$

Where $D\ (\alpha)$ is the required ultrasound demand corresponding to α.

Table 5-2 shows the comparison between the actual percentiles from the test data and the model prediction percentiles. The results show that the actual percentiles fluctuate around the determined model percentiles. On Tuesday, the actual percentiles are higher for all α, which corresponds to the bias values of Tuesday, which show that the forecasting model overestimates on Tuesday.

Table 5-2 Model percentiles compared with actual percentiles (n=126 weekdays, data for November 2021 – April 2022, source: HiX)

Weekday		***Percentiles***		
	α	*0.50*	*0.65*	*0.80*
Monday (N=25)	Actual *α*	0.40	0.72	0.84
Tuesday (N=26)	Actual *α*	0.85	0.92	1.00
Wednesday (N=25)	Actual *α*	0.36	0.64	0.80
Thursday (N=26)	Actual *α*	0.65	0.81	0.88
Friday (N=24)	Actual *α*	0.63	0.71	0.79

To conclude, based on the values from the three forecasting error measures and the actual percentiles compared to the model percentiles, we consider the forecasting model valid.

5.4. Results from changes to current schedules

5.4.1. Dedicate patient types to blueprint schedule ultrasound

Inpatients and patients with combination appointment

The forecasting model is specific for patients from the outpatient clinic or patients who receive a day-treatment, that have an ultrasound appointment combined with an appointment with a specialist. To indicate the total number of ultrasound requests on a day, a distribution is fit on the inpatient clinic patients. For each weekday, we fit a Poisson distribution on the number of ultrasound requests from the inpatient clinic. To test whether this Poisson distribution is the right distribution, a Chi-square test is performed with $\alpha = 0.05$ and degrees of freedom is 12. For Monday, the outcome of the Chi-square test ($p=0.39$) indicates that it is not significantly proven that the Poisson distribution differs from the historical data. Appendix D shows the outcomes of the Chi-square tests for the other weekdays.
Figure 5-5 shows the 50th percentile of demand for inpatients and patients with the combination appointment. On Monday and Thursday, demand is fulfilled for 50% of the weeks, when three slots are reserved for inpatients. For the other weekdays, two slots are enough. Furthermore, the figure shows that on Tuesday there is not enough capacity to have sufficient slots for both patient types. Figure 5-6 shows the average utilisation per weekday resulting from the forecasted mean of ultrasound requests from appointments combined with an appointment with the treating physician and the mean number of appointment requests per weekday for inpatients. The utilisation exceeds 100% on

Tuesday, which means that the demand for ultrasound requests exceeds capacity. From both Figure 5-5 and Figure 5-6 we conclude again that Tuesday requires the most attention in optimization.

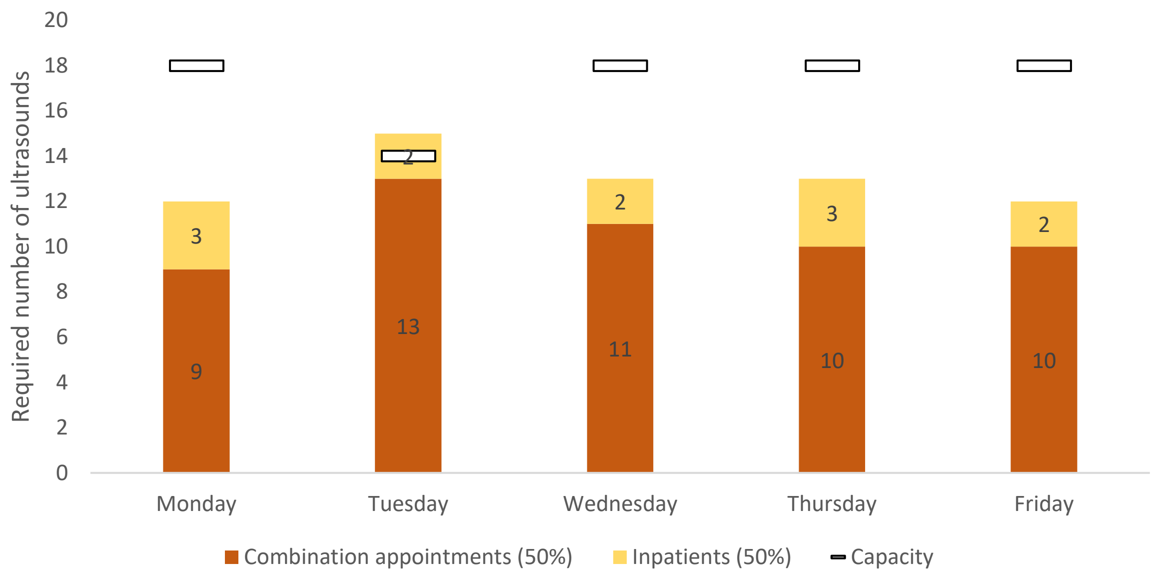

Figure 5-5: 50th percentile for inpatients and patients from outpatient clinic and day-treatments with combination appointments

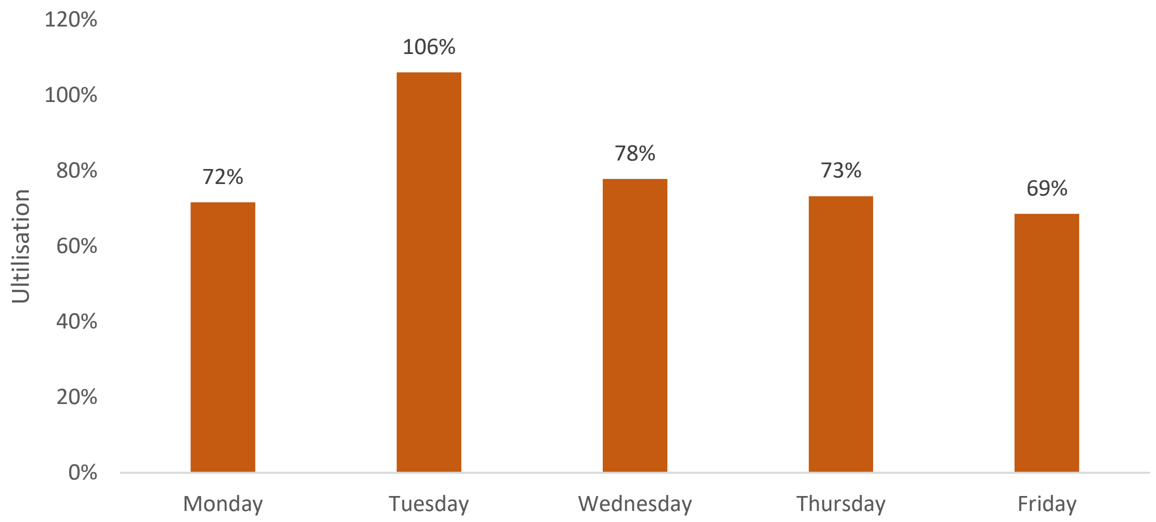

Figure 5-6: Utilisation of ultrasound per weekday for both the ultrasound requests from appointments combined with an appointment with the treating physicians and inpatients

Planning terms for patients with combination appointment

Figure 5-7 shows the percentage of ultrasound requests for each planning term for patients that have a combination appointment from the outpatient clinic and patients with day-treatment. Most requests (65.3%) are requested in the long term, so ≥ 28 days, followed by short-term requests (24.4%) and emergency requests (10.3%). Since the long-term requests have the most flexibility in scheduling the ultrasound appointment, this result shows that there is room for flexibility to change the current blueprint schedule.

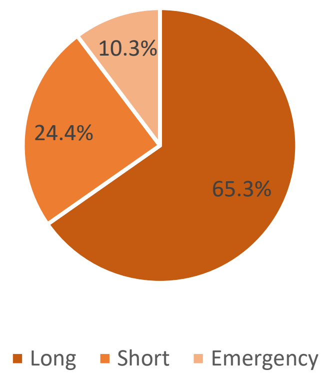

*Figure 5-7: Distribution of ultrasound requests per planning term for patients with combination appointments from outpatient clinic and patients with day-treatment (*n=3,176, data for November 2020 – October 2021, source: HiX)

The required number of ultrasound slots per planning term to cover 50% of demand, is calculated for each weekday. Figure 5-8 shows that emergency requests are equally spread over weekdays, except for Monday. This is explainable since emergency requests are classified as requests that are requested on the same day or the day before and on Sunday, fewer appointments are requested in general, compared to other weekdays. Zero does not mean there are no emergency requests, but the probability of zero requests is higher than the selected 50th percentile (namely: 0.52). The required short-term requests are either two or three for the weekdays. Most fluctuation over the weekdays is for the long-term requests. Especially on Tuesday, there is a peak in demand for the long-term requests, while other weekdays are more balanced. Appendix G shows the distribution over the weekdays per daypart per planning term.

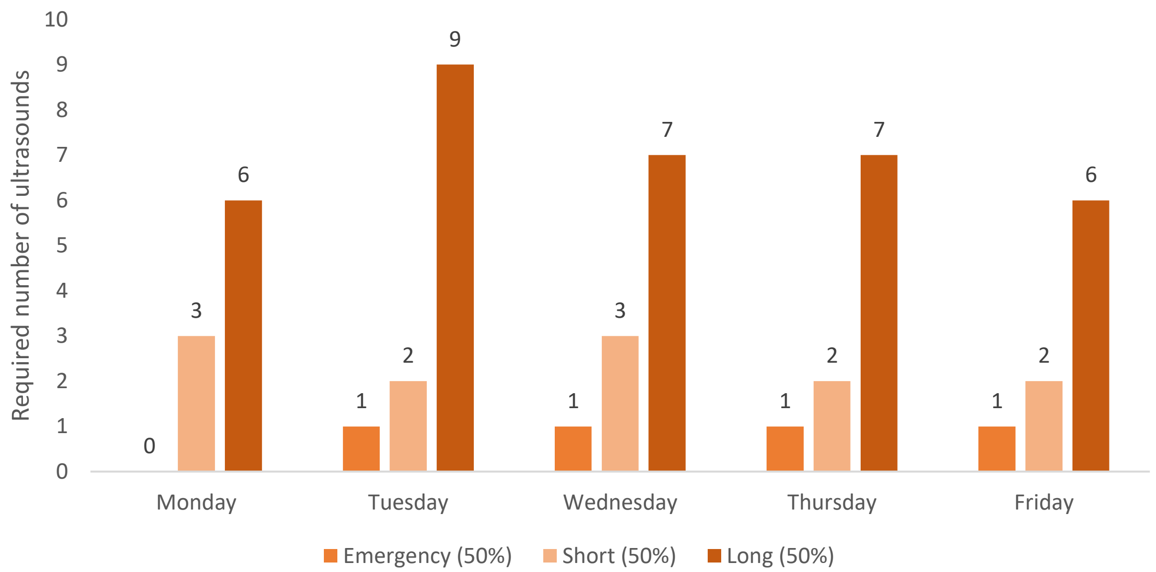

Figure 5-8: 50th percentile of demand per planning term for patients from outpatient clinic and patients who receive day-treatment per weekday

Next to showing the 50th percentile of demand for all planning terms, we specified the percentile of demand to each planning term since the different planning terms have different flexibility to schedule the appointment. Namely, an increase in the duration of the planning term increases flexibility. The patient planner is allowed to deviate more days from the requested date. Table 5-3 shows the demand percentiles we strive for, which are discussed with the management. The higher the selected demand percentile, the more demand is covered. The demand percentile of emergency requests is set highest (0.85) because security is needed to fulfil demand. With this percentile we strive that in 85% of weeks demand is not higher than the determined demand percentile. The demand percentile for long-term requests is set lowest (0.50), so the ratio between the risk of vacancy and covering all demand is equally balanced. The appointments are allowed to be scheduled on another weekday or week. To support patient planners to spread the long-term requests over weekdays, this percentile is set lower compared to the other planning terms. In Chapter 6, we elaborate on the practical aspect and implementation of this principle. For the short-term requests, fulfilling demand is also more important than the risk of vacancy, but less than for emergency requests and is therefore set to 0.70.

