Tactical planning to facilitate patient self-scheduling

- Martijn Nijhuis -

Master Thesis Report

Tactical planning to facilitate patient self-scheduling

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Management samenvatting

Aanleiding en doel van het onderzoek

Medisch Spectrum Twente (MST) is een topklinisch ziekenhuis in Enschede. Om te voldoen aan hun strategische doelstellingen wordt een nieuw Elektronisch Patiënten Dossier (EPD) geïmplementeerd aan het eind van 2021. Met het nieuwe EPD is het MST in staat om patiënten te faciliteren in het plannen van hun eigen afspraken en daardoor meer regie te geven over hun zorgproces. Zelf-planning is het proces dat patiënten, via een portaal, een keuze krijgen uit verschillende tijdsloten en een keuze maken uit deze tijdsloten voor hun afspraakdatum en tijd. Aangezien op dit moment het proces van zelf-planning nog niet gefaciliteerd wordt, is het voor het MST niet duidelijk hoe ze dit proces dienen in te richten, en welke impact dit heeft op de operationele prestatie voor alle betrokkenen.

In het huidige planningsproces dient de planner met verschillende factoren rekening te houden: de afspraaktermijn (de periode dat de afspraak plaats moet vinden), het type patiënt (bijvoorbeeld nieuwe patiënt = NP), de benodigde arts, het tactisch rooster (blauwdruk waarin per tijdslot door middel van afspraakcodes is aangegeven welk type patiënt gepland kan worden) en de planningsroutine (bijvoorbeeld first come, first serve). Met de komst van zelf-planning komen er twee extra factoren bij: het type patiënt dat zelf mag gaan plannen en het reserveringsvenster (de periode dat een patiënt een afspraak mag boeken). Doordat zelf-planning niet voor alle patiënten toegankelijk wordt (o.a. voor patiënten die binnen een week gezien dienen te worden is zelf-planning niet toegestaan), zijn er dadelijk twee stromen in het planningsproces: zelf-planning en ziekenhuis planning. De totale capaciteit (tijdsloten) dient verdeeld te worden over de twee stromen, waarbij een goede verhouding noodzakelijk is, zodat de ene stroom niet ten koste gaat in prestatie ten opzichte van de andere stroom. We meten deze prestatie aan de hand van het service level voor zelf-planning patiënten en het service level voor ziekenhuisplanning.

We definiëren het servicelevel als het percentage patiënten bij wie voldoende tijdsloten worden aangeboden binnen hun afspraaktermijn. Hierbij gelden drie sloten als voldoende sloten voor zelf-planning patiënten en voor niet zelf-planning patiënten geldt één slot. Ons doel het maximaliseren van het minimum service level. We gebruiken voor de validatie van ons model de gegevens van de afdeling Urologie.

Het doel van het onderzoek is ontwikkelen van een aanpak die het mogelijk maakt om met behulp van een tactisch rooster zelf-planning te faciliteren, waarbij een zo hoog mogelijk minimum service level voor patiënten wordt behaald

Aanpak

Ons simulatiemodel is een uitbreiding op het theoretische model van Vermeulen et al. (2009) door een terugkeer systeem toe te voegen en de mogelijkheid voor zelf-planning te bieden, zie Figuur S.1. Met behulp van de metaheuristiek Simulated Annealing (SA) bepalen we de verdeling van het aantal tijdsloten per afspraakcode. We stemmen daarmee het aantal sloten af op het type patiënt dat het ziekenhuis instroomt (standaard model).

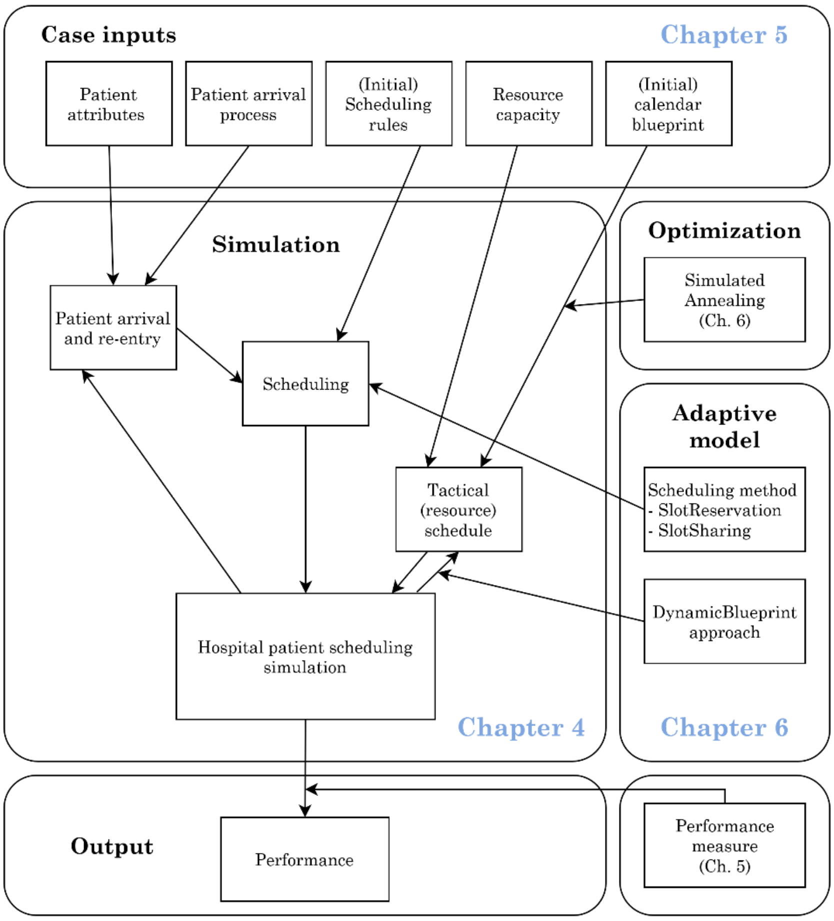


Figure S.1 – Overview of hospital patient scheduling model

Volgend op deze interventie experimenteren we met een nieuw ontwikkeld model met drie verschillende elementen.

Met behulp van het eerste element (SlotReservation) houden we capaciteit beschikbaar voor urgente patiënten om te voorkomen dat deze capaciteit al voortijdig wordt bezet door minder urgente patiënten. We creëren hiervoor een nieuwe afspraakcode, waarbij iedere patiënt met een afspraaktermijn korter dan een week (urgente patiënt) aangemerkt wordt als het type urgent.

Met het tweede element (SlotSharing) laten we, totdat een bepaalde drempelwaarde is bereikt, ook sloten zien aan zelf-planning patiënten die voor urgente patiënten zijn bedoeld. Op het moment dat de drempelwaarde wordt bereikt, worden de nog beschikbare tijdsloten geblokkeerd. Deze kunnen alleen gebruikt worden voor urgente patiënten om wederom te voorkomen dat deze capaciteit al voortijdig wordt bezet door minder urgente patiënten. Met dit tweede element bieden we meer mogelijkheden aan zelf-planning, resulterend in een hoger service level.

Aangezien alle patiënten met een afspraaktermijn korter dan een week urgente patiënten zijn, zijn alle tijdsloten met een andere afspraakcode niet meer benodigd. Het derde element (DynamicBlueprint) past de niet benodigde tijdsloten aan naar het type urgent.

We passen in onze experimenten de verschillende elementen toe in combinatie met de experimentele factoren: planningsroutine, het type patiënt dat zelf kan plannen en het reserveringsvenster. We passen een volledig factorial ontwerp toe, wat resulteert in 496 experimenten.

Resultaten en conclusies
Met behulp van Simulated Annealing zijn we voor ons standaard model in staat een absolute verbetering van het minimum service level te behalen van 6.1 procent punt; resulterend in een minimum service level van 80.6%. Voor ons model met de drie verschillende elementen behalen we met SA en enkele aanpassingen een minimum service level van 81.3%.

We concluderen dat ons model met de elementen SlotReservation + SlotSharing + DynamicBlueprint significant beter presteert dan het standaard model en dan de huidige uitgangspositie indien het MST geen aanpassing doet op haar proces. Daarnaast concluderen we dat de planning routine first come, random serve (FCRS) significant beter presteert dan first come, first serve (FCFS). Bovendien presteert het reserveringsvenster waarbij patiënten tot 15 dagen van tevoren hun afspraak kunnen plannen ook significant beter dan wanneer patiënten tot 8 dagen hun afspraak kunnen plannen. Voor verdere verklaring van deze resultaten, zie Hoofdstuk 7.2.

De keuze welk type patiënten zelf kan plannen heeft grote invloed op het minimum service level met gemiddeldes variërend tussen 57.8% en 81.4%. We bereiken met de beste configuraties een minimum service level variëren tussen 78.9% en 83.5%.

In vergelijking met de huidige uitgangspositie, concluderen we dat, voor iedere combinatie van het type patiënten dat mag zelf plannen, we een verbetering behalen met gebruik van ons model. Gemiddeld presteert ons model 14.1 procent punt beter dan de huidige uitgangspositie, met een maximum van 23.2 en een minimum van 6.9 procent punt. In - op zijn minst - 12 van de 16 mogelijke toewijzingen van afspraakcodes, presteert ons model met SlotReservation + SlotSharing + DynamicBlueprint met de planningsroutine FCRS en het reserveringsvenster waarbij patiënten tot 15 dagen van tevoren hun afspraak kunnen plannen het beste. We concluderen dat deze configuratie het meest efficiënt is voor het faciliteren van patiënt zelf-planning.

Aanbevelingen
We adviseren het Medisch Spectrum Twente om ons model met SlotReservation, SlotSharing, DynamicBlueprint door middel van een softwareapplicatie te implementeren in het nieuwe Elektronisch Patiënten Dossier. Daarnaast adviseren we het MST om hun besluit met betrekking tot het reserveringsvenster te herzien en te overwegen een reserveringsvenster van > 14 dagen te hanteren in plaats van > 7 dagen.
Voor de afdeling Urologie adviseren we het gebruik van een verbeterd tactisch rooster en daarnaast adviseren we het gebruik van FCRS als planningsroutine.

Het onderwerp patiënt zelf-planning is, bij ons beste weten, in de literatuur nog nooit wetenschappelijk onderzocht. Dit onderzoek kan als basis dienen voor vervolg onderzoeken met betrekking tot patiënt zelf-planning.

Management summary

Background and Research Objective
Medisch Spectrum Twente (MST) is a top clinical hospital in Enschede. In order to comply with their strategic objectives, a new Electronic Health Record (EHR) will be implemented at the end of 2021. With the new EHR, MST is capable of facilitating patients in planning their own appointments and thereby offering the patients more control over their care process. Self-scheduling is the process whereby patients, via a portal, are offered a selection of multiple time slots and then pick and choose their appointment date and time. Since the process of self-scheduling is not yet facilitated, it is not clear to MST how they should organise this process and what impact this has on the operational performance for all concerned.

In the current planning process, the planner needs to take into account several factors: the appointment window (the period in which the appointment needs to take place), the type of patient (e.g., new patient = NP), the required physician, the tactical schedule (blueprint in which per time slot by means of appointment codes is indicated which type of patient can be scheduled) and the planning routine (e.g., first come, first serve). With the introduction of self-scheduling, two additional factors emerge: the type of patients that are allowed to self-schedule and the booking window (the period during which a patient is allowed to book an appointment). As self-scheduling will not be available for all patients (e.g., patients that need to be seen within one week are not allowed), there will soon be two flows in the planning process: self-scheduling and hospital planning. The total capacity (time slots) must be divided between the two flows, which requires a good balance, so that one flow does not suffer in performance compared to the other. We measure this performance by the service level for self-scheduling patients and the service level for hospital scheduling.

We define the service level as the percentage of patients who are offered sufficient time slots within their appointment window. Three slots are considered sufficient slots for self-scheduling patients and one slot for non-self-scheduling patients. Our goal is to maximise the minimum service level. We use data from the Urology Department to validate our model.

The objective of the research is to develop an approach that facilitates patient self-scheduling assisted by a tactical schedule, which achieves the highest possible minimum service level for patients.

Approach
Our simulation model is an extension of the theoretical model of Vermeulen et al. (2009) by introducing a re-entry system and the ability for self-scheduling, see Figure S.2. Using the Simulated Annealing (SA) metaheuristic we determine the distribution of the number of time slots per appointment code. We match the number of slots to the type of patient that enters the hospital (standard model).

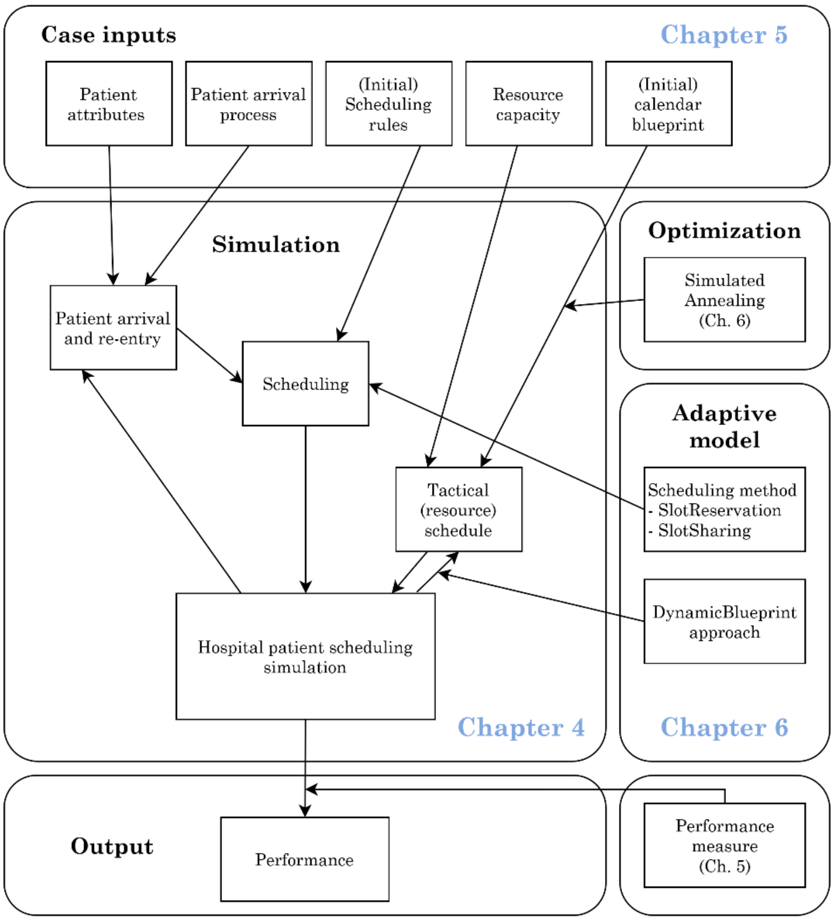


Figure S.2 – Overview of hospital patient scheduling model

As a follow-up to this intervention, we experiment with a newly developed model with three different elements.

Using the first element (SlotReservation) we keep capacity available for urgent patients to prevent this capacity from being prematurely occupied by less urgent patients. We create a new appointment code for this purpose, whereby every patient with an appointment time of less than one week (urgent patient) is classified as an urgent patient.

With the second element (SlotSharing) we also allow, until a certain threshold is reached, to show slots to self-scheduled patients that are meant for urgent patients. When the threshold is reached, the still available time slots are blocked. These can only be used for urgent patients, again preventing this capacity from being prematurely occupied by less urgent patients. With this second element, we offer more possibilities to self-scheduling patients, resulting in a higher service level.

Since all patients with an appointment time of less than one week are urgent patients, all time slots with a different appointment code are no longer required. The third element (DynamicBlueprint) adapts the not needed time slots to the type of urgent.

We apply the different elements in our experiments in combination with the experimental factors: scheduling routine, the type of patient that can schedule and the booking window. We apply a full factorial design, which results in 496 experiments.

Results and conclusions

Using Simulated Annealing, for our standard model we achieve an absolute improvement in the minimum service level of 6.1 percentage points; resulting in a minimum service level of 80.6%. For our model with the three different elements, with SA and some adjustments, we achieve a minimum service level of 81.3%.

We conclude that our model with the elements SlotReservation + SlotSharing + DynamicBlueprint performs significantly better than the standard model and than the current baseline if MST does not adjust its process. In addition, we conclude that the scheduling routine first come, random serve (FCRS) performs significantly better than first come, first serve (FCFS). Moreover, the booking window where patients can schedule their appointment up to 15 days in advance also performs significantly better than when patients can schedule their appointment up to 8 days in advance. For further explanation of these results, see Chapter 7.2.

The choice of which type of patients can schedule their own appointments has a major influence on the minimum service level with averages varying between 57.8% and 81.4%. With the best configurations we reach a minimum service level varying between 78.9% and 83.5%.

Compared to the current baseline, we conclude that, for any combination of patient types that may self-schedule, we achieve an improvement using our model. On average, our model performs 14.1 percentage points better than the current baseline, with a maximum of 23.2 and a minimum of 6.9 percentage points. In - at least - 12 of the 16 possible assignments of appointment codes, our model with SlotReservation + SlotSharing + DynamicBlueprint with the scheduling routine FCRS and the booking window where patients can schedule their appointment up to 15 days in advance performs best. We conclude that this configuration is the most efficient for facilitating patient self-scheduling.

Recommendations

We recommend Medisch Spectrum Twente to implement our adaptive model with SlotReservation, SlotSharing, DynamicBlueprint by means of a software application in the new Electronic Patient File. We also advise MST to review their decision regarding the booking window and to consider using a booking window of > 14 days.
For the Urology department we recommend the use of an improved tactical schedule and in addition we advise the use of FCRS as their scheduling routine.

To the best of our knowledge, the subject of patient self-scheduling has not yet been researched in the scientific literature. This study can serve as a basis for further research into patient self-scheduling.

Preface

In February 2020, I started looking for an assignment for my master's thesis, not knowing what an extraordinary year it would be. I consider myself lucky that, despite the pandemic, I can complete my research and with it my master's degree in time.
In the summer of 2020, I started my master thesis assignment, and now, about 7 months later, this thesis marks the end of my studies.
While graduating for my bachelor Technische Bedrijfskunde, but even more during a year of working full time, I realized that I wanted to challenge myself further and develop myself more academically. Therefore, it was obvious to choose the master Industrial Engineering and Management. In the past two years, I have been able to develop myself greatly and I can now look back on a very rewarding and satisfying time. But in the meantime, I am also looking forward to the future and all the challenges that are still to come.

Despite that I wrote my thesis almost entirely at home and that communication is much more difficult in these times, I look back on seven months in which I learned a lot, particularly in the field of patient scheduling and conducting academic research.

I am grateful to everyone who supported me during this thesis project. Some of you I'd like to thank in particular. I thank my parents Herman and Sabine for their support, their trust in me and the opportunities they always offered me during my entire study period. I also thank Sascha for all her support and sometimes endless proofreading of papers.
Furthermore, I thank Renske Bosems for her support throughout the writing of this thesis. In between the chaos in the hospital, she always managed to find a moment to help me. I also thank everyone in the Planning and Healthcare Logistics project team for their input and assistance. In particular I am grateful to Karin Derksen for all her time and effort in guiding me within the Urology Department.
Last, but certainly not least, I thank my supervisors at the University of Twente, Gréanne Leeftink and Erwin Hans. Gréanne has, with her critical view, helped me and my project to a new and higher level.

I hope you enjoy reading my thesis.

Martijn Nijhuis
Enschede, March 2021

Contents

1. Introduction

In this chapter, we introduce our research. Section 1.1. describes the hospital for which the study is carried out. The problem is discussed in more detail in section 1.2. With regard to the problem, section 1.3. describes the objective of the investigation. Finally, section 1.4. concludes the chapter with the research questions.

1.1. Company description

Medisch Spectrum Twente (MST) is a top clinical hospital in Enschede. MST was founded in 1990 as a result of a merger of several hospitals. These were hospitals from Enschede, Oldenzaal, Haaksbergen and Losser. In 2016, MST moved from the location Haaksbergerstraat and Ariënsplein to the new location Koningsplein. Alongside the main location in Enschede, care is also provided in the outpatient clinics in Oldenzaal and Haaksbergen (Medisch Spectrum Twente, 2019).

The hospital is one of the largest top clinical teaching hospitals in the Netherlands. All basic facilities are available within the MST, including a trauma centre, thoracic centre and a neurosurgical centre. The service area of MST covers the eastern part of the Netherlands and the German border region. With this coverage MST achieved a turnover of almost €435 million with a positive result of €4.8 million in 2018. Table 1.1 shows a couple of key figures for 2019 (Medisch Spectrum Twente, 2020).

Table 1.1 – Key Figures: Medisch Spectrum Twente 2019

Employees	**3,644**
• Medical specialists	250
• Nurses	1206
• Volunteers	166
Number of unique patients	**132,529**
• Admissions	26,408
• First outpatient visits	120,137
Bed capacity	**528**
Number of operating rooms	**14**

Several years ago, the financial position in MST was under debate. In order to improve this position, an efficiency programme was put into operation in the period 2016 - 2019. As part of this programme, the Integral Capacity Department (ICD) (Dutch: 'Ketencapaciteit') was set up in 2018. ICD provides insight into the availability of resources within the hospital as well as ensuring that the available resources are optimally aligned to the often changing demand for care. The aim of the department is to determine, make available and organise the capacity needs on a strategic, tactical and operational level on the basis of the expected demand for care.

In the strategic agenda 2018-2023, Medisch Spectrum Twente (2018) states that the IT within the hospital will be professionalized in the coming years. A new Electronic Health Record (EHR) will be implemented in 2021 in order to achieve this professionalization. In order to ensure that this implementation runs smoothly and correctly, the EHR programme and its structure will be operational from the end of 2019. The responsibility for the EHR programme belongs to the steering committee. In addition, project teams have been set up around various process domains with several assignments from the steering committee, such as the *Planning and Healthcare Logistics* project team. These project teams are led by process owners and supported by project leaders. The teams give their recommendations to the steering committee, after which the committee makes a decision on these recommendations. With this framework MST intends to launch the new EHR in 2021.

The reason for this research is that the project group *Planning and Healthcare Logistics* was given the assignment by the steering committee to make a recommendation whether patients can schedule their own outpatient consultations, medical examinations and treatments. This research is in line with this assignment and will provide a scientific basis on an adaptive approach to facilitate self-scheduling.

1.2. Problem description

For the period 2018 -2023, the Medisch Spectrum Twente has developed a strategy in its vision on care that includes a number of key aspects (Medisch Spectrum Twente, 2018):

- Providing 'value driven' and 'safe' care;
- Initiating further collaboration with patients and other healthcare providers in the healthcare chain;
- Focus on technological innovation, which should lead to opportunities for up-to-date knowledge sharing, partnerships and collaboration with the University of Twente;
- Care pathways are organised around the patient, whereby a portion of care may take place at home.

In order to achieve these objectives a new Electronic Health Record needs to be implemented, as the currently operating EHR is not sufficient. However, the implementation of an EHR is a complex and challenging process. Gesulga, Berjame, Moquiala, and Galido (2017) describe the fact that an alarming number of EHR implementations fail, with over 50% of EHR systems failing or being used improperly. As a result, the implementation of the system within the MST is not merely considered as an IT project, but rather as a transition trajectory for healthcare with substantial change components. In order to ensure a successful implementation, ambitions and policy frameworks of MST will be used as a foundation for the establishment of processes. In the first phase of the EHR programme, these frameworks - both new and existing - will be formulated, which will determine the (future) way of working. This is necessary to ensure that the EHR is in line with the processes and procedures in the hospital. This approach is consistent with the conclusion of the study by Ghazisaeidi, Ahmadi, Sadoughi and Safdari (2014). They state that a comprehensive roadmap and plan are necessary for a successful implementation.

The project group *Planning and Healthcare Logistics* has received assignments from the steering committee on the following themes:

1. Capacity control by the Integral Capacity Department.
2. Process planning and clustering in the wards, so that the patient is placed on the right bed.
3. Uniform planning process for the outpatient clinics and wards.
4. Admissions and OR-planning in clusters.
5. Patient can self-schedule as many outpatient activities as possible.
6. Communication with the patient takes place digitally, unless.
7. Optimally facilitating care outside the hospital.

As described in the fifth point, Medisch Spectrum Twente wants to offer the possibility of self-scheduling outpatient appointments to as many patients as possible. This is in line with the ambition to give patients control over their care process. Currently, appointments cannot be made by the patient him-/herself. As self-scheduling is not yet possible, this process has to be initiated. Because of the many dependencies, they do not know how to organise this process efficiently.

Since patients are currently unable to schedule their appointments themselves, the prospective situation is used for the problem analysis. This future situation - baseline scenario - becomes the basis of the problem analysis, as it would be implemented in this way without further thought. In the baseline scenario, it is assumed that a feasible and selected patient group is allowed to schedule its own appointments. This concerns all types of appointments. In addition, the patient has a choice of all available slots within the planning horizon. Outside the planning horizon, the appointment is planned by the hospital.

A brainstorming session with five senior managers, eight team leaders, four project leaders, the Chief Medical Information Officer (CMIO) and a medical manager OR revealed that there is a fear that the efficiency of the outpatient clinic will decrease when patients start scheduling their own appointments.

This research contributes to the prevention of the expected main problem; reduced utilization of the outpatient clinic. This problem is the starting point for the problem analysis. See the blue box of the problem cluster in Figure 1.1.

The problem analysis is performed on the basis of interviews with senior management, team managers, project leaders and operational planners. The reduced utilization of the outpatient clinic can lead to far-reaching consequences for both the patients and the staff. Examples include reduced quality of care and reduced job satisfaction. Figure 1.1 shows these consequences in a green box.

The analysis identified six root causes. These are highlighted in light red in Figure 1.1. The causes, in the context that patients can schedule their own appointments, are:

- Appointment is forgotten by the patient.
- Patient forgets to schedule an appointment.
- Planning cycle and horizon is too short.
- (Allocated) capacity is not optimal.

- Number of slots for 'self-scheduling' patients is not optimal.
- Time of slots for 'self-scheduling' patients is not optimal.

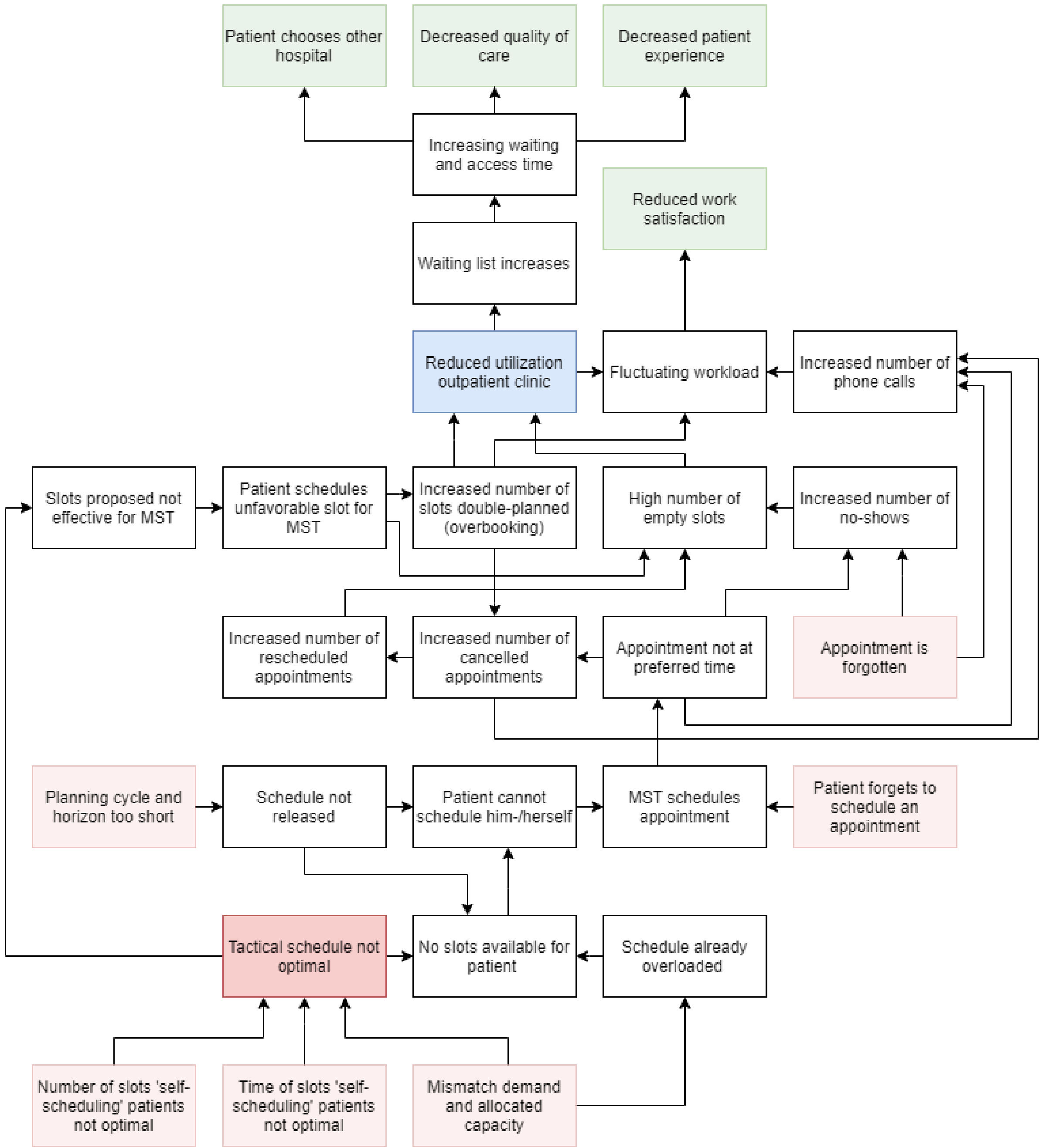


Figure 1.1 – Problem cluster self-scheduling

Appointment is forgotten by the patient
A patient may, due to various circumstances, forget the appointment at the hospital. This cause falls outside the scope of this research, since another project group is working on the concept of a reminder for the appointment. This should obviate this root cause.

Patient forgets to schedule an appointment
In addition to forgetting an appointment, a patient may also forget to schedule an appointment. In the brainstorm session this issue was also highlighted, however, the EHR provides the employees of the MST with a work list of patients to be scheduled. The focus of this study is not on this topic and the MST will have to address this issue in the future. Short-term solutions can be examined here as an extension of the reminder for a scheduled appointment.

Planning cycle and horizon is too short
Currently MST has its own planning cycle and horizon for each specialty. Due to the political connotations surrounding this subject, this cause is not included in the research. The Planning and Healthcare Logistics project group is working on an analysis of the various cycles and horizons. On the basis of this analysis, a recommendation will be made on the cycle and horizon to be used for the new EHR.

Tactical schedule is not optimal
Downstream of this problem there are three different root causes. The tactical scheme, also described as the blueprint, is not optimal due to three different causes.

1. *Mismatch demand and allocated*
   If the allocated capacity does not match the need for care, there may be an over- or underutilization in the tactical schedule. This can lead to a situation in which no slot is available for a patient.
   However, this underlying problem is not included in the research. The Capacity Department is working on a model to allocate outpatient capacities to specialties and to be able to scale up and down.

2. *Number of slots for 'self-scheduling' patients is not optimal.*
   If the number of slots for the group of self-scheduling patients is not optimal, this will result in a sub-optimal tactical schedule. If the number of slots is too low, there is a chance that no slots will be available for the patient. If the number of slots is too high, there is a risk that there will be excessive empty slots, leading to inefficient use of outpatient capacity.

3. *Time of slots for self-scheduling patients is not optimal.*
   The time in which blocks are released affects effectiveness for the MST. If this is not considered, there is a possibility that the patient is scheduling an appointment for the MST at an unfavourable time.

However, this underlying problem is not included in the research. We do not include this cause, as it makes the study too broad and we want to focus specifically on the distribution of slots and facilitating an efficient approach for self-scheduling patients.

This research provides a scientific basis for solving this problem in combination with an effective adaptive approach in order to be able to construct a tactical scheme and facilitate self-scheduling patients to the greatest extent possible.

1.3. Research objective and scope

In order to solve the future problem - a suboptimal tactical schedule - and thus to be prepared, we formulated a research objective. This objective must be achieved in order to ensure that the outpatient clinics can guarantee the highest possible level of service for both self-scheduling patients and non-self-scheduling patients.

The objective of the research is to develop an approach that facilitates patient self-scheduling assisted by a tactical schedule, which achieves the highest possible minimum service level for patients.

The research is delineated by considering one specialty, Urology, as a reference. The decision has been made for Urology, as this specialty covers a wide variety of patients. Urology has many types of patients regarding the planning, such as long and short cyclic patients. Based on Urology a method is developed whereby a tactical schedule can be determined and facilitate patient (self-)scheduling as efficiently as possible.

1.4. Research questions

In order to achieve the research objective, the main question of this research is:

" How can Medisch Spectrum Twente facilitate patient self-scheduling by using a tactical schedule?"

On the base of the research question, we answer the following sub-questions. Each question is accompanied by a brief explanation about the way in which this question is answered. In addition, it is indicated in which chapter each question is answered.

1. **How is the current planning process for outpatients organised?**

In Chapter 2 we show how the current planning process is organized. By means of interviews, literature review and examination of existing material (i.e., process descriptions) we answer this question. We explain how the Dutch healthcare system functions, what types of appointments appear in Urology, and what the patient planning process and the self-scheduling process involves.

2. **What is the current performance of the outpatient process in 2019?**

We discuss this question in Chapter 2 on the basis of interviews and analysis of existing material (i.e., business reports). We present the current performance based on a number of performance indicators.

3. **Which approaches can be adopted by the Medisch Spectrum Twente to address the challenges of introducing self-scheduling?**

In Chapter 3 we perform a literature review on self-scheduling based on various hierarchical levels. We address several approaches that can be applied by MST to the challenges related to self-scheduling.

4. **What approach or model is best applicable?**

According to the literature review resulting from Question 3, we identify the most appropriate approach or model to apply to our problem. We describe this approach or model in the conclusion of Chapter 3.

5. **What number of slots should be allocated to each appointment code?**

Using Simulated Annealing in a simulation model, we determine the number of slots per appointment code. We discuss our simulation model in Chapters 4 and 6 and Simulated Annealing in more detail in Chapter 6. We present the results in Chapter 7.

6. **Which approach is most efficient in facilitating patient self-scheduling?**

In Chapter 6 we discuss our experimental process, in which we experiment with different models, scheduling routines, allocations of self-scheduling to appointment codes and booking windows. We show the results of these experiments in Section 7.

7. **How can the most efficient approach be implemented in the organization?**

In chapter 8 we indicate how Medisch Spectrum Twente needs to implement our approach.

2. Outpatient planning process

In this chapter we discuss the outpatient planning process. This chapter describes in more detail the process surrounding the problem formulated in Chapter 1. Section 2.1. briefly explains the Dutch health system with regard to the inflow of patients. Subsequently, in Section 2.2. the types of codes that are used in the planning process to schedule appointments in the system are explained. Afterwards, Section 2.3. describes the process of planning at different levels, while Section 2.4. discusses the planning of appointments by patients. The chapter ends with Section 2.5, in which we provide an extended performance analysis. This chapter answers Question 1: How is the current planning process for outpatients organised? In addition, we also Question 2: 2. What is the current performance of the outpatient process in 2019?

2.1. Outpatient clinic inflow – Dutch healthcare system

In order to describe the planning process of the outpatient clinic, it is important to have knowledge about the different ways in which patients enter an outpatient clinic in the Dutch healthcare system. Overall, there are two flows: referred patients and emergency patients. Concerning patients with a referral, a distinction can be made between a referral by a general practitioner or a medical specialist. These are the possible flow of patients, as also shown in Figure 2.1 for the Urology Department case study, that we consider in this research.

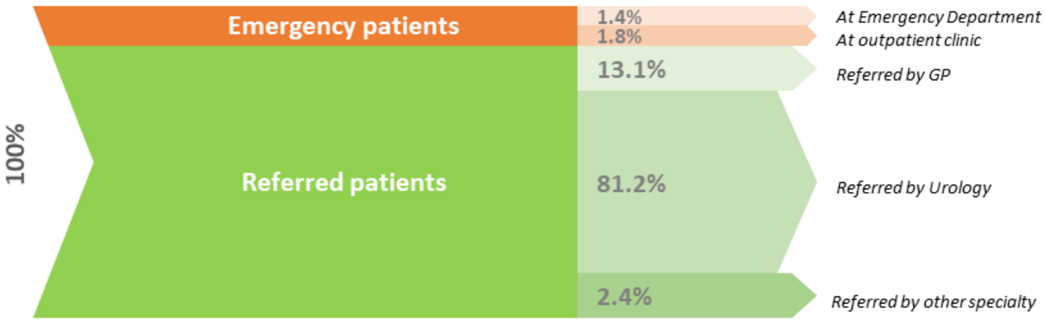


Figure 2.1 – Patient flows 2019 - Urology Department

At first, there is a flow of patients who enter the hospital with a referral. This referral is an important aspect in Dutch healthcare. The Dutch health care system is in fact divided into three types of care: primary, secondary and tertiary care (Nictiz, 2018). Primary care includes the care that everyone can use without a referral, e.g., the general practitioner (GP). Second line care is care where a referral (from a general practitioner) is required. If highly specialized care is needed, you can be referred to an institution for top clinical care. This is known as tertiary care. The Medisch Spectrum Twente provides secondary care and for some focus areas they are a referral centre offering tertiary care.

The majority of the referrals are made by the general practitioner. The general practitioner is in many cases the first contact person before being referred to a medical specialist and the hospital. In addition to the referrals from the general practitioner, a patient can also be referred by a medical specialist from one hospital to another, e.g., for a second opinion. The third group of referring physicians can be an internal referrer. This means that a patient is treated within a hospital for a medical disease and is referred by his/her specialist to another specialty.

The second flow of patients are the emergency patients. This flow of patients enters the hospital without a referral, for example with an ambulance. These patients enter the emergency department (ED) where they are first seen by an emergency physician, after which the patient - depending on his medical condition - can proceed further through the hospital in different ways. It might be the case that a medical specialist is called to the emergency department, but it is also possible that a patient has to go to the outpatient clinic.

However, it is important to mention that a patient can also be referred by a general practitioner to a hospital in an emergency. In most cases the patient is sent to an outpatient clinic instead of the emergency department. Furthermore, most emergency patients without a referral do not end up at the outpatient clinic or only at a later stage with a referral from an internal specialist.

Recall that our research focuses on the Urology Department of Medisch Spectrum Twente. In this department, [redacted][1] patients had a consultation in 2019. Of these [redacted] patients, [redacted] (1.44%) patients were seen at the emergency department and [redacted] (1.84%) patients with an emergency indication were treated at the outpatient clinic. These patients were the patients who entered the hospital without a referral. /2
The remaining [redacted] (96.72%) patients were the patients with a referral and were seen at the Urology outpatient clinic. Out of the [redacted] patients, [redacted] (13.52%) patients were referred by a general practitioner and [redacted] (84.00%) patients were referred by the Urology (e.g., recurring appointment). The remaining patients were referred internally by another specialty in the MST. Figure 2.2 shows the ratio of internal referrals per specialty.

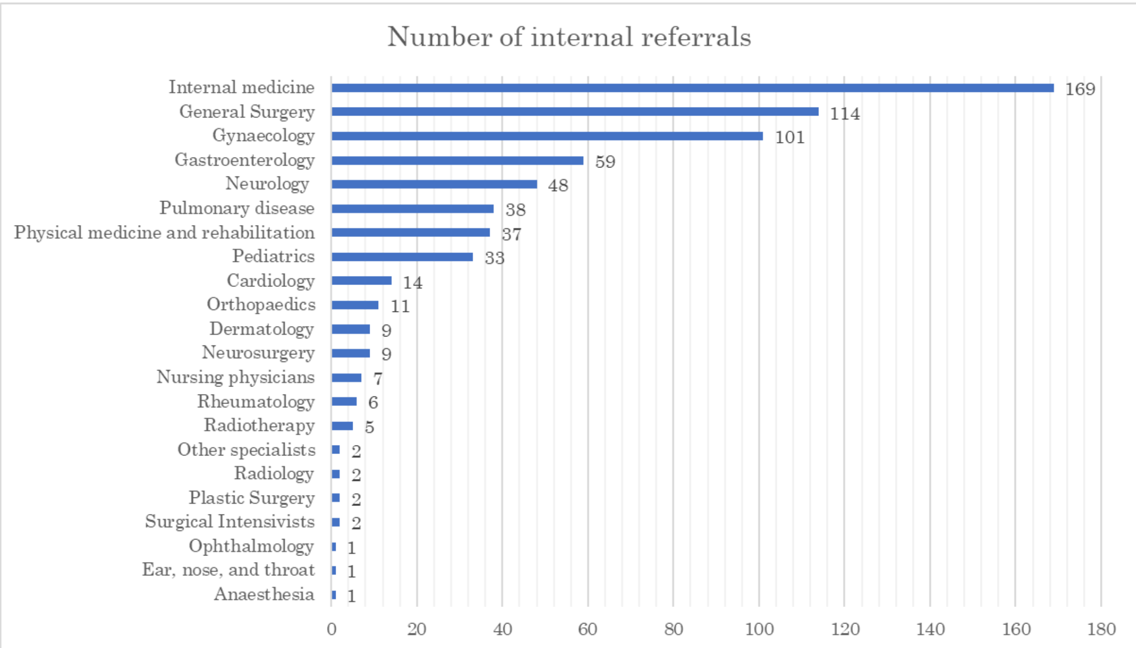


Figure 2.2 – Internal referrals outpatient appointments Urology

[1] Patients who had > 1 appointments on a single day are considered as a single patient. The referring party of the first appointment will be considered as the referrer.

2.2. Types of appointments – Urology Department

This section discusses the different types of appointments of the Urology Department. Subsection 2.2.1. discusses the use of appointment codes in more detail. In addition, Subsection 2.2.2. describes the various resources with associated codes.

