Predicting the impact of block scheduling on patient waiting time for MRI resources

A simulation study at the Isala hospital

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Preface

This thesis marks the end of my study Industrial Engineering and Management at the University of Twente. In the past six years I followed both the bachelor and master program of this study, and I am very grateful that I got the opportunity to do so. In both study programs I gathered knowledge in a wide variety of expertise, and I also gained a lot of inspiration about my opportunities after my time as being a student.

I would like to thank the healthcare logistics team and the single cost center 'Medical Imaging' of the Isala hospital for giving me the opportunity to do research at their departments and to make use of their facilities. I especially would like to thank Ryanne van Kampen and Monique Gigengack, who have been my supervisors from the Isala hospital during my research. Their expertise really helped me in getting familiar with regular hospital procedures and they were always available for me if I had any questions. Furthermore, I would like to thank Gréanne Leeftink and Patricia Rogetzer, who have been my supervisors from the University of Twente. Their extensive feedback and the substantive discussions that we had, have resulted in a thesis which I am really proud of. Besides my studies I have also really enjoyed the student life of Enschede. Aside from the regular study program, I made a lot of friends at student association 'A.S.V. Taste' and the 'Enschedese Hockeyvereniging'. They always helped me to relax after intense periods of studying, and I am really thankful for them.

And last, but definitely not least, I would like to thank my family and my girlfriend for their unconditional support during the past six years.

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Management summary

In this thesis we describe how we design a simulation model which is able to predict the impact of block scheduling for four specialties that use the MRI resources at the Isala hospital. The main KPI that we use to assess this impact is the waiting time for patients. In this research we gradually work towards a model that is able to account for several (desired) consequences, from which we assume that they are involved when block scheduling is implemented for MRI resources. The methodology that we suggest enables other individuals to perform similar research. Furthermore, our methodology is not specifically aimed at predicting the impact of block scheduling on waiting time for MRI resources only. This method is aslo applicable to other diagnostic resources.

Research motivation
The healthcare logistics team and the single cost center 'Medical Imaging' of the Isala hospital have a mutual interest in working with a block schedule to schedule MRI scan appointments. With block scheduling, a predetermined amount of scan time capacity is fixed for some or all specialties that make use of the MRI resources. The main goal of working with such a block schedule is to reward specialties that make realistic MRI production budgets for a certain year, and to make specialties more aware of their own influence on the patient waiting list. Unrealistic production budgets might lead to extra costs for a certain specialty, because scans that are not included in the budget but that are be performed, will not be reimbursed by the healthcare insurer. The single cost center also expects that the waiting times for patients decrease in the case of block scheduling, when a shift from centralized planning responsibilities towards decentralized planning responsibilities is involved as well. In that case, the hospital expects the specialties to be more careful with their own capacity. On the other hand, two other possible consequences exist on an operational level according to both departments. When implementing a block schedule, it is expected that the utilization levels slightly decrease. This is expected, because it is reasonable that there will sometimes remain a small capacity block within the schedule which is not sufficient to plan a patient anymore. Furthermore, it is expected that the scan duration for a single scan decreases as well. This is expected, because specialties are likely to only perform necessary actions while scanning the patient, because they suffer from unnecessary long scans themselves in the case of block scheduling with fixed capacity. The healthcare logistics team and the single cost center 'Medical Imaging' currently do not have insight in the exact capacity demand for the specialties that use the MRI resources in terms of scan hours. Furthermore, they have no quantified insight on the effects of the expected impact of block scheduling on the waiting time for patients. The goal of our research is to first calculate the capacity requirements for each specialty, and then make a model in which we can experiment with the expected impacts of block scheduling on patient waiting time for MRI scans.

Modeling approach
We first performed a literature review in which we gathered information about techniques that might be helpful in making calculations on the impact of block scheduling on patient waiting time. From our literature review we select the Monte Carlo type of simulation as the best technique in which we can incorporate the expected benefits of block scheduling by the Isala hospital. We made calculations on the four specialties that have the biggest production budget for MRI resources: neurology, orthopaedics, surgery and cardiology. We propose five simulation scenarios in which we account for different specialties to apply block scheduling. Scenario A is the situation in which we do not consider block scheduling for any specialty. We eventually use the output of this scenario as a validation of how our output data behaves compared to the current situation at the Isala hospital. In scenario B we only apply block scheduling to neurology, since this is the specialty that has the highest individual production budget. In scenarios C to E, we gradually add one specialty based on the volume of the production budget. Next, we made an analysis on seasonal patterns that might exist in the amount of scan requests that are handed in at each specialty throughout the year. From this analysis we conclude that we do not have to account for seasonality. This means that we can

divide the required capacity for each specialty evenly over the year, for all the scenarios that we propose. For each scenario, we identified data distributions that enable us to create realistic scan requests in our simulations by means of the software 'RStudio'. In our simulations, we basically assign capacity to specialties based on the scenario. We create patient arrivals per week, where three possible patient statuses with corresponding deadlines (in weeks) exist: acute (1), semi acute (2), and regular (4). We first schedule acute or semi acute patients that already have a waiting time. Next, we schedule acute and semi patients that have newly arrived, and lastly we schedule regular patients based on the order of their arrival, as long as capacity is available. If a patient is able to be scanned in a certain week, the average scan time of a patient of that certain specialty is deducted from the available scan time of that specialty. In our different scenarios, we account for the possible reduction in utilization by decreasing the available scan times accordingly. We account for the expected reduction in scan time by reducing the required scan time with the corresponding value. However, we only apply this scan time reduction to specialties that we assigned fixed capacity to.

Results

Our validation scenario (A) reveals that the output of our simulations is an underestimation of the actual waiting times. Two main causes for this result exist. In our model we assume that a patient is always available at the next available time slot. Hence, it does not incorporate any delay in appointment scheduling because of patient preferences. The second cause for this, is the fact that the Isala hospital already works with block scheduling to a certain extent. In the current schedule, small capacity blocks are already assigned to specific types of scans. This means that the stakeholders of the appointment scheduling process have to consider more constraints in practice, than we have incorporated in our model. The results for neurology and surgery are promising. Although the actual waiting time output is not perfectly representative, we observe output data that shows stable waiting times for these specialties. This is mainly caused by the realistic amount of scans that these specialties include in their production budget. When we decide to fix the amount of available scan hours per week for these specialties, the waiting times are stable and are expected to be between three and four weeks on average for both specialties. The results of the other scenarios reveal that orthopaedics is certainly not ready for block scheduling yet. The main reason for this, is that this specialty structurally underestimates the amount of scans that it will perform in a year. In our simulations we observe that the waiting times for orthopaedics increase rapidly, especially in the second part of the year. Hence, the waiting time does not stabilize over the year. The results of the specialty cardiology are precarious. We observe that the average waiting time already approaches the four weeks within one year. Since our output is an underestimation of the actual situation, it is realistic to assume that it transcends the treeknorm of four weeks in practice.

Conclusions and recommendations

We provide the following conclusions and recommendations to the Isala hospital:

1. The average waiting times slightly increase for specialties that we assigned fixed capacity to. However, the waiting times stabilize over the year for specialties that create realistic production budgets. This is the case for the specialties neurology and surgery, and we recommend to start the conversations with the stakeholders of these specialties in the MRI appointment scheduling process to implement block scheduling.

2. The scan requests of the specialties neurology and surgery comprise around 45% for MRI resources. If the Isala hospital would decentralize its planning responsibilities because of block scheduling for these two specialties, it might be possible to reduce the workforce at the central planning department with 1 FTE.

3. From the simulation output we conclude that the reduction in utilization has a higher impact on the waiting time than the scan time reduction. This stresses the importance of constructing a block schedule in which flexibility rules must be incorporated, such that the MRI resources will not remain empty during operating hours.

Contents

Abbreviations

The following abbreviations are frequently used in this paper:

CMP	Case Mix Problem
CT	Computed Tomography
DBC	Diagnose-behandelcombinatie (Dutch for combination of diagnosis and treatment)
FTE	Fulltime-equivalent
KPI	Key Performance Indicator
MSSP	Master Surgical Scheduling Problem
MRI	Magnetic Resonance Imaging
OR	Operating Room
SCC	Single Cost Center
SSP	Surgical Scheduling Problem
TB	Time Block

1 Introduction

We provide an introduction to the research environment and we describe the information upon which the research questions are formulated in this chapter. Section 1.1 provides a concise description of the Isala hospital in general. Next, Section 1.2 describes the motivation of the research from the perspective of the hospital. We provide information about the level of decision making and the type of block scheduling that we focus on in this research in Section 1.3. Next, Section 1.4 describes the main problem of this research. These sections altogether provide the basis for the objective of the research and the research questions, which we describe in Section 1.5.

1.1 Problem context

The healthcare sector is a complex sector which comprises various types of care that are delivered by a wide variety of healthcare providers, such as hospitals. Hospitals are complex organizations which center their operations around the needs of the patients, and they aim to increase the perception of health of these patients. The research we describe in this paper is conducted within the Isala hospital in Zwolle, the Netherlands. The Isala hospital is a top clinical hospital with 1,245 beds available. The hospital employed 415 medical specialists (384 Fulltime-equivalent (FTE)) and 6,716 employees (4,946 FTE) in 2020. The two main facilities of the hospital are located in Zwolle and Meppel. Furthermore, the hospital has three outpatient facilities in Kampen, Steenwijk and Heerde. The facility in Zwolle has an operating room (OR) capacity of 20 ORs in total and the facility in Meppel has an OR capacity of five ORs [1]. The Isala hospital facilitates outpatient services and inpatient services. A patient that receives outpatient service, visits the hospital for, for example, diagnostic research or a minor treatment, but the patient does not stay overnight. A patient who receives inpatient care stays at the hospital for a longer time and is assigned to a hospital bed. Emergency services are facilitated by the Isala hospital, for cases where a patient is in immediate need for care.

Over 20 single costs centers (SCCs) exist within the Isala hospital. A SCC can, for example, be responsible for the admission and treatment of patients, or scheduling outpatient appointment requests. There are also SCCs which are not in direct contact with patients. It is reasonable that a patient requires services from multiple SCCs during the care pathway. The research we describe in this report is conducted within the radiology department of the hospital. The radiology department is part of the SCC 'Medical Imaging'. Besides radiology, the nuclear medicine program of the hospital is part of this SCC as well. The radiology department includes different types of technical resources, which we refer to as modalities throughout this report. Angiography, X-ray, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are, among others, modalities that exist within the radiology department of the Isala hospital. The focus of this research is on the MRI resources, which are diagnostic resources that are possibly used in different stages of the care pathway of a patient. The facility in Zwolle has four MRIs available and the facility in Meppel has one MRI available. The demand for MRI scans is increasing worldwide, where the number of scans that is performed grows at a higher rate than the capacity of the MRI resources available. The technical MRI resources are regularly seen as bottlenecks for patient flows in hospitals, and hence the pressure on optimal utilization of these resources is increasing [2].

1.2 Research motivation

Before we describe the research motivation, we shortly elaborate on the current appointment scheduling process for the MRI resources within the Isala hospital. For the outpatient facility in Zwolle, an outpatient assistant hands in a scan request for a patient at the centralized planning office of the radiology department. The centralized planning office of the radiology department schedules the appointment based on the required date of scan, type of scan and the MRI availability. The planning horizon is three months. The inpatient appointment requests are not scheduled by the centralized planning office, but this task is performed by the laboratory technicians. The appointment scheduling tasks for the MRI resources at the facility in Meppel are all performed by the laboratory technicians (operational personnel). The hospital already allocated capacity blocks for inpatient scan requests, but these blocks are not dedicated to a specialty. Table 1 depicts the specialties within the Isala hospital that make use of the MRI resources. Besides scan requests from these specialties, scans for patients can also be requested by the emergency department or external care providers such as general practitioners.

Table 1: Overview of specialties that use the MRI resources at the Isala hospital.