Table 5-3: Demand percentile per planning term

Planning term	***Demand percentile***
Emergency	0.85
Short	0.70
Long	0.50

Figure 5-9 shows the corresponding required number of ultrasounds to fulfil the determined percentiles of demand. These values are only for requests where the ultrasound appointment is combined with an appointment with the treating physician for patients from the outpatient clinic and patients with day-treatment. For all weekdays, capacity is equal to or higher than the required number of slots to fulfil demand. However, flexibility varies over weekdays. This means that the difference between the ultrasound capacity and the required number of ultrasounds is not constant over weekdays. Namely, on Tuesday capacity is exactly enough, but lacks flexibility, since there is no room for appointment requests for other patient types. Other patient types are inpatients and patients from the outpatient clinic or who have a day-treatment combined without an appointment combination with the treating physician. Flexibility is highest on Monday and Friday. To validate the required number of ultrasounds, the actual percentiles are calculated by Equation 5.6. Appendix H shows that the required number of ultrasounds predicted with the model percentiles are at least the actual percentiles from the test data set, except for the long-term requests on Wednesday and the emergency requests on Friday.

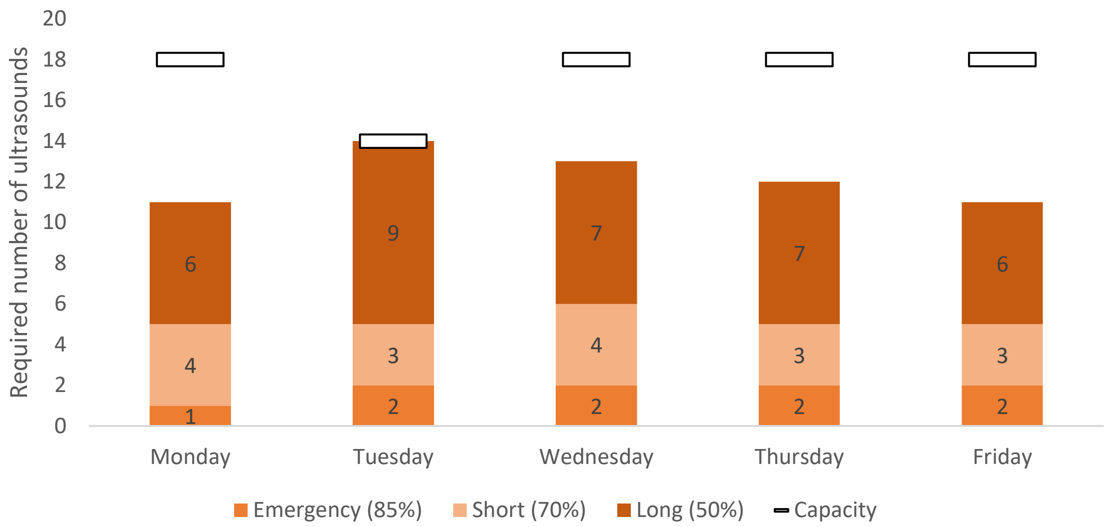

Figure 5-9: 85th, 70th, and 50th percentile of demand for emergency, short- and long-term requests respectively, for patients from outpatient clinic and patients who receive day-treatment per weekday

5.4.2. Changes in the schedule of treating physicians

For the outpatient clinic and patients that receive a day-treatment, most improvement potential is on the long-term requests since these requests are most flexible and are allowed to be spread over the weekdays. Since especially Tuesday is the bottleneck of the weekdays, a solution could be to move patients that receive a combination appointment on Tuesday, to another weekday. For example, on Monday and Friday, the least long-term ultrasounds are requested. Therefore, we try the following intervention. The consultation hour of a treating physician who requests many ultrasounds on Tuesday, is moved from Tuesday block A and B to Monday block A and B. Therefore, patients are seen on Monday instead of Tuesday. Since ultrasound is a downstream department, it is expected that the distribution of ultrasound requests moves as well. Figure 5-10 shows the result of the experiment. Indeed, the required number of long-term ultrasound slots is reduced on Tuesdays (by two) and increased on Mondays (by two), compared to the situation before the intervention.

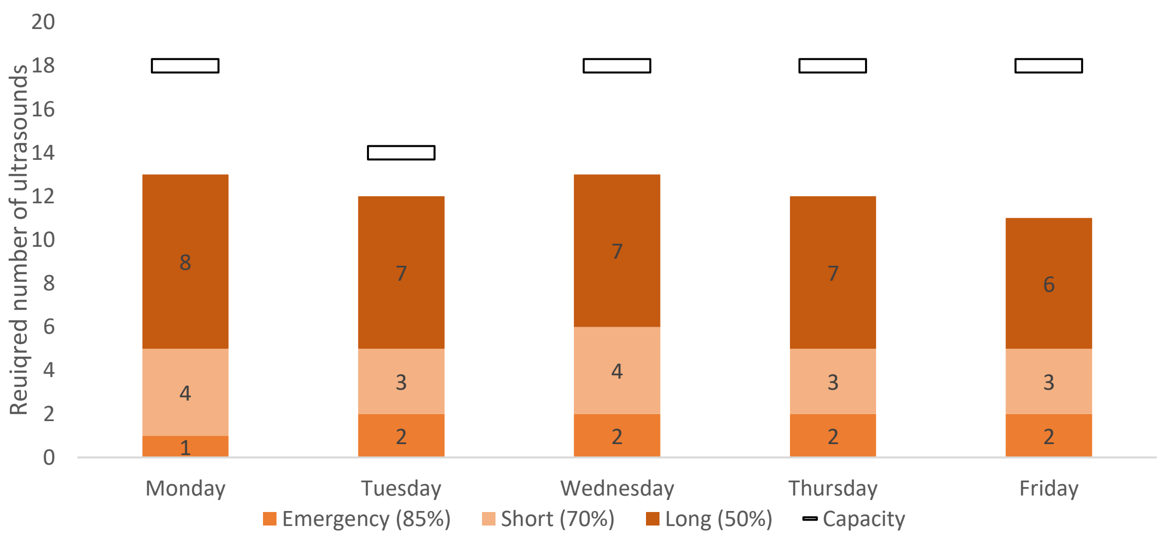

Figure 5-10: 85th, 70th, and 50th percentile of demand for emergency, short- and long-term requests respectively, after the change in schedule of one treating physician.

Flexibility, which is determined as the difference between the ultrasound capacity and the required number of ultrasounds, is still not optimally spread over the weekdays. On Tuesday there are only two slots left for other patients with the determined percentiles, while on Friday there are seven slots considered flexible. Therefore, the following second intervention is performed. The appointment blocks of a treating physician who has their consultation hour on Tuesday, but sometimes sees patients on Friday, are exchanged. More specifically, the consultation hour of Tuesday block B is moved to Friday block B, while the type of patients who were seen normally on Friday block B, is moved to Tuesday block B. Figure 5-11 shows the required number of ultrasounds after the second intervention. As expected, the required number of ultrasounds on Tuesday decreased by one for the long-term requests and one for the short-term requests, while the long-term requests increased by one for the long-term requests on Friday, compared to the first intervention.

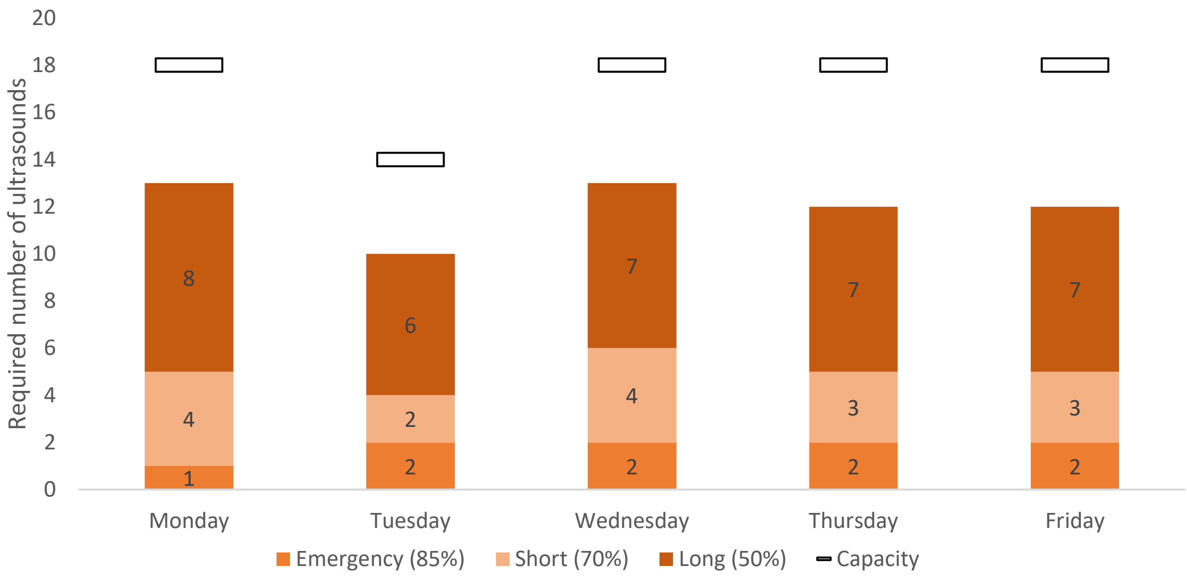

Figure 5-11: 85th, 70th, and 50th percentile of demand for emergency, short- and long-term requests respectively, after changes in schedules of two treating physicians..

Table 5-4 shows that the number of flexible slots increased on Tuesday by a change in the schedules of the treating physicians compared to the current situation (baseline measurement). Furthermore, the number of flexible slots is more evenly spread over weekdays, compared to the baseline measurement. These flexible slots are for example available for ultrasound requests from inpatients or for requests when the reserved ultrasound slots are already occupied.

Table 5-4: Flexible ultrasound slots after changes in the schedules of treating physicians, compared to the baseline measurement (current situation)

	Flexible ultrasound slots	
Weekday	*Baseline measurement*	*After changes in schedule*
Monday	7	5
Tuesday	0	4
Wednesday	5	5
Thursday	6	6
Friday	7	6

5.4.3. Combination of experiments

The results from the experiments are combined to show the difference between the forecast of the baseline measurement with the forecast of the situation after the experiments. Therefore, we show both the forecast of the required number of combined ultrasound appointments for patients from the outpatient clinic and patients with day-treatment, and the required number for inpatients, which is determined by the Poisson distribution. Figure 5-12 shows the combined results for the baseline measurement. Figure 5-13 shows the combined results for the situation after the experiments. In the baseline measurement, the required number of ultrasounds is higher than capacity on Tuesday. In the situation after changing the schedules of treating physicians, the desired demand percentiles of ultrasound requests are lower than capacity, for all weekdays. The required number of ultrasounds is not changed on Wednesday and Thursday after the experiments. On Monday, the number of required ultrasounds increased, which is caused by the change of the consultation hour of a treating physician who requests many long-term ultrasounds from Tuesday to Monday. The required number of ultrasounds for the short-term requests is three or four, except for Tuesday, which expects two ultrasounds. However, since capacity is lowest on Tuesday, it is desired to have fewer requests compared to other weekdays. The same holds for the long-term requests.

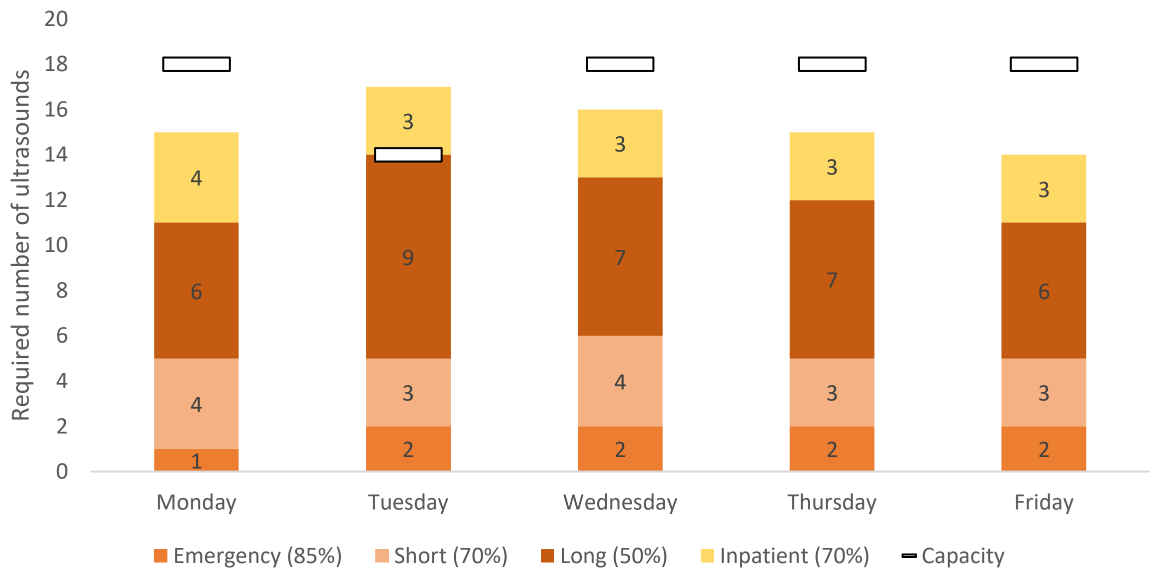

Figure 5-12: Required number of ultrasounds in baseline measurement to cover 85th, 70th, 50th, and 70th percentile of demand for emergency, short- and long-term requests and inpatients respectively.