2.2.1. Appointment codes

To plan (urology) appointments in the agenda of a medical specialist or in a consultation/treatment room various appointment codes are used in a blueprint schedule. With the help of the appointment code the planners can see which type of patient can be planned on the particular time slot. Using the appointment codes, a tactical schedule can be set up so that the right type of patient can be scheduled at the right place and time.

Over the year 2019, 93 unique appointment codes have been used for a total of [redacted] appointments. Table 2.1 shows the fifteen most frequent appointment codes. These fifteen codes represent 77.5% of the appointments. The use of the appointment codes follows the Pareto distribution, where 20% of the codes are used 80% of the time. Appendix I provides a complete list of appointment codes used in 2019 including their definitions.

Table 2.1 – Most frequently used appointment codes in 2019 - Urology

Appointment code	Number of appointments	Average duration (min.)	Standard deviation (min.)
CP	[redacted] (16.7%)	12.6	7.0
TC	[redacted] (14.2%)	12.2	5.0
NP	[redacted] (6.7%)	20.9	14.0
BELC	[redacted] (6.7%)	10.0	1.0
UCP	[redacted] (4.6%)	11.2	2.5
C-COMBI	[redacted] (4.3%)	5.2	1.3
CYCP	[redacted] (4.2%)	20.2	2.9
PATHO	[redacted] (3.6%)	14.8	2.9
NP-CYST	[redacted] (3.0%)	6.6	4.8
C-CYSTO	[redacted] (2.6%)	10.0	0.3
SPELD	[redacted] (2.4%)	15.6	6.1
CPF/E	[redacted] (2.3%)	12.3	5.0
WE	[redacted] (2.2%)	7.2	5.8
BLSP	[redacted] (2.0%)	16.3	4.7
ONCO	[redacted] (1.9%)	5.8	1.8

Table 2.1. shows very large standard deviations of the duration for several appointment codes compared to the average duration, e.g. NP and CP. This (large) standard deviation can simply be explained by the fact that the appointment codes are not uniquely dedicated to an executing healthcare provider. This means that, for instance, the CP slot can be listed in the schedule of a urologist, but also in the schedule of an oncology nurse. A nurse uses significantly more time than a urologist to monitor patients. This is because the type of patient assigned to the urologist is different from the type of patient assigned to the nurse. Therefore, the standard deviation varies so greatly.

Note that patients that receive an appointment can be scheduled on a combination of appointment codes. In the tactical schedule, these appointment codes are scheduled subsequently and the required resources (room and staff) for these subsequent appointment codes are equal. An example is NP-F/E, CP-F/E and C-COMBI.

The logic of using three codes instead of one is not related to the planning process, as the resources for all three codes are the same and the time is consecutive. This method of scheduling has a financial reason. The principle that is applied is the one-stop shop: bringing different services together in one day and location (RHIhub, 2018). In this case, the patient is first seen by a medical specialist, then undergoes examinations or treatment (by a medical specialist) and afterwards sees the medical specialist again. According to Dutch law, one outpatient clinic visit per day per specialty may be charged, unless it concerns a one-stop shop (Federatie Medisch Specialisten, 2018). For this purpose, the appointments have to be scheduled separately, so therefore the Urology Department registers the three appointments separately instead of one appointment.

For planning purposes, the combination of appointment codes can however be seen as a single appointment to be planned. Therefore, we perform a data processing step to merge these combinations of codes in the dataset with all appointments of 2019 into one appointment code, given the mentioned properties are valid. Table 2.2 shows the four most frequently used appointment codes combinations that were merged after the data modification. The resulting appointment code is presented in the first column of Table 2.2.

Table 2.2 – Most frequently used appointment codes in 2019 - Urology

Combination code	Appointment code I	Appointment code II	Appointment code III	Number of appointments	Average duration (min.)	Standard deviation (min.)
Combi-CYST	NP-CYST	C-CYSTO	C-COMBI	828	20.3	1.6
Combi-F/E	NP-F/E	CP-F/E	C-COMBI	330	15.2	1.2
Combi-TRE	NP-TRE	C-TRE	C-COMBI	191	20.0	0
Combi-PBX	NP-PBX	C-PBX	C-COMBI	10	21.0	3.2

2.2.2. Resource codes

As indicated in Section 2.2.1. the appointment codes are used to plan an appointment in the appointment calendar of the medical specialist or in a consultation/treatment room. The calendars of the staff and the different rooms are defined by resource codes. The resource codes are subdivided into two categories: healthcare provider and room.

Healthcare provider

In 2019, six urologists, one nurse practitioner and two assistant physicians not in training to become specialists (ANIOS) took care of the patients of the Urology Department. The nurse practitioner and the 2 ANIOS have only one calendar for the location Enschede of the MST and therefore one resource code. The urologists have an appointment calendar / resource code for the location Enschede and one for the outpatient clinic not in Enschede (Oldenzaal and Haaksbergen). Table 2.3 provides an overview of the different resource codes of the healthcare providers. The first letter of the resource code stands for the location and the other letters are an abbreviation of the name of the healthcare provider. The number of sessions and the average number of appointments per session is based on the data in which the appointment codes are combined, as discussed in Section 2.2.1. A session involves half a day. Two sessions per day can be scheduled (morning and afternoon).

Table 2.3 – Resource codes: Healthcare providers - Urology

	Resource code	Number of sessions	Avg. number of appointments	Resource code	Number of sessions	Avg. number of appointments
Urologist	EASSE	129	13.2	OASSE	31	20.5
Urologist	ESANT	150	11.3	OSANT	35	19.6
Urologist	EPIT	133	11.8	WPIT	37	15.9
Urologist	EKORT	115	11.5	WKORT	30	18.0
Urologist	ELEEN	96	12.6	OLEEN	46	22.7
Urologist	EWAARD	99	9.9	OWAARD	32	18.7
Nurse practitioner	EBEE	184	12.8			
ANIOS	ESCHOL	70	3.8			
ANIOS	EBERK	281	5.3			

Room

The category 'room' includes a wide variety of resource codes. This category includes calendars based on treatment rooms, meetings and nurses.

Treatment rooms

The Urology Department is equipped with four treatment rooms where outpatient interventions or diagnostics are carried out. The resource codes for these four rooms are EUROBP1 (493 sessions), EUROBP2 (258 sessions), EUROBP3 (48 sessions) and EUROBP6 (492 sessions). The average number of appointments per session scheduled on these resources respectively is 5.8, 6.0, 5.3 and 4.2. The first three rooms are mainly used by the urologists, while the last room is mainly used to schedule patients seen by the nurses for treatment (e.g. bladder flushing).

Meetings

Patients are scheduled on various meeting calendars to be discussed by the urologists in a relevant meeting. Table 2.4 lists these agendas with associated consultations.

Table 2.4 – Resource codes: meetings

Resource code	Description	Number of appointments
EURONCO	Multidisciplinary consultation oncology	524
EUROG	Urology and Gynaecology consultation	436
EURONCOP	Multidisciplinary consultation oncology specific for prostate patients	132
EURORB	Radiology consultation	69
EUROMA	Association (Dutch: Maatschap) meeting	53
ESANTRCR	Patient visits in Roessingh	33

Nurses

In addition to the aforementioned healthcare providers, patients are also seen, discussed or treated by nurses. Not every nurse has a separate calendar, but the choice has been made to set up an appointment calendar for each type of patient. Table 2.5 shows an overview of the calendars of the nurses.

Table 2.5 – Resource codes: nurses

Resource code	Description	Number of appointments
EONCOVP	Nurse's consultations for oncological patients	3207
EPTNS	Treatment (Percutaneous Tibial Nerve Stimulation)	303
EUROGV	Combined consultation Urology and Gynaecology	164
ESTOMA	Consultation for patients with a stoma	158
EESWL	Treatment of kidney stones (by external company)	136
EUDO	Patient visits in Roessingh	113

2.3. Patient planning process

This section explains the planning process within the Urology outpatient clinic. The first part of the paragraph outlines staff planning and scheduling at the tactical level. Subsequently, the operational scheduling process is described.

Staffing

The patient planning process starts with the staffing allocation.
The first step in this process is to incorporate the approved holiday days of the staff into the work schedule. In addition, for the Urologists, administrative moments (parts of the day) are also scheduled.

As soon as the Urologists' working days have been allocated, the surgery sessions (OR-days) are assigned to each urologist. The department receives the Master Surgery Schedule (MSS) from the Integral Capacity Department. This schedule specifies the assignment of an operating room to a specialty on a particular day.
When this schedule is received by Urology, the OR-days will be allocated to the urologists. This allocation will be carried out uniformly. This means that the days are distributed as evenly as possible among the urologists.

After scheduling the holiday, administration and OR-days, one urologist will be assigned for each day to carry out visits at the ward and to treat the emergency patients. The urologist has various slots during the day (9.00h - 10.00h, 11.00h - 12.00h and 13.00h - 14.30h) to treat emergency patients at the Emergency Department or in their own department. The first treatment room is assigned to the 'emergency' urologist for the full day.

Once this allocation is made, the availability of physicians for outpatient appointments and surgeries is known. First, a physician will be assigned to the second treatment room. In general, two physicians per day, each for a part of the day, will be allocated to the treatment room. The other part of the day the physician carries out outpatient appointments. Once again, this apportionment is uniform.
Finally, the sessions for the outpatient appointments remain. The remaining physicians are assigned to perform consultations. The location Enschede has the highest priority in this respect and, if possible, consultation sessions are held at the other locations (Oldenzaal and Haaksbergen). At least one day a week a physician is present at the other two locations. Figure 2.3 shows an example of a schedule of one week in April 2019.

		Mon	Tue	Wed	Thu	Fri	Sat	Sun
Urologist 1	AM	pz	OK	spr	pok	SVS		
	PM	pz	OK	spr	spr	suvi		
	EVE				DU			
Urologist 2	AM	pok	mw	C	VS	OK		
	PM	spr	UG	C	suvi	OK		
	EVE	DU						
Urologist 3	AM	spr	pz	OK	spr	rv		
	PM	pok	pz	OK	spr	rv		
	EVE					DU	DU	DU
Urologist 4	AM	OK	UG	SVS	pH	pz		
	PM	OK	spr	suvi	pH	pz		
	EVE			DU				
Urologist 5	AM	pz	SVS	pok	OK	pO		
	PM	OK	suvi	spr	OK	pO		
	EVE		DU					
Urologist 6	AM	SVS	pz	rv	pO	pok		
	PM	suvi	pz	rv	pO	spr		
	EVE							

Abbr.	Description
OK	OR-Day
pok	Outpatient surgery
DU	Duty
SVS Suvi VS	Emergency shift
Spr	Consultation (Enschede)
pH	Consultation (Haaksbergen)
pO	Consultation (Oldenzaal)
pz	
UG	Combination with Gyn
Rv	Day-off
C	Congress
mw	Association (Dutch: Maatschap)

Figure 2.3 – Example schedule April 2019 - Urology

Planning on tactical level

At a tactical level, a blueprint is used for the calendars of healthcare providers, see Section 2.2 for an overview of these calendars. A single day consists of two sessions: the morning session and the afternoon session. Figure 2.4 shows the blueprint of an afternoon session consisting of outpatient appointments. The blueprint for the morning session is the same as the blueprint for the afternoon session and applies to every urologist. Figure 2.4 shows six appointments coloured yellow. These two blocks of three appointments are the combined appointments as discussed in Section 2.2. In addition, within the blueprint, see red block in Figure 2.4, a block has been chosen to accommodate any delays or unforeseen circumstances and have some time for a (bathroom)break.
The agendas from the other category (Room) do not use a relevant blueprint. This is an open agenda with no preference for the number and type of appointments.

Operational scheduling

Within the operational scheduling process, a distinction is made between emergency patients, patients with a referral from the GP or an internal referral and patients with a referral from a urologist (re-visits).

An emergency patient can enter the hospital in two different ways, see Section 2.1. The first route is via the general practitioner. In case a GP assesses that the patient needs to be seen by the urologist today, the GP calls the attending ('emergency') urologist via an emergency phone. The urologist will inform the secretariat at which time the patient arrives and they register the patient in the calendar of the urologist.
Furthermore, a patient can also present him- or herself at the Emergency Department. If the ED physician assesses that the patient should be seen by the urologist, the physician also calls the attending urologist. This procedure is the same as for the emergency patient referred by the GP.

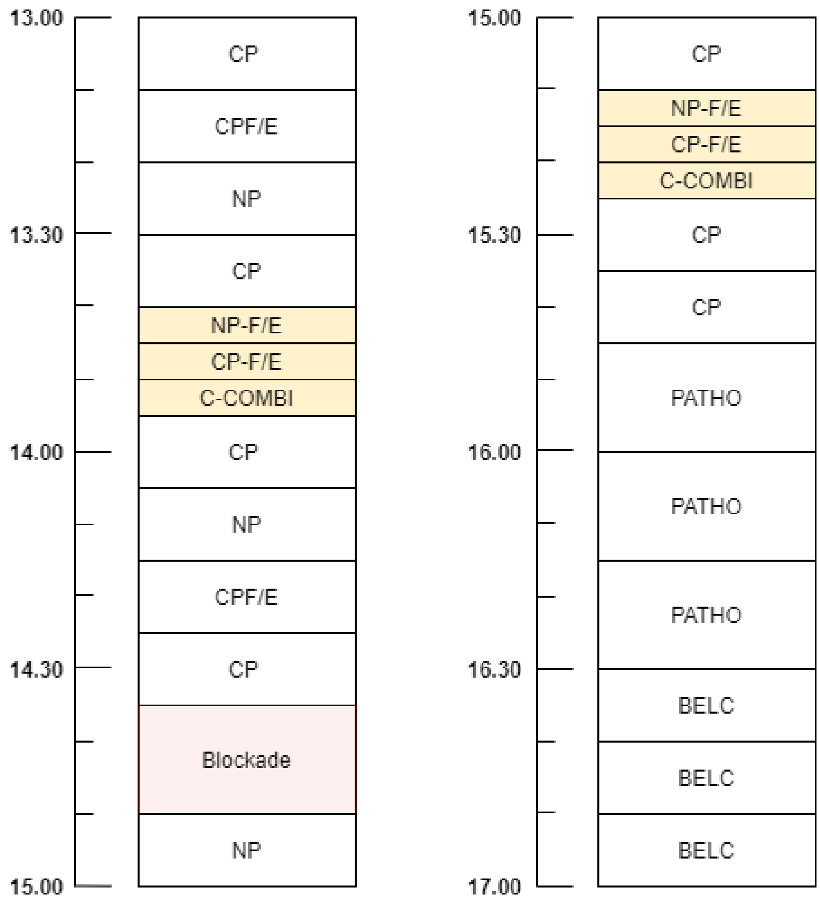


Figure 2.4 – Tactical schedule: afternoon session healthcare provider

If a patient is referred by the GP or another medical specialist, the referral arrives at the department and is reviewed by a urologist. In this triage, the urologist determines the urgency and time frame in which the patient should be seen. In addition, the urologist also determines whether (additional) examination is necessary before the consultation with the urologist will take place.

Using this information, it is clear to the planner of the Urology in which appointment calendar the appointment should be scheduled with the corresponding appointment code. The planner searches for a first free slot in the calendar with the appropriate code and schedules the patient at this particular slot. The principle first come, first serve (FCFS) is applied. The first free slot within the time frame is used for the patient who appears first. In case of not finding a vacant slot within the correct time frame, a slot with a different code will be rebooked to the required slot. For example; a NP-slot will be converted to a CP-slot, if this slot is requested. If there are no slots available left at all, then a less urgent appointment will be rescheduled to a later date, allowing a slot to be vacated.

After an appointment with the urologist, and the patient needs a follow-up visit, the patient will be sent to the reception desk. The assistant searches for a free slot in the calendar with the correct code within the given time frame and schedules the patient at the right slot. The principle FCFS is also applied at this point. The patient is also asked for their preference and this preference precedes FCFS. However, they offer the slots that will occur first. If no free slot is found within the correct time frame, a slot with a different appointment code will be converted to the required slot.

A booking period of eight weeks applied to all appointments in 2019. This means that the secretary can schedule a new and a recurring appointment eight weeks in advance. If an appointment has to be scheduled later, the patient is assigned to a waiting list. As soon as the slots have been released in the correct time frame, the appointment will be scheduled for the patient. The patient will be notified by letter regarding the appointment date and time.

2.4. Self-scheduling process

In this paragraph we will discuss the process of self-planning. As indicated earlier, a patient is currently not able to schedule his or her own appointments. As a first step towards enabling patient self-planning, the project group *Planning and Healthcare Logistics* has defined a number of criteria concerning the process of self-planning by patients. This paragraph describes these criteria in more detail. In addition, a brief introduction is included of the self-planning possibilities of the chosen Electronic Health Record, HiX from the producer Chipsoft.

Criteria self-planning process

As indicated in Section 1.2, the project group *Planning and Healthcare* has received the assignment to form criteria with regard to scheduling of appointments by patients themselves. Since the implementation of the EHR is carried out jointly with another hospital, Ziekenhuisgroep Twente (ZGT), the frameworks for the process have been drawn up collectively and are applicable to both hospitals.

Both boards of the hospitals have agreed to the following frameworks:

1. Joint vision MST and ZGT: as many appointments at outpatient clinics and diagnostics as possible are made available, so that patients can schedule their appointments via the portal.
2. When starting with the HiX portal, all single (revisit) schedulable appointments at all outpatient clinics in MST and ZGT and where possible within their own specialty with combination appointments become available for self-planning.
3. Patients can plan, change, and cancel appointments in the portal:
   a. Within the booking period, patients can plan, change, and cancel appointments.
   b. Outside the booking period, patients cannot schedule appointments.
   c. Patients can cancel or change appointments up to 1 week prior to the appointment using 'fixed' mutation reasons. Within this period the outpatient clinic will be contacted by phone.
4. Patients can choose a care provider based on rules and conditions.

For the booking period a planning horizon and planning cycle is used. The planning horizon is set for outpatient appointments at twelve weeks and the planning cycle is set at four weeks. This means that there is always a booking period of a minimum of eight weeks and a maximum of twelve weeks available. Thus, a schedule is initially released for twelve weeks. As soon as four weeks have passed - at that moment eight weeks are still available for planning - the next four weeks will be made available, resulting in a twelve week schedule again.

Self-planning possibilities of the EHR

The EHR makes a distinction between two groups of patients when it comes to self-planning of appointments: patients with a digital referral (Dutch: Zorgdomein verwijzing) from the GP and patients with a re-visit out of the booking period.

For patients with a referral via Zorgdomein, the GP defines the appointment code, time frame and the relevant medical specialist. The patient then receives all free slots in the appropriate agenda in the relevant time frame. The patient can choose between all these slots. This configuration has been chosen by other hospitals. However, the EHR also allows triage not by the GP, but by the medical specialist. If MST chooses this configuration, the GP will send a referral to the hospital. The urologist then determines the physician, the appointment code and the time frame for the appointment. The patient then receives a message that he or she can schedule his or her appointment and sees all possible slots that meet the conditions (appointment code, calendar and time frame).

If a patient needs a recurring appointment that needs to be scheduled outside the booking period, the patient will be added to a waiting list. If this is the case, the scheduler can choose to allow the patient to schedule his or her own appointment as soon as the scheduling period has become available. The scheduler then indicates on which appointment code and calendar the patient should be scheduled. Furthermore, the booking date is also indicated for when the date should be registered (booking date) and between which dates the appointment should take place (appointment date). The patient is subsequently provided with all the free slots of the required calendar with the relevant appointment code that lies between the correct time frame.
Currently, the HiX EHR does not allow patients who need a recurring appointment to schedule their own appointment if this need to be scheduled within the booking period.
However, there is a workaround which makes it technically possible for these patients to schedule their own appointments. This workaround involves fictitiously placing a patient on a waiting list by indicating that that patient should be scheduled outside the booking period. At that point, the patient is placed on the waiting list and then indicated that the patient can plan for him or herself with the correct dates in which the appointment should be scheduled. Presumably, this workaround will be converted to a permanent function within the EHR in the near future.

2.5. Process performance

Since there are concerns regarding the performance of the outpatient clinics when self-scheduling is started, this section will further highlight the performance of the (planning) process. Currently at the Urology Department, there is a monthly Business Review (BR). This report presents the performance of the entire department. This includes key figures relating to production, revenue, surgeries and personnel. In this section, we only discuss the KPIs that are relevant for the outpatient clinic. In addition to the KPIs of the BR, additional KPIs that we consider relevant for the outpatient planning process are discussed in this section. The performance indicators are based on the 2019 outpatient data after data modification (combination of appointments merged) as mentioned in Section 2.2. Finally, the appointment lead-time, which is currently used as a uniform KPI in the hospital for assessment and benchmarking all specialties.

Monthly Business Review

Number of new visits

The number of new visits reflects how many patients with a new request for care enter the hospital and are declarable. A visit is declarable if the patient has a (online) face-to-face contact with a medical specialist, assistant physician or nurse practitioner. A new request for care does not necessarily mean a new or as yet unknown patient. It could also refer to a patient who is already being treated and who presents with a new complaint. In the Business Review, this KPI is shown as a total for the entire department. We choose to make a distinction between different flows for a deeper insight. The three different flows are the regular consultation hours (care provider), Emergency Department and the treatment consultations hours (treatment room). We make a distinction between care provider and treatment room, as this implies that a patient who comes to the regular consultation is classified as a care provider and the patient who is treated at his or her first visit is classified as part of the treatment room.

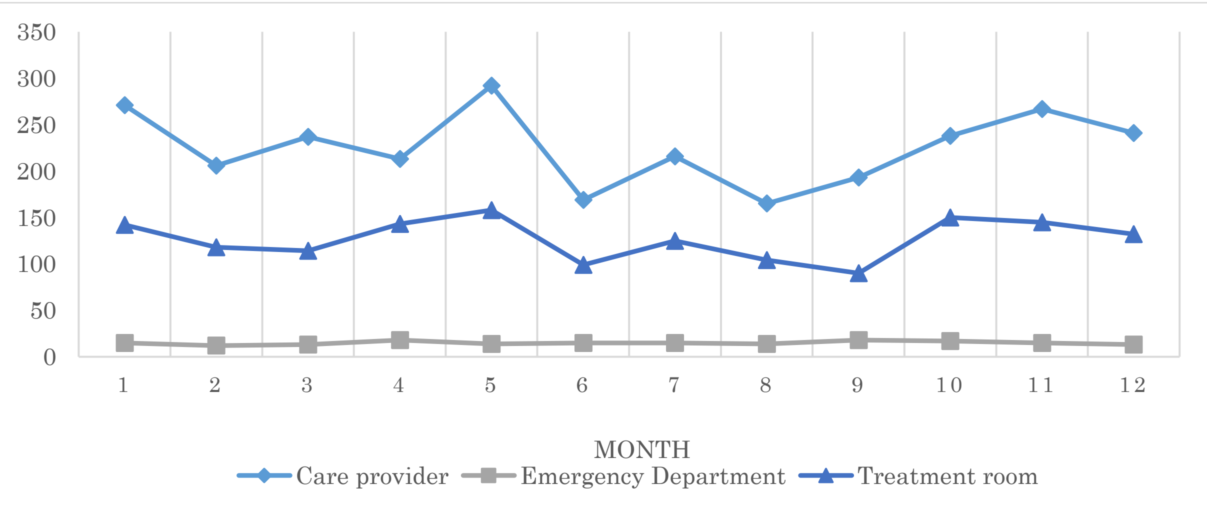


Figure 2.5 – Number of new visits per month - Urology Department 2019

It is clearly noticeable in Figure 2.5 that the number of new visits to the Emergency Department does not depend on time. These visits are evenly distributed over the year. However, the total number of new visits in the summer months (June up to September) is considerably less compared to the rest of the year. This is probably due to the fact that patients prefer to go on holiday and visit the hospital before or after the holiday period. Alternatively, it can be explained by the absence of care providers, resulting in fewer sessions for patients attending outpatient clinics.

Number of revisits

The number of revisits reflects the number of registered declarable follow-up visits. A revisit is a consultation with a known patient with a well-known health issue. As it concerns declarable consultations, this performance indicator does not include the number of visits performed by nurses. Compared to the standard Business Review report, again, a distinction is made between the three different flows. There is also a difference of approximately 300 visits per month in Figure 2.6 compared with the Business Review. This is due to the fact that telephone consultations were not included in Figure 2.6 and also due to the data modification as stated in Section 2.2. In the case of combination appointments consisting of three appointments, the third appointment is usually registered as a revisit and is thereby included in the Business Review report.

The average number of revisits per month is 772 with a standard deviation of 58, see Figure 2.6. It is interesting to note that the months of September and October are considerably lower. An explanation for this can be sought in the lower number of new visits in the summer months. The number of revisits is dependent on the number of new visits in the previous period. Furthermore, the number of revisits looks rather stable for the rest of the year.

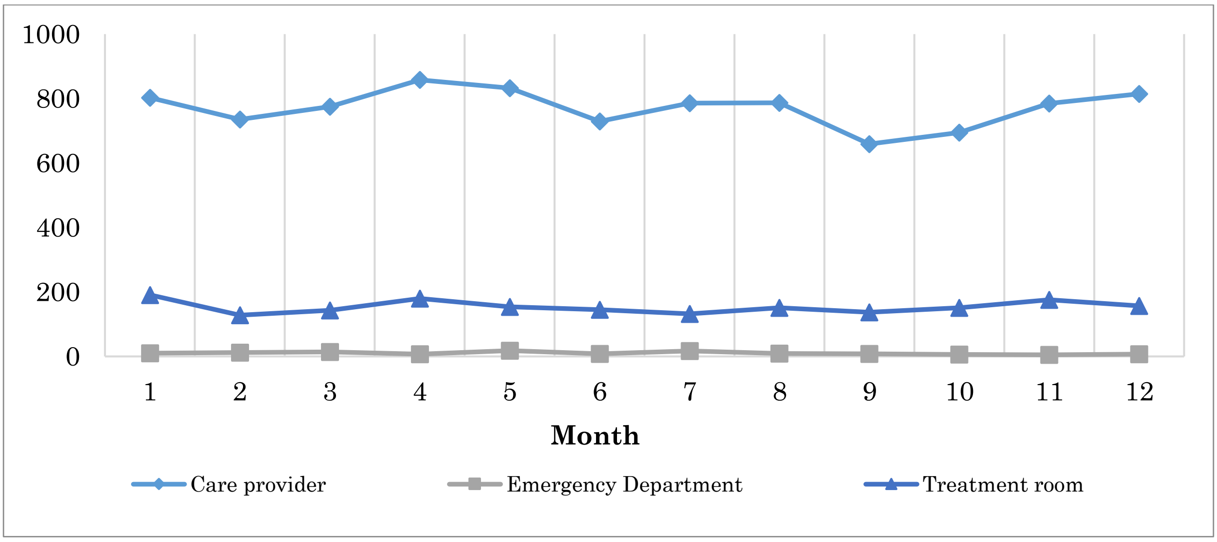


Figure 2.6 – Number of revisits per month - Urology Department 2019

Number of telephone consultations

In addition to physical contacts, patients may receive a telephone consultation in their care process. These telephone consultations comprise two categories: declarable and non-declarable. A declarable telephone consultation replaces a physical consultation, and in this consultation at least a medical specialist, assistant physician or nurse practitioner discusses both strategy and progress of the treatment. If a telephone consultation is not performed by one of these three persons or if no strategy and progress is discussed, the telephone consultation is not declarable.

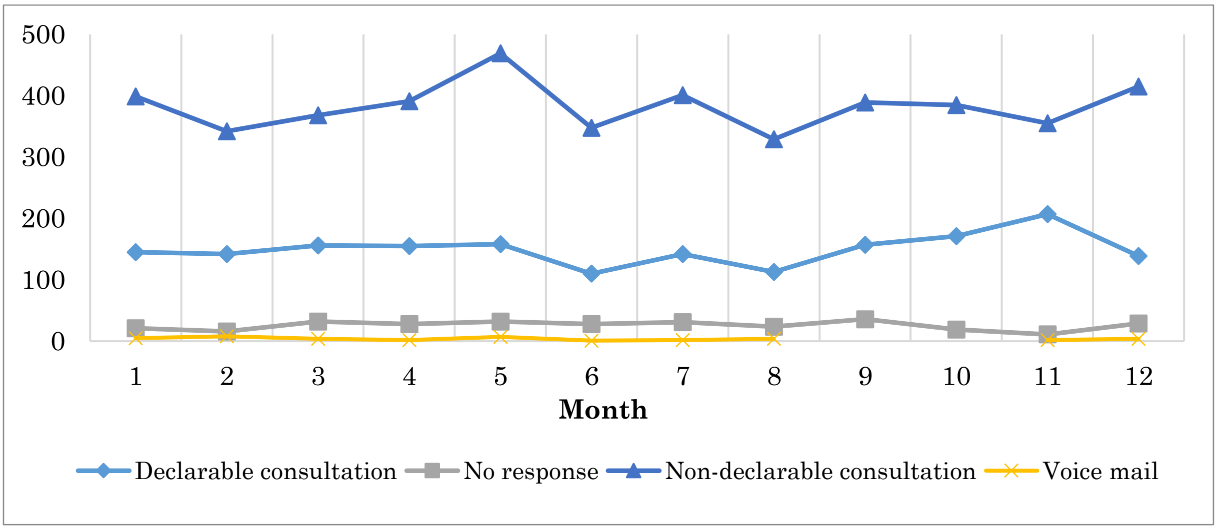


Figure 2.7 – Number of telephone consultations per month - Urology Department 2019

Unfortunately, due to inadequate data logging within the current EHR, it is not possible to distinguish between non-declarable telephone consultations. Using data analytics, it is not possible to determine whether a consultation was carried out by a nurse or whether the physician did not discuss strategy and progress. This is only possible by means of chart reviews; however, this would exceed the purpose of this research. In addition to the consultations that were carried out, it also occurs that patients do not answer their telephone or that a message is left on voice mail.

Number of no-shows and no-show rate

The number of no-shows, depicted in Figure 2.8, reflects the number of patients not showing up for their appointment. The number of no-shows does not include the number of appointments that are cancelled or rescheduled.

Figure 2.8 illustrates that there is little evidence of seasonality. The number of no-shows appears to be fairly evenly distributed throughout the year, with a few peaks upwards (January) and downwards (March and December).

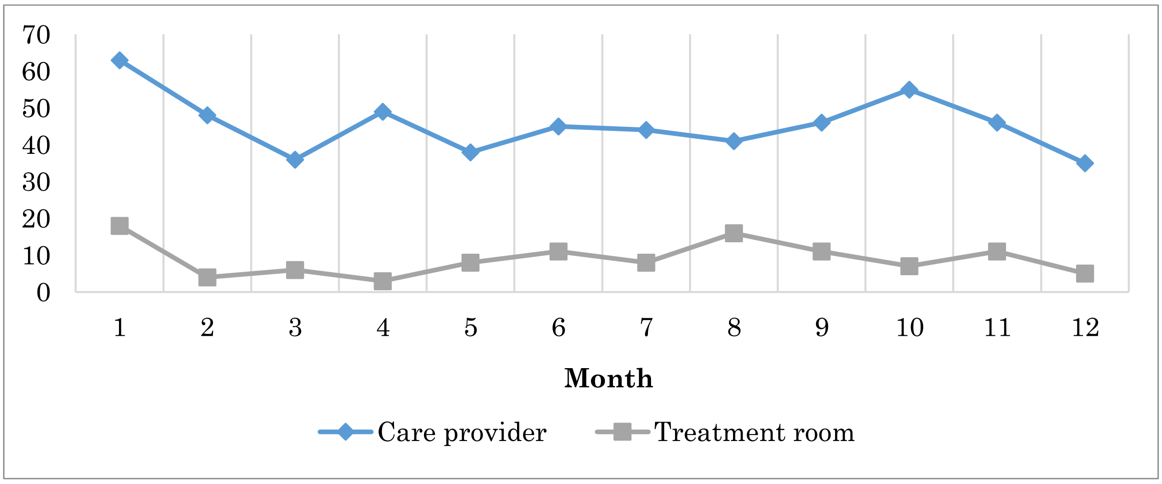


Figure 2.8 – Number of no-shows per month - Urology Department 2019

Apart from the absolute number of no-shows, the no-show rate is also reported in the Business Review. The no-show rate is based on the number of no-shows divided by the total number of physical consultations. The total number of physical consultations includes both new and repeat visits, excluding consultations by telephone.
Figure 2.9 shows that the no-show rate among care providers is around 4.5% to 5% and is relatively constant. However, the rate for patients treated in the treatment room is much more fluctuating. This is partly due to the fact that the total number of consultations is much lower, so an extra no-show has a large impact on the no-show rate. Moreover, anxiety is also a factor with regard to the treatment rooms. Patients receive interventions here and they fail to show up because they are afraid.

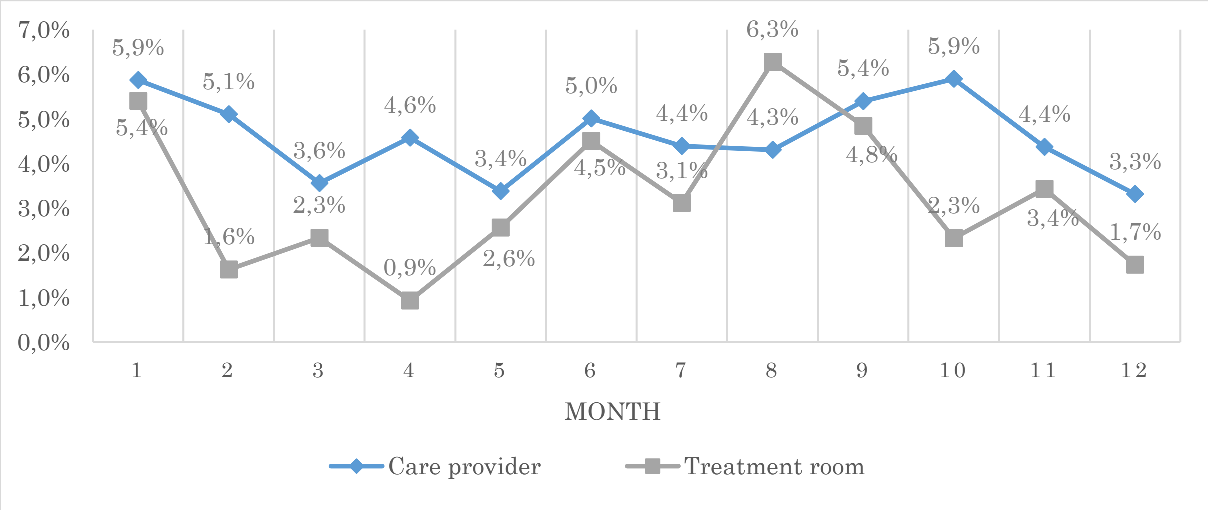


Figure 2.9 – No-show rate per month - Urology Department 2019

Additional relevant outpatient performance indicators

Utilization

A relevant performance indicator of the outpatient process is the utilization of the available time and thus the resources. To determine the available time, the number of sessions available in 2019 was quantified. Each session spans four hours (i.e. 8.00h - 12.00h and 13.00h - 17.00h). With this, we calculate the available number of minutes. Secondly, we calculate the amount of time spent on appointments. For each category of calendar and/or location the appointments that are considered as appointment time are determined separately. This variation is caused by the fact that appointments of nurses (e.g. at the outpatient clinics not in Enschede) are also booked on some calendars.

<u>Care providers - Location Enschede</u>

These schedules (resource codes) include two types of shifts, namely 'normal' outpatient consultations and daytime emergency shifts. As the second category does not give a representative indication of utilization, we excluded these sessions. The number of sessions is only the number of sessions devoted to a complete outpatient consultation session.
To calculate the appointment time, we include all physical appointments and telephone consultations (both chargeable and non-chargeable). Appointments for which patients did not show up and telephone consultations for which there was no response or a voice mail was recorded are excluded.

Table 2.6 shows the utilization per calendar and thereby care provider. The average utilization in Enschede of the six urologists is 76.6%, of the two assistant physicians not in training to become specialists (ANIOS) is 52.0% and of the nurse practitioner (NP) is 66.2%. An important factor to consider is that the available time does not take into account the blockage in each session. Each session, as depicted before in Figure 2.4, includes a 15-minute time blockage. This blockage decreases the utilization by 6.25% each session, making the maximum achievable utilization 93.5%. In total, 3380 minutes were not utilized due to patients not turning up or not being reachable by phone. This is a loss in utilization of 4.0%.

Table 2.6 – Utilisation: Care providers - Location Enschede 2019

	Number of sessions	Available time (min.)	Appointment time (min.)	**Utilization**	Overtime (min.)
	Morning				
Urologist 1	29	6960	5775	**83%**	505
NP 1	76	18240	11505	**63%**	80
ANIOS 1					
Urologist 2	14	3360	2510	**75%**	180
Urologist 3	32	7680	6185	**81%**	650
Urologist 4	21	5040	4025	**80%**	415
Urologist 5	37	8880	6755	**76%**	420
ANIOS 2					
Urologist 6	23	5520	3750	**68%**	390
	Afternoon				
Urologist 1	37	8880	7200	**81%**	20
NP 1	75	18000	12480	**69%**	80
ANIOS 1	84	20160	10760	**53%**	0
Urologist 2	44	10560	7750	**73%**	0
Urologist 3	23	5520	4470	**81%**	10
Urologist 4	39	9360	7855	**84%**	20
Urologist 5	36	8640	6180	**72%**	0
ANIOS 2	6	1440	480	**33%**	0
Urologist 6	19	4560	2610	**57%**	10

The lower utilization of the two ANIOS is natural, as they are given more time to prepare for consultations and also work together with the urologists. In addition to the utilization, the overtime can also be interpreted. For the morning, this means the number of minutes of patient care between 12.00h and 13.00h. For the afternoon, this means the number of minutes of patient care after 17.00h.

Since the focus of this study is on the regular (standard) consultation hours performed by the medical specialists, in our case urologists, the utilization rates for the other locations and calendars (i.e. treatment room) are presented in Appendix II.

Number of rescheduled appointments

The following relevant performance indicator is the number of rescheduled appointments. A rescheduled appointment is defined as an appointment for which the patient has received an invitation with date and time and the appointment is rescheduled to another date or time. The Urology Department always calls patients when appointments are rescheduled. In addition, patients can call the secretary requesting to reschedule their appointment, as the appointment is scheduled at an inconvenient time for the patient. As a result, the number of rescheduled appointments has a direct impact on the number of phone calls made and received by the department and therefore on the overall workload.

Unfortunately, due to the settings and logging method of the current EHR, it is not possible to determine the number of transferred appointments retrospectively. In some cases, the date is changed and this is not logged. For other appointments, the appointment is cancelled and a new appointment is booked in the system.
Due to the current COVID-19 crisis, and thus a completely exceptional situation with regard to patient care, it has not been possible to keep track of a representative number of rescheduled appointments. For these reasons, we decide to ask the secretariat about their experience. This reveals that, on average, one to two appointments per session are rescheduled by the planners. They also indicate that on average one or two patients per session call to change their appointment date or time. If an appointment is rescheduled at the patient's request, the responsibility for changing the appointment date lies with the patient. This responsibility relates to the time that the patient should actually at least have been consulted.

Number of cancelled appointments

The final performance indicator to discuss is the number of cancelled appointments. A cancelled appointment is defined as an appointment that is cancelled by the patient 24h in advance and no new appointment is made unless the patient is newly referred to the Urology Department. Since a patient calls the department, the number of cancellations also affects the workload directly. The difference between a no-show and a cancelled appointment is the fact that with the cancelled appointment it is known that the patient will not attend, whereas with a no-show it is not known in advance.

For the same reasons as mentioned with the indicator 'number of rescheduled appointments', it is not possible to calculate the number of cancelled appointments from a dataset. Therefore, for this indicator as well, the experience of the secretariat is questioned. They indicate that about one or two patients call to cancel their appointment in advance.

Uniform Medisch Spectrum Twente performance indicator

Appointment lead-time

The appointment lead-time is the time between the referral (or request for an appointment) of a patient and the actual appointment. For this performance indicator, only new incoming patients are considered. Within MST, the norm is that 80% of patients must be seen and/or treated within three weeks and a 100% within four weeks.

Table 2.7 presents the actual figures of the Urology Department as shared by MST and shows the percentage of patients seen within three weeks. The appointment lead-time is based on the time of registration of the appointment and the date of the actual appointment.

As can be seen in Table 2.7, the Urology Department does not achieve the hospital's target. However, the hospital's report does not give a representative (and often too optimistic) indication. There can be a (significant) difference in time between the appointment and the actual referral. This difference arises because patients are not always scheduled immediately, and when patients are rescheduled, the original date is deleted and a new date is scheduled, changing the registration date.

The third row of Table 2.7 shows the percentage of the first six months of 2019 when looking at the referral date instead of the registration date of the appointment.

Table 2.7 – Percentage appointment lead-times within 3 weeks 2019

Month	**Jan.**	**Feb.**	**Mar.**	**Apr.**	**May**	**Jun.**	**Jul.**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**
Performance (actual figures)	47.8%	54.1%	54.8%	60.1%	52.1%	44.4%	54.9%	57.6%	54.1%	50.9%	45.3%	58.2%
Performance (corrected)	50.7%	37.5%	43.1%	25.9%	39.6%	41.0%						
Difference	3.9%	- 16.6%	-11.7%	-34.2%	-12.5%	- 3.4%						

2.6. Conclusions

In this chapter we analyse the current planning process of the Urology outpatient clinic. This answers the first and second sub-question of this research.

Question 1: How is the current planning process for outpatients organised?

In the first part of the chapter, we show two different inflow patterns of patients into the outpatient clinic: emergency patients and patients with a referral. In order to plan appointments for these patients, various appointment codes are used. With these codes, patients are scheduled in a specific appointment calendar. Within these calendars, a distinction is made between two categories: care provider and room.