Ophthalmology	Ear, Nose and Throat medicine (ENT)	Surgery
Plastic surgery	Orthopaedics	Urology
Gynaecology	Neurosurgery	Dermatology
Internal medicine	Pediatrics	Gastroenterology
Cardiology	Lung diseases	Rheumatology
Cardiothoraric surgery	Psychiatry	Neurology
Radiotherapy	Radiology	Anaesthesiology
Dental specialists	First aid doctors	

In the beginning of 2021, the board of the SCC started a pilot in which it allocated capacity to the specialties cardiology and orthopaedics. This means that specific blocks in the MRI schedule are reserved for patients of those two specialties. Eventually, the hospital desires to work with a block schedule which includes reserved capacity for all specialties for which it is beneficial. The main benefit of block scheduling that is perceived by the SCC board, is that the specialties themselves have more responsibilities within the appointment scheduling process. Currently, specialties are not responsible for the actual scheduling of the scans for outpatient requests, but only for handing in these requests at the centralized planning office. In this situation, the specialties therefore feel no responsibility to regulate the scheduling of patients of their own specialty. If the SCC assigns more responsibility to the specialties, by using partly decentralized appointment scheduling in combination with a form of block scheduling, the board of the SCC expects that the scan time decreases. They do so, because they expect that specialties are more careful with their own capacity and they do not increase the scan duration when it is not necessarily useful. As a consequence of the expected decrease in scan times, the waiting lists are expected to decrease as well. However, if one specialty receives more responsibility for the appointment scheduling of its own patients, whereas this is not the case for the other specialties, a risk appears. In that case, the specialty that receives more scheduling responsibility, reduces the idle time for the MRI resources in total, by optimally using its own capacity for its own scans. All specialties benefit from this reduction and not only the specialty that is responsible for the reduction. To ensure that the specialties benefit from their own appointment scheduling responsibilities themselves, the board of the SCC desires to divide the total MRI capacity into blocks. We refer to these blocks as being assigned capacity, and the assigned capacity differs for each specialty and depends on the expected amount of requested scan time per specialty. This means, in principle, that a ratio of the total amount of MRI hours (available capacity) within the agenda is assigned to each speciality. If a specialty schedules the appointments efficiently, the idle time of the MRI resources will be reduced for that specialty and waiting lists are more likely to decrease. In this situation, the speciality benefits itself, because the specialty can treat more patients in its own dedicated blocks. On the other hand, if a speciality still schedules the appointments inefficiently, the waiting lists are likely to increase. This is then a problem for the speciality, because it cannot schedule all the patients within its own dedicated blocks.

The innovative working environment within the team of healthcare logistics and the SCC, and the working experience and interests of employees, originates the desire of the SCC to work with reserved block schedules for the modalities. So far, however, no extensive research is conducted on the actual advantages and disadvantages for a more extensive use of block scheduling for the MRI resources at the Isala hospital. Also, no research is conducted on whether the expected benefits that are expected by the SCC exist in reality, when block scheduling is applied. Hence, this research not only provides an analysis on the optimal capacity allocation for the specialties within the Isala hospital, but it also goes one step back in this process and provides the advantages and disadvantages of block scheduling for the radiology department in general. Furthermore, this research identifies the organizational changes involved for the SCC to shift from centralized planning responsibilities to decentralized planning responsibilities, since they desire a partly decentralized system.

1.3 Block scheduling

So far, we have elaborated on the desire of the SCC board to implement block scheduling from a practical point of view. In this section, we elaborate on the organizational level of decision making, variants of block scheduling for hospital departments that are known from literature and we eventually combine this information to collect knowledge regarding block scheduling for MRI resources.

We can make a distinction on the nature of decisions that hospitals make in general [3]. These decisions are divided into four managerial areas: medical planning, resource capacity planning, materials planning and financial planning. Furthermore, four hierarchical levels of control exist: the strategic level, the tactical level, the offline operational level and the online operational level. Decisions on capacity allocation by means of block scheduling, typically occur on a tactical level and are considered as resource capacity planning. The actual appointment scheduling, which considers assigning a day, time and a hospital resource to a patient, is also included in the resource capacity planning. However, the appointment scheduling activities occur on an offline operational level [3]. There exists a relation between decisions that are made within the various managerial areas and the levels of control. If we eventually conclude that block scheduling (which is a decision on the tactical level of control) is beneficial to divide MRI capacity among the specialties, it is possible that this involves changes further down in the hierarchy of the appointment scheduling procedures (which occurs on the offline operational level of control) as well.

Most information on applications of block scheduling within hospital departments relates to OR planning, which shows similarities with MRI resource planning. Within the principles of block scheduling, we can make a distinction between pure block scheduling and modified block scheduling [4]. In pure block scheduling for OR departments, specific surgeons or specialties are assigned to certain time blocks within the master surgery schedule into which the appointments of these surgeons or specialties must be scheduled. In this setting it is not allowed to release the time blocks once they are assigned. Modified block scheduling allows for more flexibility compared to pure block scheduling. Here, not all available time (capacity) within the master surgery schedule is assigned to a specialty or a surgeon, or unused block time (which is assigned to a surgeon or specialty) becomes available for other surgeons or specialties at a given time before the start time of the block [4]. In the remainder of our research, we refer to the release time being the time that unused capacity that is assigned to a specialty, becomes available for appointments of the other specialties.

Relevant differences in the application of block scheduling for ORs and MRI resources exist. Block scheduling is typically applied for surgeries that have a duration of several hours, whereas MRI scans in general have a shorter duration. The duration of MRI scans therefore also has limited uncertainty when compared to surgery durations [2]. Block scheduling for MRI resources is not researched extensively yet. Van Sambeek et al. [5] performed research on the impact of block scheduling for MRI resources on the access time for patients. Within the Amsterdam Medical Center, they identified that the complexity of the scheduling strategy increases, when the number of allocated capacity blocks increases. They also concluded that the access time for MRI resources can be reduced significantly, when the number of blocks that are only available for a specific specialty are reduced. Fei et al. [4] present an optimisation model for an MRI block scheduling problem. They assume that the patients groups that are assigned fixed capacity to, as well as the amount of capacity, are determined by the hospital already. Furthermore, they use a fixed release release time of one day for capacity that is assigned to a patient group, but for which no appointment is scheduled yet. A suggestion of Fei et al. for further research, is to develop optimization-based support models for the decisions on which patient groups must be allocated capacity to and how much capacity must be assigned to these patient groups. Furthermore, they suggest to develop decision support tools for centralized appointment scheduling and to connect this with the use of the block scheduling model.

1.4 Problem identification

A risk that is involved with the implementation of block scheduling at the radiology department of hospitals is the increase of complexity of the appointment scheduling process [5]. When we apply restrictions on appointment scheduling, by only scheduling appointments for a certain specialty in a certain time window, problems might occur. If, for example, an orthopaedics patient cancels the appointment shortly before the scan should have taken place, there exists a risk that no other orthopaedics patient can show up at that time slot, and hence the utilization of the MRI resource decreases. This is explicitly the case when we do not allow other specialties to make use of this capacity. Here, we identify an important aspect of the application of block scheduling for the MRI resources. The board of the SCC wants to know how block scheduling can be implemented and what the guidelines are to work with it on an operational level. Furthermore, our research must gain insights in the consequences of applying block scheduling for the MRI resources on the waiting time for patients. It is relevant to mention that we will not account for MRI scans that are performed for inpatient scan requests in the remainder of our research. The scan requests for these patients are already scheduled in existing capacity blocks for inpatient scan requests.

In 2018, a new central agreement is applied within the healthcare system in the Netherlands. This agreement aims to decrease the expenditures of medical specialist care over four years, to 0% in 2022 [6]. The Isala hospital deals with this agreement as well. A decrease of expenditures to 0%, however, implies a reduction of expenditures when we take the inflation rate into account. A risk that is involved with block scheduling, is that specialties will try to fully use the capacity that is assigned to them, even if it is not necessarily useful. We have not found literature that specifically supports the existence of this risk, but it is still a risk that we need to account for in this research according to the SCC board. For example, an extra scan to provide a slightly better decisive answer to a patient is not always necessary, but results in an increase in expenditures. The execution of such scans leads to an increasing access time for the MRI resources at the Isala hospital and an increase in expenditures on MRI scans, which does not correspond to the mentioned central agreement.

A problem in an organization can either be classified as an action problem or as a knowledge problem. An action problem refers to a problem or a situation in which the problem owner identifies a gap between the current performance of a certain process and the desired performance of this process. The problem owner desires to improve the current performance of the process, for example by implementing or adjusting procedures. A knowledge problem refers to a problem or a situation in which the problem owner has a lack of knowledge or insight about a specific process [7]. Currently, there is a lack of knowledge on the impact of block scheduling on the waiting time for patients that are waiting for an MRI scan, which we consider as a knowledge problem for the Isala hospital. In Section 1.3 we already concluded that not much research exists in the field of block scheduling for MRI resources. In this research, we develop a generic model that allows for experimentation on the expected impact of block scheduling for different scenarios on the waiting time for patients that require an MRI scan. We consider the desire of the SCC board to work with such a modified block scheduling model as an action problem. Hence, the main problem that we refer to in this research, consists of elements of an action problem as well as a knowledge problem.

1.5 Objective & research question

This section first describes how we derive the main research question from the research motivation. Next, it describes the research questions that eventually provide an answer to the main research question. The last part of this section provides an overview of which research question is assigned to each remaining chapter of this report.

1.5.1 Objective and main research question

As indicated in Section 1.2, the board of the SCC Medical Imaging is enthusiastic about the principles of block scheduling to allocate capacity among the different specialties for the MRI resources. Although the SCC board already started working with reserved capacity blocks in the MRI schedule, no extensive research is conducted on the impact of block scheduling on the waiting time for patients for MRI resources yet. The objective of this research is to develop a generic model to experiment with capacity allocation to specialties by means of scenarios and to predict the impact of the scenarios on the waiting time for patients. We eventually apply this model to the MRI resources of the Isala hospital.

We already concluded that the desire of the SCC to use modified block scheduling eventually involves decisions on a tactical level. In this research, however, we also pay attention to the impact of block scheduling on an operational level. It is crucial to analyse the impact of this tactical decision on an operational level as well to eventually provide a valuable advice on the use of block scheduling for the case of the Isala hospital. The objectives of this research translate into the following research question: *Which model can be designed that predicts the impact of different scenarios of block scheduling for MRI resources on the waiting time for patients?*

1.5.2 Research questions

This section describes the research questions that we derive from the problem identification, the research motivation and the main research question. We provide the answers to these research questions throughout this report and altogether they provide an answer to the main research question.

1. **How is the appointment scheduling process for MRI scans at the Isala hospital currently organized?**
The answer to this research question provides insight in the operational appointment scheduling activities for the MRI resources at the Isala hospital. The differences in processing outpatient requests, inpatient requests and emergency patients will be explained as well. The answer to this research question also provides the key performance indicators (KPIs) that we use to assess the current situation and the performance of our outcomes eventually. We provide the answer to this research question in Chapter 2.

2. **What are the current capacity requirements of MRI resources for the various specialties?**
The answer to this research question will be provided by an analysis on which different budgets we consider when we determine the capacity requirements for each specialty that requires MRI capacity. Next, we calculate the capacity requirements for each specialty and this capacity division forms the basis for the experiments eventually. We provide the answer to this research question in Chapter 2.

3. **What can we learn from literature regarding modeling modified block scheduling for hospital departments?**
We already elaborated on some literature that is relevant for this research in Section 1.3. Furthermore, we perform a literature review on how we can develop a generic method and a model that fits our research goal and we gather information on how block scheduling must be implemented in practice. We describe our literature review in Chapter 3.