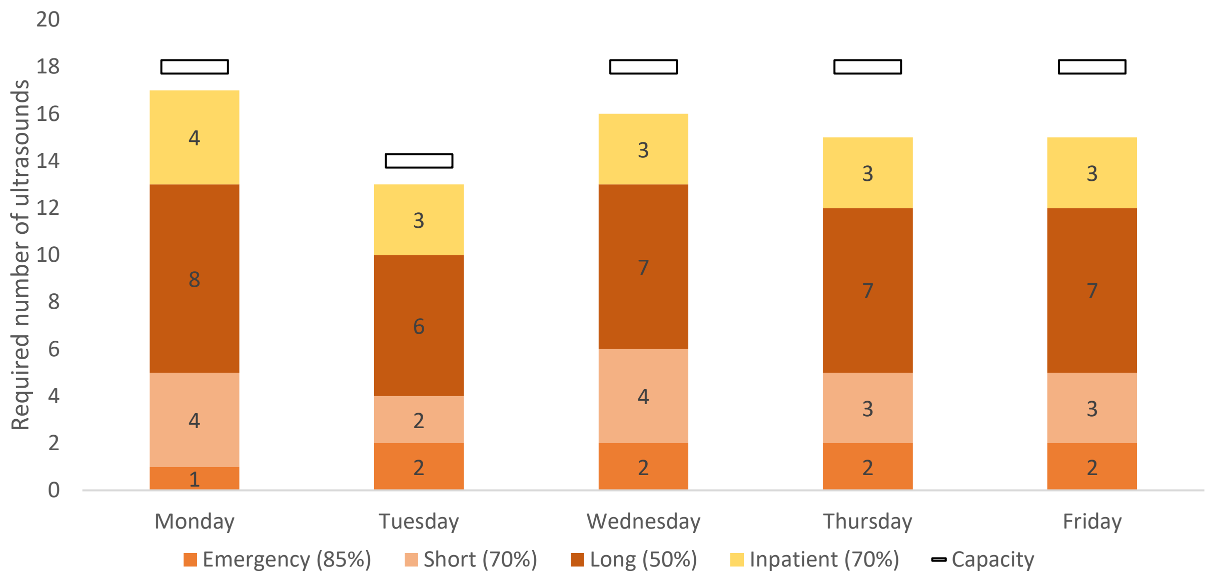

Figure 5-13: Required number of ultrasounds after experiments to cover 85th, 70th, 50th , 70th percentile of demand for emergency, short- and long-term requests and inpatients respectively.

Next, the corresponding utilisation rates are calculated with the forecasted mean. Figure 5-14 shows the utilisation of the ultrasound per weekday at the baseline measurement and after the changes in the schedules of treating physicians. As described, the required number of ultrasounds exceeds capacity on Tuesday, which results in an utilisation rate above 100%. After the changes in the schedules of the treating physicians, the utilisation rates are below 100% for all weekdays and more balanced over weekdays. As expected, the ultrasound utilisation increased on Monday and Friday after the interventions, since we moved the appointment blocks of two treating physicians from Tuesday to Monday and Friday.

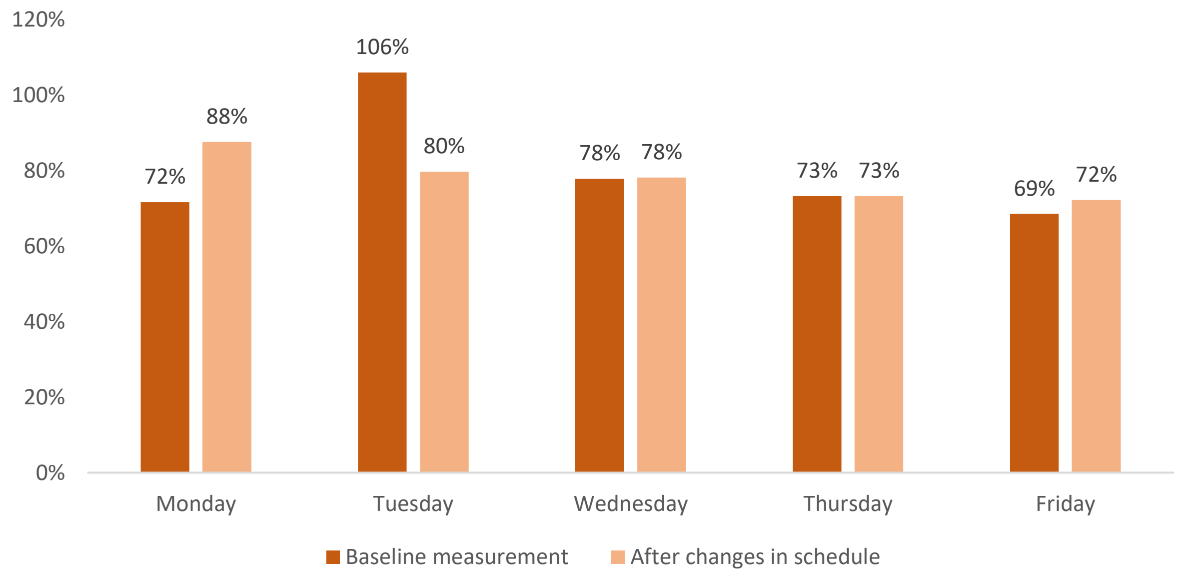

Figure 5-14: Utilisation of ultrasound per weekday for the baseline measurement and after changes in the schedules of treating physicians for both the ultrasound requests from appointments combined with an appointment with the treating physicians and inpatients

5.5. Sensitivity analysis

Sensitivity analysis is used to determine which input factors have the most impact on the measures of the model (Law & Kelton, 2007). The input factors of the forecasting model are the number of patients seen by the treating physician and the probability that the patient has an ultrasound appointment combined with the appointment with the treating physician. To examine the impact of a change in these input values, we performed a sensitivity analysis where we changed the input values of the last intervention, where we adjusted the schedules of two treating physicians.

The first experiment in the sensitivity analysis is to examine an increase in the number of patients seen by the treating physician. The number of patients that arrive at the Máxima is quite constant over the years, but we rather expect an increase than a decrease in the number of patients due to for example an extension of the Máxima. Therefore, we examine the effect on the required number of ultrasounds by an increase in the total number of patients seen by the treating physician by 10%. This is implemented in the model by proportionally dividing the increase in patients over the unique combinations of treating physician, day and time block. Figure 5-15 shows the required number of ultrasounds after the increase of 10% in the number of patients that visit the treating physicians. As expected, the increase in the number of patients results in a higher number of required ultrasound requests for all weekdays, compared to the situation after the two interventions.

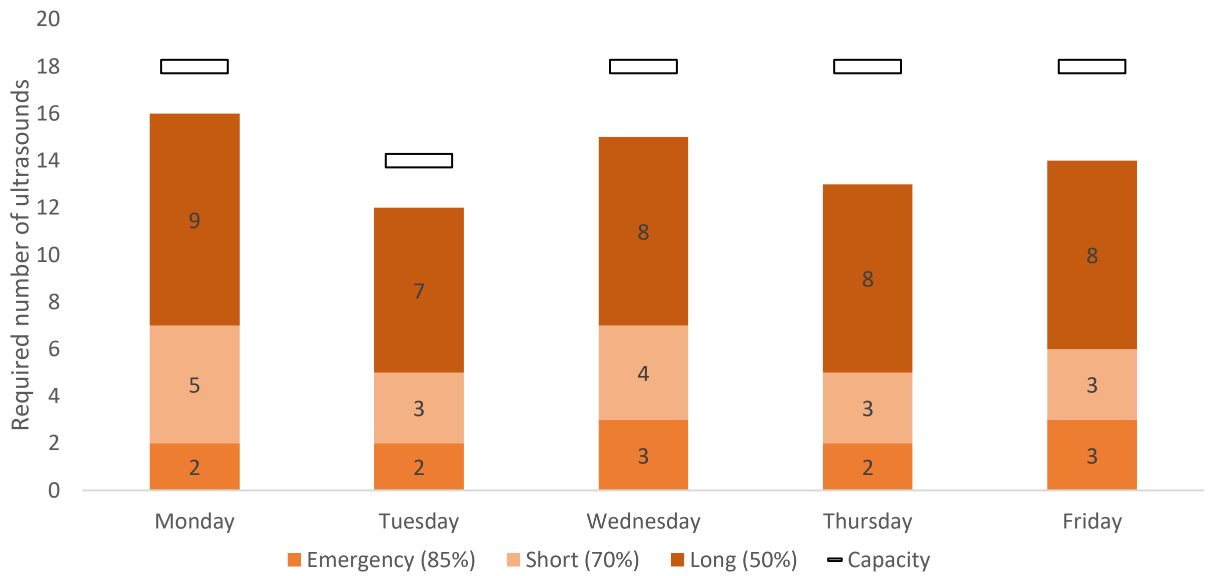

Figure 5-15: Sensitivity analysis on the required number of ultrasounds after a 10% increase of patients that visit the treating physicians, to cover 85th, 70th, and 50th percentile of demand for emergency, short- and long-term requests respectively.

Furthermore, we examined the situation where the chance increases that a patient who visits the treating physician also has an ultrasound appointment combined. This might happen when the protocols of treatment plans change for example. Suppose, new protocols in the future suggest that patients require more ultrasounds during their follow-up. This increases the number of long-term requests. We implemented this in the forecasting model by increasing the probability that a patient has an ultrasound appointment combined that is requested in the long-term by 5%. This only holds for the unique appointment blocks where there was already a probability of having a long-term ultrasound request in the baseline measurement. We did not change the number of patients that visit the treating physicians as this input variable is kept the same as the baseline measurement. Figure 5-16 shows the required number of ultrasounds per weekday after the increase of the probability of a long-term ultrasound request by 5%. As expected, the total number of ultrasounds consequently increased. Moreover, most long-term requests are requested on Monday, after the interventions where the schedules were changed. Therefore, an increase in the probability of long-term requests has the most influence on Monday. Indeed, Monday shows the highest increase in the number of ultrasounds after the change in protocol. A change in protocol can also result in a decrease of the probability that a patient requires an ultrasound appointment. This will probably lead to a reduction in the required number of ultrasound requests and results in more flexibility.

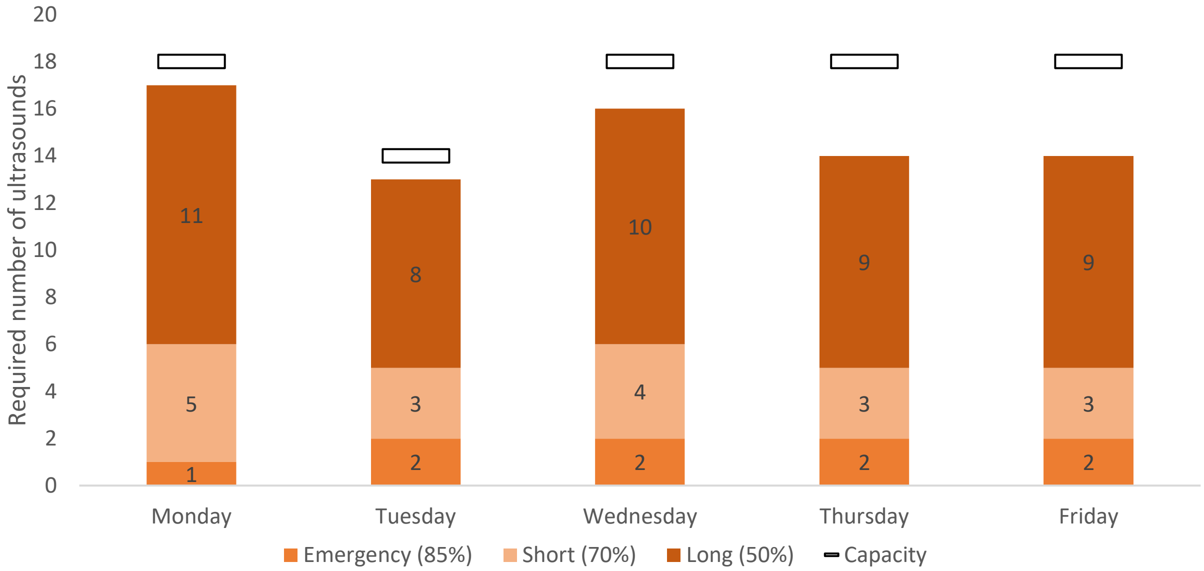

Figure 5-16: Sensitivity analysis on the required number of ultrasounds after a 5% increase in probability that a patient requires an long-term ultrasound request, to cover 85th, 70th, and 50th percentile of demand for emergency, short- and long-term requests respectively

Table 5-5 shows the flexibility of ultrasound slots after both sensitivity experiments compared to the flexibility after the two interventions, where the schedules of the treating physicians were changed. Especially on Monday and Tuesday, the increase in the number of patients and the increase in the probability of long-term ultrasound requests, results in less flexibility in capacity. As a result, there would be not enough slots available anymore for inpatients or patients that do not require a combination appointment.