The patient planning process starts with the allocation of staff, after which a blueprint is set up at a tactical level for the healthcare providers' calendar. A blueprint is not used for the calendars of the treatment rooms. At the operational level, a patient is scheduled in the correct time frame on the basis of FCFS. If no appropriate slot with appointment code is available within the time frame, another slot is rebooked or a less urgent patient is moved to a later time.

Concerning the scheduling of appointments by patients, frameworks have been formulated by the Planning and Healthcare Logistics project group. In its first phase, Medisch Spectrum Twente will start with the single (revisit) appointments. Within the possibilities offered by HiX, the outpatient clinic can provide the patient with several frameworks, such as the appointment code, the date by which the appointment must be scheduled by the patient and the time frame in which the appointment must take place.

Question 2: What is the current performance of the outpatient process in 2019?

The number of new visits per month is relatively stable throughout the year, with a slight reduction in the summer months (June until September). At the same time, the number of revisits per month is also stable, with a slight decrease after the summer months. The number of declarable telephone consultations was also quite stable throughout 2019, while the number of non-declarable telephone consultations was much higher and had its peak in May.

The percentage of people who do not show up at regular consultation hours is around 4.5% to 5.0%. For patients who have an appointment for treatment at the treatment room, this percentage varies from month to month, with a minimum of 0.9% to a maximum of 6.3%.

The average utilization in Enschede of the six urologists is 76.6%. Utilization at the outpatient clinics outside Enschede is much higher, broadly between 80 and 100 percent. Utilization for the treatment room is relatively low (around 50%-60%) and it can be concluded that there is still enough capacity to treat patients.

3. Literature review

As described in Chapter 1, Medisch Spectrum Twente does not yet facilitate patients' own scheduling of appointments. In addition to the aforementioned expected problems and root causes of these problems, MST has to answer a large number of questions in the field of resource capacity planning, in order to ultimately facilitate the patient as much as possible in scheduling his or her appointment. This chapter presents the questions that need to be answered and suggests possible directions for models and / or solutions.

Hans, van Houdenhoven and Hulshof (2011) describe a generic and practical framework for healthcare planning and control. This framework distinguishes between four different managerial areas. The focus of our study is on the second managerial area: resource capacity planning.

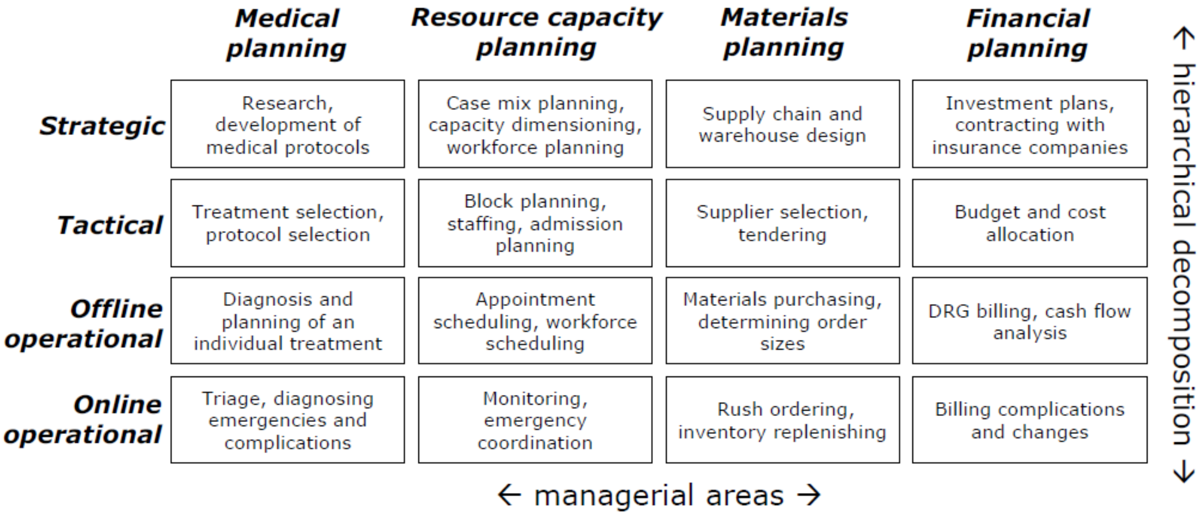


Figure 3.1 – Framework for healthcare planning and control (Hans et al., 2011)

In addition to the four different managerial areas, the framework includes four different hierarchical layers. In this framework the 'traditional' levels are used: strategic, tactical and operational. However, Hans et al. (2011) define another important distinction in the operational level. This distinction reflects a difference between making an 'in advance' decision and a 'reactive' decision. In the following four sections, for each level, questions and issues are posed that need to be answered in order to facilitate patients as effectively as possible in the context of self-scheduling. We explore and discuss the tactical level most, as the focus of our study is on this level.

3.1. Strategic level

The strategic level covers long-term structural decisions (Li, Benton, & Leong, 2002). These decisions are based on the vision and mission of the organization (Hans et al, 2011). These decisions should support the direction in which the company wants to go. In healthcare, this can include case mix planning, in which the case mix should fit the (desired) profile of the healthcare organization. Additionally, it is also possible to think about capacity distribution of, for example, the distribution of the number of surgical sessions on an annual basis.

Total allocated capacity

The first question that Medical Spectrum Twente has to answer at this level applies to all outpatient appointments of the Urology Department: *"which capacity should be allocated to the Urology Department?"* This question is not exclusively relevant in the context of self-planning, but concerns every discipline and department, independently of whether or not they facilitate self-planning. It is important to answer this question in order to ensure that sufficient resources are available to treat patients. By determining capacity, the number of patients seen can be controlled on site. Hospitals in the Netherlands agree on a so-called limit with the health insurance company. If this limit is reached, the costs related to the additional patients are charged to the hospital.

The literature review of Guindo et al. (2012) identify decision criteria for the allocation of resources. In their literature review, the most frequently identified criteria are: equity/fairness, efficiency/effectiveness, stakeholder interests and pressures and cost-effectiveness. The Medisch Spectrum Twente must determine at a strategic level on the basis of which criteria it will divide its resources. Hulshof, Kortbeek, Boucherie and Hans (2012) state in their literature research that capacity dimensioning is a key decision, as it affects how well the outpatient clinic is able to meet the demand, but also can manage access and waiting time. Methods such as computer simulation, mathematical programming, and queueing processes can be applied to provide insight into the performance of the outpatient department with different capacities. For instance, Elkhuizen, Das, Bakker and Hontelez (2007) created a computer simulation to analyse the capacity needed to reduce access time for an outpatient clinic. Using two models, they are able to analyse the access time and also examine the capacity needed to eliminate backlogs, taking into account fluctuations in demand. Smith, Over, Hansen, Golladay and Davenport (1976) use a mixed linear programming model to select the optimal staffing requirement and also showed the effect of scale and patient mix. An advanced queueing model is used by Creemers and Lambrecht (2009) to assess the length of a waiting list and the time spent on the waiting list in appointment-driven service systems. This model can be used to substantiate, based on the waiting list performance measure, how much capacity should be allocated.

Self-scheduling patient groups

In the context of self-scheduling, the following question needs to be answered: "which patient group(s) should be enabled to plan their own appointment?" Within each department, and therefore also within Urology, it is necessary to find out which group of patients are allowed to plan their own appointments.

The allocation decision for the application of self-scheduling does not only have to be based on technical and process aspects, such as single appointment versus multi appointment, but also on social aspects, like digital natives and people without internet communication. If departments deal with people who are less capable of scheduling their own appointments, a different approach may need to be adopted compared to departments that deal with a large population of patients who are well capable of scheduling their appointments.

Beside the choice based on the characteristics of the patients and/or appointments, the Medisch Spectrum Twente should also be aware of the fact that the implementation of self-scheduling entails a lot for the organisation. This aspect is not directly covered by the framework for healthcare planning and control of Hans et. al (2011), but it certainly has an impact on the success of self-scheduling. It will be a transformation to a new way of working for patients, but also certainly for the (planning) staff. Kotter (1995) describes eight errors causing a change to end in failure. In addition to the eight mistakes, Kotter (1995) formulates eight steps to achieve a successful transformation in an organisation: "1. establish a sense of urgency, 2. forming a powerful guiding coalition, 3. creating a vision, 4. communicating the vision, 5. empowering others to act on the vision, 6. planning for and creating short-term wins, 7. consolidating improvement and 8. producing still more change and institutionalising new approaches". Parallel to these steps, Grol, Wensing, Eccles & Davis (2013) describe that, at the start of the change in practice, it is important to experiment with the new routines, whereby the change is perceived to be beneficial. This requires starting on a small scale to gain experience and learn the skills. This approach corresponds to the sixth and seventh step in Kotter's process (1995).

The Medisch Spectrum Twente will not start with self-planning for all appointments, see Section 2.4. They will start with the simple schedulable (recurring) appointments, allowing them to gain experience with self-planning. The Medical Spectrum Twente will have to take into account the eight steps mentioned by Kotter to prevent the transformation to self-planning from failing.

3.2. Tactical level

Tactical planning translates the strategic planning decisions in order to facilitate operational planning and addresses the mid-term (Hulshof et al., 2012). Hans et al. (2011) describe that tactical planning focuses on the organisation of operations and execution of care. This 'what, where, how, when and who' is also done at the operational level, but decisions at the tactical level are based on a longer planning horizon. The length of this horizon lies between the length of the strategic planning horizon and the operational planning horizon (Hans et al., 2011). Consequently, the tactical level is most often forgotten or poorly addressed (Roth & van Dierdonck, 1995).
Within healthcare, some examples of tactical planning are: staffing / staff shit scheduling, admission planning and also block planning (e.g. the Master Surgical Schedule).

Allocation of capacity to different patient groups

The first question at the tactical level, which the Medisch Spectrum Twente has to take into account to facilitate patients as much as possible with regard to self-scheduling, is: *"how many slots should be offered per time unit (e.g. per week) for self-scheduling patients?"* In case of insufficient number of slots offered to patients to schedule their own appointments, the situation arises that there are patients who cannot choose a slot. The result is that they start calling the secretary, which increases the workload. Conversely, if too many slots are offered, this may mean that slots are not filled with appointments, increasing the idle time of the medical specialist and reducing utilization.
In the context of this question, a tactical scheme / blueprint should be drawn up, in which the slots for the self-scheduling patients are included. This research focuses on this question and its objective is to establish a model that can generate a tactical schedule for the Medisch Spectrum Twente that will facilitate self-scheduling patients (SSP) and the staff in their requirements as adequately as possible.

According to our best knowledge, there has been limited publications in the scientific literature on the subject of self-scheduling in hospitals. Articles that examine the subject of self-scheduling focus mainly on staffing and then especially staffing of nurses. For instance, Russell, Hawkins, and Arnold (2012) qualitatively describe guidelines for successful self-scheduling by staff (nurses) on nursing wards. As well, Svirsko, Norman, Rausch, and Woodring (2019) have established a Linear Programming (LP) model that creates daily schedules based on nursing shifts. This combined with self-scheduling resulted in an implementable schedule for the Emergency Department. A very similar technique, Integer Linear Programming (ILP), was used a few years earlier by Rönnberg and Larsson (2009). Their model is an optimization tool that automatically creates a schedule for an entire department based on schedules, with individual preferences, proposed by the nurses.

As outlined previously, to our best knowledge there are no or only few papers published on the subject of self-scheduling by patients. We believe there is a literature gap on this topic and with this study we aim to fill that gap partially.
Because of the lack of literature on this specific topic, we look at other literature that has related parts to our issue. This issue, a tactical schedule that facilitates self-scheduling of

appointments, is more similar to a capacity design problem than a patient appointment scheduling problem. A lot of literature has been published on the topic of patient appointment scheduling and will be discussed briefly in Section 3.3. In contrast to appointment scheduling problems, Nguyen, Sivakumar, and Graves (2014) state that there have been far fewer studies on how capacities should be planned for an appointment system (capacity design problem). As such, there are studies conducted regarding open-access appointments (walk-in) versus advanced (pre-book) appointments. Qu, Rardin, Williams, and Willis (2007), in their first article on this subject, examined what the optimal percentage of open-access appointments is for matching supply and demand for a single period. This research was subsequently conducted for two time periods (Qu, Rardin, & Williams, 2011). Whereas Qu et al. calculate a percentage, Kortbeek et al. (2014) go a step deeper and developed a method, consisting of two algorithms, that generates a Cyclic Appointment Schedule (CAS) for both pre-book and walk-in appointments. In the context of our topic, the latter is quite interesting, especially the first algorithm, which focuses on the amount of capacity for both types of appointments. However, in our study we do not extend this algorithm, as no distinction is made between different appointment types besides pre-book and walk-in.

Elkhuizen, Das, Bakker and Hontelez (2007) study appointment lead-times for outpatient clinics. They use an M/D/1 queuing model to investigate the capacity needed to see all new patients within two weeks and a simulation model to cope with fluctuations in demand. However, they ignore the fact of the presence of repeat visits in this study and Nguyen et al. (2014) stepped into this literature gap. Using a Mixed-Integer Programming Model (MILP), they match supply and demand in a re-entry system. Within the model, they take into account the restrictions for appointment lead-times. These models are not extended in our research either, as once more no distinction is made between different appointment types besides ‘first visit’ and ‘revisit’. In addition, this model uses a finite planning horizon and deterministic arrivals. To solve our problem in practice, we need to include a cyclical schedule and stochastic arrivals in our research.

Considering these requirements, Vermeulen et al. (2009) applied an adaptive approach for the automatic optimisation of appointment / resource schedules. In their approach, capacity is allocated for different patient groups, which is flexible and adapts to the current and future situation. In a case study, they demonstrated through simulation that they improved service levels for patients using their approach.
In their approach, they use different types of patients with different types of urgencies. For all these types of patients, they apply different appointment codes that are allocated in a tactical schedule. In addition, their approach works for a rolling schedule, which means that as time goes by, a new schedule can be released. All these properties match our issue and so we will extend this study to make it applicable to a situation where patients can schedule their own appointments.

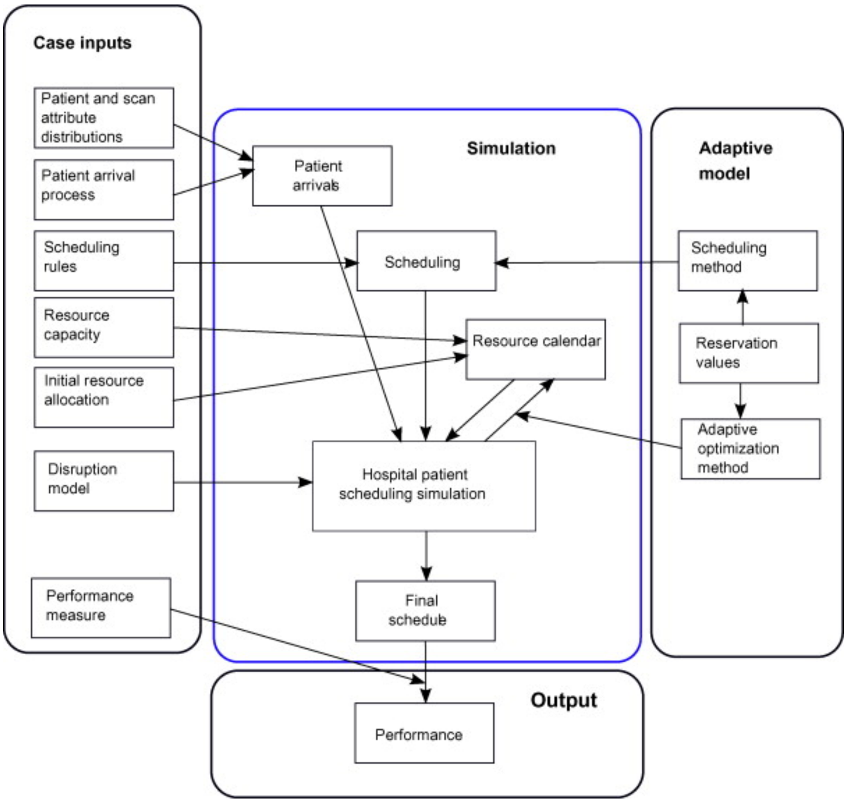


Figure 3.2 – Overview of hospital patient scheduling model (Vermeulen, et al., 2009)

An extension to the study is in any case the application of a re-entry system, as patients in the Medisch Spectrum Twente can return one or multiple times. In addition, the fact that there is not only a one-to-many principle with regard to the patient-doctor relationship should also be taken into account. In the study by Vermeulen et al. (2009), a patient can see all resources, whereas in our situation this is not always the case and a patient cannot always be seen/treated by all physicians.

Figure 3.2 shows the overview of the hospital patient scheduling model as used by Vermeulen et al. (2009). This model will form the basis of our study and will be extended to generate a tactical schedule that facilitates self-scheduling of appointments.

Distribution of slots within tactical schedule

Alongside the question regarding the number of slots to be released to the self-scheduling patients and the distribution of the number of slots between the different patient groups, the Medisch Spectrum Twente should also answer the following question: "How should the slots be distributed in the tactical schedule?".

By answering this question, a lower number of slots (i.e. less slack) may be maintained for self-scheduling patients. By examining which times are more desirable for self-scheduling patients, the probability of not selecting a slot can be reduced. In that case, the non-selected slot can be used to schedule the remaining / other patients. As a result, slots can be prevented from remaining empty, which will increase the utilization rate of the outpatient clinic.

On the subject of 'Allocation of capacity to different patient groups', the study by Kortbeek et al. (2014) has already been briefly mentioned. For that topic, the first algorithm, which focuses on the amount of capacity, was of particular interest. However, for the order of the slots in the tactical schedule, MST can expand on the second algorithm. In this second algorithm, the best possible appointment schedule is created based on the given capacity. In this appointment schedule, the times are indicated for the slots for the pre-book and walk-in patients. Next, Kortbeek et al. (2014) determine whether this schedule is acceptable with regard to the service levels. If this is not the case, then the allocated capacity for was not in accordance with the service levels and the first algorithm is used to once again determine how much capacity is required and subsequently use algorithm two to determine a new appointment schedule. This iteration continues until the service levels are at an acceptable level. This same principle of switching between two algorithms to finally determine how many and at what time the slots for self-scheduling patients are required could also be applied by MST.

An alternative way of managing this problem is by means of revenue (yield) management. In other industries, such as aviation and the hotel industry, revenue management has been successfully applied to better control demand and thus achieve higher profits, for example, through overbooking, discount (seat) allocation and traffic management (Smith, Leimkuhler, & Darrow, 1992). Revenue management is concerned with demand-management decisions and with the systems and methodology to make these decisions (Talluri & Ryzin, 2004).

At present, to the best of our knowledge, revenue management is not (yet) widely applied within the healthcare sector. However, for this issue it is very interesting to investigate how revenue management can contribute to making certain slots attractive for self-scheduling patients so that they can be filled. As an example, Zhou and Zhao (2015) have applied revenue management to outpatient appointment scheduling to determine how many physicians are needed per specialty. Their goal is to maximize revenues by using different types of physicians (with different revenues and costs). Each type of physician has a patient preference and is scheduled based on those preferences. For example, an expert physician is preferred as he/she yields more, but they are more expensive and less available. In this way, the slots of expert physicians are worth more than those of generic physicians.

Medisch Spectrum Twente could use revenue management to give different weights to slots at different times for self-scheduling and thus possibly guide demand towards less interesting slots for patients by attaching a different 'profit' to this slot (e.g. preferred physician or shorter appointment lead-times).

3.3. Offline Operational level

The third, and second lowest, level is the offline operational level. Operational planning involves short-term decisions related to the direct healthcare process (Hans et al., 2011). As mentioned above, when introducing Chapter 3, Hans et al. (2011) made an important distinction within the operational level. At this offline operational level, decisions are made in advance. These decisions on the operational level are limited by the choice made on the tactical level (Schmidt & Wilhelm, 2000). Some examples of offline operational planning are: appointment scheduling, staff to shift assignment and inventory replenishment ordering.

Slots available for self-scheduling patients

A question the Medisch Spectrum Twente needs to address at the offline operational level is: "Which slot(s) will patient *'X'* see when he/she wants to schedule his/her own appointment?". When patients want to schedule their own appointments, they should see (a selection of) all free slots to choose from. In the context of the highest quality for the patient, these should be the slots that benefit the patient the most. This differs per individual and it is therefore advisable for MST to carry out research in this regard. This research can contribute to patients being shown the preferred slots and therefore less capacity needs to be allocated to self-scheduling patients, due to the fact that fewer slots need to be offered. In the context of revenue management, it is also interesting to conduct research on how to entice patient *'X'* to choose a less preferred slot.
Using the study of McFadden (1974), Feldman, Liu, Topaloglu, and Ziya (2014) generated probabilities that a patient would like an appointment j days in the future. With these probabilities, Feldman et al. are able to develop an appointment scheduling model that maximizes the expected 'profit' per day. They define 'revenue' as patients who show up and base 'cost' on the number of scheduled appointments.
Based on McFadden's model, Medisch Spectrum Twente might be able to gain more insight into which slots should be made visible to patient *'X'*.

Appointment scheduling

A highly interesting topic, but also less in the context of self-scheduling, is appointment scheduling. Hans et al. (2011) attributed this topic to the operational level, while Hulshof et al. (2012) attributed it to the tactical level. This difference in perspective is comprehensible, since choices with regard to appointment scheduling take place at the tactical level. After all, a decision is made and this limits the choice on an operational level. However, the actual execution of the decision takes place on an operational level. We have chosen to follow Hans et al. (2011) and place this within the operational level.

Considering the fact that this subject is less related to self-scheduling, we do not want to deprive Medisch Spectrum Twente of the opportunity to take a closer look at it. MST has to consider which appointment rules should be set for each department. In the field of appointment scheduling, a large number of decisions can be made, such as: number of patients per consultation, length of appointment interval, number of patients per slot, sequence of apppointments and queue discipline in the waiting room (Hulshof et al., 2012).

Hulshof et al. (2012) and Nguyen et al. (2014) listed a number of studies in which the Medisch Spectrum Twente could take a closer look in order to improve appointment scheduling for their outpatient clinics. Table 3.1 provides an overview of some studies that looked at the influence of certain decisions using queuing theory. Table 3.2 lists studies that have been carried out using simulations.

For an overview of various appointment rules regarding the block-size, start-block and appointment interval, we refer to the literature study by Cayirli and Veral (2003). In their extensive literature review on outpatient scheduling, they provide a number of studies that show the effects of different decisions regarding appointment rules.

Table 3.1 – Appointment scheduling studies – approach: queuing theory

Study	Studied factor (decision)
Bailey (1952)	Length of appointment interval
Brahimi & Worthington (1991)	Interruptions physicians Unexpected long consultation
Hassin & Mendel (2008)	No-shows Punctuality of patients
Liu & Liu (1998)	No-shows Punctuality of physicians
Kros, Dellana, & West (2009)	Overbooking
Pegden & Rosenshine (1990)	Optimum scheduling of arrivals for single server

Table 3.2 – Appointment scheduling studies – approach: simulation

Study	Studied factor (decision)
Cote (1999)	Focus on determination bottleneck station Patients with same priority Measurement: utilization, queue length, patient flow time
Harper & Gamlin (2003)	Focus on determination bottleneck station Patients with different priorities Measurement: waiting time
Wijewickrama & Takakuwa (2005)	Focus on determination bottleneck station Patients with different priorities Measurement: trade-off waiting time versus doctor idle time
LaGanga & Lawrence (2007)	Focus: Achieve given service performance Overbooking
Fetter & Thompson (1965)	Number of patients per consultation session Measurement: trade-off access times versus patient waiting times
Fetter & Thompson (1966)	Length of the appointment interval Measurement: trade-off resource idle times versus patient waiting times
Rising, Baron & Averill (1973)	Anticipation for walk-in patients Measurement: patient waiting times, resource utilization

3.4. Online Operational level

The last and lowest level is the online operational level. At this level, it is all about reactive decisions that need to be made, as the health care process is stochastic by nature (Hans et al., 2011). It is about monitoring the process and intervening if necessary. Examples of online operational planning are: triaging, acute admission handling, staff rescheduling, scheduling of emergencies and replenishing depleted inventories.

In the field of self-scheduling, we believe that on the online operational level little has to be managed. However, in the context of the implementation of the new Electronic Health Record and perhaps check-in terminals, MST could explore a study within the thesis of Schneider (2020). With the help of this study, Leiden University Medical Centre (LUMC) managed to solve a multi-appointment problem within Cardiology. A multi-appointment patient has several appointments in a day. Schneider's model (2020) determines, based on the current situation within the outpatient clinic, which appointment should be made next, so that all patients are in the system as shortly as possible. This order of appointments is determined ad hoc and therefore online.
Medisch Spectrum Twente could conduct research into the extent to which they could apply this same model if the hospital were to switch to check-in terminals.

3.5. Conclusions

Our literature review provides insight into several challenges associated with self-scheduling, to an answer the third and fourth sub-question of this research.

Question 3: Which approaches can be adopted by the Medisch Spectrum Twente to address the challenges of introducing self-scheduling?

Challenges for the Medisch Spectrum Twente have been identified at different hierarchical layers. At the strategic level, MST will have to decide how much capacity to release for each outpatient clinic. To answer this question, computer simulation, mathematical programming, and queuing theory can be applied. On the same level, MST should also decide which patient groups can plan for themselves. Besides the choice on the basis of the characteristics of the patients and/or appointments, the impact on the organization of this change in working method also have to be accounted for. The eight steps model of Kotter (1995) can be adopted for this purpose.

On a tactical level, this study answers the question of how many slots should be allocated to self-scheduling patients. The applied model will be explained in more detail when addressing sub-question 4 in this conclusion. In addition to this aspect, MST should also consider how the slots should be distributed in the tactical schedule. In this context, MST can apply such techniques as computer simulation or yield management.

The challenge at operational level for self-scheduling is to offer the right slots to a specific patient. Based on McFadden's model, Medisch Spectrum Twente should be able to gain more insight into which slots they should make available to specific patients in order to create a strong likelihood of acceptance of a slot. On the same level, less in the context of self-scheduling, MST can study multiple studies to optimize appointment scheduling.

Question 4: What approach or model is best applicable?

The simulation model by Vermeulen et al. (2009) leads to promising results for the automatic optimization of appointment/resource schedules. However, their approach does not use the ability of patients to schedule their own appointments and does not apply a re-entry system. Therefore, we choose the hospital patient scheduling model of Vermeulen et al. (2009) as a baseline for this research, but we extend it in this study. This results in the hospital patient scheduling model shown in Figure 3.3.

In Chapter 4, we present the conceptual model and system description of the simulation. Then, in Chapter 5, we show the different case inputs and in Chapter 6 the adaptive model including experimental design is introduced.

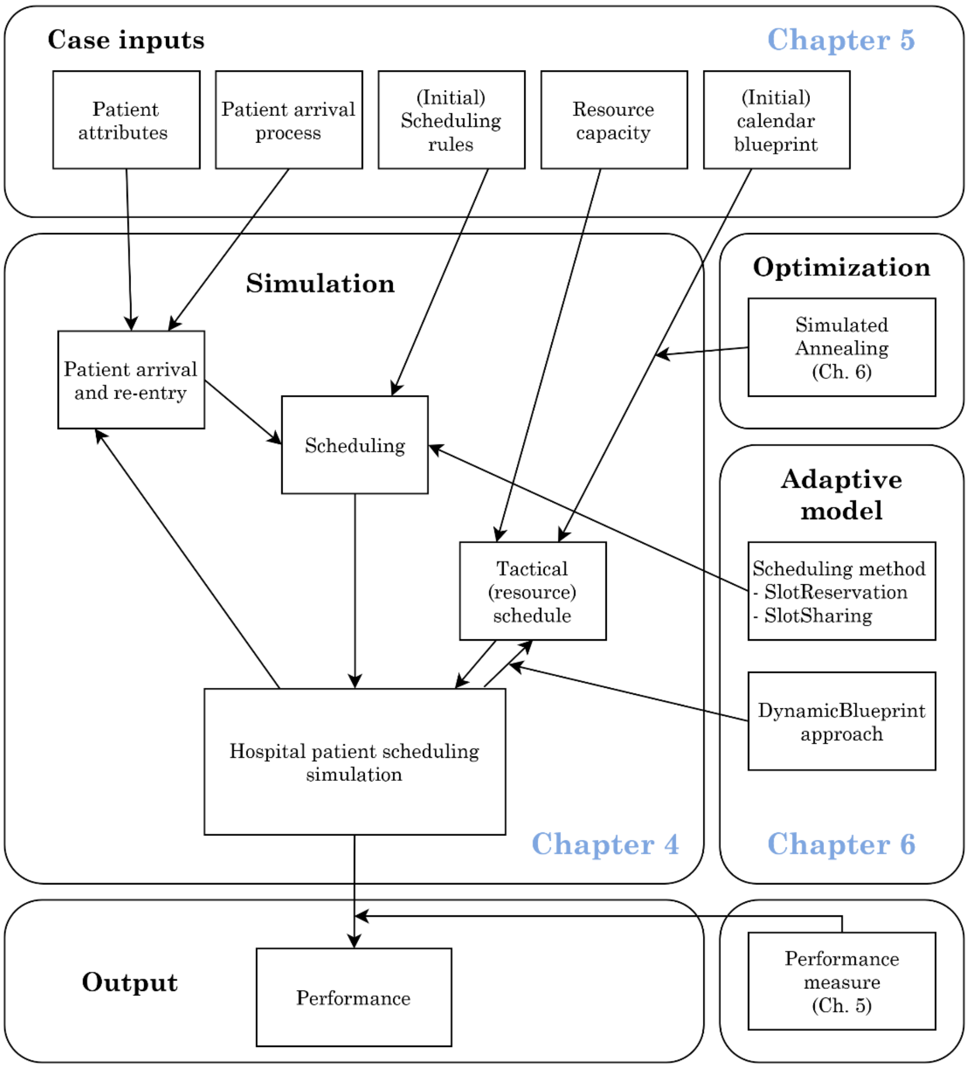


Figure 3.3 – Overview of hospital patient scheduling model

4. Simulation: System Description

To assess different settings, we use computer simulation that realistically simulates our system, the outpatient clinic. We discuss the reason for choosing simulation and the type of simulation in Section 4.1. Next, Section 4.2. describes our model, looking at the patient process, the different simulation routines and finally the assumptions we apply. In Section 4.3. we define our simulation settings with respect to the warm-up period, run length and number of replications. We finalise the chapter with Section 4.4. in which we verify and validate our model.

4.1. Discrete Event Simulation

In this section we outline our choice of simulation and specifically Discrete Event Simulation (DES). We use computer simulation to evaluate and compare our adaptive model with various settings. Simulation is a representation of reality that provides insight into how a system evolves over time. In our case, the system is the outpatient clinic, i.e. the scheduling process of the outpatient clinic. We opt for computer simulation, since our system is too complex to be solved analytically. The second reason for using computer simulation is that our research is based on the hospital patient scheduling model of Vermeulen et al. (2009) and they use computer simulation.

In our system, state variables do not change continuously with respect to time. Our system changes at separated points in time, such as the arrival of patients and the scheduling of appointments. Moreover, the passage of time plays a significant role in our system, since a number of performance indicators, see Section 5.7, are time related. It is therefore a dynamic system. Based on these grounds, a Discrete Event Simulation suits our system best and we choose to develop such a simulation.

We build our simulation in Technomatix Plant Simulation 13.

4.2. Model description

To assess our adaptive model, our simulation model has to be a representative reflection of the current planning process of the outpatient clinic. This section provides the model description of our simulation. We describe the patient process flow of the simulation model in Section 4.2.1. Section 4.2.2. explains the different simulation routines and process steps from Section 4.2.1. We conclude the section with Section 4.2.3. in which we describe the assumptions of the model.

4.2.1. Patients process flow

Based on the performance of the Urology outpatient clinic with regard to the different types of consultations (as stated in Section 2.5) and the approach of the Medisch Spectrum Twente to start with simple schedulable appointments (as stated in Section 2.4), the focus of this study is on the regular consultation hours performed by medical specialists, in which no physical treatment (i.e. outpatient surgery) or combination appointments are performed. In addition, we do not take patients into account that need to be seen or treated on the day itself. For this patient group, the emergency physician is the lead physician and this resource is outside the scope of the study and therefore not included in the simulation.

Figure 4.1 depicts the patient process flow based on these characteristics.

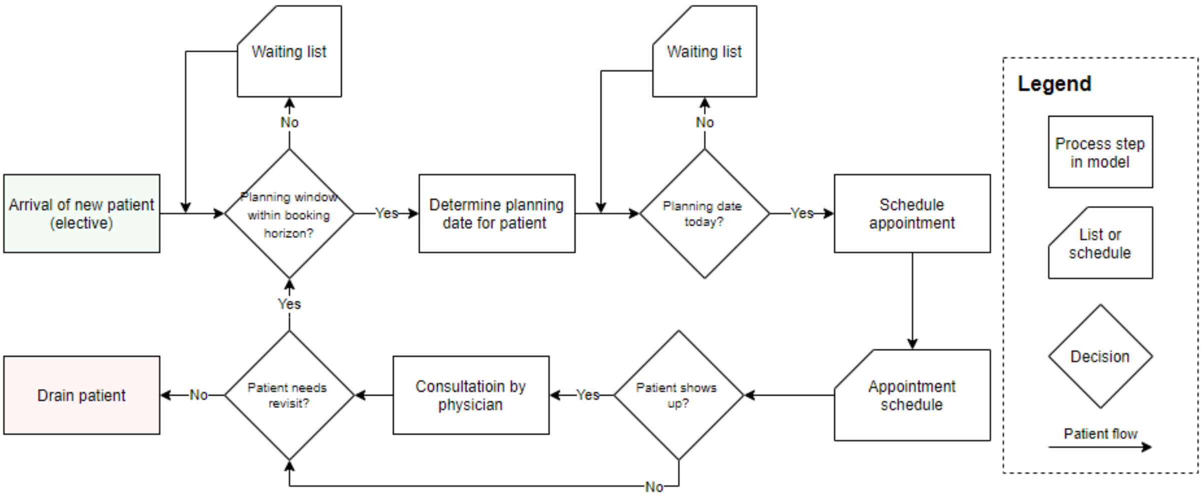


Figure 4.1 – Patients process flow

4.2.2. Simulation routines

In the simulation model, the process steps from Figure 4.1 are executed by several routines.

Patient creation routine

The number of patients entering the system is determined at the beginning of each day, based on the arrival process described in Section 5.2.

The model creates these patients and assigns the following attributes to the patient:

- Unique patient ID number;
- Arrival flow;
- (Possible) attending physician;
- Appointment window;
- Number of visits needed;
- Appointment type;
- Ability to self-scheduling.

The assigned values of these attributes are determined based on theoretical or empirical distribution, derived from historical data. Immediately after creating the patient, the booking date routine is started.

Booking date routine

This routine determines the day when a patient is scheduled. By booking date, we refer to the day when a scheduler or the patient personally (in case of self-scheduling) starts searching for a free appointment slot to schedule an appointment.

In current practice, when the appointment window (window in which the appointment should be performed) falls entirely within the booking period, a search for a free appointment slot is initiated immediately and the patient is scheduled using the scheduling routine. This process is also used in the simulation. However, for self-scheduling patients it is unknown when they will schedule their appointment. Therefore, the simulation model determines, within the set dates in which a self-scheduling patient can schedule their appointment (booking window), a random day for the booking date in which the patient will schedule his/her appointment. The booking window in which a patient may plan his/her appointment is an experimental factor and is explained in more detail in Section 6.3.3.

If the appointment window is not entirely within or entirely outside the booking period (i.e. the upper bound of the appointment window $\geq$ last day with slots released), the patient is assigned to the waiting list until the appointment window is entirely within the booking period. It is checked at the beginning of each day.

Scheduling routine

The objective of the scheduling process is to assign patients to an appointment slot. First, during the simulation, the policy for finding a slot is determined. This determination is based on experimental settings. The next step is to search for an appointment slot based on the policy.

In the current practice, the policy first come, first serve is applied for patients who are scheduled by the hospital. This process is explained in more detail in Section 5.4. Due to the unpredictable behaviour of a self-scheduling patient, the scheduling policy for self-scheduling patients is the first come, random serve (FCRS) principle. In our simulation model, a slot is randomly selected from the available slots.
Since our adaptive model focuses on improving the scheduling routine, alternative policies are explained in Section 6.3.1.

Consultation hour routine

At the beginning of each session (both morning and afternoon), patients are sent to the waiting room of the appropriate physician. Before the patients are sent to the waiting room, the no-show rate is used to determine whether the patient will show up or not. In the blueprint of the appointment schedule, no distinction is made in terms of the time of a slot, only with regard to the number of slots. As a result, during the consultation hour, no distinction is made in the order of patients; the first patient in the appointment schedule is treated first. After a patient has received a consultation from the physician, it is assessed whether the patient requires a repeat visit. If necessary, various patient attributes (i.e. appointment window and appointment type) are redefined and the 'booking date routine' is started. If the patient has received the required number of visits, the patient exits the system.

If a patient does not show up, it is assessed whether the patient has received the number of visits required, including the no-show. If so, the patient exits the system. If not, then various patient attributes (i.e. appointment window and appointment type) are redetermined and the 'booking date routine' is started.

Release appointment schedule routine

We choose to apply a rolling booking period. This implies that appointments can be scheduled in advance. We apply a planning horizon of eight weeks and a planning cycle of four weeks. This entails that the booking period is at least eight weeks and at most twelve weeks. This is consistent with the future planning approach of MST as described in Section 2.4.

Initially, an appointment schedule is released for twelve weeks. Then, after every four weeks, the next four weeks are released. The number of sessions released per week per physician is based on historical data and is discussed in more detail in Section 5.5. As the allocation of sessions for the regular consultation hours is only the last process step of the staffing allocation process (as stated in Section 2.3), we decided to randomly determine the day on which a session takes place. After establishing the day, on the basis of a distribution, the number of slots per appointment code is made available. The initial distribution of the number of slots per appointment code is described in Section 5.6. Section 6.2 explains how our adaptive model improves this distribution.

4.2.3. Assumptions of the model

Modelling every aspect of a system is often not a necessity for effective decision making (Law, 2015). Our (simulation) model is therefore based on a number of assumptions:

⇒ *No seasonal effects.* Our model is based on regular day-to-day throughput, with no reduction in capacity or healthcare demand. Based on distributions, we determine the number of arrivals per day for weekdays and weekend days. These distributions are only different for weekdays and weekends, but do not change over time. This does not reflect the reality, as there are usually more referrals after the weekend. However, we do not see this as a shortcoming, as the total number of patients during the week does reflect reality and in addition the different appointment windows provide a spread for the allocation of slots.

⇒ *No same-day patients.* As mentioned in Section 4.2.1, in our model, we do not take into account patients that need to be seen or treated on the day itself. For this patient group, the emergency physician is the lead physician and this resource is outside the scope of the study and therefore not included in the simulation. In addition, patients who are referred on Friday and have an appointment window that falls entirely in the weekend leave the system immediately. In practice, these patients are taken care of by the emergency or attending physician.

⇒ *Iterative capacity allocation.* Utilisation, service levels, and appointment lead-time are often influenced by the released capacity and demand for care. Since we base capacity and demand on historical data, we assume that the released capacity is in relation to the demand for care and therefore we do not include any imbalance. We consider an eight week repeating capacity allocation. This means that the capacity allocated in week 1 is the same as the capacity allocated in week 9.

⇒ *Random allocation of sessions throughout the week.* The allocation of a session to a particular day is carried out randomly on the basis of a uniform distribution. As the allocation of sessions for the regular consultation hours is only the last process step of the staffing allocation process (as stated in Section 2.3), this approach corresponds to current practice.

⇒ *No patient and provider unpunctuality.* Physician and patients always arrive on time, there are no disruptions and the appointment lasts as long as the scheduled time. This does not correspond to reality, but this detail of modelling is not relevant for us, as the focus of this study is not on waiting times and processing times during a consultation.

⇒ *A physician's session never breaks down.* This does not reflect reality; however, we base the capacity (i.e. number of sessions) on real data of performed sessions. As a result, our model does correspond to the number of sessions carried out in practice, so this assumption remains valid.

⇒ *5% patient no-show.* Patients do not show up for their appointments with a preset and static no-show probability (5%). We assume that these consultations are lost and not replaced. We are able to assume this since we do not include no-show appointments in our analysis for the calculation of the distributions for the number of appointments. Therefore, there is no mismatch between our model and reality.

⇒ *Constant appointment duration per appointment type.* There are no different time units for the same appointment code. This does not reflect reality, as occasionally a certain slot is extended if the patient requires this time (e.g. for patients who are assisted by an interpreter). The number of time units is based on the number of time units most often used for an appointment code in the past. We do not see this assumption as a shortcoming, since the choice to extend usually increases the workload on the day and does not affect the number of patients that can be seen (i.e. a part of the blockage in the schedule is used).

⇒ *No differentiation in time within a session.* Our model does not differentiate in terms of the time for an appointment slot. We use a distribution for the number of slots (per appointment code) per session. We do not take the time of the slots into account as this level of detail is beyond the scope of the study. Our focus is on the quantity of slots and not the distribution within the tactical schedule.
This inevitably means that we do not take into account the preference for a time of the appointment when an appointment is scheduled by a self-scheduling patient. The choice of a slot by a self-scheduling patient occurs entirely at random based on a uniform distribution, taking into account the type of slot that is required.

⇒ *Patient preference not included.* In the current scheduling practice, patient preferences are taken into account for repeat visits. Since these preferences are only taken into account for patients whose next appointment is within the booking period and who can therefore be scheduled immediately at the front desk, we do not apply this in our model. Additionally, the schedulers often offer slots to patients that fall relatively early in the appointment window, thus applying a slightly broader concept of FCFS. Consequently, we do not see this assumption as a shortcoming.