4. **How can we model and experiment the impact of allocating MRI resource capacity to the various specialties on the waiting time?**
The answer of research questions 2 and 3 provide information from practice and literature on methods and models that we can use to determine how we can model the impact of a block schedule on the expected waiting time. Based on this information, we first develop such a generic model in which we incorporate the possibility to experiment with different scenarios for fixed capacity. This means that the number of specialties that we assign capacity to will be flexible. Next, we apply the characteristics of the MRI resources and the various specialties of the Isala hospital to this model, and we run our the simulation for the proposed scenarios. We describe the development of our model in Chapter 4.

5. **What impact does the new model have on the waiting time for the MRI resources at the Isala hospital?**
To provide an answer to this research question, we elaborate on the results of the experiments that are conducted within the research in Chapter 5. Furthermore, a sensitivity analysis will be conducted to test the robustness of the results.

6. **What are the conclusions that follow from the output of our model?**
The analysis of the results eventually leads to an advice on how much capacity must be assigned to specialties, and how this affects the expected waiting time for patients. We incorporate this knowledge into a final advice for the Isala hospital on how block scheduling can be applied and how the appointment scheduling process must be possibly re-organized. We describe the insights for science, for practice and the limitations of the research in Chapter 6.

1.6 Conclusion

We described the research environment at the Isala hospital and the goal of the research in this chapter. We are going to design a model that is able to predict the impact of block scheduling for MRI resources on the main KPI of our research, by incorporating several assumed consequences of block scheduling. We elaborated on the desire of the SCC to implement block scheduling for the specialties that make use of the MRI resources. We also already conducted a brief literature review on what types of block scheduling exist. From this literature review we deduct that not much research exists on the application of block scheduling for MRI resources, but that it shows similarities with applying block scheduling in OR departments. This information helps us to set up our next chapter, the literature review, in which identify the research gap that fits our problem statement. The answers to the research questions that we have proposed in this chapter help us to gradually work towards a model that helps us assessing the impact of block scheduling on the waiting time for patients. In the next chapter we first provide an analysis of the current situation of the relevant processes around appointment scheduling for the MRI resources at the Isala hospital.

2 Current situation

In this chapter we describe the current situation at the Isala hospital regarding the MRI resources and the MRI appointment scheduling process. First, Section 2.1 provides information on the current MRI appointment scheduling process. Next, we elaborate on the approach that is currently used to determine the number of scans that the various specialties request each year in Section 2.2. In the same section, we also describe how we calculate the capacity requirements for each specialty in 2022. Section 2.3 describes the KPIs that are currently used by the SCC to determine the performance of the MRI appointment scheduling process and which we use in the remainder of our research. We perform an analysis on the current performance of the selected KPIs as well.

2.1 The appointment scheduling process

The Isala hospital currently has five technical MRI resources available in total. Table 2 shows the main characteristics of these resources. The Isala hospital provides services with these MRI resources for inpatient scan requests, outpatient scan requests, and emergency scan requests. We refer to emergency patients as acute patients throughout the remainder of this report. Acute patients need to be scanned between zero to seven days from the date of scan request. Semi-acute patients need to be scanned between zero and fourteen days. The appointment scheduling process depends on the patient type, but also on the location of the facility of the Isala hospital by which the scan request is handed in, and the location of the facility of the Isala hospital where the scan will eventually be performed. For the case of an outpatient scan request at the facility in Zwolle, an outpatient assistant fills in a scan request at a given moment during the care pathway of a patient. This scan request is sent to the centralized planning office for the radiology department, which converts the scan request into an actual appointment for the patient. The planning office is able to schedule appointments three months in advance. Inpatient scan requests are scheduled by the laboratory technicians themselves. Within the MRI schedule, capacity is reserved already for appointments for these patients. The facility in Meppel does not use a planning office. Scan requests for this facility are converted into an actual appointment by the laboratory technicians of this facility, regardless their patient type. Patients that visit the outpatient facilities in Kampen and Heerde and eventually need a MRI scan, are preferably referred to the Isala facility in Zwolle. Patients that visit the outpatient facility in Steenwijk and eventually need an MRI scan, are preferably referred to the Isala facility in Meppel. Their scan requests are treated as outpatient scan request following the aforementioned procedures. When an unforeseen gap in the appointment schedule occurs, for example because of a late cancellation of a patient, the laboratory technicians have a list available with inpatient patients waiting for a MRI scan. Another patient is called up for the vacant appointment slot based on the urgency status of the patients. The centralized planning office also tries to schedule another appointment for a vacant time slot if there is enough time to call up an outpatient for a vacant time slot in Zwolle. In Meppel, the laboratory technicians try to either call up an inpatient or an outpatient in case of an unforeseen gap in the appointment schedule.

Table 2: Summary of the available MRI resources at the Isala hospital.

Location	**MRI number**	**Developer**	**Power**
Zwolle	MRI 1	Philips	3 Tesla
Zwolle	MRI 2	Philips	3 Tesla
Zwolle	MRI 3	Philips	1.5 Tesla
Zwolle	MRI 4	Philips	3 Tesla
Meppel	MRI 5	Siemens	1.5 Tesla

The healthcare logistics team of the Isala hospital currently experiences several problems that are caused by the decentralized scheduling responsibilities in the process of appointment scheduling for the OR department. The first problem that arises here, is that a decentralized approach is often not the best approach from an integral perspective. For example, if one speciality is planning the OR appointments optimally for itself, this can cause problems for the appointment schedule of other specialties, or problems can occur at other departments of the hospital (for example the nursing ward). Another problem is that there is much deviation in the competence and the experience of the planners, and that there is a lack of a clear planning framework for these planners. Contrary to the experiences of the healthcare logistics team, various modalities within the radiology department of the hospital prefer decentralized appointment scheduling responsibilities over the current centralized appointment scheduling responsibilities. These modalities acknowledge the condition that strict rules have to be proposed and complied to, to make the decentralized approach work properly. There are also modalities, for example CT and mammography, that already work with reserved capacity for specialties to schedule appointments on the technical resources. The main benefit that is perceived by these modalities for reserving capacity blocks for specialties in combination with the decentralized appointment scheduling responsibilities, is that the specialties themselves are directly responsible for solving any appointment scheduling issues. Here, we observe that the SCC and the healthcare logistics team have contradicting beliefs on how certain processes must be organised.

2.2 The annual capacity budget

Table 1 in Section 1.2 depicts the 23 specialties that use the MRI resources of the Isala hospital. These specialties make a prediction of how many MRI scans they are going to request each year, which is called the production budget. However, there is not one single approach that is used by all specialties to come up with the production budget. Specialties are allowed to increase the budgeted scan hours by a maximum of 4% compared to the previous year. There are plenty of specialties that simply increase their demand by this maximum, without considering the realization of the number of scans compared to the production budget of that same year. Other specialties just hand in the same production budget as the previous year. This leads to unrealistic production budgets year after year, and hence there is a desire for a new approach to determine the capacity that a specialty requires in a given year. The healthcare logistics team and the SCC have proposed a new approach and we perform the corresponding calculations in our research. Before we describe how we execute this approach, we briefly explain some terminology. Patients who are treated in a hospital generally go through multiple stages during the care pathway, such as consultation sessions, diagnosis and treatment. However, health insurers or patients do not pay for each stage of the care pathway individually. This corresponds to the recommendations of the research of Porter and Lee, who prefer bundled payments for care cycles over fee-for-service reimbursement systems because this is more convenient for the patient [8]. In the Netherlands, the activities during the care pathway of a patient are financially registered by means of the diagnosis treatment combination care products (in Dutch: diagnose-behandelcombinatie-zorgproducten) [9]. For convenience, we refer to these as 'DBCs' throughout the remainder of this research. The healthcare provider opens the DBC for the patient during the first stage of the care pathway, independent of the nature of this first stage. From the moment a DBC is opened, the DBC can remain open for a maximum of 90 days and all further care activities are registered under the same DBC. The eventual costs for treatment depend on the average costs of treatment for the corresponding diagnosis, the number of consultation sessions with the specialist, whether or not the patient has to stay at the hospital during treatment and whether or not the patient has to undergo surgery [9].

We know which DBCs contain MRI activities. This implicates that we are able to derive a capacity profile of MRI activities for all applicants of MRI capacity based on the registered DBCs. We start our capacity analysis with a data set that consists of all DBCs that are opened at the Isala hospital between December 2018 and November 2019, and which consist of MRI activities. From this data we derive that a total amount of around 475,000 unique DBCs are opened in this period, divided among around 2,700 different DBCs. Multiple DBCs can be opened for a patient if, for example, the care pathway of a patient takes more than 90 days. Next, we have another data set with all characteristics of the research activities for patients that have received an MRI scan. It is important to note the difference between the two data sets: the first data set only provides us with data of the DBCs that are opened, whereas the second data set only provides us with the actual research activities that are performed. We can combine these two data sets, such that we know which research activities are performed for which DBCs and how much scan time is performed. Because a DBC can be closed in between 1 day and 90 days after the day it is opened, and our first data set consists of the DBCs started between December 2018 and November 2019, we have to include the research activities that are performed between December 2018 and March 2020. We have selected the time period of the first data set such that we do not have to work with data that is retrieved during the Covid-19 pandemic, since this data is not representative for hospital operations under normal circumstances. There are also scan requests in our data which we cannot assign to a specific DBC. However, we are able to identify which specialty has handed in the request for these scans. We have to consider these scan requests in our capacity profile as well, but we simply add this as a constant value. Based on the patient characteristics, the performed scan times for the researches and the number of times that a specific scan is performed by a certain specialty, we are able to draw up capacity profiles for each DBC. A capacity profile here refers to a realistic required amount of scan time that is required to perform a certain scan for a certain DBC. We can translate this into a total profile for each specialty, by multiplying the individual capacity profiles with the production budget of 2022 that is handed in by each specialty. This results in a total capacity budget for the MRI resources, and Figure 1 depicts this final capacity budget for 2022. From this figure we clearly observe that neurology requires the largest amount of scan capacity on a yearly basis. Orthopaedics, surgery and cardiology follow in decreasing order. With five MRI resources operating five weekdays on average, the total capacity budget reveal that each of the MRI resources will be in operation for 8.26 hours per day. In the remainder of our research, we focus on the outpatient, acute and semi-acute scan requests per specialty.

	Outpatient		Inpatient		Acute		Semi-acute	
Specialty	**Hours**	**Rounded**	**Hours**	**Rounded**	**Hours**	**Rounded**	**Hours**	**Rounded**
Ophthalmology	68,1	69	1,3	2	4,5	5	6,6	7
Ear, nose and throat medicine (ENT)	341,6	342	0,0	1	6,8	7	6,3	7
Surgery	851,6	852	17,9	18	61,6	62	67,5	68
Plastic surgery	28,6	29	0,1	1	0,0	1	1,3	2
Orthopaedics	1180,6	1181	4,5	5	16,3	17	62,5	63
Urology	349,3	350	4,7	5			24,9	25
Gynecology	131,5	132	6,3	7	7,9	8		
Neurosurgery	430,0	431	29,006	30	102,12	103	48,3	49
Dermatology	15,8	16			0,1	1	1,8	2
Internal medicine	444,4	445	49,75	50	124,48	125	59,4	60
Pediatrics	49,4	50	21,8	22				
Gastroenterology	374,6	375	18,126	19	50,787	51	57,6	58
Cardiology	539,2	540	95,5	96	27,8	28	37,6	38
Lung diseases	75,4	76	13,622	14	28,909	29	10,6	11
Rheumatology			0,4	1				
Cardiothoraric surgery	1,7	2			1,5635	2	1,1	2
Psychiatry	5,8	6	1,1	2				
Neurology	3550,9	3551	210,91	211	537,27	538	158,1	159
Radiotherapy	117,2	118	0,8	1	6,0	7	23,2	24
Radiology	49,4	50	0,375	1			14,4	15
Anasthaesiology	33,4	34	1,1	2				
Dental specialists and oral surgery	20,8	21					1,2	2
First aid doctors					5,6	6		
Total	**8659,4**	**8670**	**477,2**	**488**	**981,7**	**990**	**581,1**	**590**

Figure 1: Capacity profiles for the MRI resources based on the production budget of 2022.