Table 5-5: Flexible ultrasound slots after a 10% increase in the number of patients that visit the treating physicians and a 5% increase in the probability of long-term ultrasound requests, compared to results after changes in the schedules of treating physicians.

	Flexible ultrasound slots		
Weekday	*After changes in schedule*	*+10% patients*	*+5% long-term ultrasound request*
Monday	5	2	1
Tuesday	4	2	1
Wednesday	5	3	2
Thursday	6	5	4
Friday	6	4	4

Finally, we examined the situation when a new treating physician starts treating patients. This situation might take place when for example more foreign patients are attracted due to the expertise of the Máxima. We assume that the number of patients seen by this treating physician is the average of the number of patients seen by all other treating physicians. Moreover, we assume that the probability that these patients have an ultrasound appointment combined is the average of the probabilities of appointment blocks of already treating physicians who request ultrasound appointments. We recommend to schedule the consultation hour of this new treating physician on Thursday, since this is together with Friday the weekday with the most flexible space. This experiment did not show any difference in the output of the forecast compared to the outcome after changes in the schedules of treating physicians. Appendix I shows the outcome of this experiment.

In conclusion, the sensitivity analysis shows that the method of the forecasting model still works after a change in the input values. However, the number of flexible slots reduces and is not balanced over the weekdays anymore. Especially an increase in the probability of having an ultrasound appointment combined with an appointment with the treating physician, leads to an increase of required ultrasound appointments and reduces the number of flexible slots. Therefore, the schedules of the treating physicians require a re-evaluation by a change in one of the input factors of the model.

5.6. Conclusion

Chapter 5 describes the output of the forecasting model. First, the required number of ultrasounds are specified for the four determined patient types: 1) inpatients and 2) patients from the outpatient clinic or patients with a day-treatment combined with an (2a) emergency-, (b) short- or (c) long-term ultrasound request. The corresponding demand percentiles, which determine the required number of ultrasounds, are specified for each planning term. Results from the forecasting model show that in the current situation, the demand for ultrasound requests is not balanced over the weekdays. Especially on Tuesday, demand is high, while capacity is lowest. More specifically, the first experiment shows that especially long-term ultrasound requests are imbalanced. Most improvement potential is on the long-term ultrasound requests since these appointments are allowed to be moved between weekdays. A change in the schedule of a treating physician that requests many long-term ultrasounds on Tuesday by moving their consultation hour from Tuesday to Monday, reduces the required number of ultrasound slots on Tuesday. Moreover, the appointment blocks of a treating physician who has their consultation hour on Tuesday, but sometimes sees patients on Friday, are exchanged. This results in an increase of ultrasounds on Friday and a decrease on Tuesday which balances flexibility over weekdays even more. Furthermore, the utilisation of the ultrasound is more balanced over weekdays compared with the situation before the changes in the schedules of treating physicians.

With a sensitivity analysis, we analysed that an increase of patients that have an appointment with the treating physicians leads to a higher number of required ultrasound requests and reduces flexibility. An increase in the probability that a patient has a long-term ultrasound request combined with an appointment with the treating physician leads to an even higher number of required ultrasound requests and reduction of flexibility. So, the model still works when the input variables change, but the schedules of the treating physicians require a re-evaluation to balance flexibility over the weekdays again.

Recap from Chapter 2, patient planners experience most planning effort for the combination of an ultrasound appointment with an appointment with the patients' treating physician. Furthermore, treating physicians have to change their schedules often. If the required number of ultrasounds per patient type is translated to the number of slots that should be reserved in the blueprint schedule, patient planners are supported to schedule appointments. Moreover, balanced flexibility in ultrasound slots over the weekdays will reduce the planning effort since more slots will be available to schedule the appointments. Therefore, the combination appointments are easier to schedule and specialists do not have to change their schedules too often. From the patients' perspective, more appointments can be sequentially combined.

6. Implementation plan and recommendations

Chapter 6 answers the research question 'Which steps need to be taken to implement the solution in practice?'. Section 6.1 describes the steps required to implement the results of this study. Section 6.2 describes the evaluation steps of the new designed blueprint schedule. The results of this study together with the below described implementation and evaluation steps answer the main research question: '*How can the Máxima optimize their current multi-appointment scheduling by using a method to improve their current blueprint schedule?*'.

6.1. Implementation of results

Together with the stakeholders of the Máxima, we discussed the results of this study and the required implementation steps to translate the results of this study into a blueprint schedule suitable for the Máxima. As in the Chapters 4 and 5, we discuss the implementation steps for both the dedication of patient types to the blueprint schedule and the effects of changes in the schedule of treating physicians.

6.1.1. Dedicate patient types to blueprint schedule ultrasound

To dedicate time slots for different patient types, the following implementation steps are required. As explained in the Chapters 4 and 5, we dedicated time slots of the blueprint schedule of the ultrasound to four patient types:

1) Patients who have their ultrasound appointment while they are in the inpatient clinic
2) Patients that have their appointment combined with an appointment with their treating physician for patients from the outpatient clinic or patients that have a day-treatment combined. For these patients, a distinction in patient type is made regarding one of the three planning terms of their ultrasound request:
    a. Emergency requests
    b. Short-term requests
    c. Long-term requests

The main challenge is to schedule patients who require multiple appointments combined. Therefore, the dedicated appointment slots for these patients should be available on the most desired slots to schedule the combination appointments. With the patient planning department, it should be examined and discussed which specific time slots per weekday need to be assigned to which patient type. For example, the first time slot (08.00 a.m.) might be optimal for inpatients since these patients do not have to travel to the Máxima before their appointment. Furthermore, Chapter 2 showed that the first time slot is less utilized compared to time slots in the middle of the day. When inpatients are scheduled in the first time slot, the utilisation will be more spread over the day. So, the selection of which time slots are dedicated to which patient types can be substantiated by an examination of the utilisation of the current time slots and by the expertise and experience of patient planners. The allocation of specific time slots on a day to patient types can also be examined by another optimization model, such as a DES.

As mentioned, this research specifies a specific percentile for each patient type for which demand is covered. Recap, this percentile indicates the ratio between fulfilling the demand versus the vacancy of slots. The higher the percentile, the more demand is covered, but the higher the risk of vacant slots. Parallel to this research, the planning horizon of the Máxima increased. First, the planning horizon was equal for all appointment requests, as mentioned in Chapter 1 and 2. Now, the planning horizon for the long-term requests is longer than for the emergency and short-term requests. This requires guidelines for appointment scheduling to avoid rework of patient planners. Namely, if the long-term requests are already scheduled, there should still be slots available for the other requests. The Máxima aims to schedule appointments within 48 hours after the moment the appointment is requested, with a maximum planning horizon of six months.

We discussed with the management that within the Máxima, it is important to have enough spots for emergency requests. As emergency patients have to be treated directly, the demand percentile is high and set to 85%. Hereby, we strive that in 85% of weeks there is sufficient coverage for emergency requests. If emergency patients cannot be treated in the reserved slots, they will be treated in overtime or in between other appointments, since not all ultrasound appointments require their full appointment time. If this is not an option, patients can make use of the ultrasound in WKZ.

Figure 6-1 shows the ultrasound demand corresponding to the cumulative probability for Monday per planning term. Appendix J shows the cumulative probability distribution for the rest of the weekdays. The 85th percentile of demand is given by the minimum required number of ultrasounds for which the cumulative probability is at least 85%, which is one ultrasound. If the management decides to adjust the percentile in the future, the figure shows the corresponding required ultrasounds. For example, if the percentile is set to 90% for emergency requests, the minimum number of required ultrasounds for which the cumulative probability is at least the 90th percentile, is two.

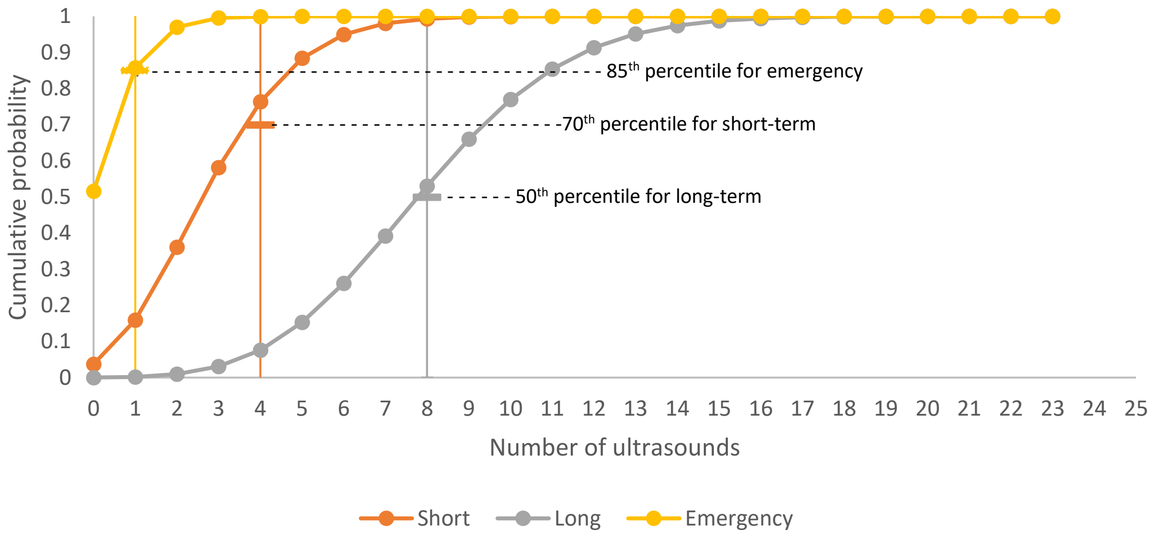

Figure 6-1: Ultrasound demand corresponding to cumulative probability on Monday, after changes in the schedules of two treating physicians. The vertical lines show the required number of ultrasounds slots to cover 85% of emergency demand, 70% of short-term demand and 50% of long-term demand.

To determine a percentile for the long-term requests, we discussed that this is dependent on the planning rules on operational level. As mentioned in Chapter 2, long-term requests are allowed to deviate from their requested appointment date and should be spread over weekdays. However, this only works if these rules are incorporated within the planning rules and more importantly, patient planners should be aware of these planning rules. For example, if the long-term slots are utilized and a new long-term request comes in, the first step is to check whether there is another slot within the range they are allowed to schedule the appointment. We discussed that the percentile of the long-term requests is set to 50%. With a 50% percentile, the risk of not fulfilling demand is as high as the risk of vacancy of slots. With this percentile, we strive that enough ultrasounds are reserved such that in 50% of the weeks there is sufficient coverage for long-term requests. This percentile is lower compared with the emergency requests since the lower percentile stimulates patient planners to spread long-term requests over the weekdays. This is explained in the following example. Appendix H shows the actual number of ultrasounds over the period November 2021 to April 2022, specified per planning term. The number of ultrasounds fluctuates over weeks. For example, on Wednesday in week 46, the actual number of the long-term ultrasounds was four. In week 47, the actual number of the long-term ultrasounds was nine. With the proposed blueprint schedule, we reserve seven time slots on Wednesday for the long-term ultrasounds, based on the 50% demand percentile. Therefore, we support patient planners to spread the ultrasound requests over the weeks and or weekdays. For example, two ultrasounds of week 47 could have been moved to week 46, where only four ultrasounds were requested. If in a certain week not enough slots are reserved for the long-term ultrasound requests, appointments should be scheduled on the weekday when the least patients are scheduled yet to keep a balanced ultrasound utilisation. If there are no slots left within the required range, flexible slots can be taken, which are not dedicated to one of the four mentioned patient types.