⇒ *Rescheduling not included.* In our model, we do not take into account the rescheduling of appointments to an earlier or later date. In practice, appointments are rescheduled, but it is not relevant to us if patient 'A' has an appointment at time 'X' and reschedules it so that patient 'B' has an appointment at time 'X'. We assume that, in practice, a request for a rescheduling takes place at the moment the patient receives the appointment date and thus in such a way that the slot is occupied by another patient, that we do not need to take rescheduling into account.

⇒ *Booking date for self-scheduling patient on the basis of uniform distribution. As* mentioned in Section 4.2.2. the booking date (i.e., the day when a scheduler starts searching for a free appointment slot to schedule an appointment) for patients scheduled by the hospital is the same as the day of the request for an appointment. If the appointment window is not entirely within or entirely outside the booking period,

the patient is immediately scheduled when the appointment window falls entirely within the booking period.
However, for self-scheduling patients it is unknown when they will schedule their appointment. Therefore, the simulation model determines, within the set dates in which a self-scheduling patient can schedule their appointment, a random day based on a uniform distribution for the booking date in which the patient will schedule his/her appointment.

4.3. Simulation settings

In this section, we discuss the settings chosen to conduct the simulation runs. Based on several indicators, we determine a warm-up period, run length and number of replications.

Warm-up period and run length

Since our simulation model starts 'empty' at the beginning of the simulation run (i.e. no appointments are scheduled) and this does not represent reality, we use initial-data deletion. This avoids the problem that the expected average value during the warm-up period does not match the expected value of the entire system (Law, 2015).

We determine the length of the warm-up period using Welch's graphical procedure (Law, 2015). For this purpose, we perform 10 replications with a run length of 250 weeks of the baseline simulation. We evaluate the parameters (see Section 5.7. for further explanation) utilization, number of patients scheduled, service level and appointment lead-time for determining the length of the warm-up period. Although the number of patients scheduled is not a performance indicator, for the determination of the warm-up period we include this indicator, since the system must reach a steady-state of the number of patients scheduled per week.

Figure 4.2 clearly shows, based on the moving averages, that a steady state is reached after 35 weeks. Therefore, we choose a warm-up period of 35 weeks. Only the moving average of the utilization is shown, since the utilization is most influenced by the initial state of the simulation. The graphical representations of the other parameters are presented in Appendix III.

As stated by Law (2015), we choose our run length to be much larger than our warm-up period. We therefore choose a run length of 11 times the warm-up period, leaving us with 10 times the warm-up period for data collection. As a result, the total run length is 385 weeks.

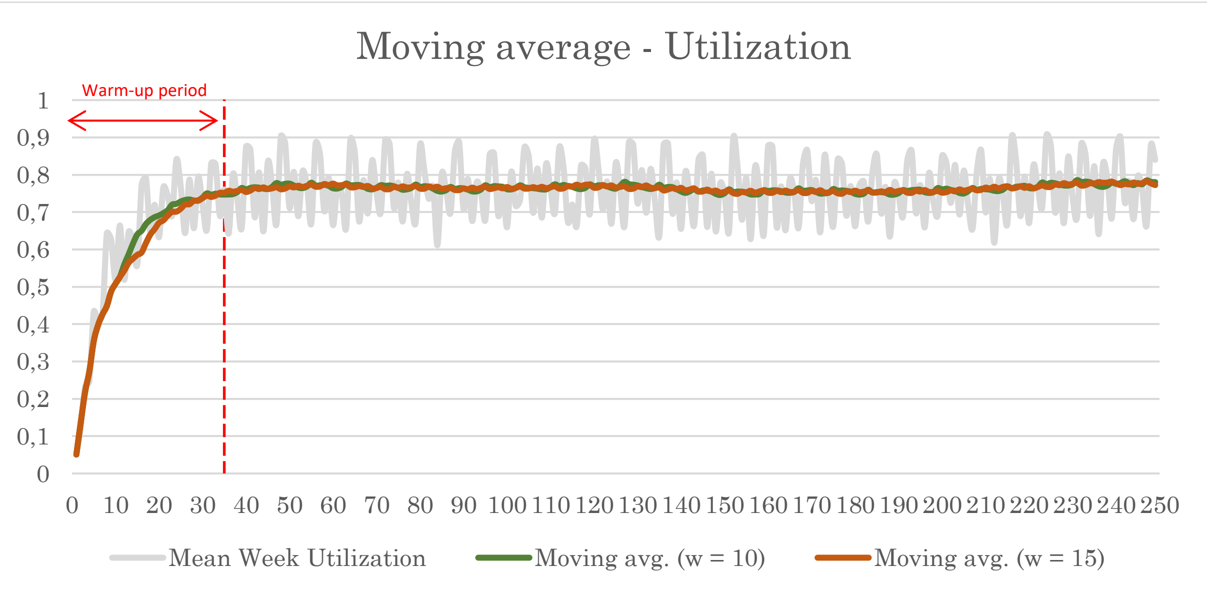


Figure 4.2 – Moving average - Utilization

Number of replications

We do not choose to apply the batch means method, as we want to avoid that the initial state is biased in some manner. Therefore, we choose the replication-deletion approach. For the application, it is necessary to choose a sufficient number of replications to ensure the accuracy of our results.

To determine the number of replications, we first estimate the number of replications required. We base this estimate on a new simulation run of 10 replications (n) with a warm-up period of 35 weeks and a total run length of 385 weeks. We estimate the number of replications required based on the performance indicator utilization. We use $\widehat{n^*} = \frac{t^2_{n-1,\alpha} * S^2}{\gamma' * \bar{x}}$, where $\widehat{n^*}$ is the estimate of the number of replications required. The values used for the estimate are shown in Table 4.1.

Table 4.1 – Input values – estimation number of replications

α	= 0.025
Υ	= 0.025
$t^2_{n-1,\alpha}$	= 7.209
S^2	= 6.11 x 10^{-5}
γ'	= 0.024
$\bar{x}$	= 0.767

The estimated number of replications is 1.40. Based on this estimated number, we use the sequential approach as stated in Law (2015). The aim of this approach is to find the optimal number of runs for which, as we have chosen, the 97.5% confidence interval for the utilization has a relative error of 2.5%. Figure 4.3 shows that this is reached as from two replications. We apply the same approach for the performance indicators service level, appointment lead-time, adjusted service level, and percentage scheduled within appointment window (see Appendix IV). In these cases, three replications are sufficient. Therefore, we run all simulation experiments with 3 replications, a warm-up period of 35 weeks and a total run length of 385 weeks.

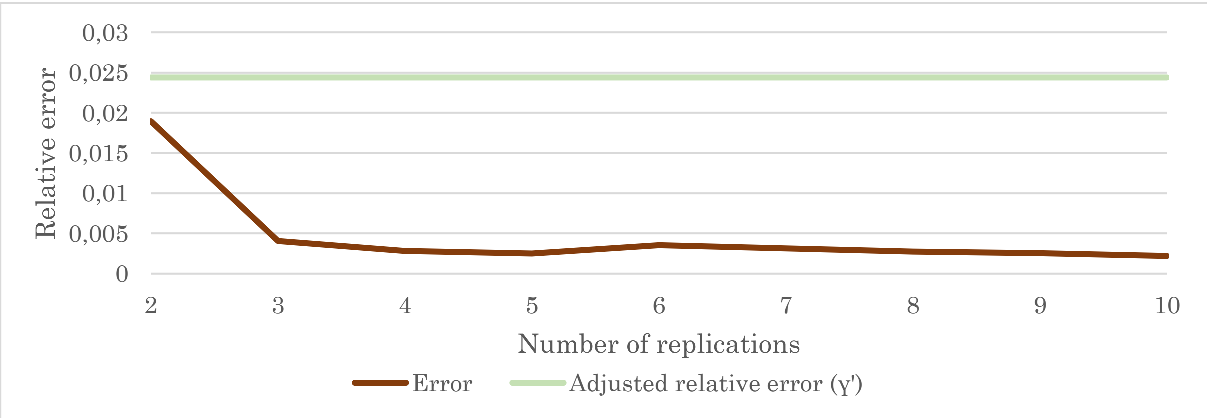


Figure 4.3 – Needed number of replications based on utilization

4.4. Model verification and validation

In this section we discuss model verification and validation. To be sure that certain interventions or experiments in reality achieve the same effects as in the simulation, our simulation model must be a representative reflection of the reality. Verification involves determining whether the assumptions and model description have been properly translated into the simulation program (Law, 2015). Validation is the process of determining whether the simulation model is a representative reflection of the current system.

Verification

We apply several techniques suggested by Law (2015) to ensure that the model description is implemented correctly. We use the technique that says we firstly have to write the main program, test it and debug it, and then add subprograms. We constantly add and debug small parts of code to ensure that the program executes as it should. We also perform a large number of test runs and check whether the outcome is reasonable.

The Urology planner successfully checks the patient planning steps for completeness. She monitors, by pausing the simulation, a number of random patients and determines for these patients in which slot the patient should be scheduled. After this, it is checked whether the patient is scheduled for the same session by the system. The steps in the simulation, apart from the assumptions, correspond to the current way of working.

Last, to verify the translation of the input variables, as described in Chapter 5, to the simulation model, we check after a simulation run whether the input variables in the simulation model correspond to reality. Table 4.2 shows the differences between the model input and the reality of the average number of sessions per week. It is clear that these are very similar and thus, together with the aforementioned steps, we conclude that our model description is correctly implemented.

Table 4.2 – Comparison model input vs. reality – Number of sessions

	Total	**Urologist**					
		1	**2**	**3**	**4**	**5**	**6**
Model output	7.75	1.5	1.3	1.3	1.2	1.5	1.0
Reality	7.73	1.5	1.3	1.2	1.3	1.5	1.0

Validation

We validate our model using the outcomes of the existing system and in addition by means of an expert opinion. For the expert opinion, we show the model and the results (see next paragraph) to the policy advisor of the Capacity Department. According to the policy advisor of the Capacity Department, the model flow with its assumptions is a good representation of reality. Also, the results (the utilization and appointment lead-time) of the model correspond to her expectation. On this basis, we conclude that the model has face validity.

We compare the results of the simulation with the actual data available from 2019. We use the data from the 41 weeks where there was no reduction in terms of capacity in Urology, as we do not include seasonal factors in our simulation. Subsequently, we relate all data, both simulation output and existing data, to one week in order to make a fair comparison. For our model validation, we compare the following model outputs:

- number of patients consulted (per urologist);
- number of consultation minutes (per urologist);
- utilization;
- percentage of first appointments fulfilling the appointment lead time of less than three weeks
- and percentage of first appointments fulfilling the appointment lead time of less than four weeks.

As shown in Table 4.3, the simulation with regard to the total average number of patients receiving appointments reveals a very small difference from reality. However, we see that the numbers differ (slightly) for each specific specialist. The largest difference is in the case of urologist 6. This difference can be explained by the fact that in reality the urologist has a slightly lower utilization rate (see section 2.5), but the simulation model does not incorporate this lower utilization rate compared to other urologists and allocates patients to urologist 6.

Table 4.3 – Comparison model output vs. reality - Number of patients consulted

	Total	Urologist					
		1	2	3	4	5	6
Model output	130.40	25.9	22.0	18.4	23.0	24.3	16.9
Reality	129.80	27.7	19.6	21.3	22.6	24.9	13.9

In addition to the number of patients, we also compare the number of minutes spent on consultations by the physicians. From Table 4.4 it is clear that the total number of minutes only differs by about 36 minutes. This is a small difference and can be explained by the assumption that an appointment code covers a fixed number of time units. However, in practice the time for an appointment code is occasionally extended, for example to provide extra time for a patient who requires this extra time (e.g., for patients who are assisted by an interpreter).

Table 4.4 – Comparison model output vs. reality - Number of consultation minutes

	Total	Urologist					
		1	2	3	4	5	6
Model output	1422.84	284	241	199	251	264	184
Reality	1458.54	303	222	251	250	277	155

For utilization, the model slightly underperforms compared to reality. This is explained by the fact that almost the same number of sessions are spent, see verification in this section, while the number of minutes is slightly lower than in reality (see Table 4.3). The percentages of new patients who come with a referral from their GP and have an appointment within three weeks hardly differ, and the same applies to the percentage of patients within four weeks. See Table 4.5. for the values of utilization and the two percentages in relation to appointment lead-times.

Table 4.5 – Comparison model output vs. reality – Utilization and percentage seen on time

	Utilization	% within 3 weeks	% within 4 weeks
Model output	76.45%	43.90%	63.09%
Reality	78.60%	43.00%	62.46%

Based on the comparison between simulation and reality outcomes and on the assumed face validity, we conclude that our model is valid and therefore applicable to perform the intended interventions as stated in Chapter 6.

4.5. Conclusions

In this chapter, we explain the motivation for using discrete event simulation. We choose to apply Discrete Event Simulation, because our system does not change continuously with respect to time. Moreover, the passage of time plays a significant role in our system, since a number of performance indicators are time related. It is therefore a dynamic system. Based on these grounds, a Discrete Event Simulation suits our system best.
In addition, we describe our model with re-entry system. As a follow-up to the description of our model, we clarify our routines in the simulation model and the assumptions made within our model. We run all simulation experiments with 3 replications, a warm-up period of 35 weeks and a total run length of 385 weeks. In conclusion, we show that our model description is correctly implemented and that our model is valid with respect to the required outcome parameters.

In the next chapter we discuss the used case inputs and in Chapter 6 the adaptive model including experimental design is introduced.

5. Simulation: Case inputs

This chapter discusses the different case inputs to the simulation model. Before describing the case inputs, Section 5.1. explains which patient flows are used within the simulation model. Next, Section 5.2. clarifies which arrival process we use for the different patient flows. Whether separate or joint, the patient attributes for each patient flow are described in Section 5.3. Section 5.4 covers the initial scheduling rules used in practice, as also briefly described in Section 2.3. Following this, Section 5.6 describes the construction of the initial blueprint of the calendars. The chapter concludes with Section 5.7 explaining the performance measurement of the system.

5.1. Patient flows

In this section we discuss the patient flows in the simulation. A (normal) care process, as it appears from the 2019 appointment data, for an urology patient involves several steps / appointments at the Urology Department. These appointments can take place at the regular consultation hours by the Urologists, but also at other urology resources such as with the nurse practitioner, at the locations other than Enschede or at the treatment rooms. Figure 5.1 shows a fictitious example of a care path as it may occur in practice. Regular consultation hour (dark blue in Figure 5.1) refers to the appointments that take place at the consultation hours in Enschede by one of the medical specialists, in our case the urologists. In light blue, appointments at other urology resources are shown, such as an appointment with the nurse practitioner or a treatment in the treatment room.

Figure 5.1 – Practical example: Care pathway Urology

Since the focus of this study is on the regular consultation hours and not on the other resources, in the simulation we split care pathways into three different flows. So, a patient can enter with a referral from the GP, a 'referral' from another urology resource or a referral from another specialty. Thus, in Figure 5.1, the patient is divided into three different processes; one time arrival via GP and two times arrival via other urology resources.

Patient flow one: Arrival via general practitioner

This patient flow is the arrival via the GP. Figure 5.2 shows the fragmentation of the care pathway with regard to the first patient flow based on the example given in Figure 5.1.

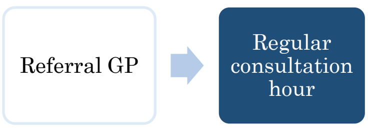


Figure 5.2 – Process patient flow one

Patient flow two: Arrival via other urology resource

Within this patient flow, we made a distinction between two different other urology resources, namely "referrals" via the treatment room and "referrals" not via the treatment room (i.e. nurse specialist, ANIOS and other locations). In practice, this does not involve an actual referral, however, in this study we define the process of being treated by another urology resource and then being seen at a regular consultation as a 'referral' from the other urology resource.

In the example of Figure 5.1, this represents two additional arrivals with associated process, see Figure 5.3.

Figure 5.3 – Process patient flow two: non-treatment rooms and treatment room

Patient flow three: Arrival via other specialty

The last possibility for patients to enter the system is by referral from another specialty. In the example of Figure 5.1, this type of arrival does not occur. However, we include this arrival type in the simulation

As mentioned, for every moment that a patient is referred by the GP, is seen or treated at another urology resource or is referred by another specialty, a new process starts and within the simulation, this patient therefore will reappear. In the 2019 data set of the Urology Department, which serves as our case input, we fragment the care process into new care processes each time one of the three abovementioned events occurs.

By dividing the process into different sub-processes, it allows us to anticipate various referral periods and the number of recurring visits that a patient has to receive, by using different distributions for different arrival flows. In this way, it is possible to simulate several types of patients, such as patients who in reality only have x number of visits to the urologist, while another patient undergoes treatment in the treatment room, or an oncological patient who sees several urology resources. For the determination of the input variables, we do not include appointments with nurses as referrals via other urology resources, as the appointment with the nurse and the possible follow-up appointment with the urologist are already known before the appointment with the nurse takes place. The nurse has no influence on this element of the care process.

Ideally, we would identify all the different possible care pathways and simulate them. Rohleder, Lewkonia, Bischak, Duffy and Hendijani (2010) applied this system in their simulation. The advantage of identifying and simulating all care pathways is that it is easier to predict in time what capacity will be needed, as it is easier to predict what process and associated resources will be required. However, identifying all care pathways is very time-consuming (i.e. in the study by Rohleder et al. (2010) it took four undergraduate business students much time to identify all patient flows from only two months of data) and in case of not standardized care it leads to a great diversity of different care pathways.

In addition, we do not opt for the use of whole care pathways, as they are not currently used in planning. In the current situation, a patient is scheduled without knowing what the follow-up appointments will be and whether or not these follow-up appointments are planned in advance.

5.2. Patients arrival simulation

The first case input covers the arrival process of the patients. Based on historical data, we determine the arrival process for each patient flow, enabling us to simulate a stochastic arrival process. This section discusses the calculation of the parameters and/or distributions for each arrival process of the different patient flows.

5.2.1. Patient flow one: Arrival via general practitioner

To determine the arrival process of patients referred by the GP, we use all referrals between 01-01-2019 and 30-09-2019. These are the referrals where the patient received the first appointment at one of the six included resources (i.e. the regular consultations hours). This results in a total of 468 referrals. Of these 468 referrals, we exclude 9 because it was not a new referral, but a repeat visit. Therefore, we determine the arrival process via the GP on the basis of 459 referrals.

Figure 5.4 shows the number of GP referrals per day - green bars - compared to the number of times this occurred. A distinction has been made between week days and days during the weekend.

Based on queueing theory, arrival rates are likely to be Poisson-distributed. Based on Figure 5.4, we also expect a Poisson distribution for the number of GP referrals.

For the week days we calculated that $\hat{\lambda} = \frac{438}{195} = 2.292$ and for the weekend days $\hat{\lambda} = \frac{21}{78} = 0.270$. We plotted the two distributions Figure 5.4. Based on Figure 5.4, we see a good fit between the empirical quantities and the expected (theoretical) distribution. In order to be sure of a good fit, we conduct a chi-square test.

For the distribution relating to the week days, the chi-square test value (based on $\alpha = 0.05$ and 8 degrees of freedom) is 15.51. The total error is 9.95. Since $9.95 < 15.51$, we can conclude that there is no (statistically) significant difference between the theoretical and empirical distribution. We therefore simulate the arrival process on weekdays with the theoretical Poisson distribution with $\lambda = 2.292$.

For the distribution concerning weekend days, the chi-square test value (based on $\alpha = 0.05$ and 4 degrees of freedom) is 9.49. The total error is 3.65. Since $3.65 < 9.49$, we can conclude that there is no (statistically) significant difference between the theoretical and empirical distribution. We therefore simulate the arrival process of patients referred by GP on weekend days with the theoretical Poisson distribution with $\lambda = 0.27$.

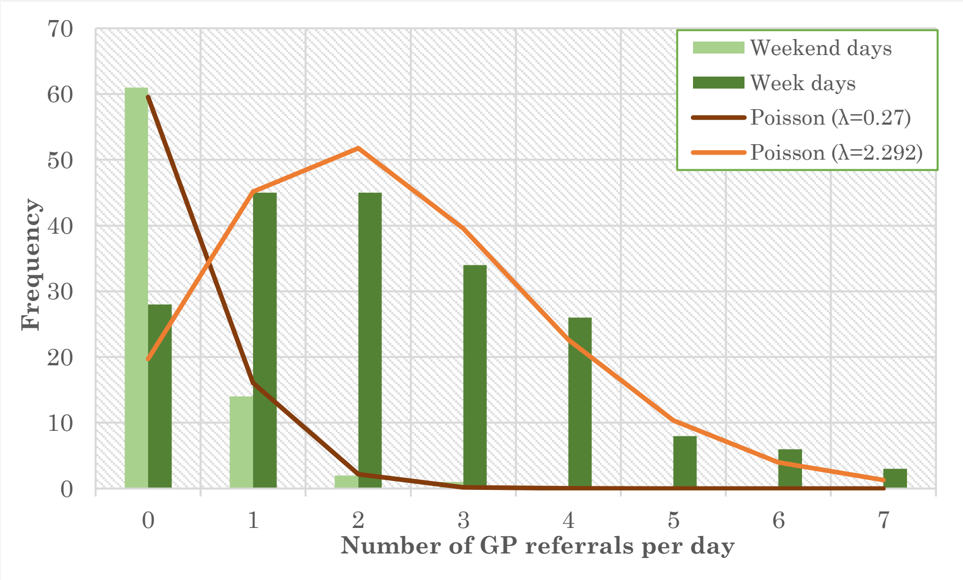


Figure 5.4 – Arrivals via GP

5.2.2. Patient flow two: Arrival via (other) Urology resource

Arrival via treatment room

As stated before, this arrival process involves patients who are treated at a treatment room (TR) and then have to go to one of the six included resources. We base the number of 'referrals' (TR-referrals) per day via this arrival process on all patients who were treated in a treatment room between 01-01-2019 and 30-09-2019 and then had to go to the regular consultation. A total of 1280 patients in that period are included.

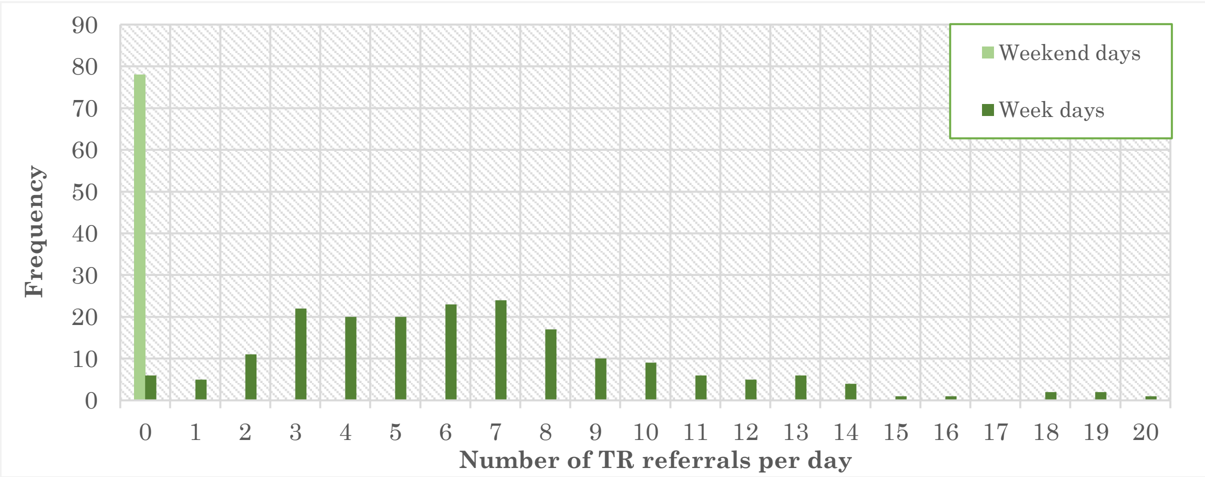


Figure 5.5 – Arrivals via treatment room

Figure 5.5 shows the frequency of referrals per day from the treatment room to the included resources. Again, a distinction is made between weekdays and weekends. There is no discrete distribution that fits this data. Therefore, to generate patients in the simulation, we use an empirical distribution. The probabilities of the number of arrivals per day during a weekday are based on Figure 5.5 and are listed in Table 5.1. During the weekend days, we will not generate patients that enter the system with a TR-referral.

Table 5.1 – Probabilities number of arrivals via treatment room

Number of arrivals	0	1	2	3	4	5	6	7	8	9	10
Probability	3.08%	2.56%	5.64%	11.28%	10.26%	10.26%	11.79%	12.31%	8.72%	5.13%	4.62%
Number of arrivals	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	
Probability	3.08%	2.56%	3.08%	2.05%	0.51%	0.51%	0.00%	1.03%	1.03%	0.51%	

Arrival via non-treatment room

This arrival process includes all patients referred by a Urology resource other than the six included resources and the treatment rooms, e.g. via the nurse practitioner. We base the number of 'referrals' (non-TR referrals) per day via this route on all patients who were treated between 01-01-2019 and 30-09-2019 by another Urology resource and then had to go to the regular consultation. This represents 960 patients in that period.

Figure 5.6 illustrates the frequency of referrals per day by Urology resources. Again, we made a distinction between weekdays and weekends. Based on Figure 4.12, we expect a Poisson distribution for the weekend days, while we do not expect a theoretical distribution for the week days.

For the week days we calculate $\hat{\lambda} = \frac{919}{195} = 4.713$ and for the weekend days $\hat{\lambda} = \frac{41}{78} = 0.526$. We plot the two distributions in Figure 5.6. Based on Figure 5.6, we clearly see a mismatch between the empirical and theoretical distribution with respect to the week days. For the weekend days, however, there seems to be a reasonable fit.

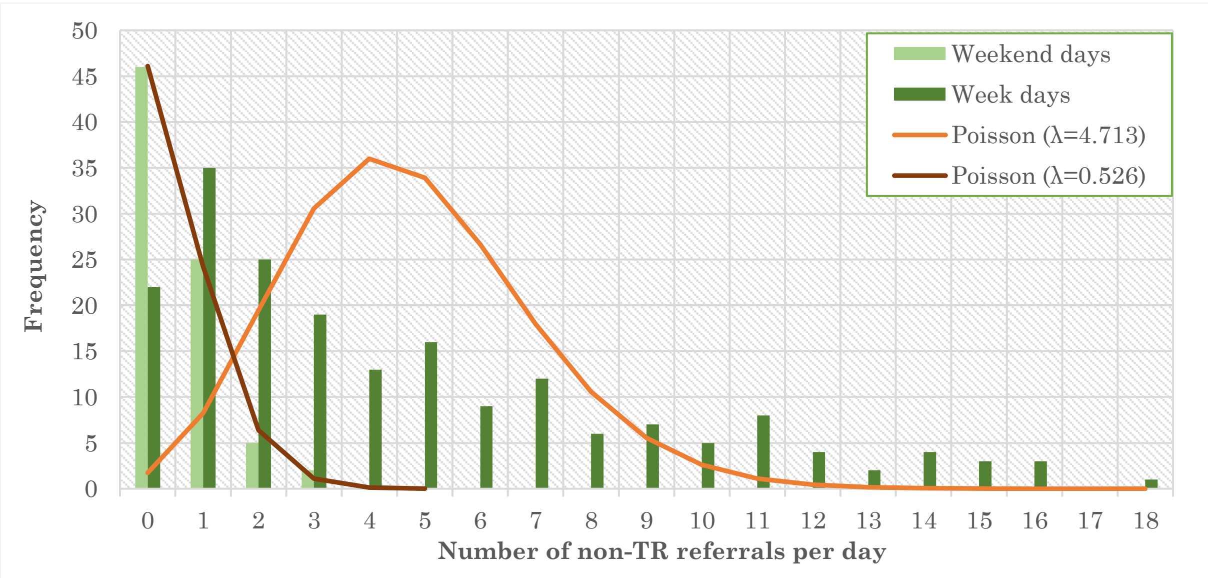


Figure 5.6 – Arrivals via non-treatment room

To verify this match, we performed a chi-square test. The chi-square test value (based on $\alpha = 0.05$ and 4 degrees of freedom) is 9.49. The total error is 1.18. Since $1.18 < 9.49$, we can conclude that there is no significant difference between the theoretical and empirical distribution. We therefore simulate the arrival process of patients referred by Urology resources (non-treatment room) on weekend days with the theoretical Poisson distribution with $\lambda = 0.526$.

Since no theoretical distribution fits the arrival process on week days, we will generate patients based on an empirical distribution. These probabilities are listed in Table 5.2.

Table 5.2 – Probabilities number of arrivals via urology resources (non-treatment

Number of arrivals	0	1	2	3	4	5	6	7	8	9
Probability	11.34%	18.04%	12.89%	9.79%	6.70%	8.25%	4.64%	6.19%	3.09%	3.61%
Number of arrivals	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	
Probability	2.58%	4.12%	2.06%	1.03%	2.06%	1.55%	1.55%	0.00%	0.52%	

5.2.3. Patient flow three: Arrival via other specialities

The remaining group of arrivals in the simulation are the patients who arrive with a referral from another specialty. To determine this arrival process, we use all appointments in which the referring physician was from another specialty in the period from 01-01-2019 to 30-09-2019. Since the date of the referral is not available for these types of referrals, we use the date of the appointment. These dates may be biased due to the fact that the inflow is spread out more evenly due to scheduling. A total of 180 referrals are included.

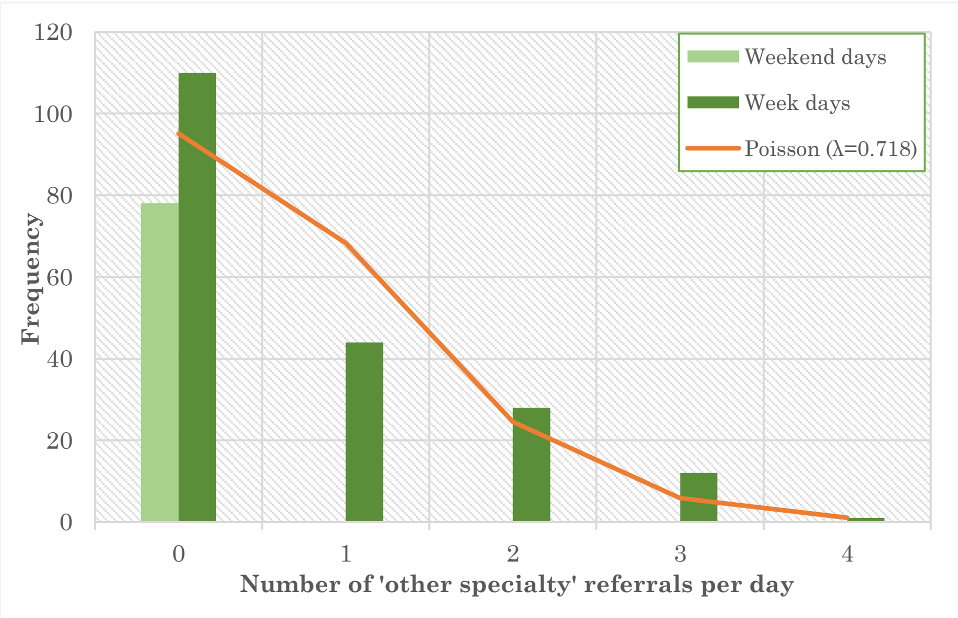


Figure 5.7 – Arrivals via other specialities

Figure 5.7 plots the number of referrals from another specialty based on the 180 referrals. Based on Figure 5.7 we expect a Poisson distribution for the arrival process on week days. For the weekend days, it is evident that there are no referrals at all on weekend days. For the week days we calculate $\hat{\lambda} = \frac{140}{195} = 0.718$. This distribution is plotted in Figure 5.7.

In order to verify whether this (theoretical) distribution does not significantly differ from the empirical distribution, we perform a chi-square test. The chi-square test value (based on $\alpha = 0.05$ and 5 degrees of freedom) is 10.07. The total error is 18.05. Since 18.05 > 10.07, we conclude that there is a (statistically) significant difference between the theoretical and empirical distribution. Hence, for the simulation we use the empirical distribution as provided in Table 5.3.

Table 5.3 – Probabilities number of arrivals via other specialities

Number of arrivals	**0**	**1**	**2**	**3**	**4**
Probability	56.41%	22.56%	14.36%	6.15%	0.51%

5.3. Patients attributes

This section describes the second case input, namely the patient attributes. The following subsections outline the values we use for different patient attributes based on the Urology Department. Because of the COVID-19 crisis, we use data from 2019, as in 2020 the care process differs excessively from the pre-COVID-19 situation. For each of the three patient flows, we determine distributions for each attribute. Table 5.4 presents an overview of the patient attributes we use.

Table 5.4 – Patient attributes

Patient attribute	Section
Appointment windows	4.2.1.
Number of (re)visits and appointment windows revisits	4.2.2.
(Possible) attending physician(s)	4.2.3.
Appointment type	4.2.4.

5.3.1. Appointment windows

In this subsection, we discuss the urgency with which new patients must be seen by the urologist. We define this urgency in terms of an appointment window. For each inflow process, based on historical data of 2019, we examine the distribution we use in the simulation to determine the urgency of each patient. As mentioned in Section 4.2.1, in our model, we do not take into account patients that need to be seen or treated on the day itself. For this patient group, the emergency physician is the lead physician and this resource is outside the scope of the study and therefore we did not include this in the simulation.

- **Patient flow one: Arrival via general practitioner**

Patients who come in via a GP referral encounter six different appointment windows:

- 0 days (today)
- 1 – 2 days
- 3 – 7 days
- 8 – 21 days
- 22 – 28 days
- 29 – 42 days

As mentioned, we exclude patients who need to be seen immediately (today). In the period from 01-01-2019 to 30-09-2019, a total of 423 patients were referred and received a new appointment. Of these 423 patients, we exclude 34 patients as the referral period for these patients was unrealistic ($\geq$ 50 days). We determine the referral time by the date of appointment minus the date of referral. These patients are excluded because we assume they have postponed their appointment to a later date. In total, 389 patients are seen within 50 days. The group of patients seen by the urologist between 43 and 50 days are allocated to the 29 - 42 day period.

Figure 5.8 shows the distribution in absolute and relative frequency. We cannot fit a theoretical discrete distribution on the basis of these data. Therefore, for the appointment window, we use an empirical distribution whereby the probability for a certain appointment window is the relative frequency as shown in Figure 5.8.

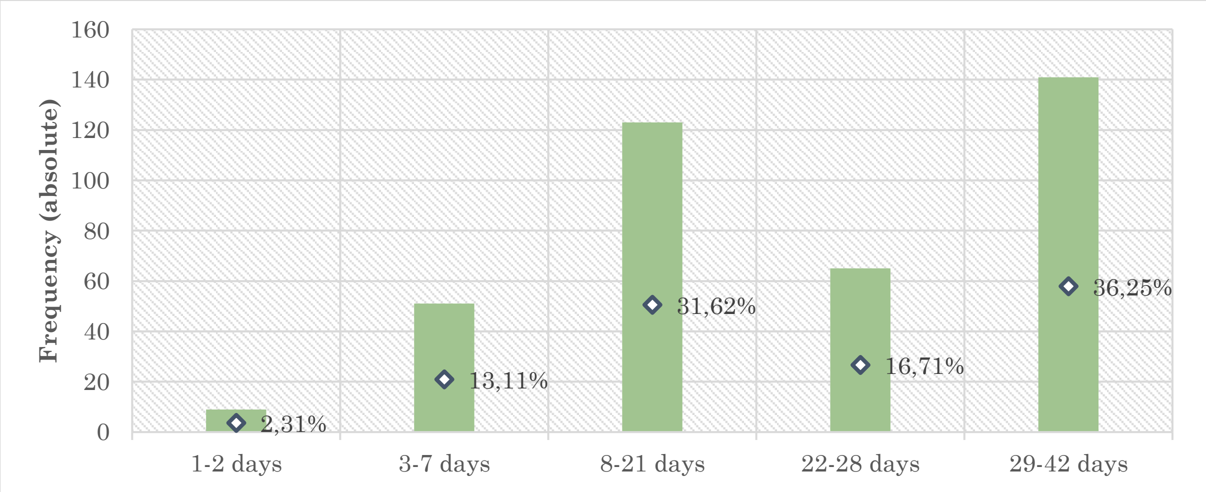


Figure 5.8 – Appointment windows: arrivals via GP

- **Patient flow two: Arrival via (other) Urology resource**

Patients referred from other Urology resources to the standard consultation hours (also called included resources) and who enter the system in this way have no typical appointment window. The department does not use a standard form, as is the case for referrals from the GP. It is not desirable to give patients a single day as an appointment window, as this is not representative of reality. In practice, a period of time is set for the next appointment; in this case, the next appointment is at an included resource, after a patient has been treated at another urology resource.

To determine the appointment windows, we include all patients who had an appointment at another resource and then at the standard consultation hour in the period from 01-01-2019 to 30-09-2019. The route via the treatment room (TR) involves 1280 patients and the route via a resource other than the treatment room (non-TR) involves 960 patients. Figure 5.9 shows the difference in days between the appointment at the other Urology resource and the appointment at the standard consultation hour.

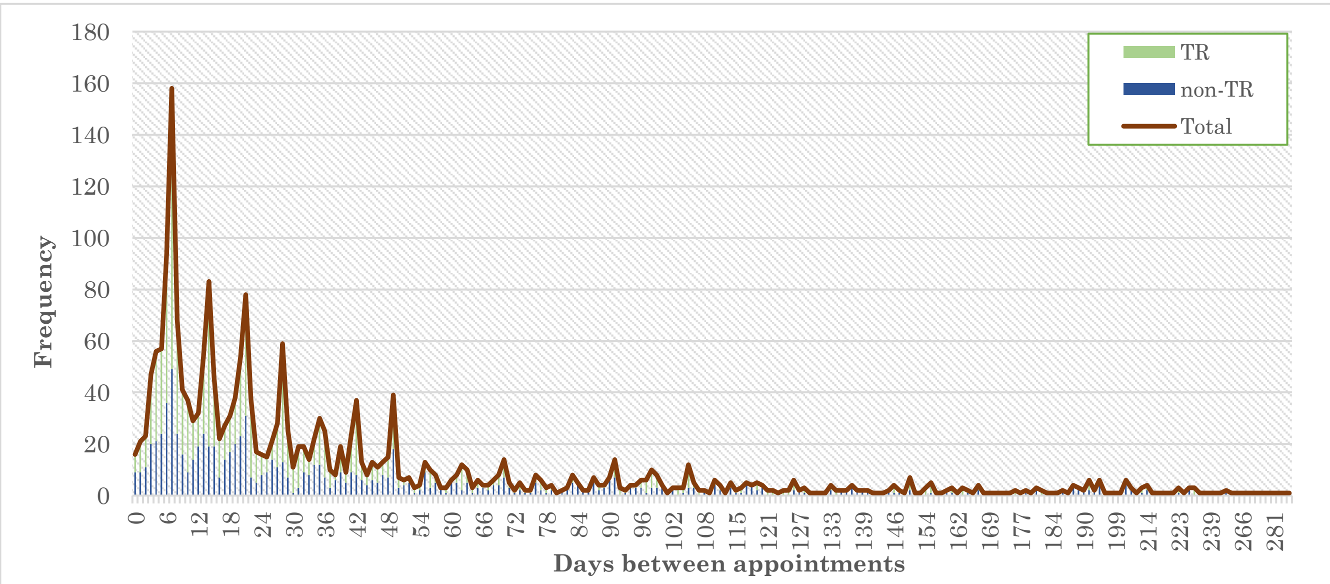


Figure 5.9 – Appointment windows: arrivals via other Urology resources

Since the distribution of the number of days differs only slightly between TR and non-TR, we base the appointment windows on the total number of patients who arrived at the standard consultation hour with a prior appointment at another Urology resource. We use the peaks in Figure 5.9 to determine the appointment windows and are shown in Table 5.5. In our simulation, 31 days are used for a month. In addition to the appointment window, the number of days from Figure 5.9 allocated to each appointment window to determine the number of patients is indicated in the second column. To determine the probabilities, we exclude all patients (54 patients (2.4%)) that were planned after more than six months since, based on the planners' experience, these are patients who postponed their appointments. The last column of Table 5.5 shows the probabilities for all appointment windows for patients entering the system via a 'referral' from another Urology resource.

Table 5.5 – Probabilities appointment window: arrival via other Urology resources

Appointment window	Allocated from Figure 5.9	Frequency	Probability
1 – 7 days	1 – 7 days	456	21.01%
8 – 14 days	8 – 14 days	344	15.85%
15 – 21 days	15 – 21 days	296	13.64%
22 – 28 days	22 – 28 days	194	8.94%
29 – 35 days	29 – 35 days	140	6.45%
36 – 42 days	36 – 42 days	131	6.04%
43 days – 2 months	43 – 62 days	202	9.31%
2 months – 3 months	63 – 93 days	156	7.19%
3 months – 4 months	94 – 126 days	128	5.90%
4 months – 5 months	127 – 167 days	76	3.50%
5 months – 6 months	168 – 195 days	47	2.17%

- **Patient flow three: Arrival via other specialities**

Patients who enter the system with a referral from another internal specialty do not use a fixed appointment window with regard to urgency, as is the case with GP. However, due to the inadequate logging of the current EHR, it is not possible to retrieve on a large scale when a referral has taken place and therefore historical referral periods cannot be reproduced. Since referrals from other specialties often concern a new request for care and for that reason, we consider this comparable with the referrals from the general practitioners. We use these 'GP' probabilities in the simulation for the appointment windows of this type of patients, as given in Figure 5.8.

5.3.2. Number of (re)visits and appointment window revisits

For each patient that enters the system, we determine in advance how often this patient will reappear, without visiting another urology resource, at the regular consultation hours and with what time interval(s). In this subsection, we show which input variables we use with respect to the recurring patients in the simulation of the case study. Since the care process is fragmented with a new process starting every time a patient comes from another urology resource (as a 'referral'), the number given in this subsection may not correspond with the feeling of the current urologists and the Urology Department how often a patient receives a revisit. So, again, we consider a revisit as an appointment at a regular consultation hour that is subsequent to an appointment at a regular consultation hour.