2.3 KPI selection and analysis

The methods and indicators to measure the performance of processes differ for each organization individually. However, there are performance indicators for certain hospital processes that are commonly used. In this section we elaborate on the possible KPIs to assess the performance of the appointment scheduling process and we provide an analysis on the current performance of the KPIs that we select.

2.3.1 KPI selection

We distinguish multiple strategic areas for measuring the performance of radiology departments: patient safety and quality of care (PSQC), customer service (CS), operations management (OM) and financial management (FM) [10]. Within the area OM, we distinguish the subareas utilization, information technology (IT), innovation, education and research. Furthermore, the performance of imaging process within radiology departments can be measured during various stages: before the appointment time of the scan, during the appointment itself and after the scan is made [11]. Before the actual scan takes place, possible KPIs are the time to the third next available appointment slot (TNAA) [12] and the cancellation rate [11]. Possible KPIs for the performance on the actual date of the appointment are the no-show rate, the scan duration and the patient waiting time. Possible KPIs after the scan is made are the dictation accuracy and the error rate [11]. The SCC currently monitors the performance of the modalities of its radiology department via various KPIs, with the most important KPIs being the production hours per week, MRI utilization, and patient waiting time. The SCC does not make a difference between the waiting time and the access time in practice. For both cases, it refers to the number of days between the date that the scan request is handed in and the actual date on which the scan is performed. However, according to literature, the common definition of the access time refers to the first consultation session that is perceived by the patient, after being redirected to the hospital by an external care provider [13]. The common definition of the waiting time refers to the time between the date that an appointment is scheduled and the actual date of the appointment [14]. We use 'waiting time' in the remainder of our research, because the aforementioned definition of the waiting time fits best to the time that we refer to. Table 3 provides an overview of possible KPIs that we can use within our research according to literature. These KPIs are specifically relevant in research that is done within radiology departments. From these KPIs, we select the waiting time for patients as the main KPI within this research since this is the main desired output of the SCC. We first analyse the current performance of the SCC on the waiting time for the MRI scans, such that we are able to compare the outcomes of our model to the current situation eventually. Although we do not select utilization as an output KPI for research, we analyse the current performance of this KPI as well since utilization is relevant when performing research in the field of block scheduling [15]. Furthermore, we briefly elaborate on the revelant scan durations in Section 4.2.3, since we incorporate these scan durations in the remainder of our research as well. Table 3 provides the motivation for the remaining KPIs on why we do not include them in our research.

Table 3: Overview of possible KPIs according to literature.

KPI	Area	Stage	Included?	Motivation
TNAA	OM	Before scan	No	This KPI is too detailed for this reseach
Cancellation rate	PSQC	Before scan	No	This KPI is not relevant for this research
Scan duration	OM	During scan	No	Scan durations are relevant but considered as scenarios in this research
No-show rate	OM	After scan	No	This KPI is not relevant for this research
Dictation accuracy	OM	After scan	No	This KPI is not relevant for this research
Error rate	OM	After scan	No	This KPI is not relevant for this research
Waiting time	OM	After scan	Yes	Block scheduling is expected to have an impact on the waiting time
Utilization	OM	After scan	No	Utilization is relevant but considered as a scenario in this research
Costs	FM	After scan	No	Based on the output for the KPI waiting time, we will draw conclusions on costs

2.3.2 Waiting time

The SCC aims to obtain a maximum waiting time for all patients of 28 days. This is the 'treeknorm', which refers to the maximum allowed waiting time for patients for a specific type of care activity. This is determined in 2005 by a delegation of Dutch healthcare providers and health insurers [16]. We analyse the average waiting time per week and we assess the current performance by plotting the realised waiting times against the treeknorm. In our data set, the average waiting times are measured for the scans that are performed for almost all types of patients. The acute patients do not appear in the regular appointment scheduling process, but are scheduled as soon as possible. Hence, these patients must not be considered in the waiting time of patients that are actually scheduled. The scans with a waiting time of more than 90 days are excluded because these are the scans that concern secondary scans such as control scans. Hence, these two types of scan requests do not have to be scheduled within the treeknorm. We analyse the performance on the waiting time for the years 2019 (before Covid-19), 2020 and 2021 (during Covid-19). Figure 2 depicts the average waiting time per day compared to the treeknorm of 28 days for 2019. We observe that the average waiting time over all days that scans are performed is 23 days, which is below the treeknorm. The average waiting time in 2020 is 21 days and the average waiting time in 2021 is 19 days, which are both below the treeknorm as well. Figure 2 already shows that there are days on which the average waiting time exceeds the treeknorm. Figure 3 depicts the ratio of scans that are performed with a waiting time above the treeknorm, relative to the total number of performed scans per day in 2019. We conclude that, on average, 34.07% of the patients that received a scan have perceived a waiting time above the treeknorm. This puts the average waiting time of 23 days in a different perspective. The percentages of patients that perceived a waiting time above the treeknorm in 2020 and 2021, are 11.65% and 4.37% respectively.

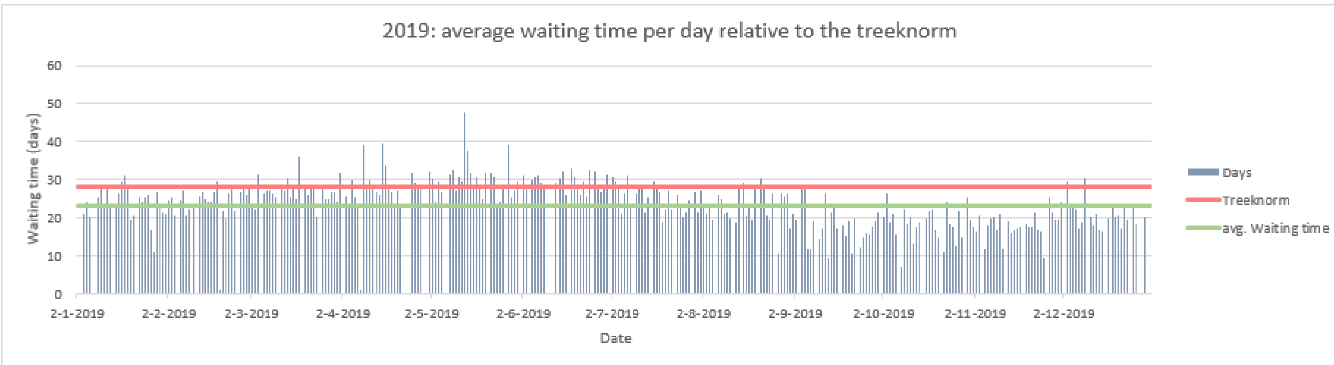

Figure 2: Average MRI waiting time compared to the treeknorm (2019)

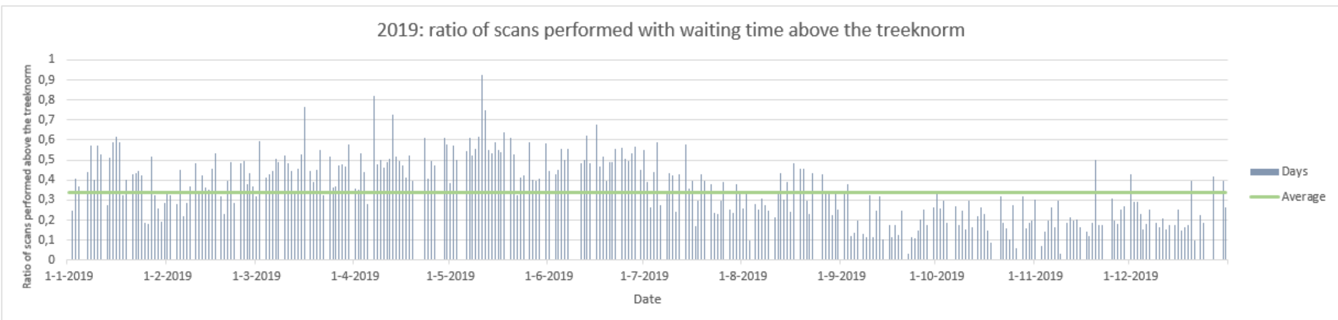

Figure 3: Ratio of scans with a waiting time above the treeknorm per day (2019)

2.3.3 Utilization rate

The SCC calculates the utilization of the MRI resources by means of Equation 1:

$$\frac{\text{Sum of expected scan time}}{\text{Opening hours of MRI resources}} \text{ x } 100\% \tag{1}$$

They use the sum of the expected scan time instead of the registered scan time, because the actual scan time is not registered properly. When a scan is finished, laboratory technicians often do not indicate the scan as "finished" within the system, so the registered scan times are often way too high and hence unrepresentative. The regular opening hours of the technical MRI resources on a given day are from 8:00 till 16:45. The target utilization rate of the MRI resources is 85%. The realised utilization rates and the target utilization are depicted for 2019 and 2020 in Figure 4 and Figure 5 respectively. We plot the graph of 2020 as well, because this graph clearly shows the impact of Covid-19 on the utilization rate of the MRI resources. After two months of adaptation, the SCC was able to stabilize the utilization rates again. The yearly average utilization rates are 91.84%, 82.42% and 83.49% for 2019, 2020 and 2021 respectively. Only the average utilization rate of 2019 is acceptable according to the treeknorm.

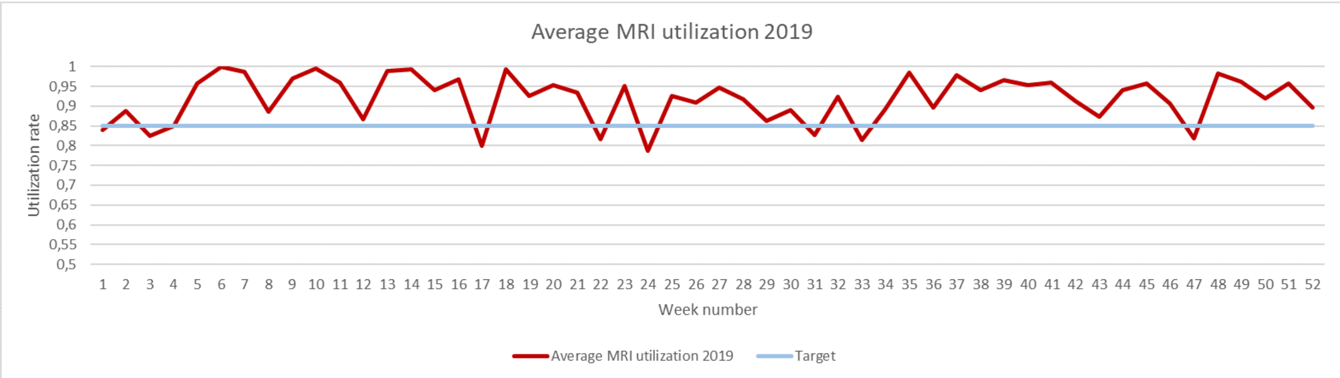

Figure 4: Ratio of scans with a waiting time above the treeknorm per day (2019)