When management decides to select a higher percentile in the future, it becomes more important to incorporate planning rules that indicate when the dedicated slots are open for other patient types when the slots are not utilized after a certain term, to reduce the risk of vacancy. Appendix J shows the effect of higher percentiles (85% for each planning term). As expected, higher percentiles lead to a higher number of required ultrasounds and especially the required number for the long-term requests increase. Figure 6-1 confirms this. If management decides to set higher percentiles in the future, the schedules of treating physicians and forecast outcomes should be reviewed.

The demand percentile of short-term requests is set to 70%. In most weeks, enough slots should be reserved, but a part of these requests are still allowed to be scheduled within a certain range instead of the requested date, and are allowed to be spread over weekdays. The percentile for inpatients is set at 70%. These patients require an ultrasound, but do not require to combine this ultrasound appointment with an appointment with the treating physician. Therefore, inpatients can be scheduled with more flexibility compared to emergency patients. Furthermore, results show that each weekday has flexible slots left after the incorporation of the required number of slots for the four patient types. These flexible slots should be incorporated in the blueprint schedule to deal with appointment requests while dedicated slots are already fully occupied or for the small volume of patients that are from the outpatient clinic but do not have an appointment in combination with the treating physician.

The dedication of patient types to appointment slots can be incorporated into the appointment planning system (HiX) by locking the appointment slots until the planning term of the specific slot is reached.

To conclude, the new designed blueprint schedule of this research contributes as a guideline for patient planners to schedule appointments. Long-term requests are spread over the weekdays and enough slots are reserved for emergency and short-term requests. As a result, the chance of rework is lower compared to the current situation, which reduces the planning effort. This contributes keeping the long planning horizon.

6.1.2. Changes in the schedule of treating physicians

The current situation and the current blueprint schedule are optimized in this study by the move and exchange of consultation hours of treating physicians. The results show that these changes result in a more balanced workload of ultrasound over the weekdays. We discussed that before the implementation of the change in consultation hours of the treating physicians, the effects of these changes in the schedules should be analysed. First, treating physicians have multiple tasks next to seeing their patients during consultation hours. Therefore, the change in the schedule of a treating physician requires wiliness to change and the treating physician should be able to reschedule other tasks. Furthermore, this research only examines the patient flow around an ultrasound appointment. For multi-appointment scheduling, other patient flows should also be examined. For example, if we move the consultation hour of one specific treating physician because this results in a more balanced utilisation of ultrasound, this might impact other patient flows. Namely, next to scheduling the combination of an appointment with the treating physician with an ultrasound appointment, it is also hard to schedule other modalities together with an appointment with the treating physician. Therefore, another step that is required before changing the consultation hours, is to investigate the balance of utilisation over weekdays for the other modalities. Moreover, the utilisation of consulting rooms and treatment rooms should be examined. If more patients are moved from Tuesday to Monday for example by changing the consultation hour from Tuesday to Monday, more of these rooms are required on Mondays. However, there should be enough space to treat these patients. All above-mentioned implementation steps require implementation time and it is expected that implementation of a change in a consultation hour of a treating physician takes about six months.

6.2. Evaluation of the new designed blueprint schedule

If the results of this study are implemented and translated to a blueprint schedule, it is important to evaluate the new designed blueprint schedule. In this research, the forecast is based on historical data and evaluated on new test data: the actual number of ultrasounds for the period November 2021 to April 2022, as shown in Section 5.3.2. We discussed that the new designed blueprint schedule requires an evaluation once in four months, which is in line with other evaluations within the hospital. For each evaluation, the new test data set consists of the ultrasound appointments from the previous four months. The steps mentioned in Section 5.3.2 can be used to evaluate the performance of the new designed blueprint schedule. For example, one of the evaluation steps is to first select a new test data set (all ultrasound appointments over the last four months at the date of evaluation). Second, specify the ultrasound appointments per patient type as defined in this research. Third, calculate the actual percentile, which is the number of weeks for which the demand was fulfilled with the predetermined percentiles (Equation 5.6). Based on this evaluation, the number of reserved slots might be adjusted.

Furthermore, the other defined multi-appointment scheduling KPIs from Chapter 2 can be evaluated. The scheduled waiting time between multiple appointments, the appointment scheduled within the consultation hours of specialists and the utilisation can be derived from the data. The planning effort and the number of rescheduled appointments can be asked to patient planners. Moreover, within HiX, data on rescheduling can be obtained when right registering this data. Recap from Chapter 2, we concluded that the KPIs described from the patient perspective should be optimized in the future. We recommend the Máxima to gather information to set a norm for the total number of appointments scheduled on one day. This might for example be incorporated in the treatment plan of patients. When this information is known, the number of appointments scheduled on one day for a patient can be evaluated. Next, we recommend to keep track of the actual waiting times between sequential appointments instead of the scheduled waiting time, to improve the evaluation of the waiting time between appointments.

Next to the suggested changes in consultation hours of treating physicians in this research, changes in consultation hours take place in general. Results of this research show that a change in the consultation hours influences downstream departments. Therefore, another iteration of the forecasting model is required if consultation hours change. Furthermore, patient volume and protocols can change in the future. In Section 5.5, we examined these scenarios by a sensitivity analysis. This sensitivity analysis showed that the forecasted demand increases when the number of patients that visit the treating physician increases or when the required number of long-term ultrasound requests increases. As a result, flexibility is not equally balanced over the weekdays anymore. Therefore, these changes also require another iteration of the forecasting model. The steps from Chapter 4 can be used for the new iteration.

To conclude, we discussed together with the management that this research contributes to create insight in the evaluation and the optimization of multi-appointment scheduling. The ideas of this research with a focus on ultrasound can be used in the future for examination of other modalities and patient flows.

7. Conclusions and discussion

Chapter 7 concludes this study (Section 7.1), indicates the research limitations and provides recommendations for further research (Section 7.2).

7.1. Conclusion

This research was performed to optimize multi-appointment scheduling and to create insight in requirements for applying multi-appointment scheduling within the Máxima. The Máxima is a centralized hospital for paediatric oncology where multidisciplinary processes take place. Since many patients do not live close to the Máxima, it is desirable to plan as many appointments as possible sequentially on one day. Currently, it is especially hard to combine the appointments of modalities with an appointment with the treating physician. Most improvement potential was found for the ultrasound modality, where demand is not optimally spread over weekdays. Therefore, the goal of this study was to optimize tactical multi-appointment patient scheduling by designing a method to create a blueprint schedule with time slots for different patient types.

The first step of the designed method is to distinguish between patients from the inpatient clinic and patients from the outpatient clinic or who have a day-treatment combined. Inpatients do not have the same requirements for multi-appointment scheduling since they are already in the hospital and do not have to combine multiple appointments. Demand for these patients is determined by a Poisson distribution.

The demand for patients from the outpatient clinic or patients with day-treatment is forecasted by the calculation of the ultrasound request distribution, based on the distribution of patients that visit the treating physicians. For these ultrasound requests, a distinction is made in three planning terms: emergency-, short- and long-term requests. For each planning term, we specified a demand percentile which determines the number of reserved slots. The demand percentile for emergency requests is set highest (85%), which means that we reserve enough ultrasound slots to cover 85% of the demand for emergency requests. The demand percentile is lower (50%) for long-term requests since these requests are allowed to deviate from the requested appointment date. Demand is not constant over weeks and ultrasound appointments should be spread over weekdays by patient planners. The demand percentile for the short-term requests is in between the long-term requests and emergency requests (70%).

Results of the model show that demand is higher than capacity on Tuesday. We changed the appointment blocks of two treating physicians from Tuesday to Monday and Friday and as a result, demand is more balanced over weekdays. This result contributes as a first step in the whole multi-appointment scheduling process. When the demand for the ultrasound is spread over weekdays, more flexibility is created to schedule combination appointments with the treating physicians. We assume that treating physicians have to change their schedule less and therefore, appointments are easier to schedule for patient planners. As a result, patients' appointments can be sequentially combined on one day.

This research has a practical contribution to the Máxima since the management confirms that this research creates insights in KPIs that are important to monitor the performance of multi-appointment scheduling. Furthermore, when the results of this research are implemented, this will contribute to a more balanced ultrasound utilisation over weekdays. Besides, the described method to design a blueprint schedule for the ultrasound can be generalized to other modalities.

Next to the practical contribution, this research contributes to theory since we contribute to two aspects of the literature gaps mentioned by Leeftink et al., (2020). First, the model is applied to a case study in an organisation with a patient-centred clinic. Patient-centred clinics require more flexibility, which we included in the designed model by spreading demand over weekdays. Second, most research is performed on the entire system performance within multi-appointment where the whole patient flow is analysed by for example calculating the total time a patient spends in the hospital. However, individual resource performance is also of interest in literature since outliers in individual performances might indicate that changes are required at individual resources to optimize the entire system performance. We contribute to this aspect by evaluating the utilisation of ultrasound. Besides, we implemented in our model that the number of reserved ultrasound slots depends on the selected percentile of demand for different types of appointment requests. In this case study, the demand percentile of emergency requests is high, to ensure enough slots are reserved. The percentile of the long-term requests is lower compared with the emergency- and short-term requests, to support patient planners to spread long-term requests over weekdays.

To conclude, the results of this study provide a quantitative basis to design a blueprint schedule dedicated to patient types to enhance the balance of utilisation over weekdays as the first step in the improvement of multi-appointment scheduling.

7.2. Discussion

The discussion describes the research limitations (Section 7.2.1) and provides recommendations for further research (Section 7.2.2).

7.2.1. Research limitations

The first limitation of this research is that it investigates one specific part of the whole multi-appointment patient scheduling process: the patient flow around an ultrasound appointment. Although this research contributes as a first step to improve multi-appointment scheduling, more research is required to optimize other patient flows and to investigate the effects of adjustments in the patient flow of this study on other patient flows within the Máxima. Next, in the patient flow around an ultrasound appointment, we only forecasted the ultrasound appointment as a downstream of an appointment with the treating physicians. Nevertheless, multi-appointment scheduling often includes more appointments, such as a blood sample test. These appointments can also be considered as downstream appointments and further research can investigate these linkages.

Second, this study assumes that improvement of ultrasound utilisation leads to an improvement of the other defined KPIs in Chapter 2: total number of appointments on one day, the actual waiting time of patients between multiple appointments, appointments scheduled within the reserved consultation hours of specialists and the effort of patient planners. However, these KPIs are not examined after the interventions in this study since the focus was on tactical multi-appointment scheduling.

Third, this research does not distinguish between appointments from the outpatient clinic and appointments from patients who have a day-treatment combined. Since patients with a day-treatment have for example more often an MRI appointment combined with their ultrasound appointment compared to outpatients, a distinction in analysing downstream appointments might result in different outcomes.

Fourth, this research created a forecasting model which assumes that all weeks require the same amount of ultrasound slots for a specific patient type. However, this might vary over weeks. For example, as we explained in Chapter 2, fewer ultrasounds are requested during public holidays while more requests are requested in the periods before and after these public holidays.

Last, the model is based on some averages and assumptions. For example, an average is taken for the absence days when these days were not known for specific treating physicians. Furthermore, the arrival process of patients is modelled as a Poisson distribution, which seems an appropriate distribution but a distribution does not fully match reality. Next, this research assumes that consultation hours of treating physicians are dedicated to one of the time blocks as described in Chapter 4. However, the consultation hours of some treating physicians deviate and are not in line with these generalized consultation hours. Since this model is based on historical data where appointments are often scheduled outside consultation hours, corresponding ultrasound distributions are calculated in line with these appointments. A distinction between ultrasounds followed from appointments within and outside consultation hours of treating physicians might result in more substantiated optimization of the schedules of treating physicians. Namely, the patients that are seen outside appointment hours might not constantly take place at the same moment and deviates over weeks and increase demand uncertainty.

7.2.2. Recommendations for further research

Following the first limitation, the forecasting model can be extended by including probabilities for other appointments around the ultrasound appointment or the whole flow of patients. Forecasting whole patient flows might contribute to improve the whole multi-appointment patient scheduling process. As a first step, existing patient flows require more examination. This is challenging, since the Máxima is a patient-centred clinic with many different patient flows.