Number of (re)visits

In Section 4.1 we already mentioned that we do not simulate complete care pathways. Therefore, we need to deal intelligently with the number of visits a patient receives. Bowers, Lyons, and Mould (2005) use a fixed follow-up rate per specialty to determine the number of revisits. However, this fixed follow-up rate per patient flow means that everyone needs a fixed number of visits, while in practice, the number of visits can differ per patient. Nguyen et al. (2014) applied a re-entry system, using a so-called discharge rate. This rate is the probability that a patient will not need a next appointment. In their study, they used two fixed discharge rates, 38% for a first visit and 32% for revisits. However, this method does not take into account that the probability of 'discharge' increases as the patient has had more visits. Instead, Nguyen et al. (2014) see the appointments independently of each other, whereas in practice they are related. In order to take this into account in a way, we choose to determine in advance the total number of appointments the patient will receive based on an empirical distribution. In this way, we take into account that patients need a varying number of visits.

Based on all patients with a referral between 01-01-2019 and 30-09-2019 we determine per flow with what probability a patient needs a revisit and the number of revisits. For this analysis, appointments in which the patient did not show up (physical consultation) and appointments in which the patient was unreachable (telephone consultation) are excluded. Based on the remaining 2802 patients, we calculate an empirical distribution per incoming flow, which we use in our simulation. Table 5.6 shows this distribution of the total visits. If a patient receives more than one appointment, it is a repeat visit.

Table 5.6 – Probabilities number of (re)visits

Number of total visits	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Via general practitioner	73.06%	18.75%	5.17%	2.37%	0.43%	0.22%	0.00%
Via treatment room	74.44%	16.33%	6.26%	1.38%	1.17%	0.32%	0.11%
Via non-treatment room	68.39%	20.02%	7.70%	2.46%	1.03%	0.32%	0.08%
Via other specialty	66.18%	19.85%	8.09%	3.68%	0.74%	0.74%	0.74%

Appointment windows revisit

We base the appointment window of a revisit on all patients who experienced at least one revisit in 2019 and were referred between the period of 01-01-2019 and 30-09-2019. Our analysis takes into account that there are also appointments where patients did not show up or were not reachable by phone (in this case described as no-show).

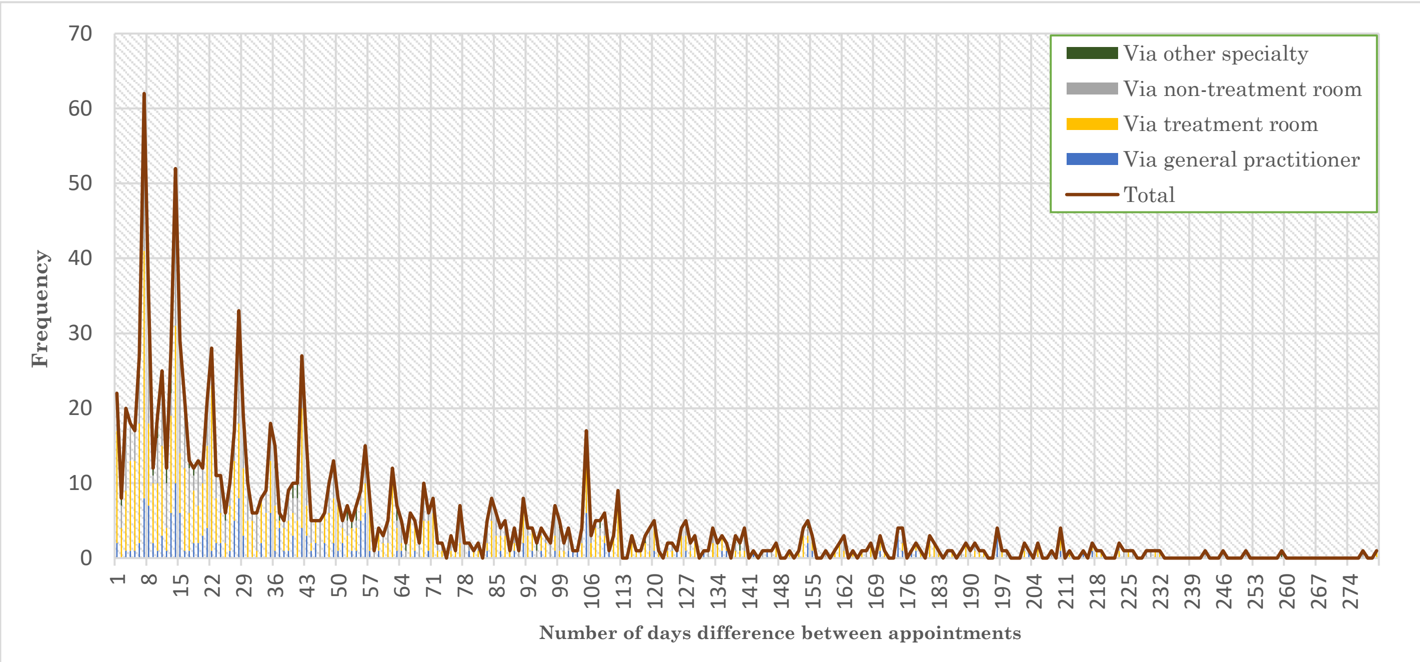


Figure 5.10 – Appointment windows: revisits

The number of days between an appointment and a subsequent no-show is included in our calculation. The number of days between a no-show and a subsequent attended appointment is not included, as this often concerns an appointment that should actually have taken place on the date of the no-show. The frequency of the number of days of difference per inflow process is shown in Figure 5.10.

It can be clearly seen that the distribution per inflow varies strongly. Therefore, we use a (empirical) distribution per inflow in the simulation. The planners of the urology department indicate that they usually work with fixed appointment windows, these being: < 1 week, < 2 weeks, < 3 weeks, < 4 weeks, < 6 weeks, < 2 months, < 3 months, < 4 months, < 5 months, < 6 months and < 9 months. Therefore, Table 5.7 shows the chosen appointment windows in the first column. However, we often see a peak one day after the appointment window, since these are usually patients who belonged to the appointment window previously, we include these days in the calculation of the probabilities for the previous appointment window (e.g. the frequency of 8 days difference is allocated to appointment window 1- 7 days). Table 5.7 provides the appointment windows with associated probabilities for the repeat visits of patients who enter with a referral from a GP, treatment room, non-treatment room and other specialty.

Table 5.7 – Probabilities appointment windows revisits
(GP = general practitioner, TR = treatment room, non-TR = non-treatment room, OS = other specialty)

Appointment window	Allocated from Figure 5.10	Arrival via GP	Arrival via TR	Arrival via non-TR	Arrival via OS
1 – 7 days	1 – 8 days	11.83%	17.82%	16.62%	16.46%
8 – 14 days	9 – 15 days	15.59%	11.88%	14.51%	24.05%
15 – 21 days	16 – 22 days	7.53%	10.91%	8.44%	7.59%
22 – 28 days	27 – 29 days	11.29%	7.22%	9.50%	6.33%
36 – 42 days	37 – 43 days	13.44%	11.56%	12.40%	12.66%
43 days – 2 months	44 – 62 days	13.44%	10.91%	8.97%	7.59%
2 months – 3 months	63 – 93 days	5.91%	9.95%	10.82%	11.39%
3 months – 4 months	94 – 126 days	8.60%	8.83%	8.97%	7.59%
4 months – 5 months	127 – 167 days	4.84%	4.98%	4.49%	5.06%
5 months – 6 months	168 – 195 days	3.76%	3.21%	2.11%	0.00%
6 months – 9 months	196 – 280 days	3.76%	2.73%	3.17%	1.27%

5.3.3. (Possible) attending physician(s)

In this subsection, we discuss the input variable 'attending physician'. In practice, a patient with a new care complaint can be treated by several physicians. It often occurs that physicians specialise in a part of their profession, as a result of which the preference of the attending physician can differ per patient. The assignment of physician(s) to patients only occurs for patients who enter the system as new arrivals. Patients with a repeat visit are treated by the physician they first visited. This corresponds to practice, as the aim here is to maintain one physician per patient as much as possible, if the complaints so require.

- **Patient flow one: Arrival via general practitioner**

If a patient enters the system with a referral from the GP, the GP forwards a brief description of the complaint. In 2019, 3578 patients were referred to the Urology department of the Medisch Spectrum Twente via Zorgdomein. Figure 5.11 shows the distribution per complaint (in Dutch) of these referrals.

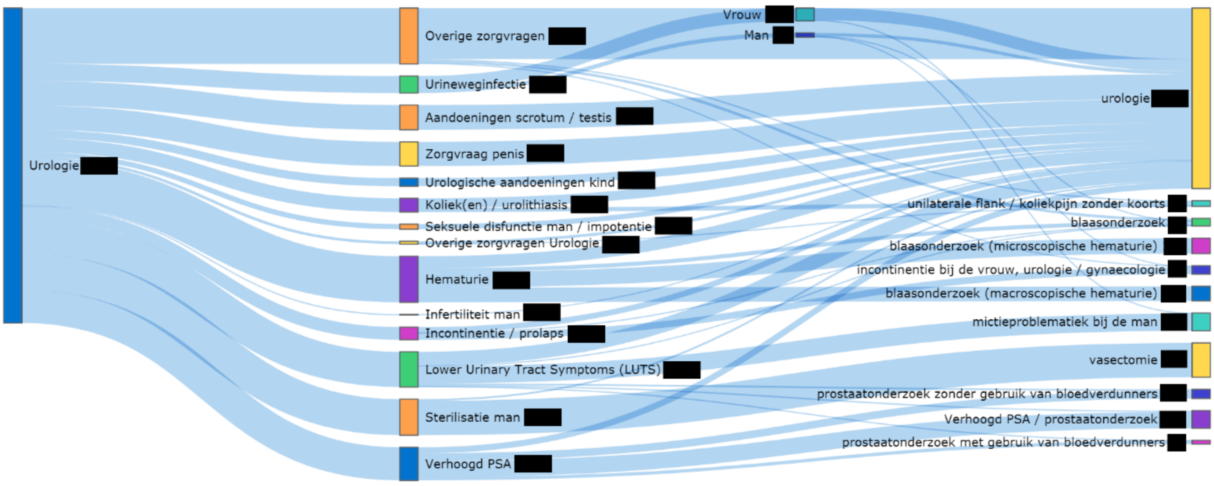


Figure 5.11 – Complaints: referred by GP

The Urology planners identify which urologists can treat which complaints, see Table 5.8. We develop Figure 5.12 on the basis of Table 5.8. This Figure 5.12 displays the probability that a patient can be treated by each physician. In our simulation, we use this empirical distribution to determine by which physician(s) the patient with a GP referral can be treated.

Table 5.8 – Attending physician: arrival via GP

Complaint	Urologist	Number of referrals	Percentage
Other health issues	All urologists	[redacted]	17.75%
Urinary tract infection	All urologists	[redacted]	5.37%
Scrotum / testis disorders	All urologists	[redacted]	7.85%
Care request penis	All urologists	[redacted]	7.66%
Urology disorders in children	Urologist 2 and 3	[redacted]	2.57%
Colic(s) / urolithiasis	Urologist 1, 5 and 6	[redacted]	4.33%
Male sexual dysfunction / impotence	Urologist 1, 4 and 5	[redacted]	1.62%
Other care requests Urology	All urologists	[redacted]	0.89%
Haematuria	All urologists	[redacted]	14.62%
Male infertility	Urologist 5	[redacted]	0.20%
Incontinence / prolapse	Urologist 2 and 4	[redacted]	4.00%
Lower Urinary Tract Symptoms (LUTS)	All urologists	[redacted]	11.18%
Sterilisation of men	All urologists	[redacted]	11.46%
Increased PSA	All urologists	[redacted]	10.51%

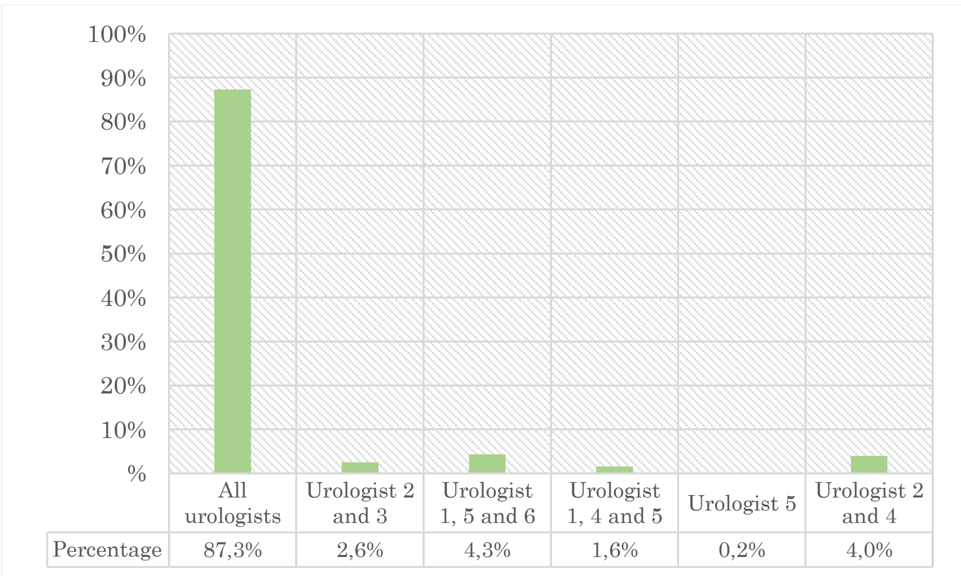


Figure 5.12 – Attending physician probabilities: arrival via GP

- **Patient flow two: Arrival via (other) Urology resource**

For patients with a 'referral' from another Urology resource, it is often the case that they are treated by a particular urologist. For instance, patients who are treated in the treatment room are assigned to a particular urologist and then consulted by the same urologist at the regular consultation hour. As a result, a patient is assigned to a single physician, whereas a patient referred by the GP may be referred to several physicians.

To determine which physician is assigned to a specific patient, data from 01-01-2019 to 30-09-2019 is used. All patients who had an appointment with another urology resource before an appointment at a regular consultation were included. This comprises 2240 patients. A distinction was made between patients (1280 patients) who were referred from a treatment room and patients (960 patients) who came from a urology resource other than a treatment room.

Figure 4.10 presents the percentage of cases in which these patients were distributed among the different urologists. This relative frequency is used as an empirical distribution in the simulation to determine which physician to assign to a patient if they are referred from another urology resource.

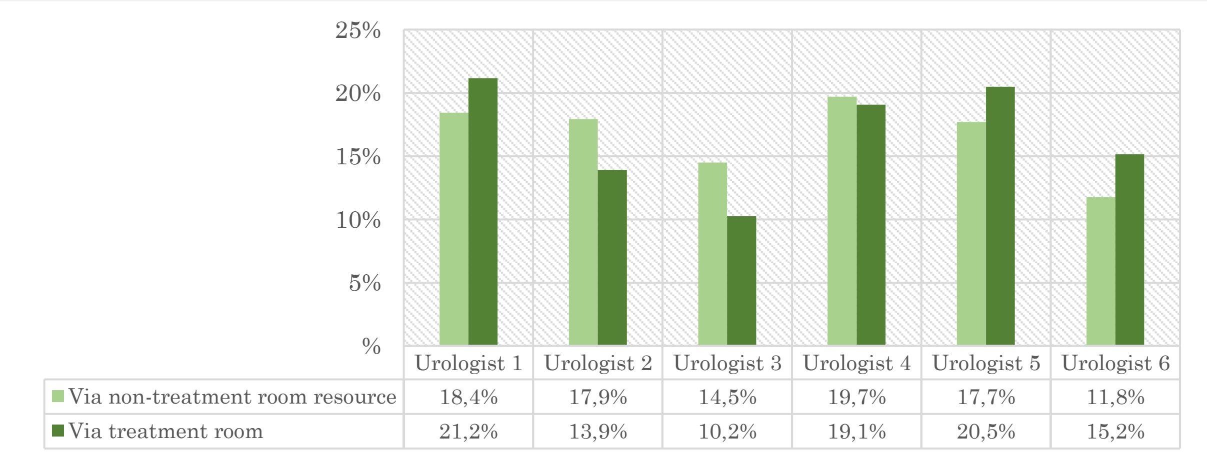


Figure 5.13 – Attending physician probabilities: arrival via other Urology resources

- **Patient flow three: Arrival via other specialities**

For this last patient flow, we use the same probabilities as mentioned in the first flow: arrival via GP. These probabilities are given in Figure 5.12. We choose to use these, because we expect the population referred by internal medical specialists does not differ substantially from the population referred by GPs. Because of this assumption, it is appropriate to use the same probabilities.

5.3.4. Appointment type

The last attribute we give to the patient for each appointment is the appointment type, or to put it in other terms, on which appointment code the patient can be scheduled. Based on the data from 01-01-2019 to 31-09-2019 we determine the distributions for the appointment types for the first visits of the different flows and based on the patients with a referral in the same period, but with a revisit in 2019 we establish the distributions for the appointment types for the repeat visits.

Table 5.9 shows per flow the probabilities used for the determination of the appointment types of the first visit of the patient. Additionally, Table 5.10 shows the probabilities per flow for the appointment type for a patient with a repeat visit. In the calculation, we include only slots with a percentage greater than 0.5%, as a smaller percentage is considered coincidence (i.e., scheduling on an incorrect slot).

Table 5.9 – Probabilities appointment type - first visit
(GP = general practitioner, TR = treatment room, non-TR = non-treatment room, OS = other specialty)

Appointment type	Arrival via GP	Arrival via TR	Arrival via non-TR	Arrival via OS
NP	75.36%	-	0.96%	75.00%
CP	-	21.96%	37.91%	6.25%
UCP	-	23.87%	14.27%	1.56%
BELC	-	14.16%	15.23%	-
PATHO	-	21.64%	14.91%	2.34%
TC	-	11.22%	11.29%	-
CPF/E	-	5.97%	3.83%	-
Combi-F/E	18.96%	-	-	14.84%
CPECHON	-	1.19%	0.75%	-
TWOC	-	-	0.85%	-
NPF/E	3.55%	-	-	-
NP-F/E	2.13%	-	-	-
CPECHOB	-	-	-	-

Table 5.10 – Probabilities appointment type - revisit

Appointment type	Arrival via GP	Arrival via TR	Arrival via non-TR	Arrival via OS
NP	1.60%	-	-	-
CP	33.51%	34.24%	34.18%	31.91%
UCP	19.15%	12.58%	24.05%	14.07%
BELC	19.15%	13.54%	11.39%	21.86%
PATHO	7.98%	21.97%	13.92%	15.33%
TC	7.98%	10.67%	11.39%	13.07%
CPF/E	5.85%	5.57%	3.80%	3.02%
Combi-F/E	2.66%	-	-	-
CPECHON	-	0.80%	1.27%	0.75%
TWOC	-	0.64%	-	-
NPF/E	-	-	-	-
NP-F/E	-	-	-	-
CPECHOB	2.13%	-	-	-

5.4. (Initial) Scheduling process

By patient scheduling we mean the process of assigning patients to the various possible slots, i.e. the process of making an appointment for patients. Patient scheduling is influenced by several factors, including resourcing capacity (i.e., the total number of slots available; more explicitly, the number of slots available for each patient type), the patient arrival process and the scheduling method. Section 5.2 describes our arrival process. Section 5.5 together with Section 5.6 details the resource capacity and the subdivision of slots. In this section we discuss the scheduling method for the simulation baseline, which matches current practice. In Section 6.3.1. other approaches of scheduling methods are elaborated to perform different experiments and compare with the current practice. Thus, this section describes the case input, as patients were scheduled in 2019.

Since our study focuses on regular consultation hours, the scheduling of emergency patients arriving on the same day is not taken into account. The same applies to referrals sent in on a Friday where the appointment window is completely falling on the weekend. All these patients are seen by the emergency physician and not at a regular consultation hour.

As mentioned in Section 2.3, appointments are currently planned manually by the planners of the department. Within MST, this takes place decentral and each specialty has its own planners. In the current situation, and our baseline simulation, we schedule based on the following scheduling method (see Appendix V for more details):

Step 1
- Use FCFS principle for correct slot
- Find first available slot within appointment window with correct appointment code

Step 2
- Use FCFS principle for incorrect slot with correct time unit
- Find first available slot within appointment window with correct time unit

Step 3
- Find first available slot after scheduling window
- Maximum of 50% of the referral time later than the appointment window with a maximum of 7 days

Step 4
- Find first available session in appointment window by correct physician
- Create an extra slot and assign patient to this slot

Step 5
- First find available session as short as possible before appointment window by correct physician
- Create an extra slot and assign patient to this slot

Figure 5.14 – Scheduling method of current practice

5.5. Resource capacity

In our simulation model, we allocate a specified number of sessions per week per urologist. Based on the 2019 data, this section discusses how much capacity we allocate per period to the resources, in our case the urologists. As mentioned in Section 4.2.3, in our simulation we use an eight week repeating capacity allocation. This means that the capacity allocated in week 1 is the same as the capacity allocated in week 9.

Regular period

The data for 2019 show that we can classify 41 weeks as a regular period. With regular period we mean a period that there is no reduction (e.g. holidays) regarding the number of sessions per week. In these 41 weeks, there were a total of 140 sessions in the morning and 177 sessions in the afternoon for the standard consultation hour. Based on this total, we construct an eight week repeating capacity allocation for both the morning and afternoon sessions. Table 5.11 shows this allocation. Calculated back to 41 weeks, this allocation means a total of 179.4 sessions in the morning and 138.4 sessions in the afternoon. Over 41 weeks this means that we allocate 0.8 sessions too many. We consider this is a negligible difference with regard to the performance of the system. With this allocation we take into account not only the total capacity, but also the distribution between the urologists compared to current practice.

Table 5.11 – Resource capacity: number of sessions per week (reduction period)

	Week	1	2	3	4	5	6	7	8
Morning	Urologist 1	1	1	0	1	1	0	2	0
	Urologist 2	0	1	0	0	0	1	0	0
	Urologist 3	1	1	0	2	0	1	1	0
	Urologist 4	0	0	1	1	0	0	0	1
	Urologist 5	1	0	2	1	0	0	2	0
	Urologist 6	0	2	0	1	0	0	1	0
Afternoon	Urologist 1	0	2	0	2	0	1	0	1
	Urologist 2	2	0	1	0	2	1	1	1
	Urologist 3	1	0	1	0	1	0	1	0
	Urologist 4	1	1	1	0	1	2	0	1
	Urologist 5	0	0	1	2	1	1	1	0
	Urologist 6	0	1	0	1	0	1	0	1

5.6. Construction of input blueprint calendar

In Section 2.3 we point out that the Urology Department uses a blueprint for the regular consultation hours. Figure 2.4 shows this blueprint for an afternoon session and from this blueprint follows a distribution of the number of slots per appointment type / appointment code. As mentioned in Sections 4.2.2. and 4.2.3, in the simulation we do not distinguish the time of day, as this is beyond the scope of this study. The focus is on the number of slots per appointment type and specifically the number of slots for self-scheduling patients and not on the distribution of these slots over time. As a result, a specific blueprint, in which the slots are recorded per time point, is not necessary and only a distribution of the number of slots per code per session is sufficient.

Table 5.12 indicates the initial distribution of the number of slots (capacity) per appointment code per session and the required number of time units (tu). One tu represents 5 minutes. We use this distribution for the baseline situation. In Section 6.2. we discuss an approach for adjusting the capacity per appointment code.

Table 5.12 – Appointment code distribution

Appointment code	**NP**	**CP**	**UCP**	**BELC**	**PATHO**	**TC**	**CPF/E**
Number of slots	3	7	0	3	3	0	2
Time units	2	2	2	2	3	2	2
Appointment code	**Combi-F/E**	**CPECHON**	**TWOC**	**NPF/E**	**NP-F/E**	**CPECHOB**	**Blockade**
Number of slots	2	0	0	0	0	0	1
Time units	3	2	2	3	3	2	3

Interestingly, although important, a considerable number of codes are used in practice but do not appear in the blueprint of the schedule. Also, in this case, we match the actual practice with the simulation by using the same approach in the simulation as is used in reality. As a result, patients with appointment type:

- UCP, CPECHON, TWOC or CPECHOB are scheduled on a slot with code CP;
- TC are scheduled on a slot with code BELC;
- and NPF/E or NP-F/E are scheduled on a slot with code Combi-F/E.

5.7. Performance measurement

The last topic we will discuss in this chapter is not a case input, but a measurement. In our case, we use four different performance indicators: minimum service level, utilization, fraction within appointment window and service level adjusted to the number of changes. In this section, we present these four performance indicators in more detail.

Minimum service level

This performance measure is our primary indicator. This performance measure states that self-scheduling patients or planners (for non-self-scheduling patients) must be offered a sufficient number of slots within their appointment window. Per patient group, self-scheduling patients (SSP) and non-self-scheduling patients (NSSP), we take the percentage of patients for whom sufficient slots are offered within their appointment window. This percentage is called the service level of the group. It is important that both groups have a service level that is as high as possible. For the SSP group, this is important, as it gives them a real choice in their care process, and with a low service level they will still often contact the secretariat to schedule an appointment, which will increase their workload. For the NSSP group, a high service level is important, as patients may be scheduled outside their appointment window or appointments may be rescheduled. This performance measure also addresses the fear that self-scheduling patients may get too few slots and therefore no service is provided to this group.

Since we want to get both service levels as high as possible, our goal is to maximize the minimum service level (MSL):

$$\textbf{maximize Z} = \min_{P}\left(\frac{\text{\# patient} \in \text{P} \mid \text{sufficient number of slots}}{\text{\#P}}\right),$$

where P stands for each group of patients (SSP or NSSP) and where sufficient number of slots is defined as the number of slots offered. In our opinion, at least three slots for the SSP group are sufficient. For group NSSP, we consider one slot sufficient

Utilization

Our second performance indicator is the utilization of resources. There is currently a fear that the utilization of the outpatient department will drop when patients are able to schedule their appointments themselves. By including this indicator, the influence of various settings on the utilization can be assessed.
In our study this is considered a secondary indicator, meaning that no optimization takes place on the basis of this indicator. Utilization is calculated as follows:

$$\textbf{utilization} = \frac{\textit{time units occupied}}{\textit{total allocated time units}}$$

Fraction within appointment window

We chose to measure the not appointment lead time, as stated in Section 2.5. We do not consider this performance indicator to be a valuable and appropriate indicator, as a group of patients does not necessarily need to be scheduled within three or four weeks. There are patient groups where the appointment window is (22,28) or (29,42) and the patient should therefore get an appointment within 28 days or within 42 days. It is not sensible to give these patients an appointment within three or four weeks for the purpose of the appointment lead-time indicator. Therefore, we present a more meaningful indicator, the percentage of patients that get an appointment in their appointment window. Despite the fact that this is not (yet) measured within the Medisch Spectrum Twente, we do include this indicator. We also consider this as a secondary indicator.

$$\textbf{fraction within planning window} = \frac{number\ of\ visits\ wihtin\ plannning\ window}{total\ number\ of\ visits}$$

Service level adjusted to the number of changes

The final performance indicator is the one we use for our Simulated Annealing (SA) to determine the number of slots per appointment code. We want to minimise the number of changes of an appointment code for a slot by step 2 of the scheduling routine, as there is a slot available with the required number of time units, but the distribution of the codes is not optimal. If we use this indicator (the number of slots changed) our SA will lead to a solution where all the slots to be distributed are assigned one specific code and the remainder of the codes are not assigned any number of slots. The result is a dramatic drop in service level. To overcome this, we also include the service level in the indicator to prevent this level dropping significantly. After all, our goal is the highest possible MSL.

We therefore define the following indicator:

$$\textbf{service level adjusted to the number of changes} =$$

$$\frac{\#\ patients\ with\ sufficient\ number\ of\ slots - \#\ appointment\ codes\ changed}{total\ number\ of\ appointments}$$

5.8. Conclusions

In this chapter, we discuss the case inputs of our study. We use three different flows of patients entering our system. The number of patients entering our system per day is based on the Poisson distribution or an empirical distribution. Each patient is assigned attributes, which are: appointment window, total number of visits required, doctor to visit and appointment type. All these attributes are assigned to a patient based on empirical distributions.

In addition to the patient inflows and attributes, we also discuss the initial scheduling process, which is based on the first come, first serve principle. The other case inputs are the number of sessions used per week per urologist and the distribution of the number of slots per appointment code. These are both derived from daily practice in 2019. We show that we use the performance indicator minimum service level. This performance measure states that self-scheduling patients or planners (for non-self-scheduling patients) must be offered a sufficient number of slots within their appointment window.

6. Simulation: Adaptive model and experimental design

In our simulation, we perform multiple experiments. This chapter outlines the different models and experimental factors resulting in various experiments. Our experimental process is shown in Figure 6.1. First, we perform Simulated Annealing to determine the optimal distribution of the number of slots for our standard and for our adaptive model. We explain the adaptive model, and the difference with the standard model, in Section 6.1. After describing our adaptive model, Section 6.2 discusses the application of Simulated Annealing.

Next, we apply one of the two models in combination with several experimental factors to generate outcomes. These experimental factors are explained in Section 6.3.

Finally, we discuss the experimental design in Section 6.4. Here, we indicate which experiments we will run.

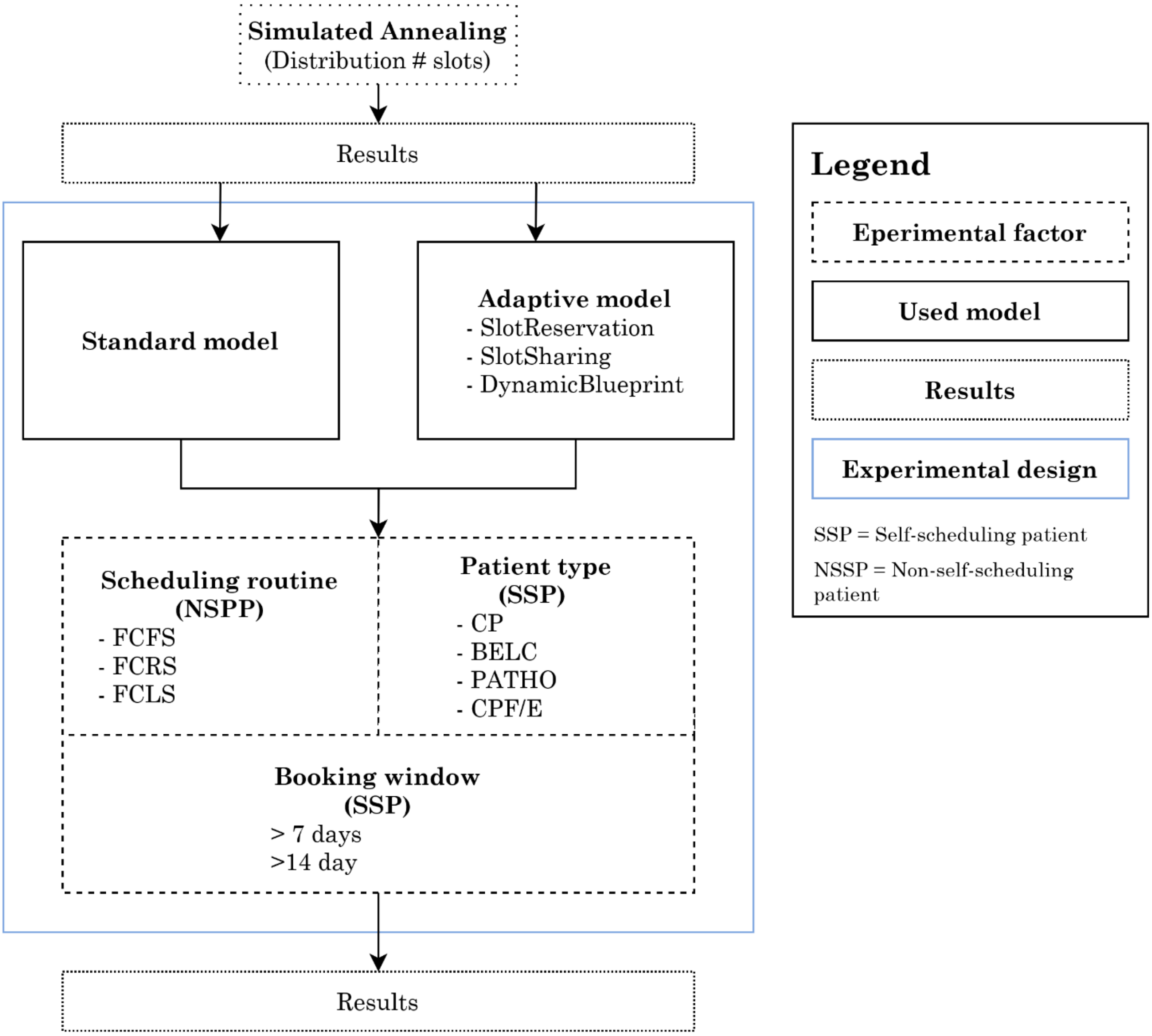


Figure 6.1 – Total experimental process

6.1. Adaptive model

Our adaptive approach consists of three different elements: SlotReservation, SlotSharing and DynamicBlueprint. The difference between our standard model and the adaptive model is at the use of SlotReservation. In our standard model, we do not use any of the three elements and we only apply the SA optimized number of slots per appointment code. Our adaptive model includes SlotReservation and the number of slots optimised for our adaptive model by SA. In addition to SlotReservation, SlotSharing and/or DynamicBlueprint can be applied. In the following subsections we discuss the three different elements of our adaptive model.

6.1.1. SlotReservation

Vermeulen et al. (2009) showed that the use of slots reserved for more urgent patients has a positive impact on the ability to schedule an appointment within the appointment window of the patient. They indicate that there is a trade-off between scheduling patients in the first available slot so as not to lose capacity and keeping slots free to accommodate more urgent patients. In their approach, for multiple appointment codes, they reserve a number of time slots for patients with a specific appointment window.

To maintain capacity for more urgent patients, we use a similar approach and call it SlotReservation. We define patients as urgent if they have to be seen within a week, i.e. an appointment window with upper bound ≤ 7 days. In the tactical schedule, we keep capacity available for more urgent patients by introducing a new appointment code, whereby only urgent patients can be scheduled in this time slot. In this way, we increase the likelihood of a free slot for the urgent patients, contributing to a better service level. To apply this principle, we create the additional appointment code $SOON_{tu}$, where tu is the number of required time-units (tu = 2 or 3). Hence, every urgent patient in our system is assigned to type $SOON_{tu}$ and we discard the other appointment types (e.g. NP, CP, etc.) for this urgent patient group. As this group of urgent patients is not part of the group of self-scheduling patients (patients are not allowed to schedule their appointment within one week), SlotReservation is only applied to the non-self-scheduling patients.

In our study we identify three different urgent appointment windows (A.W.): (1,2), (1,7) and (3,7). On the $SOON_{tu}$ slots, only patients can be scheduled with appointment window = (1,2) or (1,7). In our approach we attribute the appointment window (1,7) to the patients with A.W. = (3,7), as we assume that this will not be detrimental to the care process and gives us a technical advantage (i.e. longer appointment window = higher probability of an available slot).

To take into account the patient group with appointment window = (1,2) and to avoid that there is no available slot for this patient group, we reserve a number of slots for this patient group. This means that we use a number of slots with appointment code $SOON_{tu}$ only for patients with A.W. = (1,2). The number of slots we reserve for this patient category is based on the expected number of patients per working day that arrive and meet these characteristics and an additional surplus of capacity. We reserve $E(SOON_{tu}^{A.W.})$ number of slots for the expected number of patients with appointment window (1,2) for a slot of two time units (= 10 minutes). Table 6.1 shows the estimate $\hat{E}(SOON_{tu}^{P.W.})$ of the expected number of patients per weekday for the various time units and appointment windows.

Since $\hat{E}(SOON_3^{P.W.})$ is a very small number (0.573), we will determine through a number of experiments whether to apply the appointment code $SOON_{tu}$ only for tu = 2 or also for tu = 3. These experiments are discussed in Section 6.2. We do not apply the reservations for patients with A.W. = (1,2) and tu = 3, since $\hat{E}(SOON_3^{(1,2)})$ = 0.030 is very small.

Table 6.1 – Estimates of expected number of patients

	tu = 2	**tu = 3**
$\hat{E}(SOON_{tu}^{(1,2)})$	0.137	0.030
$\hat{E}(SOON_{tu}^{(1,7)})$	2.230	0.543

To determine which slot we assign to a particular patient, we use the following approach:

- Patients with type $SOON_2$ and A.W. = (1,2) are scheduled on the first available $SOON_2$-slot within their scheduling window. If this is not possible, the scheduling routine from Step 2 in Figure 5.14 is applied.
- For patients with type $SOON_2$ and A.W. = (1,7) it is examined for each day whether the number of available slots is more than the number of reserved slots for A.W. = (1,2). If this is the case, the patient is assigned to the corresponding day. If this is not the case for any day within the appointment window, the patient is scheduled on the first possible slot within the appointment window. Thus, a reservation violation is allowed. If no slot is available within the appointment window, the scheduling routine from step 2 in Figure 5.14 is applied.
- If we use $SOON_3$, then the same approach applies as for patients with type $SOON_2$ and A.W. = (1,2) and we schedule patients on the first available $SOON_3$-slot. If this is not possible, the scheduling routine from step 2 in Figure 5.14 is applied.

The algorithm <u>SlotReservation</u> for patients with type $SOON_2$ and A.W. = (1,7) is:

1. *patient* is the current to be scheduled patient at day 0
2. $E\left(SOON_2^{(1,2)}\right)_d$ is the number of slots reserved for patients with appointment window (1,2) and tu = 2 for day d.
3. $AVAIL(SOON_2)_d$ is the number of slots available for patients type $SOON_2$ on day d.
4. STS is to be scheduled time-slot.
5. FOR d := 1 to 7

```
        IF AVAIL(SOON_2)_d > E(SOON_2^(1,2))_d then
                STS = Slot on day d
                EXITLOOP
        END
NEXT
```

6. IF STS /= found then
   FOR d := 1 to 7
      IF $AVAIL(SOON_2)_d > 0$ then
         STS = Slot on day d
         EXITLOOP
      END
   NEXT
   END
7. IF STS /= found then
   Start 'normal' scheduling routine from step 2, Figure 5.14
   END
8. schedule *patient* to STS

We reserve 1 slot for patients with type $SOON_2$ and A.W. = (1,2), so $E(SOON_2^{(1,2)}) = 1$. Despite the fact that $\hat{E}(SOON_2^{(1,2)})$ is very small, we choose to apply this, since patients with type $SOON_2$ and A.W. = (1,7) still get the possibility to violate this reservation if no other day is possible within the scheduling window.

6.1.2. SlotSharing

With SlotSharing we present a newly developed approach to make effective use of the different characteristics of self-scheduling patients (SSP) and non-self-scheduling patients (NSSP). With SlotSharing, we exploit the fact that SSP patients cannot schedule within 1 week in any case (see Section 2.4), and NSSP patients have specific slots (i.e., $SOON_{tu}$) for patients that need to have their appointment within a week by using SlotReservation.

If an SSP-patient wants to schedule an appointment, with SlotSharing we ensure that this patient not only has a choice of the codes corresponding to the patient type (by means of the appointment code), but also has a choice of the $SOON_{tu}$-slots corresponding to the number of time units the patient needs. If the total number of available slots intended for SSP patients (independent of the appointment code) together with the number of $SOON_{tu}$-slots is more than the number of expected required $SOON_{tu}$, the SSP patient is presented with all codes corresponding to the required appointment code and all $SOON_{tu}$. In case the number of available slots equals the number of expected needed $SOON_{tu}$-slots (following from the distribution of tactical schedule), then these slots are reserved and the slots cannot be used by the SSP-patients. Appendix VI provides the algorithm of the Slot Sharing process.

Figure 6.2 is a visual representation of the application of SlotSharing. The 8 different slots in a row represent one session that the SSP-patient can choose out of (Step 0).

Step 1. When SSP-patient (P1) wants to schedule an appointment for code 2, this patient sees, besides slots 4 and 5, also slots 1, 2 and 3. Then the patient chooses a slot (randomly). In this case slot 3.

Step 2. Then SSP-patient (P2) arrives with code 4. This patient has the choice of slots 6, 7 and 8. Since the total number of free slots = 7, the patient also sees slots 1 and 2. The patient chooses slot 6.

Step 3. Again, an SSP-patient (P3) with code 4 arrives. This patient has a choice of slots 7 and 8 and of slots 1 and 2. The patient chooses slot 1.

Step 4. Next comes SSP-patient (P4) with code 2. This patient gets a choice of slots 4 and 5 and 2. The patient chooses slot 4.

Step 5. Again, an SSP patient (P5) with code 4 arrives. This patient gets the choice between slots 7 and 8 and slot 2. The patient chooses slot 8.

Step 6. Initially, 3 $SOON_2$-slots were released. After scheduling patient 5, a total of 3 slots (SSP slots and $SOON_2$-slots) are still available. So, the available slots become $SOON_2$-slots and reserved for only $SOON_2$-patients.