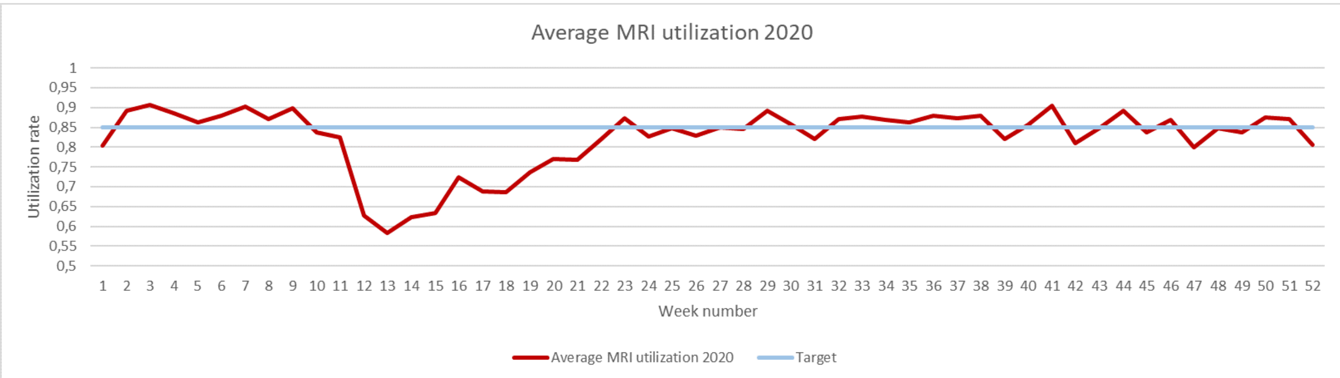

Figure 5: Ratio of scans with a waiting time above the treeknorm per day (2019)

2.4 Conclusion

In this chapter we described the current situation of the MRI appointment scheduling process. We first described the main procedures in Section 2.1. In Section 2.2 we calculated the capacity budgets for the various specialties that use the MRI resources. These calculations provide insight in which specialties request the highest amount of scan capacity on a yearly basis. Next, we did research on several possible KPIs for radiology environments, and we selected the patient waiting time as the main KPI for this research in Section 2.3. From our analysis on the current waiting times, we conclude that the average waiting times are below the treeknorm of 28 days in 2019 (23 days), 2020 (21 days) and 2021 (19 days). However, we also concluded that there are still patients that perceived a waiting time that is higher than the treeknorm. This was the case for 34.07%, 11.65% and 4.37% of the patients in 2019, 2020 and 2021 respectively. We analysed the current utilization rates of the MRI resources as well, since we expect that block scheduling affects the utilization rates. From our analysis we conclude that the average utilization rate in 2019 was 91.84%, which is above the target utilization rate of 85%. The average utilization rates of 2020 are 2021 are lower, which are a direct cause of the impact of Covid-19. The average utilization rates for these years are 82.42% and 83.49%, which are below the average target utilization level of 85%. The next chapter of this research describes our literature review, in which we search for a research gap that fits to the desired implementation of block scheduling by the Isala hospital.

3 Literature review

This chapter describes our literature review. The objective of this literature review is to obtain knowledge about the state of the art of block scheduling for healthcare processes. Furthermore, we collect knowledge on how to model the expected impact of block scheduling on the waiting time for MRI departments. Lastly, we describe research that provides us with more insight in how organizational change can be achieved within healthcare organizations. We incorporate the latter part in the literature review because we want to know how we can create support among the stakeholders of the MRI appointment scheduling process if we eventually conclude that organizational changes result in significant benefits for the hospital. We use the search engines Scopus, PubMed, Web of Science and Google Scholar with the following key words: *block scheduling healthcare, modified block scheduling, OR appointment scheduling, OR block scheduling, organizational change in healthcare, engaging medical staff in organizational change.*

3.1 Block schedules for healthcare departments

This section describes how healthcare organizations can prepare their organization for the use of block scheduling, and which rules they must follow once block scheduling is applied within the organization. We also describe the different possible models to test the usefulness of block scheduling for healthcare organizations.

3.1.1 Problem classification

Block scheduling is a widely studied topic, but it is mostly applied to OR departments. However, block scheduling for OR departments shows similarities with (and potential for) block scheduling for MRI departments [2], so we can possibly learn from the knowledge that is available in that field. We identify three types of OR scheduling problems [17, 18]. The first problem is the Case Mix Problem (CMP). Such problems refer to determining the time that ORs must be dedicated to each surgical specialty, in which the goal is to maximize profit or minimize cost. This problem is considered a problem on a strategic level. The second problem is the Master Surgical Scheduling Problem (MSSP). This problem concerns allocating surgical specialties to OR time. In such problems the goal is to maximize utilization. The third type of problems is the Surgical Scheduling Problem (SSP). These problems refer to allocating patients to an OR and common objectives here are to minimize waiting time or minimize OR overtime [17]. The interest of our research is the impact on the waiting times when block scheduling is applied in the appointment schedule for the MRI resources. This contains elements of both the CMP and the MSSP, so we focus on these types of problems in the remainder of our literature review.

3.1.2 Models for block scheduling

Not much research exists on the impact of waiting times when block scheduling is applied within an MRI environment yet. Hence, we obtained knowledge on the application of allocated capacity for OR departments so far. However, it is not possible to directly use the principles of block scheduling from the OR departments onto MRI resources. OR departments tend to allocate large capacity blocks, because surgery duration can take multiple hours. In that case, surgeries that are performed in the morning might cause troubles for the afternoon schedule when they take longer than expected beforehand, or a gap in the schedule occurs when the surgery in the morning is finished earlier than expected [19]. The risk of this happening is expected to be lower for MRI departments, because of the shorter research duration and less absolute overtime [2]. Furthermore, the case of handling no-shows is different for MRI departments. Within a two hour capacity block for a specialty that makes use of the MRI resources, for example six patients can be scheduled. However, it is possible that the fifth patient does not show up. It requires another strategy to cope with this risk of no-shows when compared to the OR department, because it is more likely that an unforeseen vacant time slot in the MRI schedule can still be assigned to an inpatient patient. Gullhav et al. [2] provide a mathematical formulation for the case of block scheduling for MRI resources, which shows many similarities with the

MSSP. This is the only research that we found that applies a modified block scheduling strategy on MRI resources. This research, however, uses a predetermined set of specialties that is assigned capacity to, and the output of the model of this research does not provide insight on the impact of block scheduling on the waiting time for patients. The results of this research show potential for an optimization-based approach that determines the boundaries for capacity demand to base capacity allocations on, as well as the optimal number of hours per week to be assigned to each specialty. A fixed amount of capacity for a fixed set of specialties is expected to have consequences for the resource utilization and the patient waiting times, since the demand for scan requests of the specialties varies each year. Therefore, Gullhav et al. indicate that there is also potential for a simulation-optimisation framework, in which demand for scan capacity is simulated.

Besides the potential for a simulation-optimisation framework, there are many other opportunities to experiment with block scheduling for healthcare departments. As indicated by Hof et al. [20], the CMP is frequently modeled as a linear program (LP). Such problems mostly refer to patient volumes, and hence the decision variables in these problems are mostly integer as well. Mathematical modeling is another approach that is commonly used for optimally allocating the available capacity of surgical groups in OR scheduling problems. The objective for this type of problems can be to minimize costs, maximize utilization, or to minimize or maximize a certain multi-objective function [21]. Blake and Donald [22], performed research in which the total number of ORs that are available each day are predetermined, as well as the number of hours that each room will be open each day. Therefore, they consider their OR problem as an allocation of departments (specialties) to a set of ORs over a fixed planning horizon. They applied integer programming to solve their problem and conclude that the OR scheduling process has improved significantly with the introduction of the model. Simulation is another method that is frequently used to allocate blocks in OR scheduling problems. However, a perceived drawback of simulation models is that there is the risk of getting stuck in a local optimum, instead of the global optimum [20]. Such problems can, to some extent, be avoided by means of integrating heuristics such as simulated annealing or variable neighbourhood search within the simulation. However, this can be applied in types of simulations in which the goal is to optimize some sort of objective function, which relates to a simulation-optimisation framework again.

All research that have been mentioned so far, is not able to predict the impact of the implementation of a block schedule on the waiting time for patients. Wen et al. [23] have developed a multi-objective model to help hospitals in making appointment scheduling decisions based on the real time arrival of regular patients and emergency patients for a diagnostic facility. They use a Monte Carlo simulation technique which calculates the impact of the waiting time for different scenarios and with using variable input variables. The impact on the waiting time is here calculated by means of an increasing penalty function if the waiting time of a given patient exceeds a certain waiting time target. Although this model is quite extensive and mainly focused on online operational decision making, we derive useful ideas from this research. In our research we are, among others, dealing with a demand of scan request, which is not fixed for a given day, week or month within a year. The randomness in such a variable can be be approximated towards reality by means of running a certain kind of simulation for a sufficient number of times. A Monte Carlo simulation is the type of simulation which allows for this type of repeated simulation runs. The Monte Carlo simulation technique also fits bets to our research, since our interest is to gain insight in the effect of assigned capacity for MRI resources on the waiting time of patients. Our goal is not to maximize some objective function. This fits to the properties of Monte Carlo simulation and hence we prefer this type of simulation over the other techniques that are presented in this section.

3.1.3 Modified block scheduling in practice

Agnetis et al. describe the modified block scheduling strategy as convenient for OR management because it can assign other operations to perform in the OR to prevent the loss of late cancellations [24]. Furthermore, this research mentions that modified block scheduling is capable of solving problems that arise for applications of open scheduling and pure block scheduling, such as possible long waiting times because of dynamic patient arrival [24]. Modified block scheduling is most effective when it is included in a process for assigning the blocks and reallocating them depending on utilization [25]. Since each specialty is different, a tailored approach for determining the release time for each specialty is necessary. Data on the scheduling dates for a given specialty must be collected and analyzed, upon which the specialties determine what the release times should be [25]. The same research provides an example for an organization which tried 72 hours and 96 hours, respectively, as the release time, but it found out that that was not long enough. With such a release time it was not possible to arrange another patient for the vacant appointment slot. However, with a release time of one week the utilization of OR capacity for the given specialty increased significantly. It is important to note that the latter findings are derived from a paper that is written in 1996 already. Nowadays, it is easier to contact patients shortly before the start time of a vacant appointment slot. We also found research that raises questions about the usefulness of release times for OR blocks. Dexter and Traub concluded that there is no clear advantage of releasing OR time of a speciality, until there is a patient from another speciality that can be scheduled in the vacant time slot [26]. Once the block scheduling dimensions are determined for a certain OR department, management must be careful with making adjustments to the schedule. Adjusting block time for specialties is a sensitive topic, so changes in the allocated block time must be based on data that is available to the physicians as well [27]. It is considered sensitive, since the assigned capacity is the basis for multiple planning routines that are performed by the corresponding specialties. Irregularly and frequently changing the assigned leads to distortion of routines for the specialties and might consequence frustrations between the specialties. Regardless of the release times for reserved capacity, it can be that one of the specialties does not reach the utilization targets of the capacity that is reserved for that same specialty. In this case it is better to take away one capacity block of that specialty instead of cutting a few hours from multiple capacity blocks. The latter adjustment is more likely to make the system dysfunctional [19]. Saver [27] describes a procedure for making adjustments in block capacity allocation that is used by a healthcare network in the United States. Here, speciality groups that are not fully utilizing their block capacity in a give quarter of a year, receive a notification and are then monitored for another quarter. If necessary, adjustments in the allocation of block capacity can be made accordingly. However, before these adjustments are made, the quarterly results of the OR utilization are discussed with the surgeons from the specialties as well.

A problem that occurs when determining the amount of capacity that must be reserved for specialties in the case of block scheduling, concerns the translation to the operational level [22]. For the case of block scheduling for the OR department, the supply of staffed ORs or specialty equipment may restrict the actual number of hours that can be assigned to a specialty. Hence, it is important to consider the practical feasibility of proposed capacity allocations. Other relevant key points when reserving block time within OR departments are [28]:

- Allocated block time must be monitored and reevaluated systematically;
- The data upon which decisions regarding block time are made must be valid and representative for the actual situation within the OR department;
- Surgeons must be involved in the process of block time allocation;
- Clearly define the indicators upon which the performance of the block time allocation will be assessed.