Furthermore, the forecasting model for the distribution of ultrasound requests can be generalized to other modalities within the Máxima. Some adjustments are required. In the current forecasting model, a cycle of one week is examined. However, when MRI appointments are analysed for example, it is preferred to extend the cycle to two weeks since some schedules of treating physicians only have appointments once in two weeks.

Recap from the second limitation of this research, the focus is on tactical multi-appointment scheduling with a specific examination of the balance of the ultrasound utilisation over weekdays. For further research, it is recommended to investigate operational performances by measurement of the other mentioned KPIs, where stochasticity can be included for example by a DES. Furthermore, it can be examined which specific time slots on a day should be allocated to which patient types.

The fourth recommendation is to investigate possibilities to make the forecasting model dynamic instead of static. A disadvantage of a static model is that the blueprint schedule requires a regular evaluation. Moreover, as mentioned, the forecasting model of this research is generalized for all weeks and not able to adjust to fluctuations in demand. A dynamic model can analyse a change of capacity over time and allows insight into low and high-demand periods such that temporary capacity changes can be applied for example, when necessary. Another suggestion is to incorporate the work list of patients and to analyse what is already in the schedule at the moment the blueprint schedule is analysed, to improve multi-appointment scheduling on the operational level.

The fifth recommendation is to investigate if it is relevant to forecast more upstream by forecasting patients' appointments based on disease protocols and/or stage of the disease. For example, forecasting the number of ultrasounds for a patient with a specific disease in the diagnosis phase. Furthermore, literature shows that patient arrival at emergency departments is predictable (Gul & Celik, 2020). Patients that arrive at the Máxima are considered as emergency patients and therefore it might be examined whether the arrival of patients at the Máxima is also predictable.

Sixth, the Máxima can investigate a distinction in appointment interval among specific appointment types since the duration of ultrasound appointments differs per appointment type. This might result in lower waiting time and resource idle time as mentioned in Chapter 3. Moreover, the start times of the time slots within the current blueprint schedule are the same for both ultrasounds. A final recommendation is to investigate whether the waiting time between an ultrasound appointment and another appointment reduces when the start times of both ultrasound time slots would deviate from each other.

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Appendices

Appendix A Average ultrasound utilisation per patient type and time slot

Average number of appointments per patient type per weekday

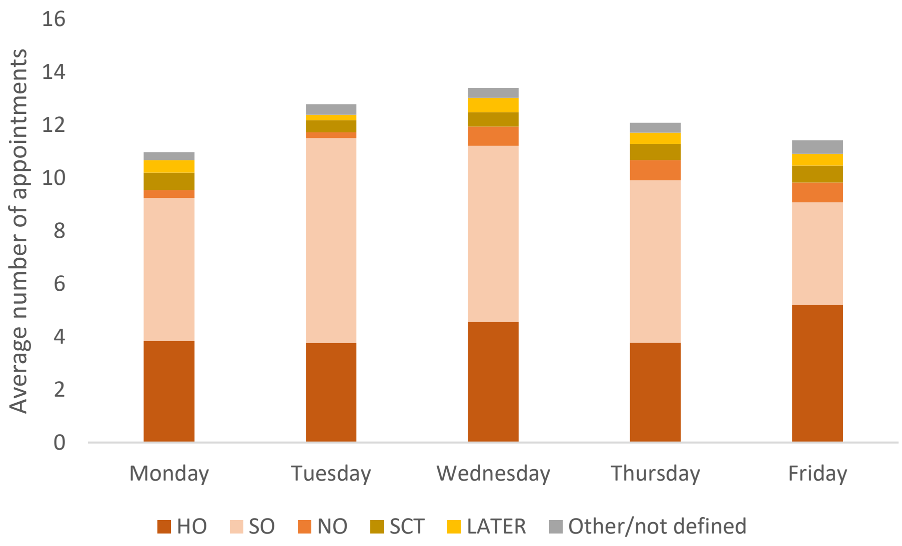

Figure A-1: Average number of scheduled ultrasound appointments for each weekday for each patient type per diagnosis department (n=6,331, data for December 2019 – November 2021, source: HiX)

Average utilisation per time slot per weekday

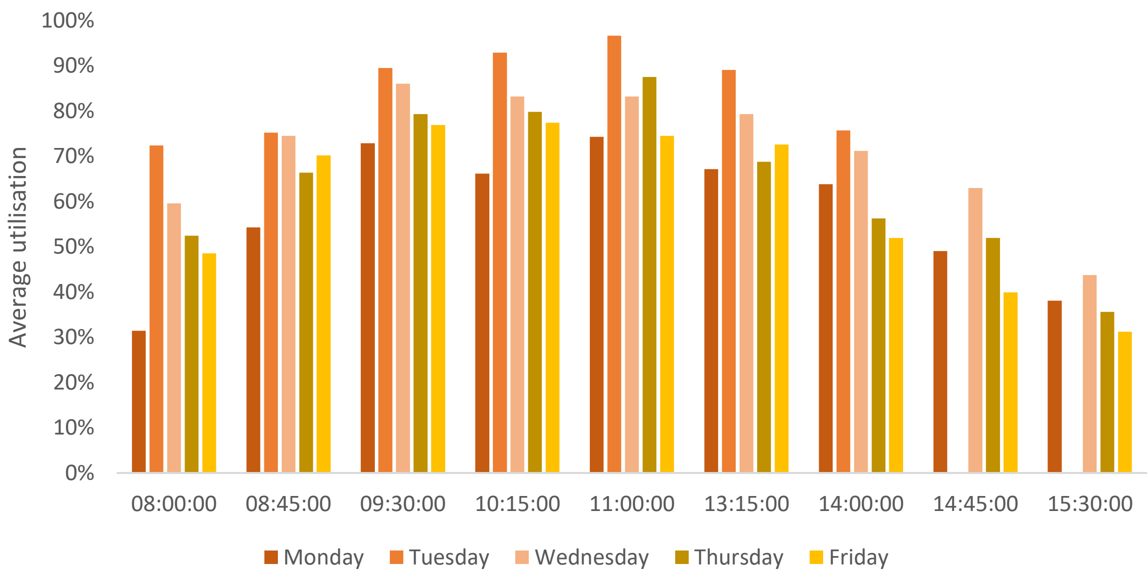

Figure A-2: Average % utilisation per weekday per time slot for the ultrasound (n=6,033, data for December 2019 – November 2021, source: HiX)

Appendix B Literature review

To answer the research question *'Which model types can be found in literature to improve tactical multi-appointment scheduling?'*, a literature review is performed. First, the literature reviews of (Leeftink et al., 2020; Marynissen & Demeulemeester, 2019) about multi-appointment scheduling were examined to get familiar with terminologies within multi-appointment scheduling. After that, we conducted a systematic literature review. Scopus is used as database to find relevant articles. The keywords used are:

- Tactical OR (Capacity Planning)
- Multi-appointment OR Multi-Disciplinary
- Hospital OR Healthcare OR Clinic OR Patient

The search string used by combining above-mentioned key words is:

(TITLE-ABS-KEY (tactical OR (capacity AND planning) OR scheduling) AND TITLE-ABS-KEY (multi-appointment OR multi-disciplinary) AND TITLE-ABS-KEY (hospital OR healthcare OR clinic OR patient))

This resulted in 80 documents. Only articles written in English or Dutch were included, which resulted in 76 articles. Documents published before 2005 are also excluded and limited the research to 64 documents. By reading titles, abstracts and key-words, relevant articles with the following keywords or synonyms were selected: *'Optimization', 'Waiting time', 'Combined appointments', 'Clinician idle time and/or overtime', 'resource utilisation, 'Patient scheduling', and 'Oncology'*. Table A1 shows the selected documents from the literature review. Furthermore, we used forward and backward search for the articles found to find other relevant papers.

Table B1: selected articles from literature review

Document	Application area	Objective	Model type
(Otten et al., 2021)	Rheumatology and a medical oncology & haematology clinic	Maximize number of in-person consultations	ILP / Monte Carlo Simulation
(Leeftink et al., 2019)	Cancer clinic	Patient waiting time, clinician idle time and overtime	Sample average approximation
(Apergi et al., 2020)	Outpatient scheduling cardiology department	Minimizing the number of visits to the hospital, and waiting time in the hospital	IP
(Morrice et al., 2020)	Integrated practice unit	Determine number of patients seen per day in IPU while constrain overtime, length of stay and waiting time	Simulation
(Marynissen & Demeulemeester, 2019)	Hospital	Classification scheme to classify scientific work on multi-appointment scheduling	Review
(Vieira et al., 2016).	Radiotherapy	Presents application of operation research methods for logistic optimization in radiotherapy	Review

Appendix C Leave of absence of treating physicians

Table C-1: Average leave of absence per weekday for treating physicians (n=260 weekdays, data for November 2020–October 2021, source: HiX)

Weekday	*Average leave of absence (days)*
Monday (n=52)	7.6
Tuesday (n=52)	8.7
Wednesday (n=52)	7.8
Thursday (n=52)	8.8
Friday (n=52)	8.2

Appendix D Patients from inpatient clinic

Ultrasounds combined or not combined with treating physician

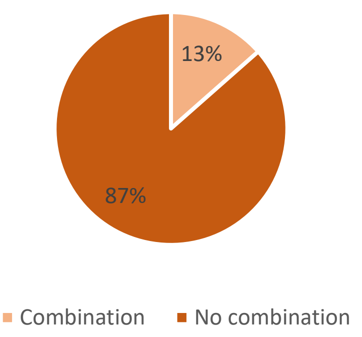

Figure D-1: Ultrasound appointments from the inpatient clinic with and without a combination appointment with treating physician (n=689, data for November 2020–October 2021, source: HiX)

Chi-square tests for demand of inpatient clinic

Table D-1: Outcomes of chi-square test per weekday for inpatient (n=260 weekdays, data for November 2020–October 2021, source: HiX)

Weekday	***λ***	***P-value***
Monday (n=52)	3.3	0.39
Tuesday (n=52)	2.0	0.91
Wednesday (n=52)	2.5	0.88
Thursday (n=52)	2.7	0.94
Friday (n=52)	2.6	0.68

Ultrasounds per planning term

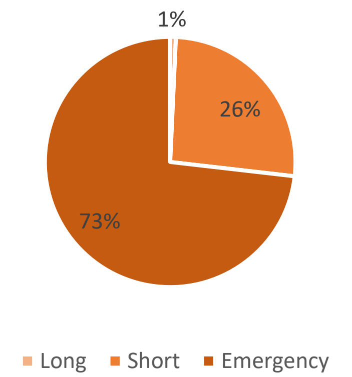

Figure D-2: Ultrasound appointments from the inpatient clinic divided into planning terms (n=689, data for November 2020–October 2021, source: HiX)

Poisson distribution

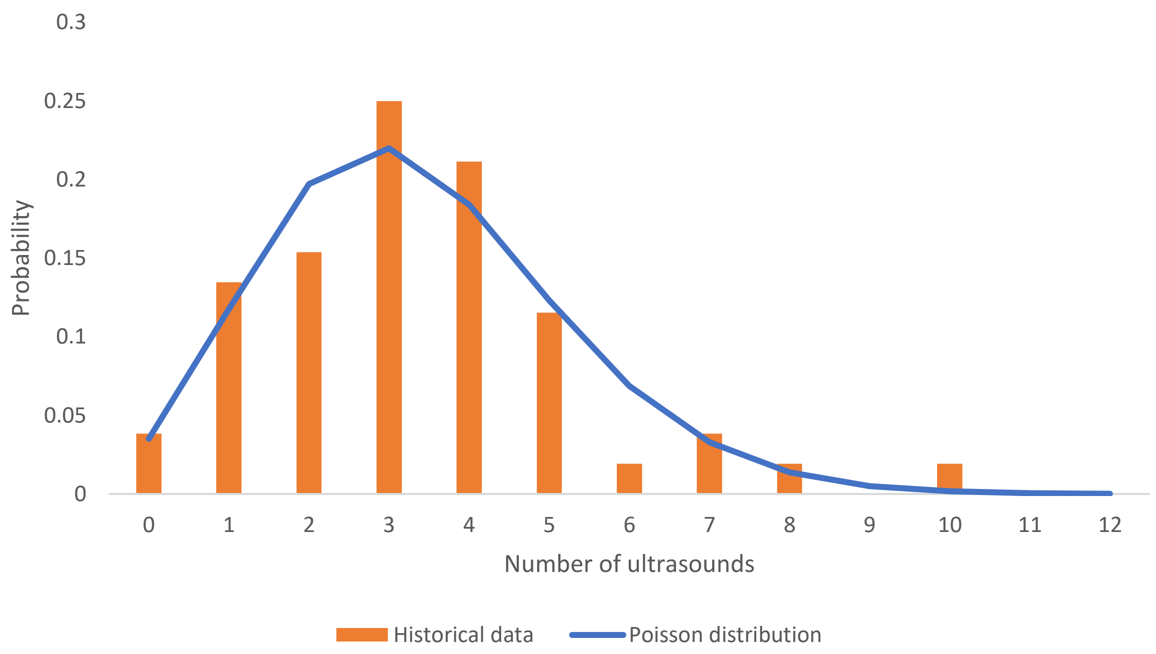

Figure D-3: Historical data and Poisson distribution of ultrasound requests on Monday (n=52 weeks, data for November 2020–October 2021, source: HiX)