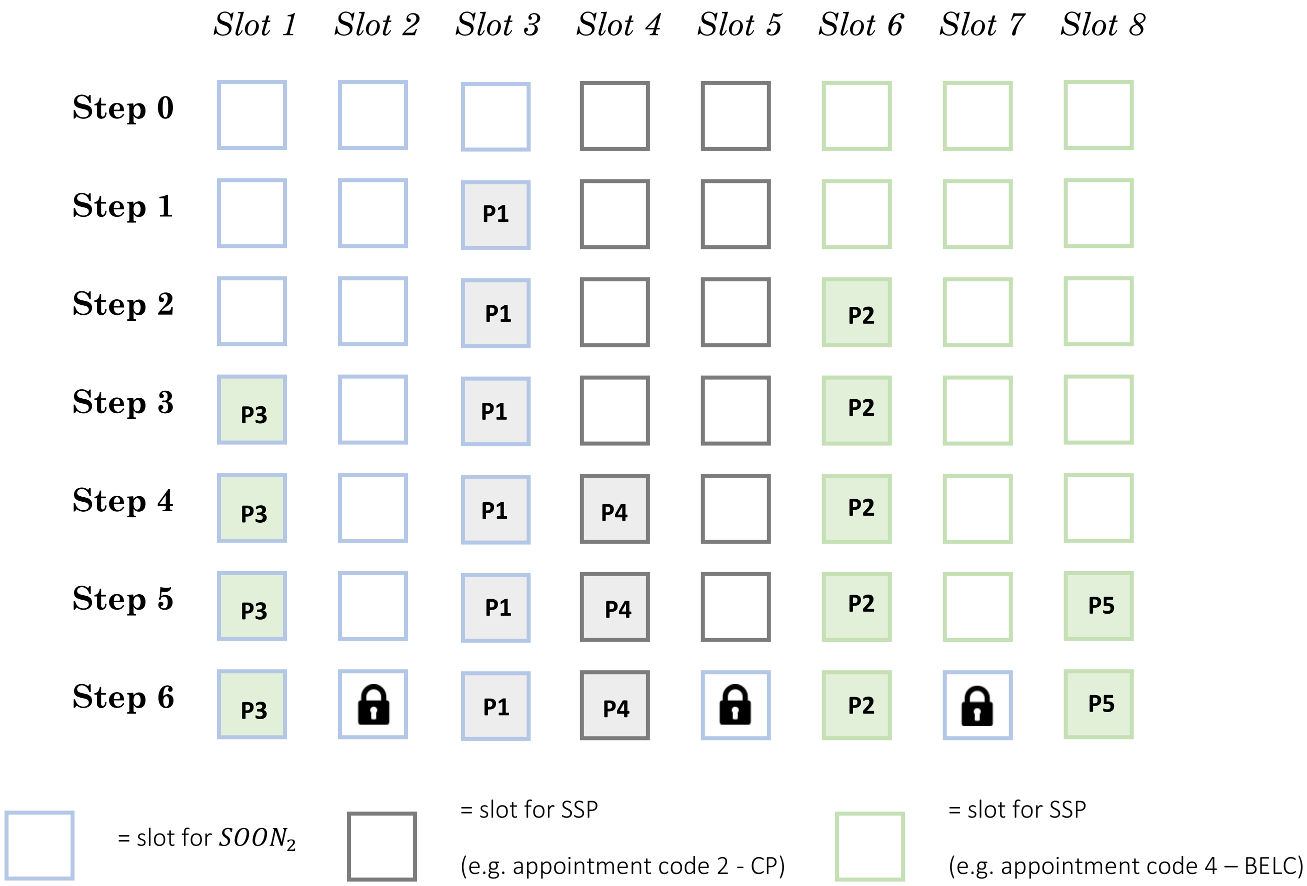


Figure 6.2 – Application of SlotSharing

6.1.3. DynamicBlueprint

The third and final part of the adaptive model is DynamicBlueprint. Using this approach, we exploit the fact that patients that need to be scheduled within a week are always $SOON_{tu}$ patients, and need to be scheduled to $SOON_{tu}$-slots. Since other available appointment codes with the same time units (tu) cannot be used anymore within a week given the system settings, we convert all appointment codes to $SOON_{tu}$ using the DynamicBlueprint procedure.

The principle is straightforward. On day d the available appointment codes of day $d+7$ not being $SOON_{tu}$ are converted to $SOON_{tu}$ corresponding to the tu of the initial appointment code.

The algorithm DynamicBlueprint is the following:

1. day d is the current day
2. $AVAIL(Slot_{tu})_{d+7}$ is an available slot not being $SOON_{tu}$ with time unit tu at day $d+7$
3. FOR every $AVAIL(Slot_{tu})_{d+7}$
   CHANGE $AVAIL(Slot_{tu})_{d+7}$ TO $SOON_{tu}$
   NEXT

6.2. Simulated Annealing - Distribution of the number of slots

Before simulating the different experiments, we first determine the distribution of slots per appointment code using the Simulated Annealing metaheuristic. In this section we explain our use of Simulated Annealing to obtain the best possible distribution of slots for our standard and adaptive model.

We choose to use a local search, since we want to construct a final solution from an initial one by iteratively adapting the current solution. However, a potential danger with a local search is that we get stuck in a local optimum, which is why we choose a metaheuristic that allows us to balance intensification and diversification (Rader JR., 2010). We choose Simulated Annealing, as it has the advantage of being easy to implement because only a few parameters need to be defined (Rader JR., 2010). The parameters used by us are:

Objective function

As mentioned in Section 5.7, we use the indicator 'fraction service level minus appointment codes changed'. Our aim is to maximize this indicator, as it ensures that we have the best possible service level in combination with the number of codes that are changed. If codes are changed in the simulation, this indicates that there is potential to change the distribution of slots to increase the service level.

Initial solution

For our standard model, we use the distribution of slots per appointment code mentioned in Section 5.6. For our adaptive model, we test the use of $SOON_{tu}$ with tu = 2 or with tu = 2 and tu = 3. Based on the results of both scenarios, we use one of the two scenarios in our adaptive model. These results, together with the final distributions, are described in Section 7.1. As an initial solution for our adaptive model, we allocate several slots to $SOON_2$ and $SOON_3$, based on $\hat{E}(SOON_2^{P.W.})$ and $\hat{E}(SOON_3^{P.W.})$. Table 6.2 shows the initial solution.

Table 6.2 – Initial solution - Simulated Annealing

Appointment Code	Standard model	Adaptive model (with tu=2)	Adaptive model (with tu=2 and tu=3)
NP	3	3	3
CP	7	6	6
BELC	3	2	2
PATHO	3	3	2
CPF/E	2	1	1
Combi-F/E	2	2	2
$SOON_2$	N/A	3	3
$SOON_3$	N/A	N/A	1

Transition mechanism

As a neighbourhood operator, we use the 'move' principle. This means that, compared to the current solution, for one appointment code we increase the number by one (+1) and for another appointment code we decrease the number by one (-1). The choice of which code is increased by one and which is decreased by one is based on the difference how often a code is requested to change (i.e. changed from code *x*) and how often a code requests to change (i.e. changed to code *x*) in combination with an application of the roulette wheel principle. The choice of the 'move' principle implies that the total number of time units, currently 45 tu, used can be lower and higher. For example, if NP (tu = 2) is decreased by 1, and PATHO (tu = 3) is increased by 1, then the total becomes 46 tu. We choose this approach since we do not want to strictly maintain 45 tu, but we also want to prevent the number of tu from becoming to be 48 or more. We expect this will not occur unless the demand for the slots with tu = 3 turns out to be very high. We will possibly have to apply a correction to the best result if the total number of tu turns out to be too high or too low.

Given the set of appointment codes J that qualify for +1 (i.e. to this code had to be changed more than the code was changed to another), w_j is the difference between how many times a code was requested to change and successfully changed, and how many times a code requested to change and successfully changed, based on the last iteration. We select appointment code j to increase by one with probability $p_j = \frac{w_j}{\sum_{i \in I} w_i}$, with $\sum_{j \in J} p_j = 1$.

We apply the same principle for the codes that qualify for -1. Thus, the code that was changed most often to another code has the highest probability of being reduced by one.

Cooling schedule

Length Markov chain: We use three different lengths for the three different times we apply SA. For the standard model, the number of neighbour-solutions is $3 * 3 = 9$. For the others, these are respectively $3 * 4 = 12$ en $4 * 4 = 16$. Therefore, we use the lengths 9, 12 and 16.

Initial temperature: We use the initial temperature of 15, as this achieves an initial acceptance ratio of approximately 1.

Cool down factor: We use a cool down factor $a = 0.80$ with the cooling scheme $T_{k+1} = \alpha T_k$, where T_k is the temperature of Markov chain k.

Stopping criteria

The SA optimization stops after 20 Markov chains or if the solution has not changed after two Markov chains.

6.3. Experimental factors

Based on three different factors, we generate outcomes in combination with the standard or adaptive model. This section describes the three different experimental factors: scheduling method NSSP-patients, appointment codes for SSP-patients and the booking window for SSP-patients. Figure 6.3 shows the different possibilities for the experimental factors.

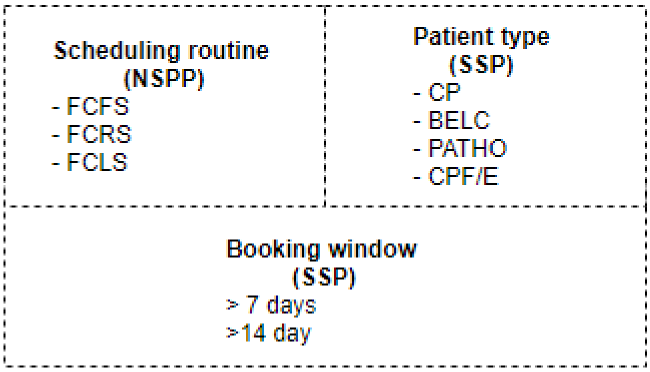


Figure 6.3 – Experimental factors

6.3.1. Scheduling method non-self-scheduling patients

In current practice, as described in Section 5.4, the FCFS principle is used. Besides this principle, we also evaluate two other principles: first come, random serve (FCRS) and first come, last serve (FCLS). Therefore, this experimental factor has three levels.

First come, random serve

As stated in Section 4.2.2, self-scheduling patients follow the FCRS principle, since it is not known which slot is chosen by self-scheduling patients in practice.
However, we can also apply this principle for non-self-scheduling patients, where the schedulers randomly select a feasible slot. In the simulation, we implement FCRS in Step 1 of the algorithm, in order to randomly select a slot out of the possible slots within the scheduling window that match the appointment type of the patient. If no slot is available, the process starting from Step 2 in Figure 5.14 is applied.

First come, last serve

The first come, last serve principle is to schedule on the last available slot within the appointment window. In the simulation, we implement the FCLS principle in Step 1 of the algorithm, in order to select the last slot within the scheduling window that meets the appointment type of the patient. If no slot is available, we apply the process starting from Step 2 in Figure 5.14.

6.3.2. Appointment codes self-scheduling patients

Since the Medisch Spectrum Twente has to decide which appointment codes to make available to self-scheduling patients, we include this as an experimental factor. If an appointment code is designated as an SSP code, this means that the type of patient who requests an appointment for this code is a self-scheduling patient.

The Medisch Spectrum Twente has already stated that they want to start with recurring visits, leaving us with the possible codes CP, BELC, PATHO and CPF/E. In this process, it is possible to designate only one appointment code, but also a combination of codes. This means that this experimental factor has $\binom{4}{0} + \binom{4}{1} + \binom{4}{2} + \binom{4}{3} + \binom{4}{4} = 16$ levels.

6.3.3. Booking window self-scheduling patients

The last experimental factor is the booking window for self-scheduling patients, specifically up to which day patients can (re)schedule their appointment. In Section 2.4 it is indicated that the Medisch Spectrum Twente chooses to allow patients to change their appointment up to 1 week, so ≤ 7 days is not allowed. In the simulation we take this into account by indicating that the maximum day for patients to schedule their appointments is 8 days before the lower bound (LB) of their appointment window.
In addition, patients are considered to be non-self-scheduling patients if they receive an appointment window in which the upper bound of the appointment window is ≤ 7 days. The booking window is thus $[current\ day\ ; LB\ planning\ window - 8\ days]$

Besides this booking window (> 7 days) for self-scheduling patients, we also include as an experimental level the booking window of > 14 days $[current\ day\ ; LB\ planning\ window - 15\ days]$. This means that patients can schedule up to 14 days before their lower bound of the appointment window. With this we offer MST insight into the influence of the booking window. We do not opt for an even shorter booking window, as this would not be desirable as otherwise too few patients would be regarded as self-scheduling patients. An even shorter window necessarily means that fewer patients can plan their own appointments.

6.4. Experimental design

After determining the distribution of the number of slots per appointment code, we combine our models with different experimental factors. In this section, we explain which experiments we evaluate.

We consider the following models:

- Standard model
- Adaptive model (SlotReservation)
- Adaptive model (SlotReservation + SlotSharing)
- Adaptive model (SlotReservation + DynamicBlueprint)
- Adaptive model (SlotReservation + SlotSharing + DynamicBlueprint)

Since the running time is not particularly long (approximately 1.5 minutes per experiment), we choose to apply a full factorial design to each model. This entails that we simulate and evaluate each factor combination. In total, this results in $3 * 16 * 2 = 96$ experiments per model. Altogether, we simulate 480 experiments. Figure 6.3 shows the result of all possible appointment system configurations.

Model

- Standard model
- Adaptive model (SlotReservation)
- Adaptive model (SlotReservation + SlotSharing)
- Adaptive model (SlotReservation + DynamicBlueprint)
- Adaptive model (SlotReservation + SlotSharing + DynamicBlueprint)

Scheduling routine (NSSP)

- First come, first serve
- First come, random serve
- First come, last serve

Appointment code (SSP)

- CP [Yes/No]
- BELC [Yes/No]
- PATHO [Yes/No]
- CPF/E [Yes/No]

Booking window (SSP)

- > 7 days
- > 14 days

Figure 6.4 – Experimental design

In addition, we intend to show Medisch Spectrum Twente what will happen if they do not adjust their tactical schedule, continue to use FCFS, maintain the booking window of $[current\ day\ ; LB\ planning\ window - 8\ days]$. Therefore, we also simulate and evaluate a baseline experiment, which represents the performance when implementing the new Electronic Patient File without adjusting one of the aforementioned factors. This baseline consists of 16 experiments.

6.5. Robustness analysis

We perform a robustness analysis to evaluate the impact of changes in the input data on the performance of the system. This tests the robustness of our algorithms, as we prefer algorithms that are efficient for all parameter values.

We perform the analysis for the baseline, best configuration for the standard model and the best configuration for the adaptive model. We choose the experiments based on the performance following from the results of the experiments as shown in Section 6.4. We classify each experiment according to the assignment of the appointment codes (e.g. CP: 1, BELC: 0, PATHO: 1, CPF/E: 0, i.e. 1-0-1-0). We look for the best result with at least 1 code assigned as SSP, with accompanying experimental factors (scheduling routine and booking window), in this appointment code distribution. In total there are 15 best results, since the factor 'appointment code SSP' consists of 16 levels minus the scenario 0-0-0-0. From these 15 results, we choose the best and the worst result as experiments for our robustness analysis.

Regarding the input parameters, only first order effect considered, which means that we change one input parameter at a time. We change the following parameters:

Number of sessions

In the eight weekly cycle we change the number of sessions for each physician. On the total number of sessions in the eight weekly cycle we increase the number of sessions with 1 for each physician and we also test the robustness if we decrease the number of sessions with 1 for each physician. In practice this number of sessions also fluctuates, and therefore we choose to test with this input parameter. In doing so, we also automatically test robustness in case of a deterioration of the match between demand for care and capacity. By increasing the capacity, we expect an increase in the service level and the percentage of patients in the appointment window, but a decrease in the utilisation. Since there is more capacity, the choice of the number of slots and thus the flexibility is greater, leading us to expect this. With a reduction in capacity, we expect exactly the opposite.

Because we influence the number of sessions and thus the balance between demand and capacity, we choose not to test the input parameter 'arrival rate'. We assume that reducing the capacity has the same effect as increasing the number of arrivals. In both cases, there will be more pressure on the system due to a negative difference in the demand-capacity ratio.

Distribution of sessions throughout the week

Besides adjusting the supply and demand, we are also carrying out an analysis in which we distribute the sessions evenly throughout the week. In our current system, sessions are distributed randomly over the days, which creates the possibility that there are several sessions on one day, while on another day no sessions are allocated. In this evaluation we allocate the sessions proportionally over the week. In this way, we test whether the algorithms can also be applied to, for example, diagnostic sessions (e.g. MRI sessions) in which the distribution of the number of sessions is distributed more evenly over the week.

We expect the results to improve with regard to the minimum service level, as a better distribution ensures that there are more opportunities during the week to schedule, which increases the likelihood of an available slot within the appointment window. However, we expect a slight increase as the random approach already provides a partially proportional distribution.

Possible attending physician(s)

In the model, we assume a varying doctor-patient relationships, which means that not every patient can be seen by every physician. We therefore also evaluate how the algorithms perform if this doctor-patient relationship is irrelevant and therefore every patient can be examined by every physician. For revisits, we still use the fact that patients are seen by the same physician as at their previous visit. We therefore adjust the preference for patients who arrive via a referral from their GP or other specialty. In this way, we again test the applicability of our models for example for diagnostic sessions, where there is no preferred patient-doctor relationship. We also expect a slight increase in the minimum service level, as patients can be seen by more physicians, so there are more options with regard to the number of available slots. We expect a slight increase, however, as the percentage of patients who can be seen by all physicians is already high (87.3%) and it only applies to arrivals via the GP or other speciality.
Table 6.3 shows the overview of the robustness analysis.

Table 6.3 – Scenarios robustness analysis

Input parameter	Change	Scenario
Number of sessions	+1 session per physician	A
Number of sessions	- 1 session per physician	B
Distribution of sessions	Distributed evenly	C
Possible attending physician(s)	No restriction	D

6.6. Conclusions

In this chapter we present our adaptive model, which applies at least one of the following three elements: SlotReservation, SlotSharing or DynamicBlueprint. With SlotReservation, we reserve capacity for more urgent patients to increase the probability that a slot is available for the more urgent patients. With the SlotSharing principle, we enable self-scheduling patients to experience a larger availability by offering shared slots until a threshold value is reached. Finally, the DynamicBlueprint algorithm ensures that slots which are no longer needed are converted into slots for urgent patients.
In order to achieve the best possible distribution of slots per appointment code, we use Simulated Annealing, using the move principle as an operator. This distribution is used as input for the 496 experiments, in which we experiment with: the model, the scheduling routine, the assignment of self-scheduling to appointment codes and the booking window. We test our model for robustness by: adjusting the number of sessions, adjusting the distribution of the number of sessions over the week and adjusting the possibility of different physicians.

7. Results

In Section 7.1. we describe the results of our Simulated Annealing, which serve as input for our follow-up experiments. The results per model or factor of these experiments, as described in Section 6.4, are presented in Section 7.2. Then, in Section 7.3, we present the results of the baseline scenario in combination with the overall results. Section 7.4. discusses the robustness analysis and we conclude with the conclusions in Section 7.5.

In this chapter, we answer the fifth sub-question of this study: What number of slots should be allocated to each appointment code? In addition, we also answer sub-question six: Which (adaptive) approach is most efficient in facilitating patient (self-)scheduling?

7.1. Simulated Annealing – Slot distribution

As mentioned in Section 6.2, we run our metaheuristic three times: once for the standard model and twice for the adaptive model. The goal of this optimization is to find the most appropriate distribution of the number of slots per appointment code.

Standard model

Table 7.1 shows the results of the best performing experiments based on the service level adjusted to the number of changes. From the Simulated Annealing it results that experiment 11 performs best.

Table 7.1 – Result SA: Standard model

Experiment	Adjusted Service Level	Overall Service Level	Utilization
Initial	64.9%	74.52%	76.4%
11	71.9%	78.40%	76.5%
11+	74.7%	80.57%	76.5%

If we observe the distribution of the number of slots, Table 7.2, we notice that 44 time units are used instead of the usual 45 (excluding 3 tu of blockage). As a result, we run experiment 11+, increasing the number of slots for CP by one. This slot emerges as the slot receiving the most frequent changes. The performance of this experiment 11+ is the greatest. With the distribution of experiment 11+ we use a total number of 46 time units. This means that we take into account 1 time unit (= 5 minutes) less for the blockage for unforeseen circumstances. We find this acceptable, as the average utilization (76.5%) leaves enough room for contingencies and possible short break.

Table 7.2 – Distribution appointment codes: Standard model

Appointment Code	Initial	Experiment 11	Experiment 11+
NP	3	4	4
CP	7	7	8
BELC	3	4	4
PATHO	3	3	3
CPF/E	2	1	1
Combi-F/E	2	1	1
Total tu	**45**	**44**	**46**

For the experiments from Section 6.4 for the standard model, we therefore apply the distribution of experiment 11+.

Adaptive model

Table 7.3 shows the results of the best performing experiments, where we run the adaptive model with $SOON_2$. From the Simulated Annealing it follows that experiment 20 performs best.

Table 7.3 – Result SA: Adaptive model ($SOON_2$)

Experiment	Adjusted Service Level	Overall Service Level	Utilization
Initial	68.3%	75.9%	76.5%
20	69.9%	76.7%	76.5%
20+	73.9%	79.8%	76.5%
20++	75.8%	81.3%	76.5%

As with the standard model, 44 time units are used in experiment 20, see Table 7.4. Again, we run an extra experiment 20+ with 46 time units, where we increase the number of BELC slots by one, as this is the slot that is changed most frequently. However, we notice in experiment 20+ that the code CP is often (extra) required and has $SOON_2$ a sufficient number of slots. Therefore, we run experiment 20++, in which we increase the number of slots for CP by one and decrease the number of slots for $SOON_2$ by one. Again, we find 46 time-units acceptable, considering the utilization rate.

Table 7.4 – Distribution appointment codes: Adaptive model ($SOON_2$)

Appointment Code	Initial	Experiment 20	Experiment 20+	Experiment 20++
NP	3	4	4	4
CP	6	5	5	6
BELC	2	2	3	3
PATHO	3	3	3	3
CPF/E	1	1	1	1
Combi-F/E	2	1	1	1
$SOON_2$	3	4	4	3
Total tu	**45**	**44**	**46**	**46**

Table 7.5 shows the best result of the adaptive model when we apply $SOON_2$ and $SOON_3$. In experiment 4, 45 time units were used, so there is no possibility to run a variant of experiment 4. Since experiment 4 performs less than experiment 20++ ($SOON_2$) and there are no options regarding an adjustment, we choose to apply only the slot $SOON_2$ in our adaptive model.

Table 7.5 – Result SA: Adaptive model ($SOON_2$ and $SOON_3$)

Experiment	**Adjusted Service Level**	**Overall Service Level**	**Utilization**
Initial	66.5%	75.0%	76.5%
4	68.4%	76.1%	76.5%

7.2. Performance Experimental Factors

In this section, we discuss the results per model or experimental factor. We cluster the results per model or factor with the same settings, and per subsection we compare either the model or one of the factors.

7.2.1. Standard and adaptive model

In total we compare the different performances between the models of 90 different configurations (3 scheduling routines times 15 options with appointment codes times 2 booking windows). We exclude the option CP: 0, BELC: 0, PATHO: 0, CPF/E: 0 (0-0-0-0), as no self-scheduling possibility is provided here. For each configuration we generate results, given that we use a full factorial design, and compare them with the performance of the models.

Minimum service level

As shown in Table 7.6, the average minimum service level (MSL) of our adaptive model with SlotSharing performs better than the standard model, however, the adaptive models without SlotSharing perform less. This is due to a lower service level for self-scheduling patients (SL SSP). On the other hand, all variants of the adaptive model perform better on average with respect to the service level for non-self-scheduling patients (SL NSSP). Both results can be explained by the fact that SlotReservation and DynamicBlueprint provide a better service level for NSSP. This comes at the cost of less flexibility for SSPs, as there are fewer potential slots available for SSPs. The allocation of slots for SSPs is reduced, and NSSPs are typically scheduled more in advance than SSPs, which increases the probability that a slot for an SSP is already occupied (whether or not by an SSP or an NSSP).

Besides the better performance of the adaptive model with SlotSharing, the standard deviation between the different configurations is also smaller for the adaptive model with SlotSharing compared to the standard model and the adaptive model without SlotSharing. Thus, the adaptive model with SlotSharing gives more stable results.

Table 7.6 – Results models (Minimum service level and SL SSP and SL NSSP)

	Mean MSL	**Max.** MSL	**Min.** MSL	**Std. dev.** MSL	**Mean** SL SSP	**Mean** SL NSSP
Standard	72.9%	82.0%	40.2%	8.5%	76.2%	78.4%
SlotReservation	68.2%	80.3%	38.7%	9.3%	68.6%	81.1%
SlotReservation + SlotSharing	76.7%	83.0%	67.7%	3.5%	80.2%	80.1%
SlotReservation + DynamicBlueprint	68.2%	80.8%	38.4%	9.5%	68.4%	81.8%
SlotReservation + SlotSharing + DynamicBlueprint	77.5%	83.5%	67.1%	3.8%	80.2%	82.1%

We construct a boxplot to compare the difference in percentage points in performance in terms of the MSL of the adaptive models compared to the standard model. Figure 7.1 shows this boxplot. It clearly shows that the adaptive model (SlotReservation + SlotSharing + Dynamic) performs best.

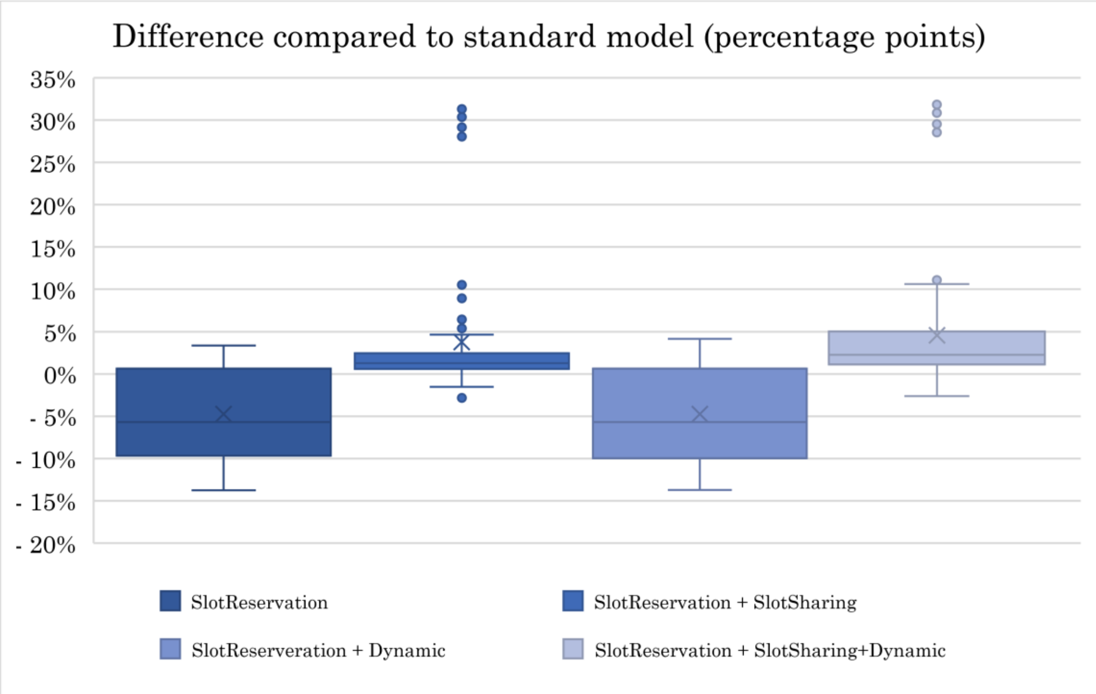


Figure 7.1 – Boxplot: difference compared to standard model

Using the paired-T approach, with α = 0.025 and d.f.= 89, we calculate the confidence interval to determine whether there is a significant difference between the standard model and the adaptive model (SlotReservation + SlotSharing + Dynamic). The confidence interval is (0.028 ; 0.063). Based on this interval, we conclude that the adaptive model (SlotReservation + SlotSharing + Dynamic) performs significantly better than the standard model.

In 80 out of 90 (89%) of the configurations, the adaptive model (SlotReservation + SlotSharing + Dynamic) outperforms the standard model. Nine times the standard model performs (slightly) better when a self-scheduling patient can plan his/her appointment up to 7 days in advance (booking window > 7). The influence of the booking window on the performance is discussed in Section 7.2.3.
The other configuration where the standard model performs better is at 0-0-1-0, i.e. only the PATHO-patients (tu=3) are allowed to schedule. This is reasonable, as SlotSharing cannot be used here (i.e. it cannot be applied as there are no $SOON_3$ slots) and as can be seen in Table 7.6. the adaptive models SlotReservation and SlotReservation + Dynamic perform less with regard to the minimum service level.

Utilization and Fraction within appointment window

As indicated, the utilization and fraction within appointment window performance indicators are secondary indicators, and therefore we discuss them briefly.
Regarding the utilisation of the different configurations in combination with the models, the average for each model is 76.5% with a standard deviation of 0.03%. The model has no influence on utilisation as patients enter the system and receive an appointment (within or outside their appointment window).

With respect to the number of patients scheduled within the appointment window, the standard model (87.1%) performs slightly better on average than the adaptive models with SlotSharing (86.7%) and the adaptive models without SlotSharing (86.8%). However, the minimum value for the standard model is slightly lower than for the adaptive models, 85.1% vs. 85.3%. In addition, the maximum value is slightly higher for the standard model (88.0%) compared to the adaptive models with SlotSharing (87.9%) and the adaptive models without SlotSharing (87.8%).

7.2.2. Scheduling routines

In total, we compare 150 different configurations to assess the three scheduling routines (FCFS, FCRS and FCLS). Again, we exclude the 0-0-0-0 option, as it does not offer the possibility of self-scheduling.

Minimum service level

On average, FCRS performs best compared to FCFS and FCLS, as shown in Table 7.7. For both SL SSP and SL NSSP, there is roughly the same difference in results, so we do not attribute the differences to SSP or NSSP. The difference can be explained by the fact that in FCRS patients are randomly assigned to a slot, while in FCFS and FCLS they are assigned to the first or last available slot respectively. For this reason, under FCFS it can happen that slots are already occupied while a more urgent patient arrives. With SlotReservation we take care of this for the patients that need an appointment within one week, but the problem occurs even for patients with an urgency of more than one week.

Table 7.7 – Results scheduling routines (Minimum service level and SL SSP and SL NSSP)

	Mean MSL	**Max.** MSL	**Min.** MSL	**Std. dev.** MSL		**Mean** SL SSP	**Mean** SL NSSP
FCFS	72.8%	81.7%	38.4%	8.5%		74.8%	80.8%
FCRS	73.3%	83.5%	39.5%	8.6%		75.0%	81.9%
FCLS	71.9%	80.1%	38.7%	8.1%		74.3%	79.3%

We calculate the confidence interval using the paired-T approach, with $\alpha = 0.025$ and d.f. = 149, in order to prove whether there is a significant difference. The confidence interval is (0.0036 ; 0.0060). Based on this interval, we conclude that the FCRS performs significantly better than (the currently applied) FCFS.

In 108 out of 150 (72.0%) configurations FCRS performs better than FCFS. We do not see a clear trend in which cases FCFS performs better. There is no underlying pattern in the combination of the applied model, allocation of code to SSP and/or the booking window.

Utilization and Fraction within appointment window

Utilisation is again on average for all scheduling routines 76.5% with a standard deviation for FCFS of 0.04% and a standard deviation of 0.03% for FCRS and FCLS. Utilisation is not affected by the scheduling routine, as patients enter the system and receive an appointment (inside or outside their appointment window).

The percentage of patients scheduled within the appointment window is on average best with the use of FCRS (87.5%). We see a small difference with FCFC (87.1%) and a larger difference with FCLS (86.0%). A higher maximum (both 88.0%) does apply to FCFS and FCRS compared to FCLS (87.2%). A lower minimum applies to FCLS (85.1%) compared to FCFS and FCRS (both 86.6%).

7.2.3. Booking window

To assess the two booking windows for SSP, we compare a total of 225 different configurations. Again, we exclude the option 0-0-0-0, as it does not offer a possibility for self-scheduling.

Minimum service level

It is evident from Table 7.8 that the booking window in which patients have to schedule their visits more than 14 days before the lower bound of their scheduling window performs better, by an average of 7.1 percentage points, than when patients are allowed to schedule up to 7 days. The effect is largest for the service level of the self-scheduling patients. We explain this by the fact that self-scheduling patients can book less late, which increases the probability of a free slot. The later they schedule their appointment (booking date), the higher the probability that slots are already occupied. Naturally, the SL for NSSP is lower, as slots are booked earlier by SSP (note: if no slot is available for SSP, then a NSSP slot can be booked), meaning that a free slot for NSSP will become more scarce.

Table 7.8 – Results booking window (Minimum service model and SL SSP and SL NSSP)

	Mean MSL	**Max.** MSL	**Min.** MSL	**Std. dev.** MSL	**Mean** SL SSP	**Mean** SL NSSP
> 7 days	69.1%	80.8%	38.4%	8.9%	69.2%	82.3%
> 14 days	76.2%	83.5%	49.8%	6.1%	80.2%	79.1%

We construct a boxplot for the comparison of the difference in performance in terms of the MSL of the configurations with > 14 days compared to > 7 days. Figure 7.2 presents this boxplot. It can clearly be seen that > 14 days performs better in many of the configurations.

Using the paired-T approach, with α = 0.025 and d.f. = 224, we calculate a confidence interval.
The confidence interval is (0.058 ; 0.084). Based on this interval, we conclude that > 14 days performs significantly better than the (current desired, see Section 2.4) booking window for SSP of > 7 days.

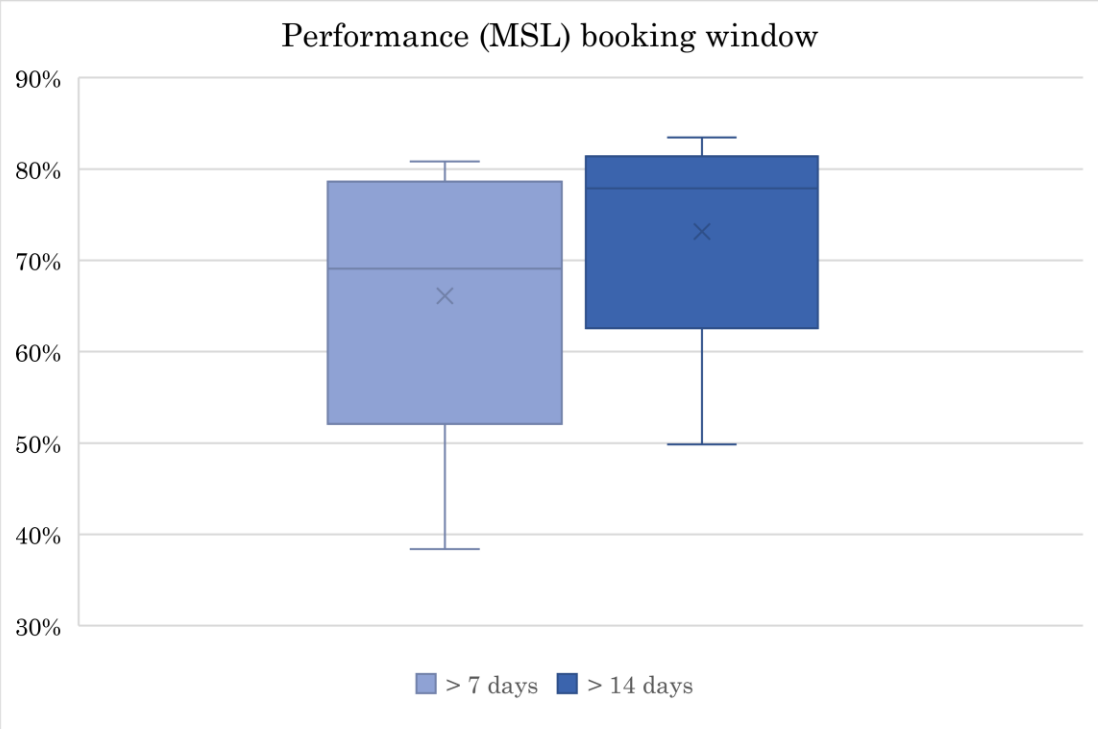


Figure 7.2 – Boxplot: performance (MSL) > 7 days and > 14

Utilization and Fraction within appointment window

Utilisation is on average 76.6% for both booking windows, with a standard deviation for >7 days of 0.03% and a standard deviation of 0.04% for >14 days. The booking window has no effect on utilisation, as patients enter the system and receive an appointment (within or outside their appointment window).

The percentage of patients scheduled within the appointment window is on average best with the use of > 14 days (87.0%), however, we see a small difference with > 7 days (86.7%). A standard deviation of 0.07% applies to both.

7.2.4. Appointment codes

To assess the 15 different options for designating appointment codes as SSP and the one option for not designating an appointment code as SSP, we compare 30 different configurations.

As illustrated in Table 7.9, on average, the best performance is achieved when no appointment code is designated for self-scheduling. This is easily explained by two aspects. The first aspect is in the definition of service level, where NSSPs only needs to have one slot available, SSPs are required to have three slots available. Therefore, the SL for SSP is achieved harder than for NSSPs. The second aspect explaining this is the difference in booking window between SSPs and NSSPs. For NSSPs, appointments are planned immediately, while for SSPs this does not happen. This causes the effect discussed in Section 7.2.3, that SSPs have a higher probability of having slots already occupied. This in combination with the first aspect usually results in a lower MSL. However, it does not mean that not allocating patients as SSPs always performs best. This is shown in the maximum MSL in Table 7.9. For instance, the maximum MSL for 0-0-0-1 is higher with a specific configuration. We discuss this overall performance in more detail in Section 7.3.

Table 7.9 – Results appointment codes (Minimum service level and SL SSP and SL NSSP)
SSP code: CP – BELC – PATHO – CPF/E

SSP code	**Mean** MSL	**Max.** MSL	**Min.** MSL	**Std. dev.** MSL	**Mean** SL SSP	**Mean** SL NSSP
0-0-0-0	81.4%	83.4%	78.9%	1.5%	N/A	81.4%
0-0-0-1	57.8%	83.5%	38.4%	16.5%	58.1%	81.5%
0-0-1-0	73.3%	79.1%	67.1%	5.4%	73.3%	80.9%
0-1-0-0	71.5%	82.7%	56.8%	8.4%	72.4%	81.6%
1-0-0-0	77.0%	80.8%	68.6%	4.2%	81.0%	80.6%
0-0-1-1	70.1%	80.0%	61.6%	6.4%	70.1%	81.0%
0-1-1-0	72.2%	81.8%	61.0%	6.6%	72.7%	81.1%
1-1-0-0	75.6%	80.7%	65.2%	5.0%	79.0%	80.6%
0-1-0-1	70.5%	83.2%	54.2%	9.6%	71.6%	81.8%
1-0-1-0	75.7%	79.8%	68.2%	3.7%	79.1%	79.8%
1-0-0-1	76.8%	81.3%	66.1%	5.2%	79.9%	80.7%
0-1-1-1	71.4%	82.3%	59.0%	7.2%	72.2%	81.3%
1-0-1-1	75.5%	79.9%	66.5%	4.4%	78.3%	79.9%
1-1-0-1	74.9%	81.0%	63.9%	5.4%	77.8%	80.5%
1-1-1-0	74.3%	78.9%	65.7%	4.3%	78.0%	79.6%
1-1-1-1	73.8%	79.6%	64.7%	4.7%	77.0%	79.6%

Table 7.10 shows the average based on the number of slots dedicated to SSPs (e.g. 0-1-1-1 = 3). It is clearly noticeable that the relevance of the choice of a configuration with respect to the model, scheduling routine and booking window becomes less important if more appointment codes are allocated to SSP, since the performance with respect to the difference between maximum and minimum is less. We explain this disparity by the fact that the standard model and the adaptive model without SlotSharing will perform better if more codes are designated as SSP. This is due to a logical consequence that the standard model does not use intelligent techniques for SSPs, as a result of which the SL for SSP remains low. As the number of codes assigned and thus the total number of patients able to schedule their own appointments increases, these patients will automatically be offered more options, increasing the probability of achieving the SL. In addition, the effect of the booking window (see Section 7.2.3.) compared to directly scheduling NSSP becomes smaller, since proportionally a larger number of patients schedule their appointment later if more patients are able to schedule themselves.

Table 7.10 – Results per number of SSP appointment codes

Number of SSP codes	**0**	**1**	**2**	**3**	**4**
Mean MSL	81.4%	69.9%	73.5%	74.0%	73.8%
Max. MSL	83.4%	83.5%	83.2%	82.3%	79.6%
Min. MSL	78.9%	38.4%	54.2%	59.0%	64.7%

Utilization and Fraction within appointment window

Utilisation is on average 76.5% across all the various options, varying with a standard deviation of 0.02% to 0.04%. As patients enter the system and receive an appointment (inside or outside their scheduling window), the designation of appointment codes to SSP does not affect utilisation.

The percentage of patients scheduled within the appointment window varies very little between the 16 different options (max. 87.1% and min. 86.6%) with an average of 86.7%. Therefore, the system is not sensitive, with regard to fraction of appointments within appointment window of the patient, to different allocations of SSP to codes.

7.3. Baseline and overall performance

In this section, we provide results of the scenarios if the Medisch Spectrum Twente does not implement any adjustments to their system, but does implement self-scheduling for patients. In addition, we present a comparison between this baseline and the best possible performance. Finally, we report the differences between the baseline, the configuration of the best performing standard model and the best performing adaptive model. We present the differences for all different options of assigning the appointment codes as SSP.

7.3.1 Baseline performance

As mentioned in Section 6.4, the baseline consists of no change to the tactical schedule with regard to the distribution of slots per appointment code, the use of the scheduling routine FCFS, the booking window in which patients are allowed to schedule up to 7 days in advance.

We estimate that scheduling without changing the current system will lead to the results shown in Table 7.11. It is evident that the Medisch Spectrum Twente will experience problems with regard to the minimum service level. This is often below 70%, which will lead to additional work pressure in the outpatient department due to possible calls that self-scheduling patients do not see an available appointment or to rescheduling appointments to make time for more urgent patients. The utilization of the outpatient department, a concern at the moment that this will decrease with the implementation of self-scheduling, will not or only slightly decrease. In contrast, more appointments will be scheduled in the appointment window. We explain this by the fact that self-scheduling patients do not follow the FCFS principle, which means that there is a larger probability that there will be a slot for the more urgent patient, as described in Section 7.2.2.