Furthermore, there are three common errors that must explicitly be avoided when applying block scheduling within healthcare departments [28]. First, the organization should not block more than 85% of the total weekly available capacity. This statement corresponds with Tolk et al. This research indicates that there is no perfect ratio for open and dedicated OR time, but that allocating 80% of the total capacity "is about right" [19]. Second, specialties must not block too much capacity for one specialty on a given day, because of capacity restrictions (such as required tools or personnel). The last error that must be avoided, is to put the release times for reserved capacity so close to the actual start time of the time slot that it is not possible to find another patient for that time slot [28].

3.2 Behavioural change in healthcare organizations

In recent years, healthcare organizations wee forced to reduce costs and medical errors, and they face an increase in the number of standardized processes [29]. This leads to medical personnel that has to give up their established and comfortable procedures for new procedures. Introducing innovations or changing existing procedures can be very difficult within organizations. Especially in the the healthcare sector it is hard to get all the involved people on board [29]. When a proposed innovation of a healthcare organization does not correspond with the deep-rooted patient care values of the medical personnel, they are less likely to adopt the new procedures that are involved with the innovation. Brett and Luciano provide three focus points for managers in healthcare organizations to engage medical personnel in organizational changes [29]. The first focus point is that managers must try to understand why medical personnel could be hesitant for innovations or why the medical personnel might think that these innovations do not correspond with the existing culture and mission of the organization. Managers must not take the decisions for innovations individually, and the eventual decisions for innovations must also be communicated properly. It is recommended to do this in a personal setting instead of via an electronic communication channel. The second focus point is that medical personnel must be engaged with data to explain the problem, why it is urgent and how it is going to be solved. For example, a visual representation of the increase in medical errors or the decrease in resource utilization already works to create awareness among the medical personnel about problems within the organization. The third and last focus point that is proposed, is to pay attention to behaviour that must be rewarded and tolerated. Nilsen et al. also describe success factors for applying changes in healthcare organizations. Their research is performed among healthcare professionals who are active in the Swedish healthcare system. The results of this research show that medical personnel desires the opportunity to influence the change, needs to be prepared for the change that is planned and, lastly, needs to be informed about the expected added value of the change [30].

3.3 Conclusion

Our literature review reveals potential for the development of a model that provides insight in the impact of block scheduling within an MRI department. Besides that, we have collected relevant guidelines for the practical implementation of a block schedule once a hospital department has decided that they want to implement such a block schedule. Gullhav et al. [2] have performed research on implementing block scheduling within an MRI department specifically, but the output of their model does not provide insight in the impact of a block schedule on the waiting time for patients. Wen et al. [23]. have performed research on appointment scheduling techniques within a diagnostic environment, but they propose a model that is too detailed such that we cannot directly translate it to the desired outcome of the SCC. Furthermore, both papers consider their problems as being on an operational level. However, the SCC wants to determine which specialties must receive fixed capacity, based on the expected impact on the waiting time. In the current situation we have no block schedule that we can build on. Hence, our problem is better classified as a tactical or maybe even a strategic problem, according to literature. A Monte Carlo simulation model which allows us to draw conclusions on the impact of several scenarios for block capacity on the waiting time for an MRI environment, fits well to the desired outcome of the research according to the SCC. Besides that, it is a topic which is not specifically addressed in the research that we have encountered during our literature review. Therefore, we focus on the development of such a model in the remainder of our research. After we developed this model and obtained our results, we propose an advice on how the SCC can implement block scheduling for the MRI resources based on the literature that we have described in Section 3.1.3 and Section 3.2.

4 Simulation modeling approach

From our literature review we concluded that there exists a research gap in how we can determine which specialties must receive fixed capacity in the case of block scheduling for MRI resources. We propose a model to close this research gap, where we are interested in the effects of block scheduling on our main KPI: the waiting time for patients that need to receive an MRI scan. We also concluded from our literature review that the technique of Monte Carlo simulation is promising to test the outcome of a given scenario against multiple possible values of input variables. We combine this knowledge in our simulation modeling approach, which we gradually describe in this chapter.

4.1 Scenarios for fixed capacity

We provided an overview of the specialties that use MRI capacity in Table 1 in Section 1.2. We are interested in the effects of fixing the capacity for specialties on the expected waiting time for patients in a block schedule. From our analysis on the capacity budgets for all specialties that request MRI scan capacity in Section 2.2, we know that there exists variation in the amount of capacity that each specialty requires. To determine the effects of fixed capacity, we perform simulations in which we consider multiple scenarios. These scenarios differ in which specialties we assign fixed capacity to. We fix capacity for the four specialties that require the largest amount of capacity, according to Figure 1 in Section 2.2. The scenarios are determined based on the specialties for which we calculated the highest capacity budget in decreasing order. We develop the model such that we are able to add specialties as well. The specialties that we initially consider are neurology, orthopaedics, surgery and cardiology. Hence, the scenarios are as follows:

- **Scenario A**: no specialty receives fixed capacity;
- **Scenario B**: only neurology receives fixed capacity;
- **Scenario C**: neurology and orthopaedics receive fixed capacity;
- **Scenario D**: neurology, orthopaedics and surgery receive fixed capacity;
- **Scenario E**: neurology, orthopaedics, surgery and cardiology receive fixed capacity.

For the scenarios in which we fix capacity for one or more specialties, we do not fix capacity for the remaining specialties. We also assume that all the capacity that is assigned to a specialty is fixed. For example in scenario B, all scan requests for neurology need to be performed in their fixed capacity. The last assumption that we make, is that all the urgent patients and semi-urgent patients must be treated within the fixed capacity of a given specialty as well. If we allow specialties to perform scans for urgent patients outside their fixed capacity, specialties have the opportunity to create more capacity by just putting an "urgent" label on an outpatient scan request. This contradicts with the goal that the SCC tries to achieve with block scheduling: making specialties responsible for their own capacity and having to deal with the impact of worse decision-making regarding this capacity themselves.

As we already mentioned before in Chapter 1 and Chapter 3, several consequences are involved with the implementation of block scheduling according to the SCC and literature. First, it is expected (and desired) that the amount of scans that is requested and performed will be spread more evenly throughout the year. Second, it is expected that the scan duration decreased because specialties are more careful with their own capacity. Lastly, it is expected that the utilization rate decreases for the specialties that use block scheduling, because specialties have a higher probability to end up with some time in which they are not able to schedule a patient. We incorporate these consequences for the specialties that receive fixed capacity as follows in our model:

- **Balanced amount of scans per week**: specialties receive a predetermined amount of capacity in each week in which the specialties have to schedule scan requests. However, it is not possible for such a specialty to schedule a patient outside this assigned capacity. This leads to a more balanced amount of scans that will be performed for each specialty. We perform an analysis on potential seasonal effects in the desired capacity per week for each scenario. However, if we conclude that no relevant seasonal patterns exist, we balance the annual requested amount per year over all weeks in the year.
- **Decrease of scan duration**: the board of the SCC expects an absolute scan duration for all scans of five minutes at maximum. To test the actual impact of this factor on the output of our model, we will run the model with an absolute reduction in scan duration of three minutes and an absolute reduction of five minutes.
- **Decrease of MRI utilization**: the board of the SCC believes that they are capable of designing a block schedule such that the impact on utilization will be minimal. Therefore, we consider a reduction in the utilization rate of 2%, 4% and 6% in our simulation scenarios. We model this by reducing the available scan time by the aforementioned percentages.

We know from literature about block scheduling that it is reasonable to assume that the utilization of healthcare resources decreases, when capacity is divided in blocks [15]. Therefore, in all our scenarios, we account for some decrease of MRI resource utilization. However, we have not found support in literature about the decrease in scan duration that is expected by the board of the SCC. Therefore, we also incorporate the scenario of zero scan time reduction in our simulations. All 37 scenarios that appear from the above assumptions are described in Table 7 in Appendix A (Section 7.1).

4.2 Input variables

We define the input variables of our simulation model in this section. We analyse the requested scan hours for MRI resources per week and we assess whether or not seasonal patterns can be detected in the data that we use. By combining this information with the calculated capacity budget (Section 2.2), we are able to determine the capacity levels per week for all our scenarios. Furthermore, we describe how we derive the distributions and the corresponding parameters to create patients arrivals in our simulations in this section.

4.2.1 Scan requests per week

Several possible approaches exist to determine the level of patient arrivals throughout the year. We can analyse this by means of the desired scan date, the date that a scan is performed, and the date that a scan is requested. Ideally, we would perform this analysis with the data of the desired scan date. If all scan requests were provided with such a desired scan date, we can just plot the scan time of the desired scans per week and then derive the seasonal patterns from this plot. However, this data is not fully available within Isala. Only when it is actually necessary, scan requests are provided with a desired scan date. For scans that are requested and performed on a given date, but with no indication of a desired scan date, we do not know the urgency of the scan. It is possible that a scan that is performed on a given day, could also have been performed three weeks later or earlier. The same holds for the date of scan request. A scan that is requested on a given day, can be performed in the same week, but can also be performed in time if it is performed three weeks later. This can lead to skewed conclusions on the actual patient arrivals. However, since we do not have the desired scan data fully available, we must base this analysis on either the data of the date of scan requests or the data of the date of scan performance. We select the date of scan requests, because this fits better to the goal of our research: we want to draw conclusions on the impact of block scheduling on the waiting time of patients that require an MRI scan. If we generate patient arrivals on data of scan requests, we provide ourselves the flexibility to scan patients after their week of arrival. If we would use the date of scan performance, we basically say that each patient that arrives in our simulation must be scanned immediately, because this patient is scanned in that week in reality as well. This would fit better in a study where the aim is to calculate the overtime of MRI resources with a given amount of patient arrivals that must be scanned in a given week. Hence, we only consider the data of the date of scan requests in our analysis of the seasonal patterns. Unfortunately we are only able to use the data of arrivals of a full year of 2019 for this analysis. The Isala hospital has switched to a new patient registration system in 2018, which is why we do not have access to data of previous years anymore. Furthermore, as mentioned before, the data of 2020 and 2021 is not representative because of the influence of Covid-19.

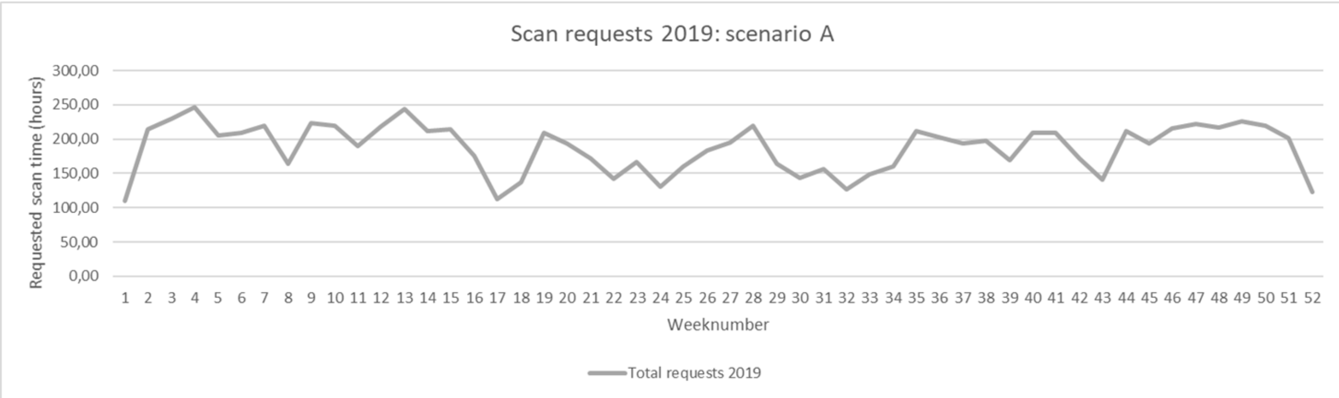

Figure 6: Scan hours per week in 2019 for scenario A.