Appendix E Number of ultrasounds versus the number of patients

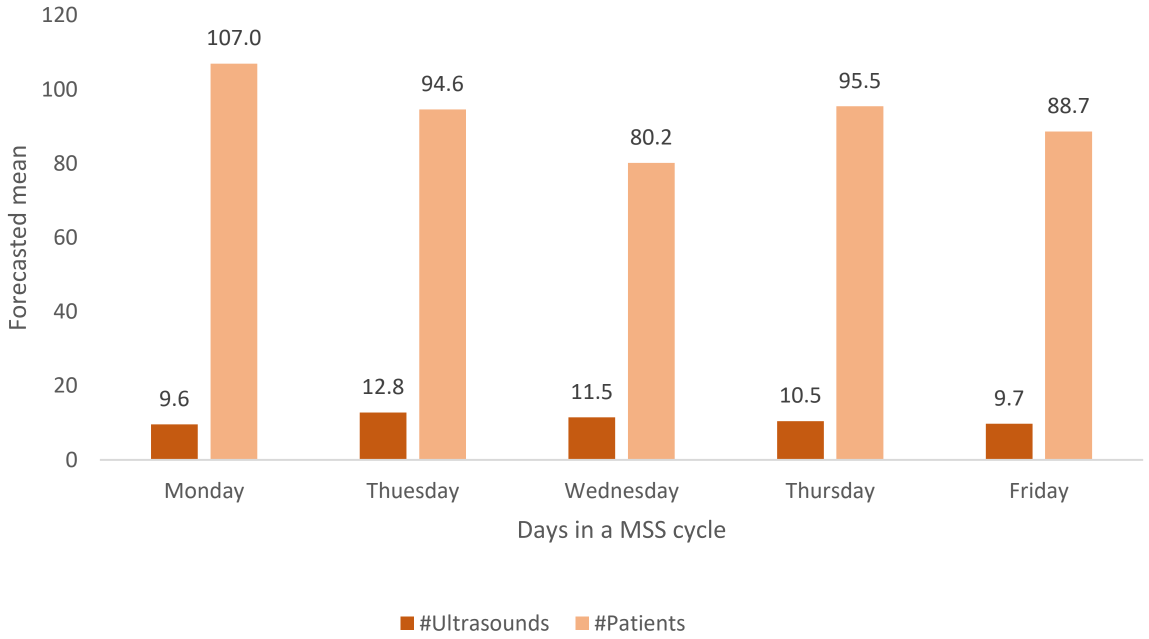

Figure E-1 the number of ultrasounds versus the number of patients seen by the specialists for each weekday.

Appendix F Forecasted mean

Equation F1 shows the formula used to calculate the mean of the forecasted binomial distribution.

$$\mu = \sum_{x=0}^{\tau} H_t(x) * x \qquad \textit{Equation F1}$$

Where $H_t(x)$ is the probability of x ultrasounds on day t. τ is the largest x which can result from the convolutions.

Table F-1: Forecasted mean of required number of ultrasounds per weekday (N=52 weeks).

Weekday	*Forecasted mean*
Monday (N=52)	9.6
Tuesday (N=52)	12.8
Wednesday (N=52)	11.5
Thursday (N=52)	10.5
Friday (N=52)	9.8

Appendix G Number of required ultrasound spots per planning term per daypart

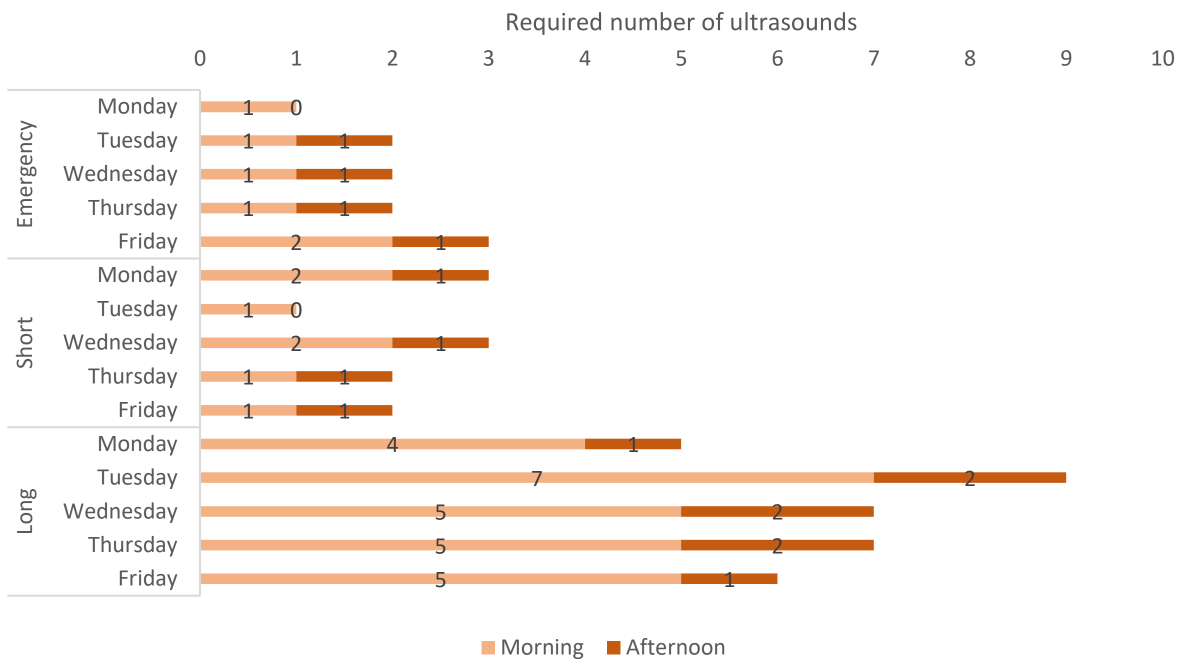

Figure G-1 Required number of ultrasounds to cover 50th percentile of demand for patients from outpatient clinic and patients who receive day-treatment per daypart per weekday

Appendix H Validation of percentiles per planning term

Forecasted versus historical percentile

Table H-1 Forecasted percentile versus historical percentile per weekday per plan – term. The red lines indicate that the historical percentile was lower than the forecasted percentile. Therefore, the defined percentiles of demand were not met with the number of reserved ultrasound slots.

Weekday	***Planning term***	***Reserved ultrasound slots***	***Forecast percentile***	***Historical percentile***
Monday	Long	6	50%	60%
	Short	7	70%	84%
	Emergency	**8**	**85%**	**80%**
Tuesday	Long	9	50%	69%
	Short	3	70%	88%
	Emergency	2	85%	96%
Wednesday	**Long**	**7**	**50%**	**40%**
	Short	4	70%	72%
	Emergency	2	85%	92%
Thursday	Long	7	50%	65%
	Short	3	70%	85%
	Emergency	2	85%	96%
Friday	Long	6	50%	63%
	Short	3	70%	75%
	Emergency	**2**	**85%**	**79%**

Actual number of ultrasounds

Table H-2: Actual number of ultrasounds per weekday (n=126 weekdays, data for November 2021 – April 2022, source: HiX)

		2021									2022																
	Week	44	45	46	47	48	49	50	51	52	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Monday	Long	6	6	0	5	11	5	6	11	1	2	9	7	7	5	4	8	2	3	7	10	7	7	6	5	Public holiday	5
	Short	4	1	2	3	3	3	4	3	2	3	1	3	3	3	5	2	3	2	6	1	6	3	6	3		3
	Emergency	0	2	1	0	0	0	2	0	0	0	2	0	0	1	2	0	0	1	1	0	0	1	0	3		1
Tuesday	Long	11	2	5	9	8	8	9	8	5	6	9	11	6	5	3	5	10	7	8	12	8	12	10	10	11	9
	Short	2	1	4	2	2	1	2	2	3	2	1	0	1	2	2	2	4	3	1	1	3	0	3	1	1	4
	Emergency	1	0	0	2	1	1	1	1	1	2	0	1	1	4	0	2	1	1	1	0	0	2	0	0	1	2
Wednesday	Long	7	2	4	9	4	12	12	15	0	8	8	4	7	2	5	7	8	8	12	13	8	8	8	11	9	Public holiday
	Short	5	2	1	5	5	1	2	1	1	5	4	6	5	6	4	3	1	0	2	2	4	3	1	2	3	
	Emergency	0	4	0	1	2	1	2	2	1	0	2	3	2	1	1	2	1	2	0	2	0	1	0	2	1	
Thursday	Long	5	5	8	4	9	6	8	4	0	8	7	6	4	8	4	5	10	5	10	4	9	7	6	8	7	1
	Short	3	2	3	1	0	2	6	4	2	2	2	0	0	2	2	3	2	3	4	1	0	2	2	1	3	7
	Emergency	1	1	2	2	2	0	1	1	2	1	2	1	1	0	0	1	1	1	1	1	5	0	2	1	2	0
Friday	Long	4	3	3	6	7	7	7	Public holiday	Public holiday	2	12	11	7	5	4	3	2	1	6	4	0	7	7	1	8	1
	Short	2	1	2	1	2	4	4			2	2	4	3	2	4	2	1	4	1	3	2	4	3	2	2	3
	Emergency	1	1	0	4	1	1	2			2	4	2	4	1	0	1	1	1	1	0	5	1	3	0	1	1

Appendix I Number of required ultrasound spots by a new treating physician

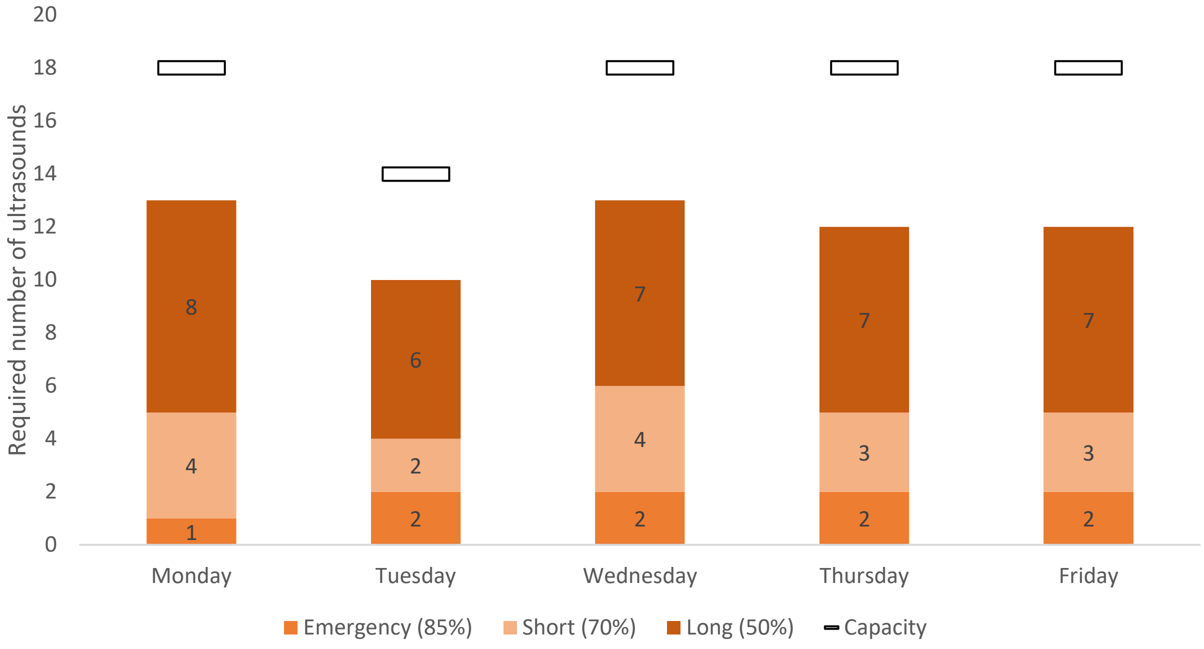

Figure I-1: analysis on the required number of ultrasounds after adding a new treating physician to the schedules, for 85th, 70th, 50th percentile of demand for emergency, short- and long-term requests respectively.