Table 7.11 – Results baseline
SSP code: CP – BELC – PATHO – CPF/E

SSP code	**Minimum Service level**	**Service level SSP**	**Service level NSSP**	**Utilization**	**Fraction within appointment window**
0-0-0-0	76.5%	N/A	74.8%	76.5%	84.2%
0-0-0-1	60.3%	60.3%	74.9%	76.5%	84.6%
0-0-1-0	69.6%	69.6%	73.6%	76.5%	84.3%
0-1-0-0	57.5%	57.5%	75.0%	76.5%	84.4%
1-0-0-0	72.0%	75.6%	72.0%	76.4%	85.2%
0-0-1-1	67.4%	67.4%	73.4%	76.5%	84.5%
0-1-1-0	62.3%	62.3%	73.9%	76.5%	84.8%
1-1-0-0	70.6%	70.6%	70.9%	76.5%	85.0%
0-1-0-1	58.5%	58.5%	74.9%	76.5%	84.6%
1-0-1-0	69.8%	74.0%	69.8%	76.5%	85.1%
1-0-0-1	71.8%	74.8%	71.8%	76.5%	85.3%
0-1-1-1	62.5%	62.5%	73.2%	76.4%	84.7%
1-0-1-1	69.1%	73.3%	69.1%	76.5%	85.3%
1-1-0-1	70.0%	70.3%	70.0%	76.5%	85.1%
1-1-1-0	67.6%	70.4%	67.6%	76.4%	85.3%
1-1-1-1	66.1%	70.0%	66.1%	76.4%	85.0%

7.3.2 Comparison baseline and best performing configuration

Table 7.12 lists the best performing configurations (CNF) per code allocation for SSP. For 12 out of 16 different code allocations for SSP, our adaptive model with SlotReservation + SlotSharing + DynamicBlueprint performs best. This enables us to achieve considerably better results compared to the baseline. In Section 7.3.3. we elaborate on the effect of changing the distribution of slots per appointment code in the tactical scheme whether or not in combination with our adaptive model.

Table 7.12 – Results best configurations and baseline
SSP code: CP – BELC – PATHO – CPF/E

SSP code	Model	Scheduling routine	Booking window	MSL Best CNF	MSL Baseline	Difference
0-0-0-0	SlotReservation + Dynamic (1)	FCRS	> 7	83.4%	76.5%	6.9
0-0-0-1	SlotReservation + SlotSharing + Dynamic	FCRS	> 14	83.5%	60.3%	23.2
0-0-1-0	SlotReservation (2)	FCFS	> 14	79.1%	69.6%	9.5
0-1-0-0	SlotReservation + SlotSharing + Dynamic	FCRS	> 14	82.7%	57.5%	15.3
1-0-0-0	SlotReservation + SlotSharing + Dynamic (3)	FCRS	> 14	80.7%	72.0%	23.2
0-0-1-1	SlotReservation + SlotSharing	FCRS	> 14	80.0%	67.4%	21.4
0-1-1-0	SlotReservation + SlotSharing + Dynamic	FCRS	> 14	81.8%	62.3%	19.5
1-1-0-0	SlotReservation + SlotSharing + Dynamic	FCRS	> 14	80.7%	70.6%	18.2
0-1-0-1	SlotReservation + SlotSharing + Dynamic	FCRS	> 14	83.2%	58.5%	11.2
1-0-1-0	SlotReservation + Dynamic	FCRS	> 14	79.8%	69.8%	8.0
1-0-0-1	SlotReservation + SlotSharing + Dynamic	FCRS	> 14	81.3%	71.8%	11.5
0-1-1-1	SlotReservation + SlotSharing + Dynamic	FCRS	> 14	82.3%	62.5%	13.3
1-0-1-1	SlotReservation + SlotSharing + Dynamic	FCRS	> 14	79.9%	69.1%	9.3
1-1-0-1	SlotReservation + SlotSharing + Dynamic	FCRS	> 14	81.0%	70.0%	11.0
1-1-1-0	SlotReservation + SlotSharing + Dynamic	FCFS	> 14	78.9%	67.6%	11.3
1-1-1-1	SlotReservation + SlotSharing + Dynamic	FCFS	> 14	79.6%	66.1%	13.5

(1) In addition to this model, 3 other configurations achieve exactly the same results, namely the same configuration with booking window > 14 and the configurations with SlotReservation + SlotSharing + Dynamic, FCRS and the booking windows > 14 and > 7. We account for this because there are no SSPs, so SlotSharing and the different booking windows do not influence the performance of the system.

(2) Here, the configuration SlotReservation + SlotSharing achieves the same result. This is due to the following: only PATHO (tu = 3) patients are assigned to schedule their appointments themselves. Since SlotSharing has no effect for slot with tu = 3, SlotSharing does not influence the system, so the performance is identical.

(3) In this case SlotReservation + DynamicBlueprint has a better MSL, however the difference is very small (0.08%), but SlotReservation + SlotSharing + Dynamic performs more than 8 percentage points better based on the service level for SSPs. Due to this difference, we still consider SlotReservation + SlotSharing + Dynamic as the best performing configuration.

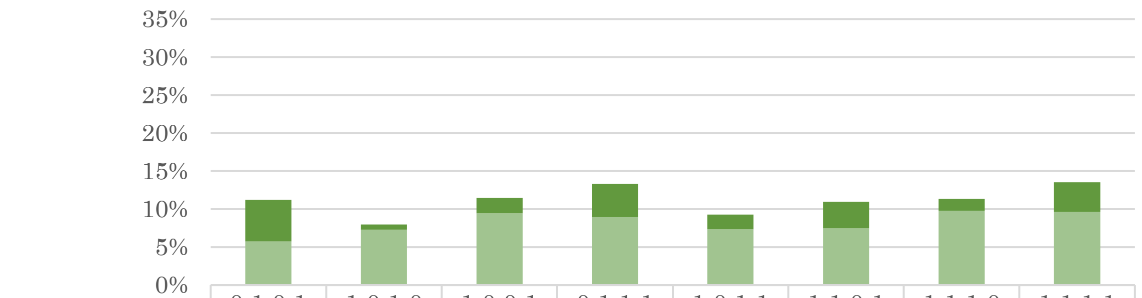
7.3.3 Comparison baseline, standard and adaptive model

In Figure 7.3.1 and Figure 7.3.2 we present the differences of the best performing standard model in percentage points compared to the baseline and the differences of the best performing adaptive model compared to the standard model. For instance, for 0-0-0-0 our standard model performs 6.7 percentage points better than the baseline, and our adaptive model provides an additional improvement of 0.2 percentage point.

Except for one possibility (0-0-0-1; CPF/E is allowed for self-scheduling) for the allocation of a slot to SSP, we see that our standard model outperforms our expected baseline performance if the Medisch Spectrum Twente implements self-scheduling without modification of their system. We explain the decrease in performance of the standard model at 0-0-0-1 due to the fact that in the initial distribution in the tactical schedule at baseline 2 slots per session are allocated for the CPF/E, while this is less (1 slot per session) in the distribution after Simulated Annealing. This reduces the probability of reaching the service level for SSP, resulting in a deteriorated MSL. However, it can clearly be seen that SlotSharing is effective in this case, as our adaptive model subsequently gives an improvement over the standard model of 31.4 percentage points.

	0-0-0-0	0-0-0-1	0-0-1-0	0-1-0-0	1-0-0-0	0-0-1-1	0-1-1-0	1-1-0-0
Adaptive model	0,15%	31,42%	0,66%	0,74%	0,04%	6,51%	1,39%	1,58%
Standard model	6,74%	-8,24%	8,86%	14,60%	23,13%	14,90%	18,12%	16,63%

Figure 7.3.1 – Performance difference baseline, standard model, and adaptive model (percentage points)



	0-1-0-1	1-0-1-0	1-0-0-1	0-1-1-1	1-0-1-1	1-1-0-1	1-1-1-0	1-1-1-1
Adaptive model	5,47%	0,67%	2,00%	4,34%	1,97%	3,49%	1,57%	3,89%
Standard model	5,73%	7,29%	9,47%	8,96%	7,33%	7,47%	9,77%	9,62%

Figure 7.3.2 – Performance difference baseline, standard model, and adaptive model (percentage points)

The best configuration of the adaptive model works better than the best configuration of the standard model in all different cases. We do not recognize a trend if more or less patients are assigned to schedule their own appointment, see Figure 7.4. In Figure 7.4. we exclude a few options from assignment as SSP, namely 0-0-1-0 and 0-0-1-1. In these patient groups the representation of PATHO (tu = 3) is very high, and since our adaptive model with SlotSharing has no effect for patients with tu = 3 we exclude this. In addition, we also exclude 0-0-0-1, as the standard model performs poorly here and this is an outlier, see Figure 7.3.1.

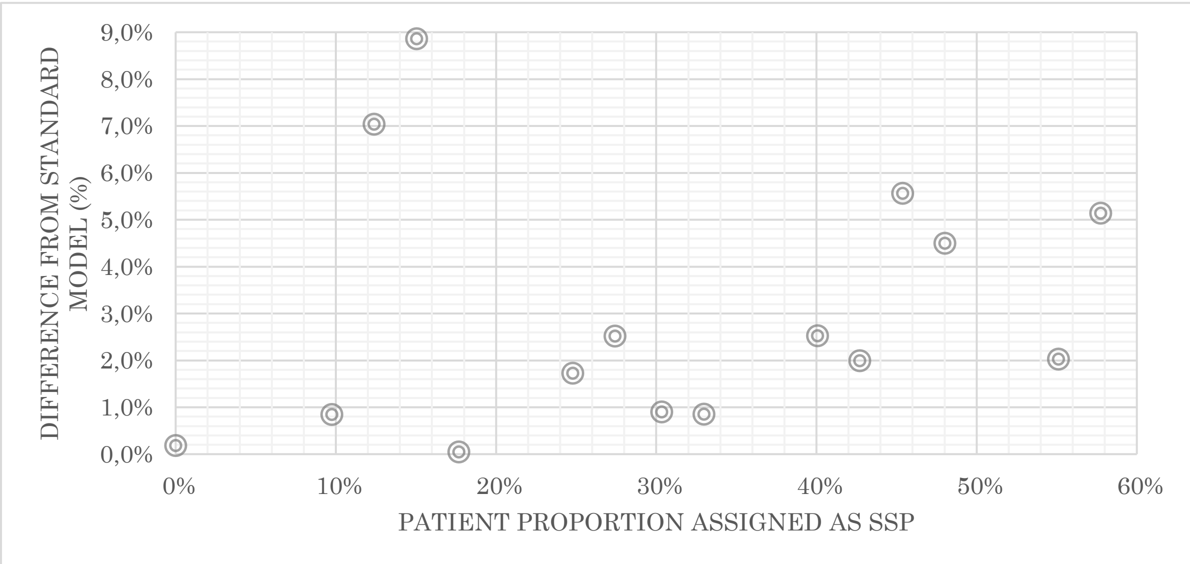


Figure 7.4 – Difference performance standard and adaptive model compared to the proportion of patients SSP

7.4. Robustness analysis

In this section, we present our results concerning the robustness analysis that tests the efficiency of our model with different input parameters. As mentioned in Section 6.5, we perform the analysis for the baseline and best configurations of the standard and adaptive model for the best and worst performing scenario.

As shown in Table 7.12, the scenario 0-0-0-1 performs best, however, we choose not to incorporate it in this analysis since Figure 7.3 shows that this scenario is highly extraordinary. We therefore choose the second-best scenario, being: 0-1-0-1. The configuration for the standard model is: FCRS and booking window > 14 days. The configuration for the adaptive model (SlotReservation + SlotSharing + DynamicBlueprint) is: FCRS and booking window > 14 days.

The worst performing scenario is 1-1-1-0, where we use the configurations for the standard model having FCRS and a booking window > 7 days. For the configuration for the adaptive model (SlotReservation + SlotSharing + DynamicBlueprint) we use FCFS and a booking window > 14 days.

Experiment A: Number of sessions +1 per physician

In Figure 7.5 we compare the performance of the minimum service level with the initial data with the performance of experiment A. Since all points are above the threshold, we can expect that our system is responsive in a positive sense to an increase in the number of sessions. Releasing more sessions, as expected, results in a better service level, since more slots are released and thus a higher probability of an available slot.

With respect to the robustness of our model, our algorithm is slightly (positively) affected by changing this input parameter. This can be seen in Table 7.13 where we show the distances to the threshold. An approximately equal distances means that the algorithms are robust. A larger distance means that the algorithm or model will perform better if the input parameter is influenced.

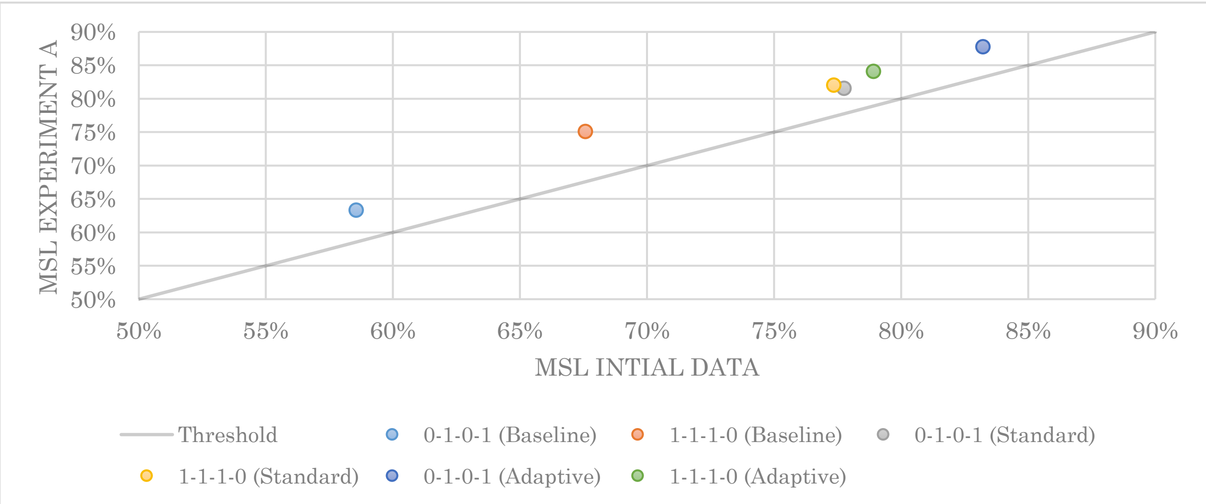


Figure 7.5 – Results experiment A: sessions +1

Table 7.13 – Experiment A: distance to threshold

Scenario	0-1-0-1 (Baseline)	0-1-0-1 (Standard)	0-1-0-1 (Adaptive)	1-1-1-0 (Baseline)	1-1-1-0 (Standard)	1-1-1-0 (Adaptive)
Distance to threshold	0.03	0.03	0.03	0.05	0.03	0.04

Experiment B: Number of sessions -1 per physician

As a result of reducing the number of sessions by one, we clearly observe in Figure 7.6 that the system will perform less favourably if the capacity is reduced. The points are situated under the threshold. This is obvious and expected, as the pressure on the system increases, which reduces the probability of a vacant slot. We also see in Table 7.14 that the distance with the adaptive model is smaller than with the baseline, so that the influence of changing this factor is smaller on our algorithms than on the baseline. From this we conclude that our model is more robust to this change than the baseline.

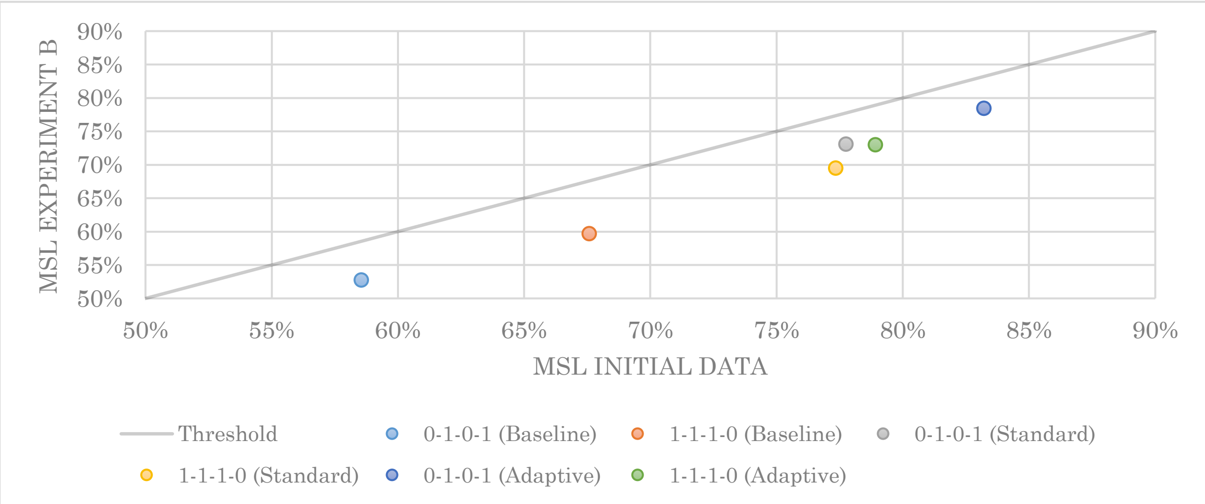


Figure 7.6 – Results experiment B: sessions -1

Table 7.14 – Experiment B: distance to threshold

Scenario	0-1-0-1 (Baseline)	0-1-0-1 (Standard)	0-1-0-1 (Adaptive)	1-1-1-0 (Baseline)	1-1-1-0 (Standard)	1-1-1-0 (Adaptive)
Distance to threshold	0.04	0.03	0.04	0.06	0.06	0.04

Experiment C: Distribution of sessions

Figure 7.7 shows that distributing the sessions evenly over the working days has very little influence on the baseline, while it has a slightly positive influence on our standard and adaptive model. This is as expected, since the random distribution of the session already ensures a more equal distribution. Given the very small distances to the threshold, we conclude that our algorithm is robust with respect to distributing the sessions evenly.

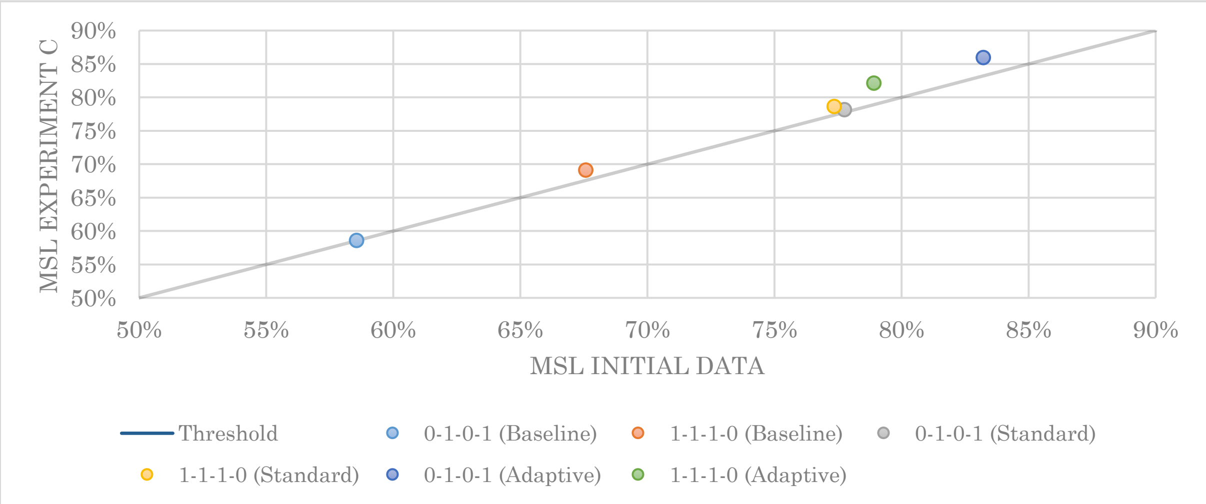


Figure 7.7 – Results experiment C: distribution of sessions

Table 7.15 – Experiment C: distance to threshold

Scenario	**0-1-0-1** (Baseline)	**0-1-0-1** (Standard)	**0-1-0-1** (Adaptive)	**1-1-1-0** (Baseline)	**1-1-1-0** (Standard)	**1-1-1-0** (Adaptive)
Distance to threshold	0.0003	0.003	0.02	0.01	0.01	0.02

Experiment D: Possible attending physician(s)

As can be seen in Figure 7.8 and Table 7.16, the system reacts marginally to the change in this input parameter. We expect this to be the case, as an increase in the number of attending physicians will increase the number of available slots. However, we notice that this does not apply to our standard model. Here we see a very minor decrease in performance, however, we consider this decrease to be minimal which means that the effect is negligible.

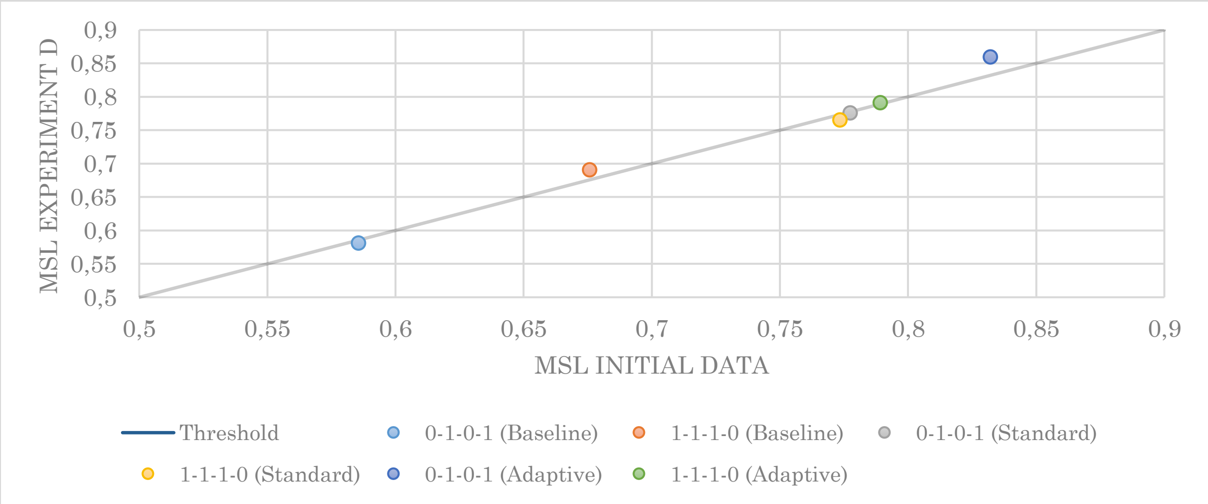


Table 7.15 – Experiment D: distance to threshold

Figure 7.8 – Results experiment D: possible attending physician(s)

Scenario	**0-1-0-1** (Baseline)	**0-1-0-1** (Standard)	**0-1-0-1** (Adaptive)	**1-1-1-0** (Baseline)	**1-1-1-0** (Standard)	**1-1-1-0** (Adaptive)
Distance to threshold	0.003	0.001	0.002	0.002	0.006	0.002

7.5. Conclusions

In this chapter we show the results of the baseline, the standard and the adaptive model when self-scheduling is applied. Initially, we calculate the number of slots per appointment code that should be allocated per session. This answers the fifth sub-question. In addition to the fifth sub-question, we also present the answer to the sixth sub-question in this chapter.

Question 5: What number of slots should be allocated to each appointment code?

Using the Simulated Annealing metaheuristic, for the MSL we obtain - compared to the baseline - an improvement of 3.9 percentage points for the standard model. By allocating one more time unit (from 45 tu to 46 tu) and allocating one time unit less as a block (from 3 tu to 2 tu), we achieve an additional improvement of 2.2 percentage points, resulting in a minimum service level of 80.6%. We consider it acceptable to reduce the number of time units for the block, as the average utilization (76.5%) leaves enough margin for unforeseen circumstances. Table 7.2 shows the distribution of the number of slots per appointment code for the baseline and standard model.

With Simulated Annealing, we conclude that applying SlotReservation for $SOON_2$ yields improved performance compared to using $SOON_2$ and $SOON_3$. Therefore, we choose to apply only $SOON_2$ in our adaptive model. With our metaheuristic we achieve a gain of 1.6 percentage points for the minimum service level. After adjusting the number of time units to be allocated (from 45 tu to 46 tu), we obtain an additional gain of 4.0 percent point. An alteration to this distribution (CP +1, $SOON_2$ -1) results in another additional gain of 1.9 percentage points, making the minimum service level 75.8%. Again, we consider it reasonable to reduce the number of time units for the blockage, as the average utilization (76.5%) again leaves enough margin for unforeseen circumstances. Table 7.17 shows the distribution of the number of slots per appointment code for the adaptive model.

Table 7.17 – Distribution appointment codes: Baseline, Standard and Adaptive model

Appointment Code	Baseline	Standard model	Adaptive model
NP	3	4	4
CP	7	8	6
BELC	3	4	3
PATHO	3	3	3
CPF/E	2	1	1
Combi-F/E	2	1	1
$SOON_2$	N/A	N/A	3
Total tu	**45**	**44**	**46**

We conclude on the basis of these results that adjusting the distribution of the number of slots per appointment code can generate improvements with regard to the minimum service level.

Question 6: Which (adaptive) approach is most efficient in facilitating patient (self-)scheduling?

If we assess the different models and factors independently (OFAT), we conclude the following:

- Our adaptive model, using the option SlotReservation + SlotSharing + DynamicBlueprint, performs statically significantly better than our standard model. We see an average improvement of 4.6 percentage points for our adaptive model (option SlotReservation + SlotSharing + DynamicBlueprint) compared to the standard model, with our adaptive model outperforming in 89% of the configurations. Only in a few configurations where the booking window is > 7 days, the standard model has a superior performance.

- The scheduling routine FCRS achieves significantly better results than FCFS, with FCLS performing worst in relation to the minimum service level. FCRS results on average in a higher service level for both SSP and NSSP.

- The booking window in which patients can schedule their appointment up to 14 days in advance performs significantly better than the booking window in which patients can schedule their appointment up to 7 days in advance. On average, the minimum service level increases by 17.1 percent points when using a booking window > 14 days.

- Assigning appointment codes as SSP strongly influences the minimum service level, with a maximum of the average MSL of 81.4% when assigned 0-0-0-0 and a minimum of 57.8% when assigned 0-0-0-1. However, if we apply the best configuration, we see a smaller difference between the different allocations. It ranges between 78.9% and 83.5%.

Compared to the baseline, we conclude that we can achieve an improvement for each allocation by using our adaptive model. On average, based on the different assignments of slots as SSP, the best configuration of the adaptive model performs 14.1 percentage points higher (max. 23.2 and min. 6.9 percentage points). In at least 12 out of 16 different code allocations for SSP, our adaptive model with SlotReservation + SlotSharing + DynamicBlueprint with booking window > 14 and FCRS performs best. We conclude that this configuration is the most efficient to facilitate patient (self-)scheduling.

In all best configurations of the adaptive model compared to all best configurations of the standard model, our adaptive model performs better. We do not identify a pattern depending on the number of patients who are assigned to schedule their own appointments.

Based on our robustness analysis in Section 7.4, we conclude that our standard and adaptive model are robust and give similar improvements - regarding the baseline - with different input parameters.

8. Implementation

In this chapter, we discuss the implementation process for introducing our adaptive approach in the Medisch Spectrum Twente.

At the moment, it is not yet possible for patients of Medisch Spectrum Twente to schedule their own appointments. At the end of 2021, the new Electronic Health Record is planned to go live, which will also mark the starting point for facilitating self-scheduling. The new EHR provides the facilities to offer self-scheduling to patients.

On a tactical level, but also on an operational level through the scheduling routine, our approach offers a solution for efficient facilitation of patient (self-)scheduling. Our approach consists of two phases:

1. **Determine for the specialty the optimal distribution of the number of slots per appointment code, including the required $SOON_{tu}$ slots.**

To carry out this step, data analysis is required. In this data analysis the different distributions for the varying input parameters are established. The required distributions are: the arrival process, the appointment windows, the number of repeat consultations and associated appointment windows, the patient-doctor relationship and the appointment types of the patient. On a strategic level, the number of sessions per physician per week is determined.

After determining these input parameters, the Simulated Annealing can be executed to determine the optimal number of slots per appointment code.

2. **Through simulation, determine the configuration of the adaptive model to match the desired choice of allocating slots for self-scheduling.**

Once the optimal distribution of slots per appointment code has been determined, the configuration of the adaptive model that is most suitable for the characteristics of the specialty is determined. The simulation determines which configuration most efficiently facilitates the process of (self-)scheduling.

If changes occur within the specialism (e.g. changed case-mix or composition of physicians), steps 1 and 2 need to be repeated. We recommend performing these steps at least annually, as this will keep the distribution of slots in line with current circumstances.

Module design in EHR

In order to optimally facilitate the options (SlotReservation, SlotSharing, DynamicBlueprint) within the adaptive model, the Medisch Spectrum Twente will have to implement them in the EHR. The three different options need to be facilitated by the EHR in order to achieve the best possible performance.

SlotReservation is easy to implement, as it only requires an adjustment in the blueprint of the tactical schedule. To apply SlotSharing properly, a software program has to be developed that automatically shows the correct corresponding slots (appointment code) for the self-scheduling patient and also the $SOON_{tu}$ slots. If the threshold of the number of free slots is reached, the system will have to automatically convert the slots to $SOON_{tu}$ and no longer show these slots to self-scheduling patients.
Also, DynamicBlueprint can be automatized. The system updates the slots for the coming week every day. All slots that are not $SOON_{tu}$ will be converted to $SOON_{tu}$.

9. Conclusions and Recommendations

The chapter describes the conclusions and recommendations of our research. We refer back to Section 1.3. in which we describe our research objective:

> "*The objective of the research is to develop a method and approach which enables designing a tactical schedule that facilitates self-scheduling of appointments, whereby the specialties in Medisch Spectrum Twente do not suffer a loss in service levels for (non-)self-scheduling patients.*"

In Section 9.1. we present our conclusions of the study by repeating and answering the sub questions. Subsequently, we propose our recommendations for the Medisch Spectrum Twente in Section 9.2.

9.1. Conclusions

As mentioned, our research focuses on the tactical scheme that facilitates self-scheduling. In this section we answer the research questions.

Question 1: How is the current planning process for outpatients organised?

We show that there are two categories of patients entering the outpatient department: emergency patients and patients with a referral. Emergency patients are usually seen at the Emergency Department, while elective patients receive an appointment at the outpatient clinic. To schedule these patients, different types of appointment codes are used to indicate the type of patient. These codes are used to schedule appointments in specific appointment calendars of the different resources within the outpatient department. There are two types of appointment calendars: those of the care provider and of the treatment rooms.

The patient planning process starts with the allocation of staff, after which a blueprint is set up at a tactical level for the healthcare providers' calendar. This blueprint is only used for the care providers, and no blueprint is used for the calendars of the treatment rooms. At operational level, patients are scheduled in their appointment window by means of the FCFS principle. If no slot is available, an alternative slot is rebooked or a less urgent patient is rescheduled.

With regard to self-scheduling, frameworks have been drawn up by the Planning and Healthcare Logistics project group. In the first phase of the implementation of self-scheduling, the Medisch Spectrum Twente will start with single (revisit) appointments.

Question 2: What is the current performance of the outpatient process in 2019?

As for 2019, we see a relatively stable trend in the number of new visits per month. In the summer period (June to September), we recognize a slight decrease in the number of new visits. In addition, the number of revisits per month is also stable, however, with a small decrease after the summer months. The number of declarable telephone consultations was also quite stable throughout 2019, while the number of non-declarable telephone consultations was much higher and had its peak in May.

The percentage of patients who do not turn up for regular consultation hours is stable and varies between 4.5% and 5%, while the no-show rate fluctuates widely for the treatment rooms. This rate varies between 0.9% and 6.3%.

The average utilization in Enschede of the six urologists is 76.6%. Utilization at the outpatient clinics outside Enschede is much higher, broadly between 80% and 100%. We explain this by the fact that the appointments with the nurses are booked on the same calendar. Utilization for the treatment room is relatively low (around 50%-60%) and it can be concluded that there is still enough capacity to treat patients.

Question 3: Which approaches can be adopted by the Medisch Spectrum Twente to address the challenges of introducing self-scheduling?

We identify challenges for the Medisch Spectrum Twente at different hierarchical levels within the framework for healthcare planning and control (Hans et al., 2011). At the strategic level, MST has to make decisions on how much capacity to allocate to each outpatient clinic. By means of computer simulation, mathematical programming, and queuing theory, this issue can be answered by MST. On the same level, MST has to determine which patient groups are allowed to use self-scheduling.

On the tactical level, this research answers the question how slots should be distributed for the different appointment codes. In addition to this aspect, MST should also consider how the slots should be distributed in the tactical schedule with respect to time frames. In this context, MST can apply such techniques as computer simulation or yield management.

At the operational level, MST faces the challenge of which slot should be shown to a specific patient. Using McFadden's model, the Medisch Spectrum Twente is able to gain more insight into which slots they should make available to specific patients in order to create a strong likelihood of acceptance of a slot. On the same level, less in the context of self-scheduling, MST can study multiple studies to optimize appointment scheduling.

Question 4: What approach or model is best applicable?

We conclude that the best applicable approach for this problem is a computer simulation, since our system is too complex to solve analytically. We base our computer simulation on the hospital patient scheduling model of Vermeulen et al. (2009), and extend it as shown in Figure 3.3. We choose to implement a Discrete Event Simulation, because our system does not change continuously with respect to time. Furthermore, the passage of time plays a significant role in our system, since a number of performance indicators are time related. It is therefore a dynamic system. Based on these grounds, a Discrete Event Simulation suits our system best.

Question 5: What number of slots should be allocated to each appointment code?

Using the Simulated Annealing metaheuristic, we obtain - compared to the baseline - an improvement of 3.9 percentage points for our standard model. After adjusting this distribution, we achieve an additional improvement of 2.2 percentage points, resulting in a minimum service level of 80.6%.
For our adaptive model, Simulated Annealing also improves the minimum service level by 5.3 percentage points, resulting in a minimum service level of 81.3%. We conclude from our Simulated Annealing results that using $SOON_2$ has an advantage over using $SOON_2$ and $SOON_3$. Based on this, we only apply $SOON_2$ in our adaptive model.
We conclude based on the results in Section 7.1 that adjusting the distribution of the number of slots per appointment code can generate improvements with regard to the minimum service level. For the most appropriate distribution for our study, we refer to Table 7.17.

Question 6: Which (adaptive) approach is most efficient in facilitating patient (self-)scheduling?

We can conclude that our adaptive model, with the option SlotReservation + SlotSharing + DynamicBlueprint, performs statically significantly better than our standard model. We see an average improvement of 4.6 percentage points for our adaptive model (option SlotReservation + SlotSharing + DynamicBlueprint) compared to the standard model, with our adaptive model outperforming in 89% of the configurations.

We also conclude that the scheduling routine FCRS performs statistically significantly better than FCFS and FCLS. Furthermore, the configurations with the booking window in which self-scheduling patients are allowed to schedule their appointment up to 14 days in advance perform statistically significantly better than scheduling up to 7 days in advance.

The allocation of appointment codes for self-scheduling has a substantial impact on the minimum service level, with the average varying between 57.8% and 81.4%. However, if we apply the best configuration, we see a smaller difference between the different allocations. It ranges between 78.9% and 83.5%. In addition, we observe that no single model and/or factor influences the average utilization.

Compared to the baseline, we conclude that we can achieve an improvement for each allocation by using our adaptive model. On average, based on the different assignments of slots as SSP, the best configuration of the adaptive model performs 14.1 percentage points higher (max. 23.2 and min. 6.9 percentage points). In at least 12 out of 16 different code allocations for SSP, our adaptive model with SlotReservation + SlotSharing + DynamicBlueprint with booking window > 14 and FCRS performs best. We conclude that this configuration is the most efficient to facilitate patient (self-)scheduling.

In all best configurations of the adaptive model compared to all best configurations of the standard model, our adaptive model performs better. We do not identify a pattern depending on the number of patients who are assigned to schedule their own appointments in relation to an improvement of the minimum service level.

Based on our robustness analysis in Section 7.4, we conclude that our standard and adaptive model are robust and give similar improvements - regarding the baseline - with different input parameters.

Question 7: How can the most efficient approach be implemented in the organization?

Our adaptive approach with SlotReservation, SlotSharing and DynamicBlueprint should be implemented to facilitate the patient (self-)scheduling process as well as possible. This approach will have to be integrated in the new Electronic Health Record to automate the process. In doing so, SlotReservation can be easily implemented as it only requires a change in the blueprint of the tactical schedule. In order to use SlotSharing appropriately, a software application needs to be developed that automatically shows the correct corresponding slots (appointment code) for the self-scheduling patient and also the $SOON_{tu}$ slots. If the thresholds with regard to the number of free slots is reached, the system has to automatically change the slots to $SOON_{tu}$ and reserve them for this type of patient only. In addition, DynamicBlueprint should also be automatized, meaning the system should automatically update the slots for the upcoming week every day.

9.2. Recommendations

We have various recommendations for Medisch Spectrum Twente. In this section, we will discuss these recommendations.

Implementing the adaptive model

Our main recommendation is to implement our adaptive model with SlotReservation, SlotSharing and DynamicBlueprint. Medisch Spectrum Twente requires finding a third party to develop a software application that facilitates all three options within the new Electronic Health Record. Since our adaptive model is significantly better than the standard model and the baseline, it is very important that Medisch Spectrum Twente implements this approach to facilitate self-scheduling as effectively as possible and to build trust within the organisation with respect to this.

If Medisch Spectrum Twente decides not to adjust their current work process, it will be evident that the Medisch Spectrum Twente will encounter difficulties if they start facilitating self-scheduling. It will cause additional workload for the departments and will also lead to dissatisfaction among self-scheduling patients if they do not see any available slots to schedule an appointment.

Booking window self-scheduling patient

We advise the Medisch Spectrum Twente to review its decision regarding the booking window for self-scheduling patients. At the moment the decision is taken that self-scheduling patients will be able to schedule their appointment up to 7 days in advance. However, we prove that a booking window of > 14 days performs significantly better with an average improvement of 7.1 percentage points. We therefore recommend using a booking window in which self-scheduling patients are given the possibility to schedule their appointment up to 14 days in advance.

Adjustment of the number of slots per appointment code

We recommend adjusting the distribution of slots per appointment code for the Urology Department, as the standard model - with adjusted distribution - outperforms the baseline. This change can already be implemented directly, so that the secretary experiences a better service level and therefore the workload, with regard to searching and adjusting the slots, is reduced. However, given the current situation with COVID-19, this impact will not be immediately noticeable as the distribution is based on data prior to COVID-19. If the input parameters do not change by the time the pandemic is past, we recommend the Urology Department to adjust its tactical schedule.

For the remaining departments, we cannot estimate to what extent the tactical schedule matches the actual demand for care. However, we recommend calculating this distribution for each specialty, as we saw a major impact in performance of the MSL for Urology.

Application of first come, random serve

With regard to the scheduling routine, we advise the Urology Department to no longer use the FCFC principle, but instead to apply the FCRS principle. We prove that FCRS performs significantly better, allowing the Urology Department to adopt this scheduling routine. The implementation is simple by allocating a random slot to a patient instead of the first slot.

Data quality

As mentioned in Section 2.5, it was not possible to measure a number of performance indicators, as there is no data available for this purpose. In order to be able to improve processes in a data-driven way and to make improvements verifiable, we advise the Medisch Spectrum Twente to focus more on the registration but also the logging of data. The presence of high-quality data is necessary to make good decisions and improvements in the long term.

10. Discussion

In this chapter, we discuss the study limitations and opportunities for further research.

10.1. Study limitations

Seasonality

In our model, we do not take seasonality into account, while in reality it exists. We see a 40% reduction in capacity in practice, while demand for care only decreases by 15%. Due to the absence of data regarding the size of the waiting list, however, we cannot determine how this difference is compensated for in practice. We suspect that the waiting list increases in the summer period and that afterwards, the waiting list is eliminated by means of extra capacity. Our model does not take this seasonality and large differences in the decrease of capacity compared to demand into account. We assume that there is a balance between supply and demand. Our model is therefore limited in terms of seasonality and we are unable to predict with any confidence how our approach will perform in the summer period. Especially when capacity is already reduced, but demand does not proportionally decrease.

Emergency patients

In our model, we do not take into account the arrivals of (emergency) patients who need to be seen on the same day. Each outpatient department organizes this process differently. Some departments use an emergency physician, while others reserve slots for these patients. The lack of influence of emergency patients on our model is a limitation. We can assume that emergency patients, and especially the reservation of slots for emergency patients, have a major impact on the minimum service level.

Booking date self-scheduling patients

We can conclude that the effect of the booking window on the minimum service level is significant. However, this study is limited by the unavailability of data on when patients schedule their own appointments. We expect the effect of this distribution to be significant. If patients schedule their appointments immediately when they are offered the possibility, the minimum service level will increase, but if patients wait until the last possible moment, this could have a negative effect on the service level. In our simulation we use a uniform distribution, while in practice this can be different, causing the outcome of our approach to change.

Inability to change appointments

As data is not available on how often appointments are changed, we did not include this in our simulation. Therefore, we do not know the effect of appointment changes by patients and planners on the performance of our system. This is a limitation, as the possibility of changing appointments can have an impact on the factor booking window for SSP. If appointments are changed last minute, there may be large fluctuations in utilization, as gaps may occur but patients still need to be seen at another time (i.e. peak demand).

10.2. Further research

Patient preference distribution during the day

In our model, we did not make any differentiation with regard to the time of slots. It is interesting and recommended to do follow-up research on patients' preferences when they prefer to schedule their appointment. If we know what day of the week or what time of day patients prefer to plan their appointments, we could increase patient satisfaction by using this information when designing the tactical schedule. We expect that this may have a significant effect on the performance of the system (in terms of service level and changing appointments). If time slots and days better match patient preferences, this will lead to better performance.
In addition, it is interesting to apply yield management to this topic in order to fill less desirable slots by applying special techniques (e.g. you can go to your preferred physician). This can prevent slots from remaining empty or reduce patient experience.