Figure 6 depicts the pattern of the total requested scan hours per week in the initial situation at the Isala hospital. From this plot we observe that the number of scan requests per week fluctuates over the year. We observe low values for the requested scan time in weeks 1, 17 and 52. Furthermore, between weeks 22 and 24 and weeks 29 and 35, we observe short periods in which the requested hours are obviously below average. There is no clear explanation for the low values of requested scan time in week 17 and weeks 22 to 24. This can be an observation that is not repeated in other years. However, there is a clear explanation for the low values of requested scan time in week 1 and 52 and weeks 29 to 35. The lower requested scan times in these weeks are caused by the summer holiday period and the Christmas holiday period, where less patients are seeing their doctor. The MRI availability in these weeks is also reduced by the hospital. We briefly elaborate on these so-called 'reduction weeks' in Section 4.2.2.

Figure 6 shows us the pattern of scan requests per week over 2019 of all specialties combined. However, we need to analyse the scan requests for all specialties that we are going to consider in our model as well. We also analyse the patterns of scan requests for each scenario (B,C,D and E) individually. The demand patterns for the specialties do not change when we consider a different scenario. However, for example, between scenario B and C, there is a difference in the requested amount of scan hours for the specialities that we do not assign capacity to. In scenario B, we only exclude the scan requests for neurology from the total amount of scan requests. In scenario C, however, we exclude the scan requests for neurology and orthopaedics from the total amount of scan requests. The disconnection of the scan requests of orthopaedics leads to a different pattern of the scan requests of specialties that we do not fix capacity for. We illustrate this with Figure 7 and Figure 8.

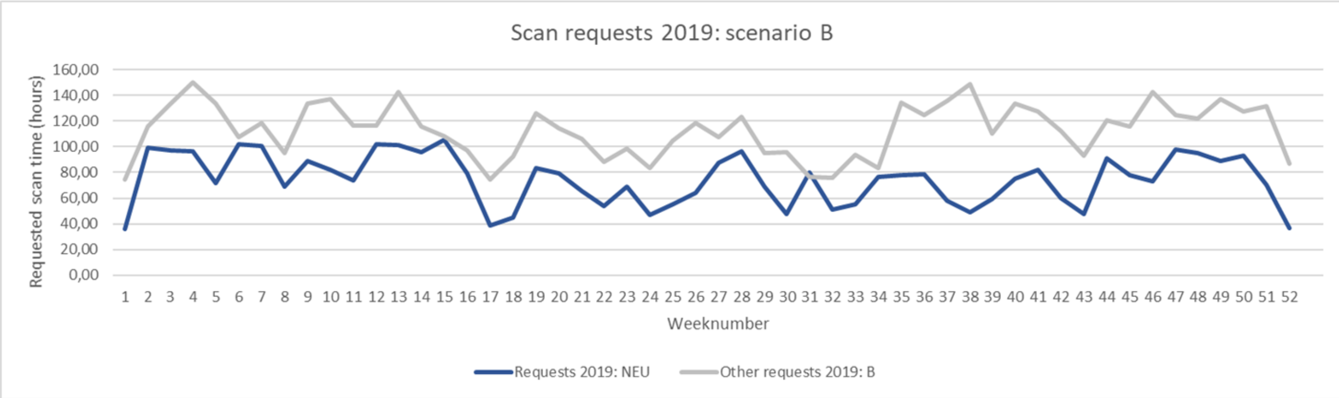

Figure 7: Scan hours per week in 2019 for scenario B.

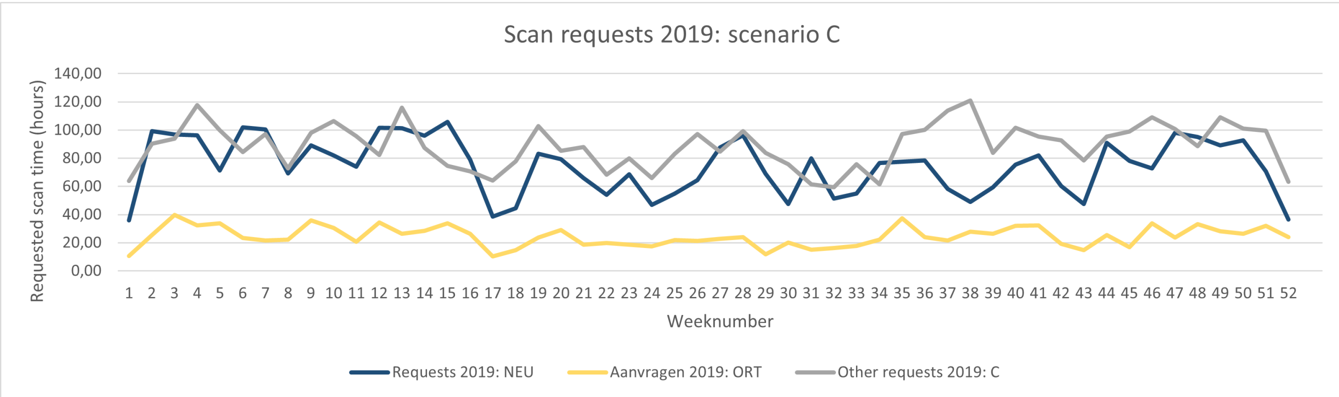

Figure 8: Scan hours per week in 2019 for scenario C.

In these plots we notice that the biggest fluctuations in requested scan time exist in the scan requests of neurology. The pattern of this data is similar to the pattern of the scan requests data of the other specialties in scenario B. Again, we observe some short periods in which the scan time drops below average, but this is not the case for longer periods of time. For all plots we observe that there are some short periods in which the amount of scan requests is below average, and that there is a lot of fluctuation in the amount of scan requests throughout the year. Since we have not identified any major seasonal patterns in any of our plots, we decide to assign the required capacity for each specialty (that we consider in our scenarios) evenly over the year. In Section 1.4 we explained why we do not consider the inpatient scan requests in our research. Therefore, we are only interested in the capacity budget of 2022 with regard to outpatient scan requests, acute scan requests and semi-acute scan requests. From Figure 1 we derive the capacity profiles per week for our scenarios:

- **Scenario A**: all capacity is available for all specialties;
- **Scenario B**: the total demand of capacity for neurology is 4248 hours per year. Hence, we assign 82 hours per week to neurology. The remaining capacity is available for the other specialties;
- **Scenario C**: the total demand of capacity for orthopaedics 1261 hours per year. Hence, we assign 82 hours per week to neurology and 25 hours per week to orthopaedics. The remaining capacity is available for the other specialties;
- **Scenario D**: the total demand of capacity for surgery is 982 hours. Hence, we assign 82 hours per week to neurology, 25 hours per week to orthopaedics and 19 hours per week to surgery. The remaining capacity is available for the other specialties;

- **Scenario E**: the total demand of capacity for cardiology is 606 hours. Hence, we assign 82 hours per week to neurology, 25 hours per week to orthopaedics, 19 hours per week to surgery and 12 hours per week to cardiology. The remaining capacity is available for the other specialties;

4.2.2 Available scan hours per week

The capacity that is remaining for the specialties that we do not consider in a block scheduling scenario, is the result of the total available capacity minus the capacity that is requested by the specialties that we do consider in a certain block scheduling scenario. We need to propose a realistic amount of total available capacity per week, given the assumption that we do not account for inpatient scan requests in our model. The regular opening hours of the MRI resources are on weekdays from 8:00 in the morning until 16:45 in the afternoon. There is, however, a reduced amount of scans that is possible to be performed during the weekends or after 17:00 on weekdays. Together with the board of the SCC we concluded that it is a reasonable assumption that if we do not consider the inpatient scan requests in our model, we must also not incorporate the possibility to work during these overtime hours. This means that we are only going to use the total regular capacity for the outpatient scan requests, acute scan requests and semi acute scan requests. The availability of 8.75 hours in 5 weekdays for 5 MRIs results in 218.75 available scan hours per week.

Throughout the year there are some weeks in which less scans can be performed. For example during holiday season when laboratory technicians go on holiday, but also during weeks where (international) radiologists conferences take place. These conferences are regularly visited by radiologists of the Isala hospital as well and comprise three weeks in a year. The number of MRI scans that can be performed in a conference week is reduced. This is the case, because radiologists need to look at all the images of the scans that are performed by the laboratory technicians, to see whether something noticeable is present at the images of the scans. In such weeks, Isala closes one MRI to make sure that the workload of scans that need to be evaluated by radiologists is not increased too much. Closing one MRI of the possible five means that we have 80% of our original capacity left. Therefore, we apply a reduction factor for available capacity in our model of 80% in weeks 1, 8, 28-35 and 52 (because of holidays) and in weeks 15, 22 and 42 (because of conference weeks). Hence, we remain with a total available capacity of 175 hours in these weeks.

4.2.3 Distributions and parameters for model data

In this section we elaborate on our approach to create realistic values of scan requests for each week in our simulation. We identify the distributions such that we are able to create scan requests per week for a full year for each scenario. We use the software 'RStudio' to perform the data analysis for the scenarios, because this is a software which is able to quickly test a lot of possible distributions on the constructed data sets. With this software we are also able to easily derive the parameters for the distribution that fits best to the data. Within our analysis we assume that we are always dealing with continuous data, since the hours of requested scan time in a given week can take on any value. Therefore, we only test our data against continuous data distributions and not against discrete data distributions such as the Poisson distribution or the Binomial distribution. For this analysis we use the data of scan requests which we also used to create Figures 6, 7 and 8. We identify a data distribution that holds for all 52 weeks for scenario A. However, when we analyse the data of scan requests that are handed in by all other specialties than neurology and orthopaedics we observe that there is no continuous distribution function which (approximately) fits the data. Therefore, we manually cut the data set of the scan requests that are not handed in by the specialties neurology and orthopaedics into smaller data sets. Now, our interest is in whether or not we are able to find data distributions that fit the smaller data sets. After manually testing several data sets, we know that we can use a uniform distribution for weeks 1 to 35, and a lognormal distribution for weeks 35 to 52. We summarize the different data distributions and the corresponding periods of the data distributions in Table 4.

Table 4: Data distributions for all scenarios in corresponding weeks.

Specialty/scenario	Distribution 1	Period 1	Distribution 2	Period 2	Distribution 3	Period 3
Neurology	U(35.80, 105.74)	1-52	*NA*	*NA*	*NA*	*NA*
Orthopaedics	N(24.43, 7.09)	1-52	*NA*	*NA*	*NA*	*NA*
Surgery	N(15.75, 4.07)	1-52	*NA*	*NA*	*NA*	*NA*
Cardiology	N(10.86, 3.75)	1-52	*NA*	*NA*	*NA*	*NA*
Scenario A	N(124.67, 34.31),	1-52	*NA*	*NA*	*NA*	*NA*
Scenario B	U(74.39, 150.12)	1-34	LN(4.95, 0.18)	35-39	LN(4.82, 0.11)	40-52
Scenario C	U(63.92 117.82)	1-18	U(59.42, 102.69)	19-35	LN(4.56, 0.15)	36-52
Scenario D	U(48.64, 97.82)	1-35	LN(4.36, 0.18)	36-52	*NA*	*NA*
Scenario E	U(37.76, 81.51)	1-35	U(58.30, 72.93)	36-52	*NA*	*NA*

To enable ourselves to draw conclusions on the waiting time for patients in our model, we translate the generated hours of requested scan time per week into actual patient arrivals. We do this by dividing the generated hours of scan time by the average scan time for the specialty or the scenario that concerns a certain patient. This division is rounded up to the next integer. We decide to not further analyse how many times a specific scan is performed by which specialty with its corresponding scan time because of two reasons. The first reason is that this analysis is unnecessarily time consuming while the average scan times that we determine from our data set already give a good indication of the actual average scan time per patient. The second data set that we have described in Section 2.2 comprises over 32,000 MRI scans that are performed between November 2018 and March 2020. We consider this as being a data set that is sufficiently large to calculate the average scan times per specialty. The second reason is that the incorporation of a probability that a certain patient from a certain speciality must be assigned a probabilistic scan time, will result in an unnecessary increase in run time of our model. Therefore, we use the average scan times that result from our data set. For example, for scenario C we exclude all the scans that are performed for neurology and orthopaedics and calculate the average over all performed scans that remain. Table 5 depicts the scan times that result from these calculations. We have verified these values with the board of the SCC as well and they concluded that these values are realistic for all scenarios that we consider.