Appendix J adjustments in demand percentiles

Tuesday

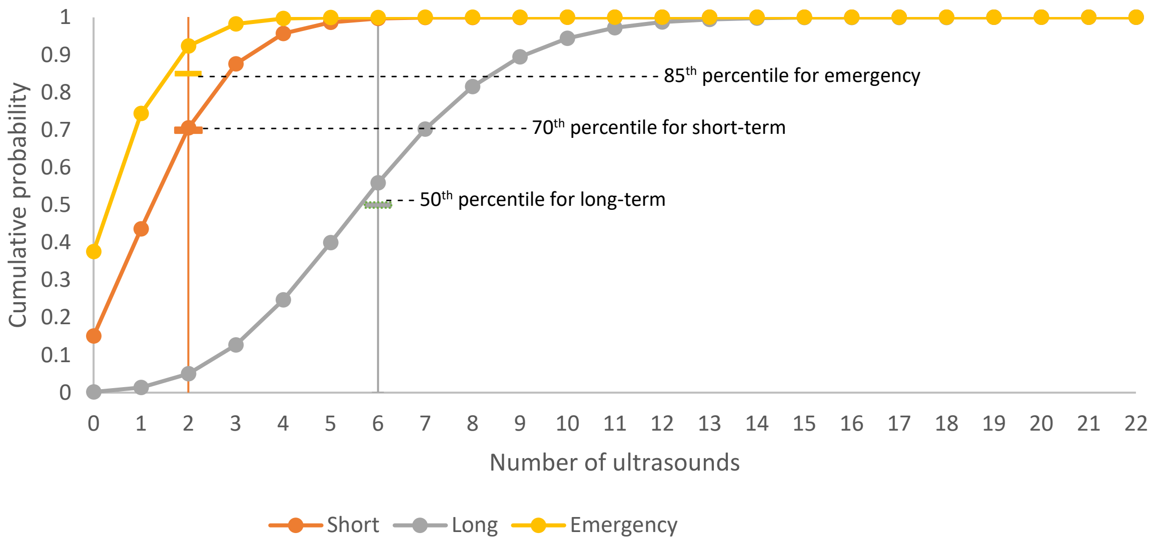

Figure J-1: Ultrasound demand corresponding to cumulative probability on Tuesday, after changes in the schedules of two treating physicians. The vertical lines show the required number of ultrasounds slots to cover 85% of emergency demand, 70% of short-term demand and 50% of long-term demand.

Wednesday

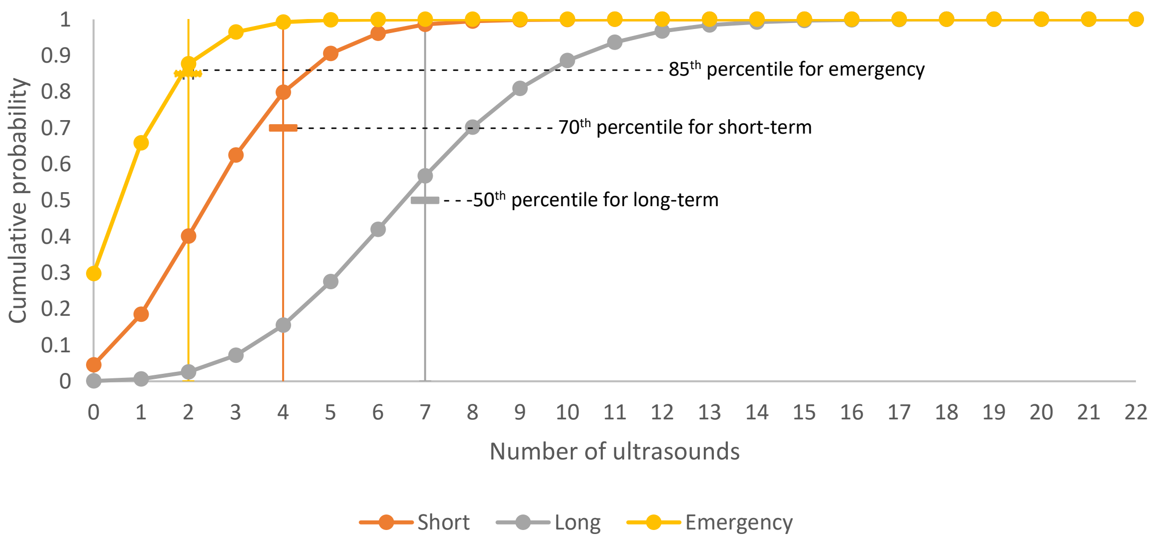

Figure J-2 Ultrasound demand corresponding to cumulative probability on Wednesday, after changes in the schedules of two treating physicians. The vertical lines show the required number of ultrasounds slots to cover 85% of emergency demand, 70% of short-term demand and 50% of long-term demand.

Thursday

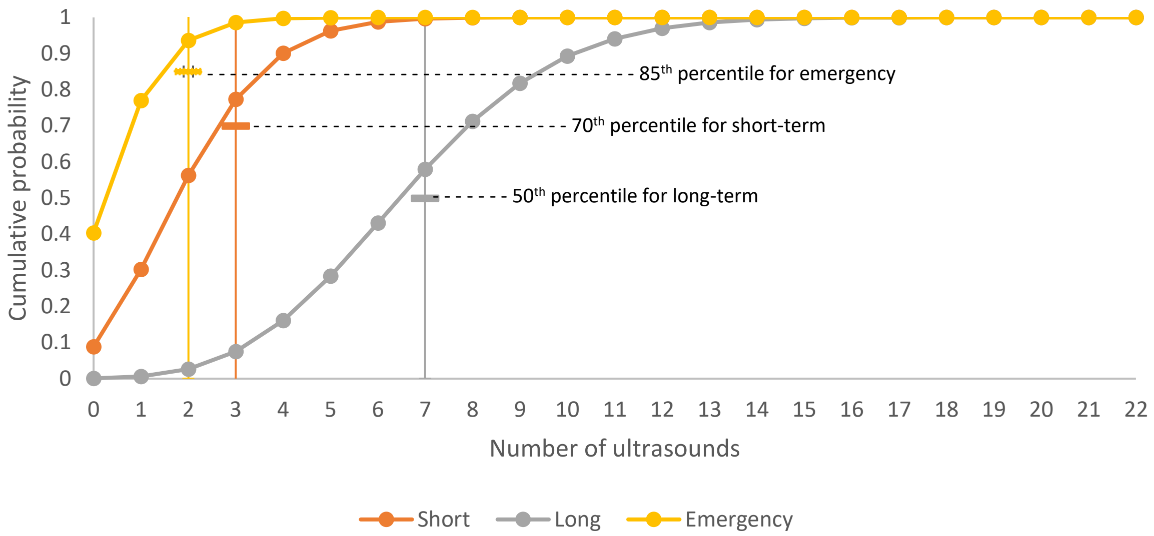

Figure J-3 Ultrasound demand corresponding to cumulative probability on Thursday, after changes in the schedules of two treating physicians. The vertical lines show the required number of ultrasounds slots to cover 85% of emergency demand, 70% of short-term demand and 50% of long-term demand.

Friday

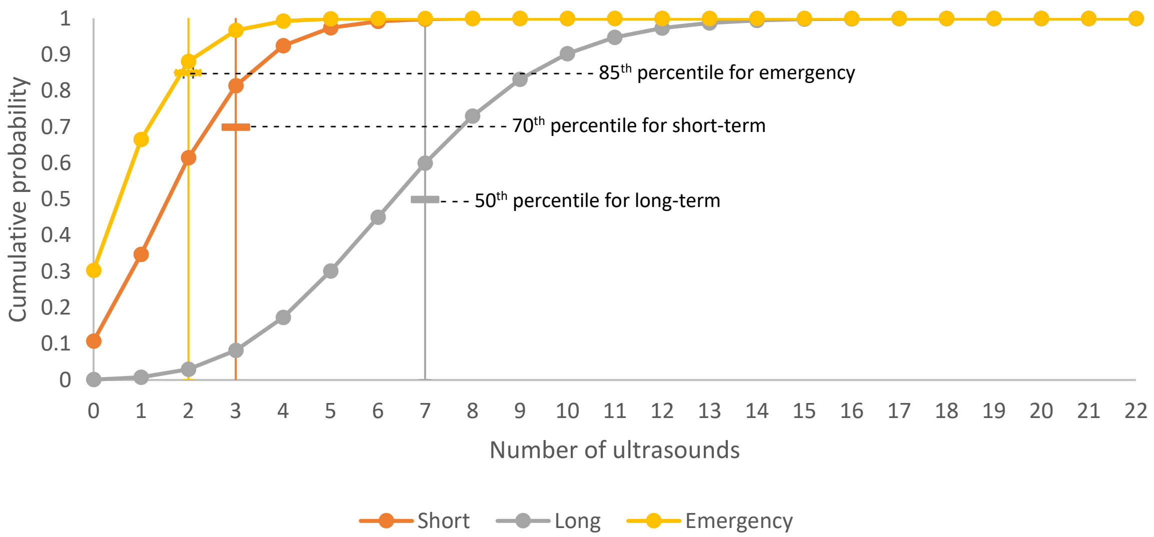

Figure J-4 Ultrasound demand corresponding to cumulative probability on Friday, after changes in the schedules of two treating physicians. The vertical lines show the required number of ultrasounds slots to cover 85% of emergency demand, 70% of short-term demand and 50% of long-term demand.

Increase to 85% demand percentile for all patient types

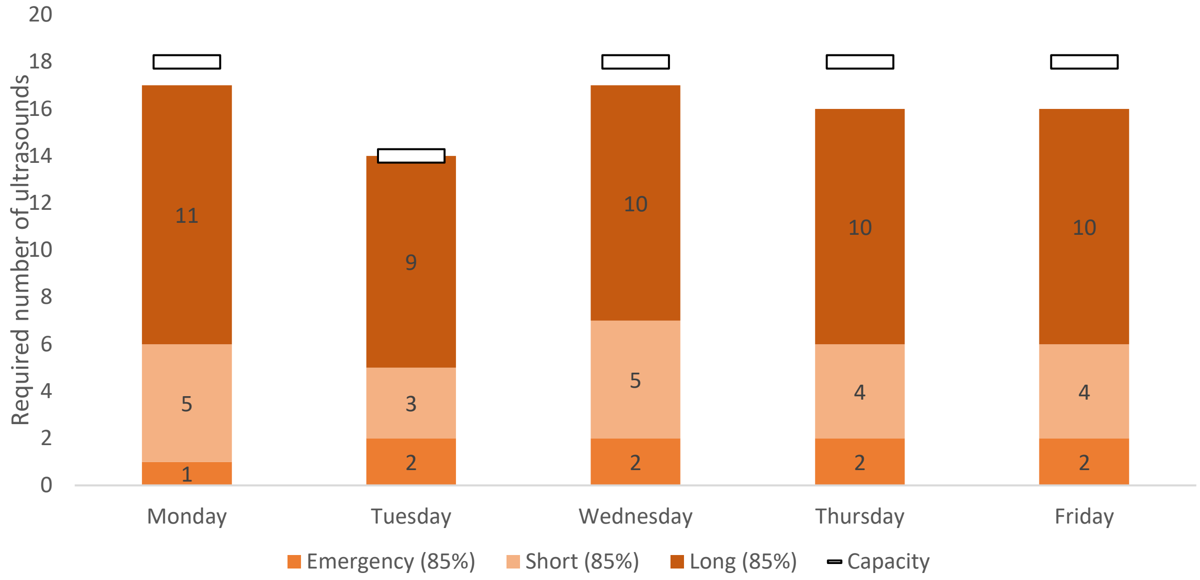

Figure J-5: Required number of ultrasounds by increasing percentiles of all planning terms to cover 85% of demand after the change of schedules of two treating physicians.