Booking period

At the moment we apply a planning horizon of 12 weeks with a planning cycle of 4 weeks, which results in a minimum booking period of 8 weeks and a maximum booking period of 12 weeks. A follow-up study on the influence of the length of the booking period will contribute to the impact of these factors. Especially the influence of the booking period on the no-show rate is interesting. Is there a correlation between the no-show rate and the time between the booking date and the actual appointment?

Use of appointment codes

MST uses appointment codes, but it is interesting to explore the effect of these appointment codes on the care process. If it has no effect, it is worthwhile to examine whether it is sensible to use different appointment codes. By not using appointment codes and only setting slots based on the number of time units, capacity pooling can be used and we expect this to lead to a better service level.

Batching of (self-scheduling) patients

Batching of (self-scheduling) patients is an interesting follow-up study on the impact on the minimum service level. We recommend a further study to investigate the effect of batching as we expect to be able to achieve an improvement. With the outcome of this research, self-scheduling can be further improved.

Patient experience

We have assumed in our research that offering a minimum of three slots to self-scheduling patients is sufficient for a good patient experience. However, this is an assumption and based on a hunch. We recommend research to determine what is received as 'good service'. This will allow the Medisch Spectrum Twente to serve its patients in the best possible way.

10.3. Contribution to practice

In this study, we prove to the Medisch Spectrum Twente that it is not a sensible approach to implement self-scheduling without making modifications to the current process. We illustrate that a major improvement in the minimum service level can be achieved by matching the number of slots per appointment code to actual patient flow into the hospital. Since we have used Urology as a case study, we conclude that this improved distribution, compared to the current distribution, has a significant result for Urology. However, we have not determined the effect for the other specialties, but we do demonstrate that a correct distribution is of major importance. As stated in the recommendations, Medisch Spectrum Twente is required to calculate this distribution for each specialty.

In addition, we show that the use of the newly developed adaptive model with all three elements (SlotReservation + SlotSharing + DynamicBlueprint) can be of significant value to the Medisch Spectrum Twente if they decide to apply it. By performing the robustness analysis, we state that the positive effect on the MSL will not only be for Urology, but also for the other specialties. Therefore, as mentioned in Section 9.2, we recommend the Medisch Spectrum Twente to apply this model for every specialty.

10.4. Contribution to theory

With this study, we have investigated a problem that is rarely discussed in the scientific field. Whereas patient scheduling has been extensively explored, this is not the case for patient self-scheduling. Through this study, we demonstrate a new possible approach to facilitate self-scheduling. We show that the impact of the distribution of the number of slots per appointment code has a significant impact on the performance of the MSL. In addition, we develop a new model that facilitates self-scheduling as effectively as possible and performs significantly better than the standard model.

This model, in combination with self-scheduling, is a new theory for the scientific field and can serve as a basis for further research.

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Appendix

I. Appointment codes

Appointment code	Dutch definition	Number of appointments	Average duration (min.)	Standard deviation (min.)
CP	Controle patient	[redacted] (16.8%)	12,6	7,0
TC	Telefonisch consult	[redacted] (14.3%)	12,2	5,0
NP	Nieuwe patient	[redacted] (6.7%)	20,9	14,0
BELC	Belconsult	[redacted] (6.7%)	10,0	1,0
UCP	Uitslag Controle Patient	[redacted] (4.6%)	11,2	2,5
C-COMBI	CP-Combi	[redacted] (4.3%)	5,2	1,3
CYCP	Cystoscopie CP	[redacted] (4.2%)	20,2	2,9
PATHO	PA - Uitslag	[redacted] (3.6%)	14,8	2,9
NP-CYST	NP Cystoscopie	[redacted] (3%)	6,6	4,8
C-CYSTO	Cystoscopie	[redacted] (2.6%)	10,0	0,3
SPELD	Spoedeisende hulp Elders Zh.	[redacted] (2.4%)	15,6	6,1
CPF/E	CP Flow/Echo	[redacted] (2.3%)	12,3	5,0
WE	Weggebleven	[redacted] (2.2%)	7,2	5,8
BLSP	Blaasspoeling	[redacted] (2%)	16,3	4,7
ONCO	Oncologie Bespr. Radiotherapie	[redacted] (1.9%)	5,8	1,8
BLSPCY	Blaasspoeling Cytologie	[redacted] (1.8%)	20,0	0,0
SPSEH	Spoed PATIENT SEH afd.	[redacted] (1.3%)	11,2	14,0
NP-F/E	NP FLOW / ECHO	[redacted] (1.3%)	7,3	5,9
CP-F/E	CP-c Flow/Echo	[redacted] (1.1%)	5,3	2,6
MCYSTO	(M) Cystoscopie	[redacted] (1.1%)	12,7	4,7
VAS	Vasectomie	[redacted] (1%)	18,5	5,1
VASECTO	Vasectomie Gesprek	[redacted] (1%)	8,6	6,1
PTNS	PTNS	[redacted] (1%)	38,3	5,9
CATH	Catheter Wisselen	[redacted] (0.9%)	18,2	6,2
TWOC	Trial Without a Catheter	[redacted] (0.9%)	14,2	4,6
NP-TRE	NP zorgpad prostaat	[redacted] (0.9%)	9,4	6,6
PBX	Prostaatbiopsie	[redacted] (0.9%)	20,2	3,6
ALG	Alg. Verrichting	[redacted] (0.6%)	17,8	7,6
C-TRE	Controle zorgpad prostaat	[redacted] (0.6%)	10,0	0,0
ONVPC	Oncologie Verpl. Consult	[redacted] (0.5%)	23,1	4,5
CATHUIT	Catheter uit	[redacted] (0.4%)	18,1	4,5
ESWL	ESWL	[redacted] (0.4%)	30,0	4,1
VERSP	Verwisselen Sup.Pub	[redacted] (0.4%)	19,2	0,0
JJUIT	Verwijderen JJ	[redacted] (0.4%)	18,2	4,6
CPECHON	Controle echo nieren	[redacted] (0.4%)	11,7	3,7
NPF/E	NP Flow/Echo	[redacted] (0.4%)	20,9	8,0
BES	Bespreking	[redacted] (0.4%)	8,0	2,6
CIC	Zelf Catheteriseren	[redacted] (0.4%)	53,1	13,4
EUDO	Udo-behandeling	[redacted] (0.3%)	45,0	0,0
CCC	Circumcisie	[redacted] (0.3%)	35,2	6,9
JJWISS	Verwisselen JJ	[redacted] (0.3%)	31,5	2,3
VUL	Pad - test vullen	[redacted] (0.3%)	10,6	4,9
MET	Pad-test meten	[redacted] (0.3%)	10,4	1,9
GOUDM	inbr goudmarkers	[redacted] (0.3%)	19,9	1,7
VCYSTO	(V) Cystoscopie	[redacted] (0.2%)	12,3	4,6
INBRJJ	Inbrengen JJ	[redacted] (0.2%)	29,3	3,1
CYSTO	Cystoscopie	[redacted] (0.2%)	20,3	3,4
URRA	Urologie / Radiologie Besprek.	[redacted] (0.2%)	5,4	1,4
KLVER	Verrichting-klein	[redacted] (0.2%)	26,8	11,5
C-ECHO	Echo	[redacted] (0.2%)	17,7	5,3
TRE	Transrectale Echo	[redacted] (0.2%)	18,5	5,3
CPECHOB	Controle echo blaas	[redacted] (0.1%)	12,3	3,3
FREPL	Frenulumplastiek	[redacted] (0.1%)	21,7	5,1
COR	Correctie	[redacted] (0.1%)	10,0	0,0
RETRO	Retrograde	[redacted] (0.1%)	33,3	5,6

BOTOX	BOTOX	[redacted] (0.1%)	41,3	10,7
HPSEH	Herhaal PATIENT SEH afd.	[redacted] (0.1%)	9,8	1,0
NP-PBX	NP Prostaatbiopsie	[redacted] (0.1%)	9,3	6,7
CPECH	CP Echo	[redacted] (0.1%)	10,0	0,0
CPUDO	Controle UDO	[redacted] (0.1%)	10,0	0,0
C-PBX	Prostaatbiopsie	[redacted] (0.04%)	10,8	0,0
SEHOV	consult voor overname	[redacted] (0.04%)	10,0	2,9
NP-VCYST	NP (V) Cystoscopie	[redacted] (0.03%)	20,0	6,6
NP-MCYST	NP (M) Cystoscopie	[redacted] (0.03%)	16,0	0,0
PUC	Poliklinische urine controle	[redacted] (0.03%)	6,7	2,5
DILA	Dilatatie	[redacted] (0.02%)	23,1	8,8
LVEC2	2 zak bloed	[redacted] (0.02%)	240,0	0,0
HYDR-INF	Hydratie infusie	[redacted] (0.02%)	564,0	12,0
AUDO	Udo-behandeling	[redacted] (0.02%)	45,0	13,4
INBRSP	inbr sup pub cath	[redacted] (0.02%)	37,0	0,0
BLCOAG	Blaascoagulatie	[redacted] (0.02%)	26,0	5,5
NP-CYSTXL	NP Cystoscopie XL	[redacted] (0.01%)	31,3	17,5
BLBIOP	Blaasbiopten	[redacted] (0.01%)	22,5	7,5
CYNP	Cystoscopie NP	[redacted] (0.01%)	22,5	5,0
PADT	Pad Test	[redacted] (0.01%)	20,0	5,0
ECHO	Echo	[redacted] (0.01%)	12,5	0,0
NP-ECHO	NP Echo	[redacted] (0.01%)	11,3	5,0
C-CYSTOXL	Cystoscopie XL	[redacted] (0.01%)	23,3	5,8
CP-C	CP-Combi	[redacted] (0.01%)	5,0	0,0
CTGELPUNCT	CT geleide punctie	[redacted] (0.01%)	360,0	7,1
ECHOGPUNCT	Echogeleide punctie	[redacted] (0.01%)	360,0	0,0
HAEMP	Haemate-P	[redacted] (0.01%)	60,0	0,0
C-ECHOS	Echo Scrotum	[redacted] (0.01%)	20,0	0,0
ECHOS	Echo Scrotum	[redacted] (0.01%)	15,0	0,0
ECG	ECG	[redacted] (0.01%)	10,0	0,0
ECHOLP	Echogeleide Leverpuntie	[redacted] (0.003%)	360,0	N/A
LVEC3	3 zak bloed	[redacted] (0.003%)	360,0	N/A
INF	infuus	[redacted] (0.003%)	240,0	N/A
OVERIG 2U	Overig (uitloop) 2 uur	[redacted] (0.003%)	120,0	N/A
C-MCYSTO	(M) Cystoscopie	[redacted] (0.003%)	20,0	N/A
ECHCP	Echo CP	[redacted] (0.003%)	15,0	N/A
SAECG	SA-ecg	[redacted] (0.003%)	10,0	N/A
NPPBX	NP + Prostaatbiopsie	[redacted] (0.003%)	5,0	N/A

II. Utilization Urology Department

In this appendix the utilization figures for the other calendars are further discussed. First, the utilization rates of the care providers for the other locations are presented. Then we conclude with the utilization rates for the treatment rooms in Enschede.

Care providers - Location Haaksbergen and Oldenzaal

A key difference between the schedules in Enschede and the schedules for Haaksbergen and Oldenzaal is that appointments with a nurse are booked in the urologist's schedule, while in Enschede a separate schedule is in use. As a result, time slots are booked twice, whereby one patient is consulted by the urologist, while the other is consulted by the nurse. Due to the inadequate logging possibilities of the current EHR, it is again not possible to distinguish between these consultations. As a result, not all appointments in which only nursing care was provided to the patient can be excluded.
Two appointment codes were excluded from the calculation of appointment time, namely BLSP (bladder flush) and CATH (catheter replacement). Patients with these appointment codes were only seen by nurses, which allows this to be excluded.

Table II.1 shows the utilization of the outpatient clinics in Oldenzaal and Haaksbergen. The average utilization of these external locations is 84.9%. A remarkable fact is the utilization rate of 108% in the afternoon at OLEEN. An utilization rate higher than 100% is not realistic in practice, however, due to the problem of double bookings, a rate higher than 100% is possible. Table II.1 also clearly shows that the utilization at the external locations is higher than the utilization at the Enschede location.
The difference with the locations is particularly large considering the number of minutes lost due to patients not turning up or being reachable by phone. For the external locations, 460 minutes were lost in 2019. This affects utilisation by 0.9%, compared to 4.0% in Enschede.

Table II.1 – Utilisation: Care providers - Location Oldenzaal / Haaksbergen 2019

	Number of sessions	Available time (min.)	Appointment time (min.)	**Utilization**	Overtime (min.)
			Morning		
OASSE	16	3840	3425	**81%**	200
OLEEN	23	5520	5435	**87%**	310
OSANT	18	4320	4080	**86%**	255
OWAARD	16	3840	3540	**78%**	310
WKORT	16	3840	3570	**80%**	160
WPIT	19	4560	4275	**78%**	520
			Afternoon		
OASSE	15	3600	3615	**97%**	10
OLEEN	21	5040	5675	**108%**	35
OSANT	17	4080	3835	**90%**	0
OWAARD	16	3840	3640	**89%**	0
WKORT	14	3360	2700	**80%**	0
WPIT	18	4320	2640	**60%**	0

Treatment room

A major difference between the calendars (resource codes) of the care providers is that the number of sessions for the care providers is clearly defined, while this is not the case for the treatment rooms. Therefore, we estimated the number of sessions for the treatment rooms on the assumption that there was or was not a patient receiving treatment on that part of the day. The number of sessions is thus determined on the basis of the number of dayparts when at least one treatment has been carried out. For the calculation of the appointment time, all appointments are included, except for the patients who did not show up or were not available by telephone.
The overtime associated with the morning includes all appointments performed between 12:00 and 13:00. Table II.2 shows the utilisation of the four treatment rooms.

Table II.2 – Utilisation: Treatment rooms 2019

	Number of sessions	Available time (min.)	Appointment time (min.)	**Utilization**	Overtime (min.)
			Morning		
EUROBP1	248	59520	26225	44%	135
EUROBP2	182	43680	20470	47%	225
EUROBP3	22	5280	2655	50%	30
EUROBP6	251	60240	23750	39%	90
			Afternoon		
EUROBP1	245	58800	28336	48%	0
EUROBP2	76	18240	11140	61%	0
EUROBP3	26	6240	3455	55%	0
EUROBP6	241	57840	16385	28%	0

As shown in Table II.2, the utilization rate is mostly around 50%. This percentage is low compared to the utilization of regular consultation hours. A possible cause for this low utilization is the calculation of the number of sessions. A part of the day is considered a session when one treatment has taken place.

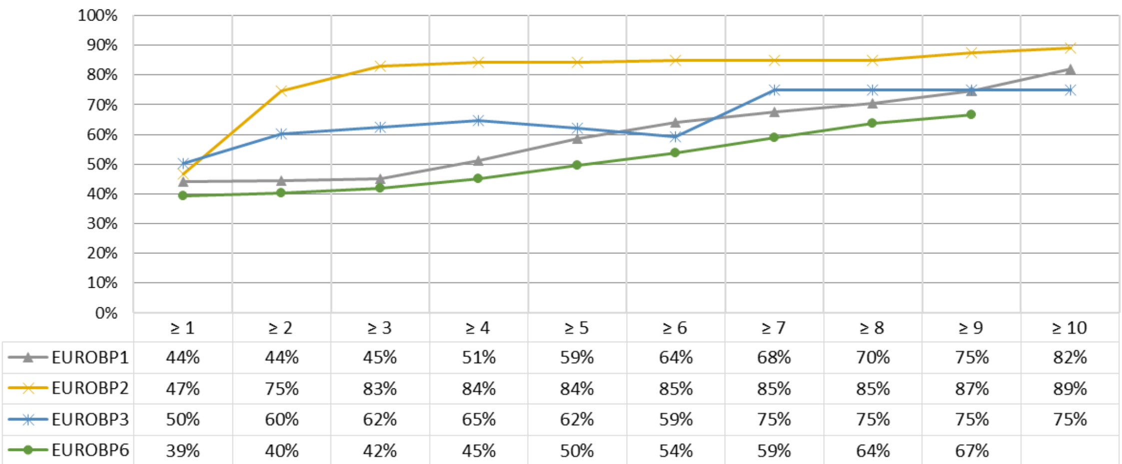
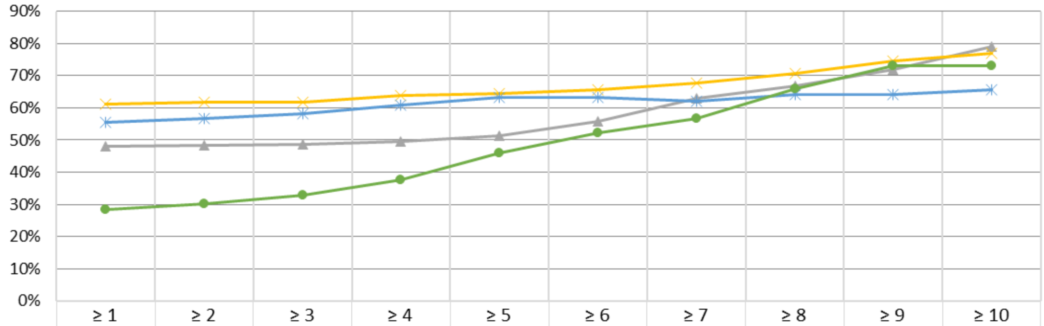


Figure II.1 – Utilization Treatment rooms: Morning 2019

However, some schedules are used for the emergency patients that need to be treated with an outpatient surgery in the treatment room. As a result, it sometimes occurs that on a particular part of the day no session was planned for the room, but nevertheless a patient is treated.

To show the influence of this calculation, nine additional utilizations were calculated for each treatment room. In this calculation, the minimum number of treatments per daypart is taken as the variable. Figure II.1 (morning) and Figure II.2 (afternoon) show what happens to the utilization when dayparts are excluded if they do not meet the minimum number of treatments. The x-axis indicates the minimum number of treatments that must be carried out in order to be included in the calculation.



	≥ 1	≥ 2	≥ 3	≥ 4	≥ 5	≥ 6	≥ 7	≥ 8	≥ 9	≥ 10
EUROBP1	48%	48%	49%	50%	51%	56%	63%	67%	72%	79%
EUROBP2	61%	62%	62%	64%	64%	66%	68%	71%	75%	77%
EUROBP3	55%	57%	58%	61%	63%	63%	62%	64%	64%	66%
EUROBP6	28%	30%	33%	38%	46%	52%	57%	66%	73%	73%

Figure II.2 – Utilization Treatment rooms: Afternoon 2019

For EUROBP2 in particular, this variable has a great influence and utilization rises rapidly with at least two treatments per half-day. However, for EUROBP1, the schedule on which most patients are booked in 2019, utilization remains low. Only with a minimum of eight (morning) or nine (afternoon) treatments per daypart the utilization rate reaches a decent rate. However, it is questionable whether this is realistic with regard to emergency patients. On average (Figure 2.1), there are one to two emergency patients per day. It can be concluded that there is still enough capacity to treat more patients in the treatment rooms.

III. Warm-up period – Moving averages indicators

Indicator **Number of patients scheduled per week**

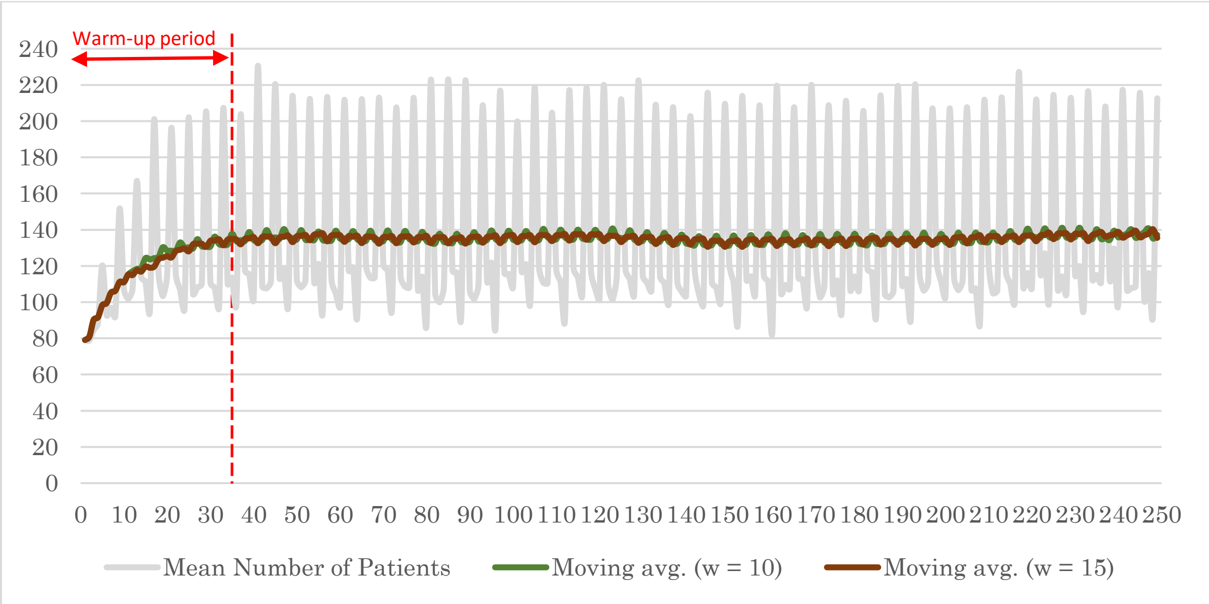


Figure III.1 – Moving average - Number of patients scheduled

Indicator **Service level per week**

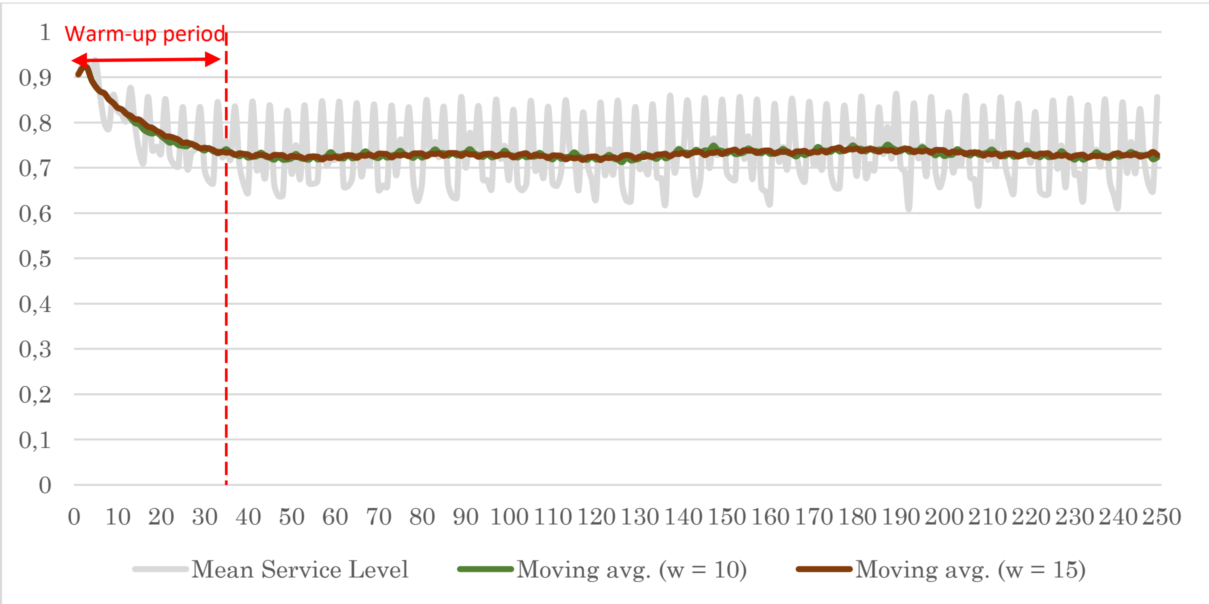


Figure III.2 – Moving average - Service level per week

Indicator **Appointment lead-time (% < three weeks)**

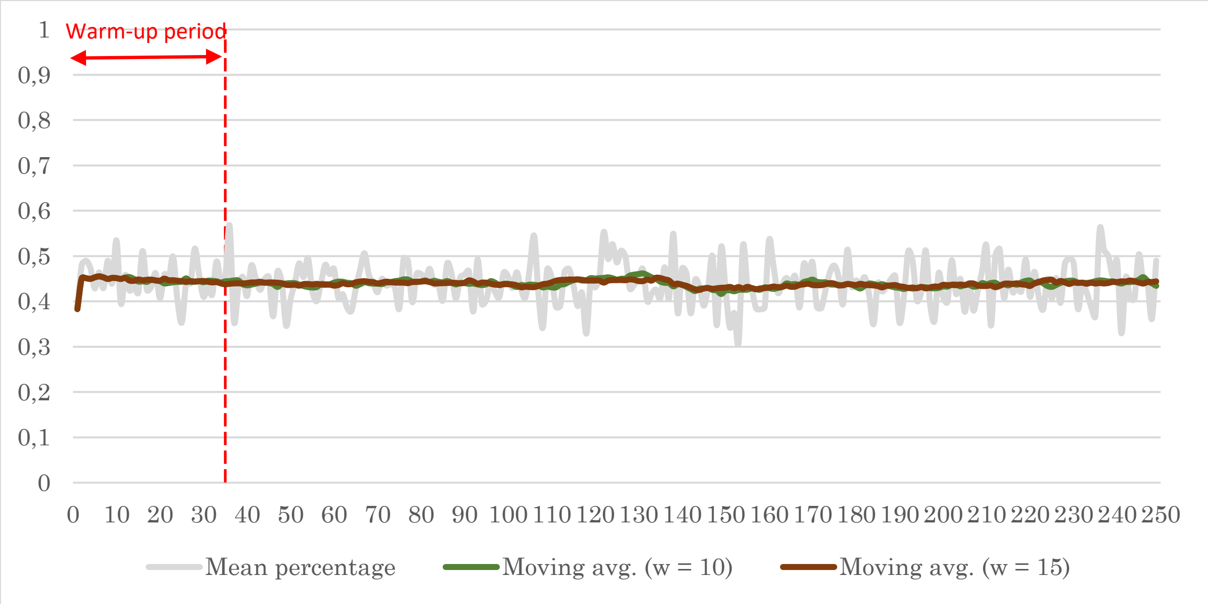


Figure III.3 – Moving average - Appointment lead-time (% < three weeks)

Indicator **Appointment lead-time (% < four weeks)**

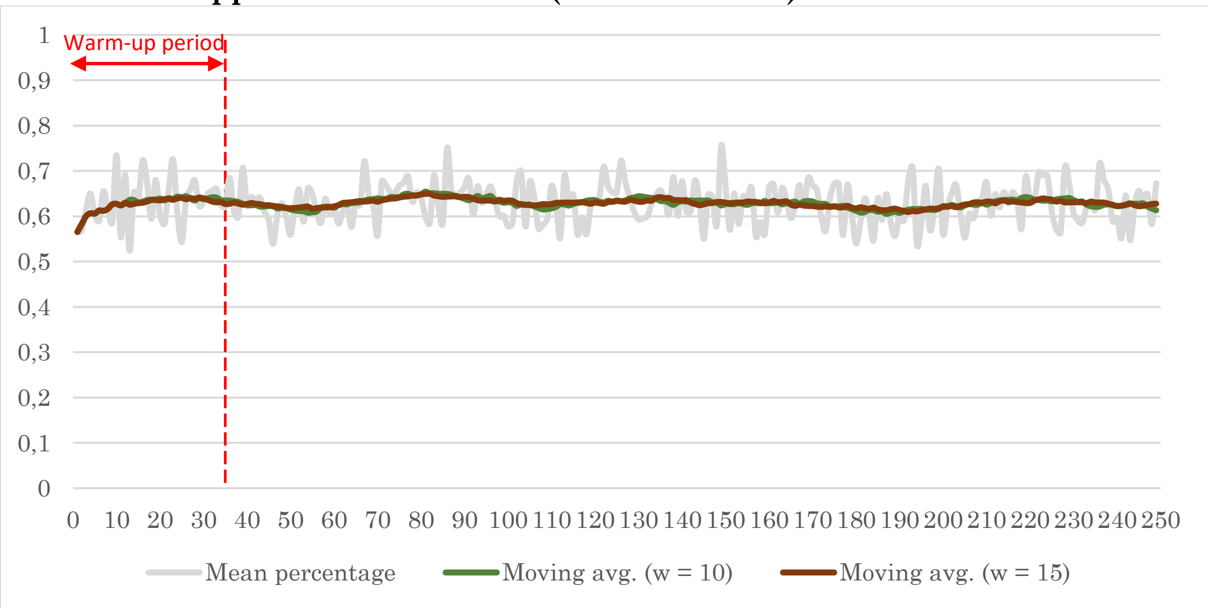


Figure III.3 – Moving average - Appointment lead-time (% < four weeks)

IV. Number of replications

Indicator **Service level**

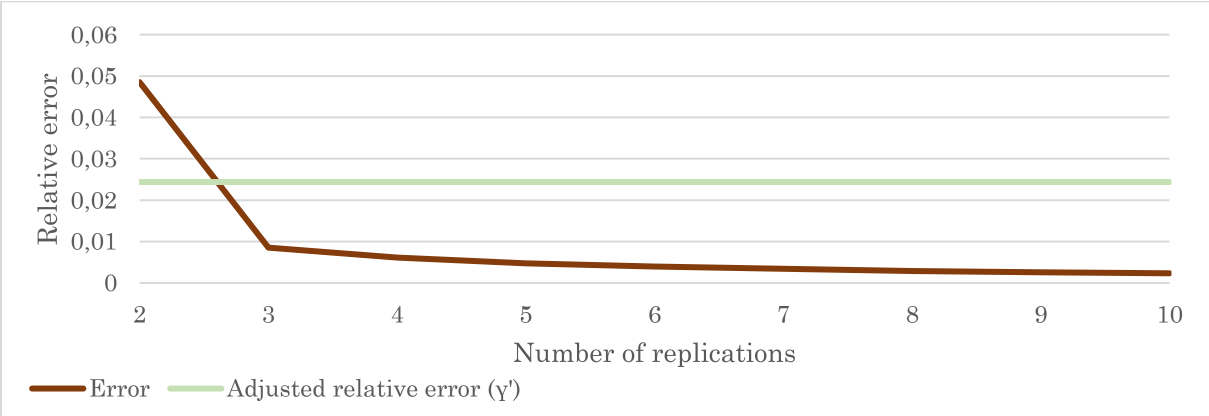


Figure IV.1 – Needed number of replications based on service level

Indicator **Appointment lead-time (% < three weeks)**

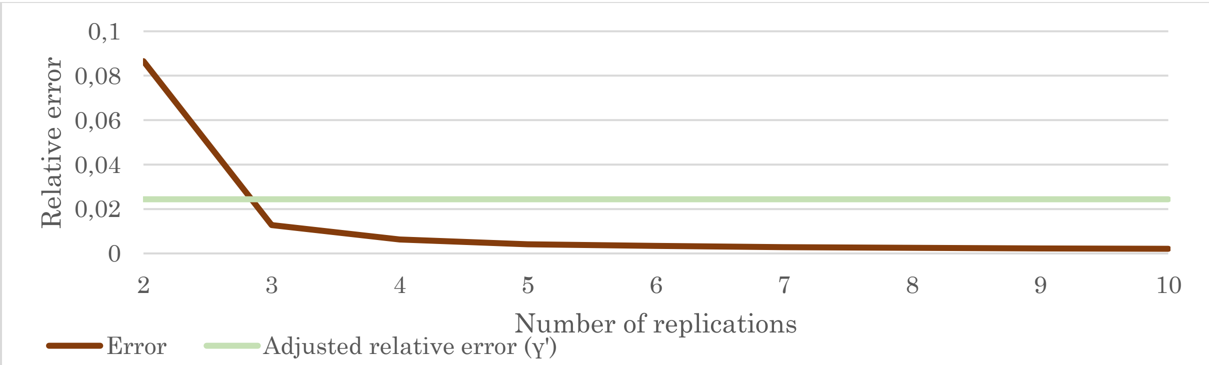


Figure IV.2 – Needed number of replications based on appointment lead-time (< 3

Indicator **Appointment lead-time (% < four weeks)**

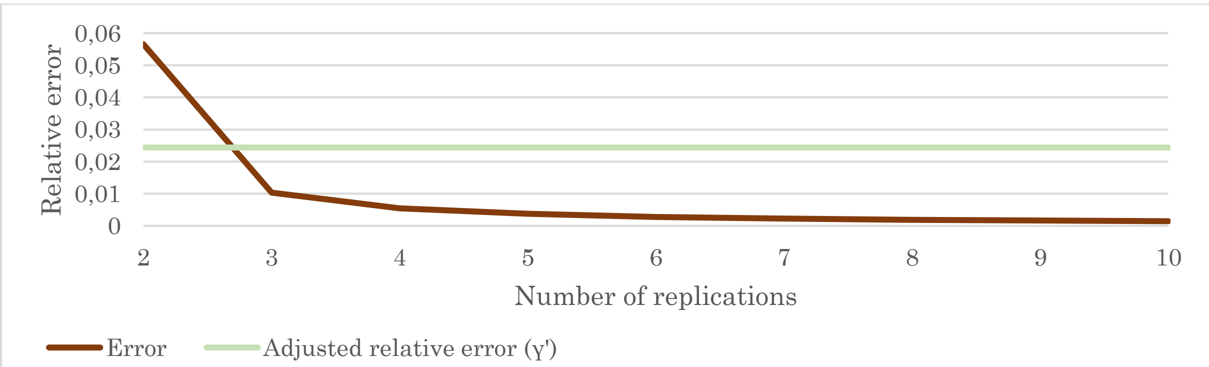
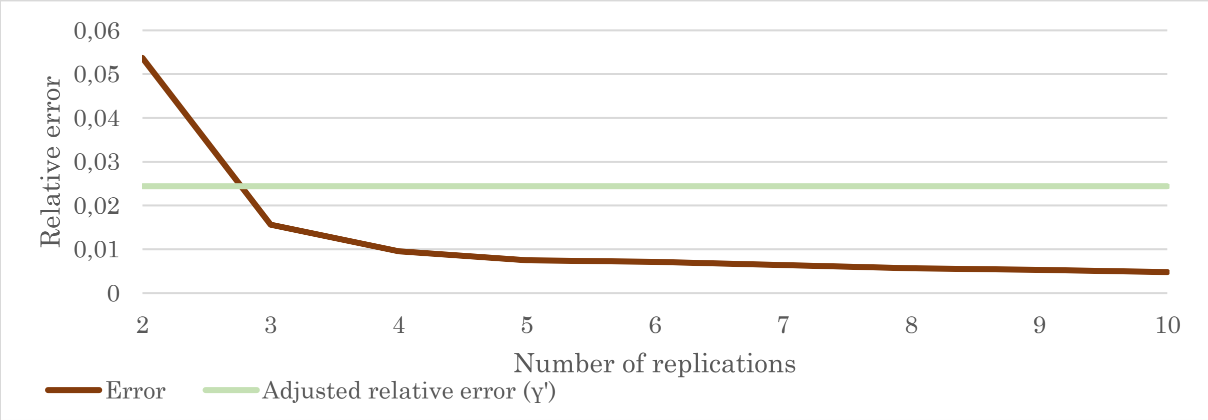
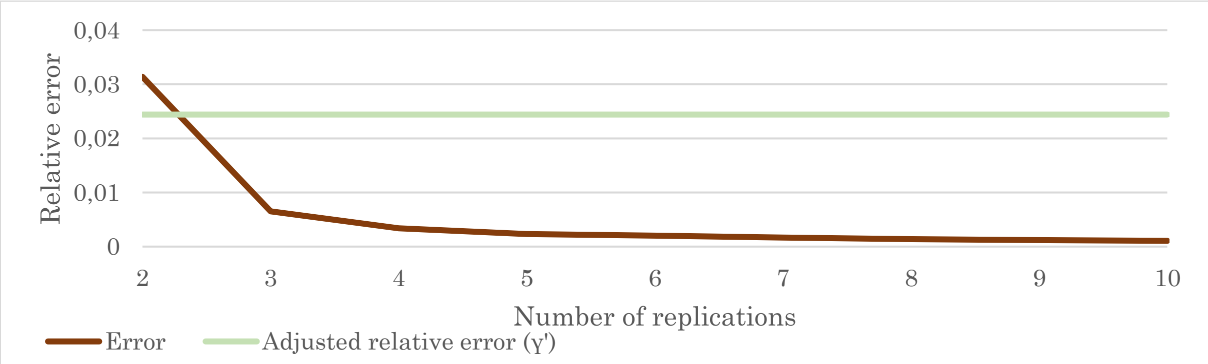


Figure IV.3 – Needed number of replications based on appointment lead-time (< 4 weeks)

Indicator **Adjusted service level**



Indicator **Fraction within appointment window**



V. Scheduling method – Current practice

Figure III.1 provides a visual overview of the scheduling method used in the simulation, corresponding to the current practice.

1. The first step is to apply the first come, first serve (FCFS) principle. This implies a search for the first available slot with the correct appointment code within the appointment window of the patient and, as applies to all steps, with the appropriate physician.

2. If there is no slot vacant, the second step is to select an alternative slot with the correct time unit.

3. If again no slot is found, a patient with a less urgent appointment is rebooked to a later date, leaving an empty slot. This last principle is deliberately not included in our simulation, since, after discussing it with the Capacity Department, it is a very undesirable situation and should not occur in the future. Therefore, if the two previous searches have not yielded any result, it is decided to search for the first available slot after the appointment window with the correct time slot. However, this may be up to 50% of the maximum referral time to a maximum of 7 days to prevent patients from getting an appointment well beyond their appointment window (i.e. to prevent patients from being consulted too late in practice).

4. Should this also not result in an available slot, an additional appointment will be created at the end of the session at the first possible session within the appointment window and the patient will be assigned to this slot.

5. As a last option, if the previous four steps did not result in an available slot, an extra appointment is created for the patient at the end of the session on the first possible session before the appointment window and is booked at this slot.

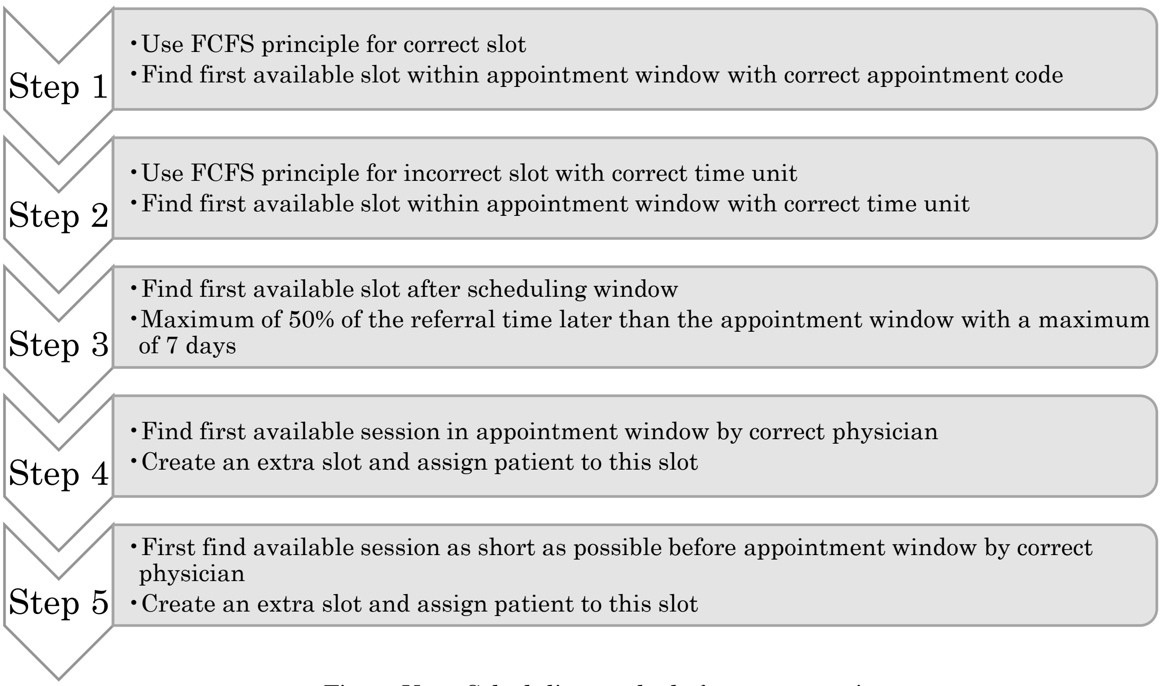


Figure V.1 – Scheduling method of current practice

VI. Algorithm - SlotSharing

The SlotSharing algorithm:

1. $patient^{AC}$ is the current self-scheduling patient with appointment code AC, with the corresponding number of time units $reqtu$
2. $REQ(SOON_{reqtu})$ is the number of slots required per session for patients with A.W. = (1,2) or (1,7) and with the requested number of time units *reqtu* by $patient^{AC}$
3. $AVAIL\left(SOON_{reqtu} + Slot^{SSP}\right)_s$ is the total number of available slots in session s with appointment code $SOON_{reqtu}$ together with the number of slots $Slot^{SSP}$ which are dedicated to SSP patients.
4. *LIST[PossibleSlots]* is the list of possible slots from which $patient^{AC}$ can choose.
5. FOR every session s WITHIN appointment window WHERE physician = allowed
   IF $AVAIL\left(SOON_{reqtu} + Slot^{AC}\right)_s > REQ(SOON_{reqtu})$ then
   ADD every $SOON_{reqtu}$ and $Slot^{AC}$ to *LIST[PossibleSlots]*
   END
   NEXT
6. $patient^{AC}$ randomly assigns to itself a slot from *LIST[PossibleSlots]*

Figure VI.1 – Application of SlotSharing