To be able to make a realistic simulation, we cannot start with an empty hospital or an empty schedule. We therefore create a workload of patients that are waiting for their scan that corresponds with reality. We know from our analysis in Section 2.3.2 that the average waiting time for patients is currently around three weeks (23 days). Furthermore, the SCC has indicated that, on average, they observe a workload of 600 to 900 patients throughout the year. From test simulation runs for our different scenarios, we observe that we can simulate this workload by creating a waiting list with patients from weeks 51 and 52. This means that in week 1 of the simulation runs, the patients that arrived in weeks 51 and 52 of the previous year, and in week 1 of the current year need to be scheduled as well. The MRI appointment scheduling process at the Isala hospital is a non-terminating process. Therefore we also not include a natural end event in our simulation. For non-terminating simulations, warm up periods are used to ensure that simulation output is converged properly. However, for our simulation, we expect that the output quickly converges towards representative waiting times with the described waiting list approach. For the waiting list approach, also less run time is needed to generate the results. Therefore, we decide to use this approach instead of a warm up period.

Table 5: Average scan times per specialty and scenario.

Specialty/scenario	Average scan time per patient
Neurology	26.73 minutes
Orthopaedics	26.16 minutes
Surgery	31.37 minutes
Cardiology	55.57 minutes
Scenario A	28.62 minutes
Scenario B	30.40 minutes
Scenario C	31.47 minutes
Scenario D	31.49 minutes
Scenario E	29.44 minutes

4.3 Model output

We create the model such that we are able to derive various output values from the simulation runs of the several scenarios. We already described in Section 2.3 that we use the waiting time for patients as the main KPI in this research. To be able to calculate the waiting time, we store the arrival week of the patients and we store the week number in which the patient is scanned. For simulation purposes we assume that all scan requests for the next week, arrive just before the next week starts. Hence, it is not possible that extra scan requests appear for the current week while the model already runs for this current week. This means that if an acute patient arrives at, for example, week 30, this patient must also be scanned in week 30. This is the case, because acute patients must receive their MRI scan within one week. With the same reasoning we know that a semi acute patient that arrives in week 30, must be scanned in week 31 the latest. A regular patient that arrives in week 30 must be scanned in week 33 the latest. In our model we update the waiting time for a certain patient once this patient is scheduled. In our analysis of the waiting times in Section 2.3.2 we concluded that only considering the average waiting time leads to skewed conclusions on the performance of appointment scheduling in reality. We also made a brief analysis of the number of patients that perceived a waiting time that was above the treeknorm. We construct our model such that we are able to generate this output as well: after a simulation run is performed, the model calculates the ratio of patients that has perceived a waiting time that is higher than the treeknorm. Furthermore, we want to know for each scenario how many capacity of MRI resources remains unused. Hence, the third output value that we are going to store is the remaining scan time. For a given specialty in a certain week, scan time can remain unused if all patients of previous weeks are already scanned and the patient arrivals of the current week are all able to be scheduled in the capacity of the current week. The fourth and last output value that we create are penalty costs. The output value of the ratio of patients that perceive a waiting time above the treeknorm, does only apply to regular patients since acute and semi acute patients have a deadline below the treeknorm. To be able to create insight in how many times we scan a patient too late, we propose penalty costs for all types of patients that have a waiting time that is higher than their prescribed waiting time. When the deadline for a patient to be scanned has passed, a patient still needs to be scanned as soon as possible. Hence, we decide the penalty costs to increase exponentially when a patient needs to wait longer after their initial waiting time is already exceeded. Table 6 depicts the penalty costs for scanning a patient too late in a certain scenario. There are some scenarios in which we count the same penalty costs. For example, we assume that an acute patient that is scanned one week too late, is equally bad as a semi acute patient that is scanned three weeks too late and a regular patient that is scanned four weeks too late. For these three situations, 81 penalty costs are assigned. The relation of the penalty costs between the different situations are validated with the board of the SCC and the healthcare logistics team of the Isala hospital.

Table 6: Penalty costs.

Patient status	**Weeks too late**	**Penalty costs**
Acute	1	81
Acute	2	243
Acute	3 +	729
Semi acute	1	9
Semi acute	2	27
Semi acute	3	81
Semi acute	4 +	243
Regular	1	3
Regular	2	9
Regular	3	27
Regular	4	81
Regular	5 +	243

4.4 Model setup

We already described our model scenarios, our input variables and our model output. In this section we describe how we construct the model that is able to generate the results that we described in Section 4.3. Figure 9 depicts the flowchart of processes that follow after each other. These processes comprise one simulation run. In this section we further elaborate on each process individually, and we present additional flowcharts for the processes that are indicated in blue and green.

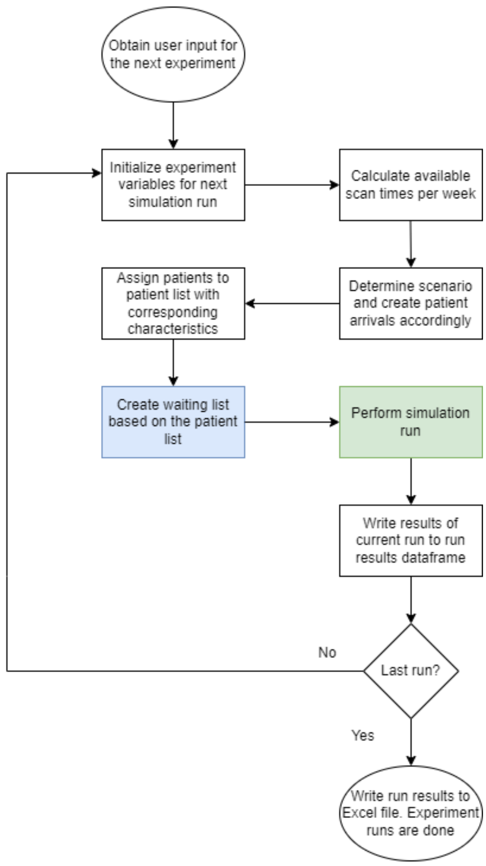

Figure 9: Flowchart of processes to be able to perform a single simulation run of the model.

4.4.1 Obtain user input and initialise experiment variables and data

The first step is to initialise the model by means of the user input. The user of the model is able to manually adjust the following data and parameters:

1. The reduction factor for each week;
2. The number of MRI resources available, opening hours per day and the number of operating days per week;
3. The specialties that the user wants to fix capacity for. In our current model, it is possible to fix capacity for neurology, orthopaedics, surgery and cardiology. More specialties can be added, but the user of the model has to derive the data distributions of scan requests for such a specialty and the corresponding parameters themselves;
4. The hours of available scan time that are assigned to each capacity that the user wants to fix capacity for;
5. The scan time reduction that must be considered in the next simulation run for the specialties that the user wants to fix capacity for. The user can enter the values 0, 3 and 5 here;
6. The reduction in utilization that the user wants to account for in the next simulation run. The user can enter the values 0.98, 0.96 and 0.94 here. This is called the utilization factor;
7. The probability that a patient that is generated is an acute patient or a semi acute patient. In our case we use a 10% and a 5% probability respectively, based on the data set of MRI scans that we have used to determine our capacity budget (Section 2.2) and to derive the average scan times (Section 4.2.3);
8. The penalty costs for not scanning a patient in time;
9. The number of runs that the user wants to perform for each scenario.

When these parameters are set, the model initialises several counters, such as the counter for the current run, current week number and the current row of the Excel-file in which the model has to store all available data eventually. The model also initialises the current scenario to scenario 'Z'. This variable is only able to be adjusted when the input of the capacities that must receive fixed capacity is entered correctly. Next, the model calculates the available scan times per week. For each week the model knows the number of MRI resources available, the opening hours per day, the number of operating days per week and the reduction factor. Furthermore, we know the the utilization factor that we need to account for in the current simulation run. The multiplication of these parameters results in the available scan hours per week. Because we have generated patients with a scan time that is based on the speciality that they are assigned to, we want to be able to deduct the scan time of this patient from the available scan times when this patient is scheduled by the model. Therefore, for convenience, we multiply the available scan hours per week by 60, such that we always work with remaining available scan time in minutes in our simulation runs. We store the available scan times per week in a separate data frame.

4.4.2 Determine scenario and create patient list

The next step is to determine the scenario for the next simulation run. The user of the model is able to indicate if a specialty needs to be considered as a specialty that receives fixed capacity (1) or if the specialty belongs to the group of 'other' specialties (0). Based on the combination of the input, the scenario is determined (A,B,C,D or E). Based on the scenario, the model creates an amount of scan requests (in hours) for all 52 weeks of the next year. Furthermore, the model creates an existing waiting list based on data distributions that correspond to scan requests of weeks 51 and 52. Next, the model assigns the following characteristics to the patients that are created for each specialty that is considered in the next simulation run:

1. Patient number;
2. Arrival week;
3. Specialty;
4. Scan time. Here, we directly reduce the scan time with the scan time reduction that is entered as parameter for the next simulation run. This means that, for example for scenario C, we reduce the scan time of the patients of neurology and orthopaedics with the input scan time reduction. We do not apply this reduction to the patients that are generated for other specialties, since the scan time reduction only applies to specialties that are considered in the block schedule;
5. Patient status. This patient characteristic can take on the value acute, semi-acute or regular;

All these patients and their corresponding characteristics are stored in a separate data frame: the patient list. In this patient list, the patients are stored per specialty but not based on urgency of being scheduled next. For modeling convenience, we want to create a list with patients that is sorted on urgency. With such a list, we can make an easier loop that assigns patients to capacity in a certain week, until there is no capacity left. Therefore we transform our current patient list in a list of patients that is sorted on urgency, which we call the waiting list. The method to create the waiting list basically sorts all patients from a current week based on their urgency. That means that, for all the weeks that we consider in our scenario, we first list all the acute patients. We do this for all the specialties that we consider in the current scenario. Next, we list all semi-acute patients and lastly, we list all the regular patients. For a given week, the patients are always automatically sorted on specialty. This is the case because for the patient list we first create the patients for the first specialty before we start creating patients for the next specialty. Figure 33 in Appendix B (Section 7.2) depicts the logic to create the waiting list from the patient list in a flowchart.

4.4.3 Perform the simulation run

The model is now able to perform the simulation runs for the current scenario based on the input from the user. We are able to assign patients to scan time, but we have to ensure that the model uses the same procedures to schedule patients as is the case in practice. Patients that arrive on a given day are basically scheduled on their urgency. Hence, acute patients are scheduled first, then the semi acute patients and the regular patients are scheduled last. However, the planners also need to schedule patients of the waiting list of previous days and weeks. If there are any acute or semi acute patients of previous days that are waiting to be scheduled, then these patients are scheduled before the acute, semi acute and regular patients for which a scan requests is handed in later. However, regular patients that have arrived earlier are scheduled after the acute and semi acute patients for which a scan request is handed in later. This is due to the deadlines of the corresponding patients. We use this logic in our model as well. However, we have to make an important adjustment to be able to correctly use it. The planning department can refer to a specific day on which a scan request for a certain patient is handed in. The scope of our model, however, is not that detailed. We use the same logic but then refer to the waiting time in weeks instead of the waiting time in days (in reality). This means that in a given week of the year, we first check if all acute and semi acute patients of previous weeks are already scheduled. If this is the case, we schedule all acute and semi acute patients that have arrived in the current week as long as there is scan time capacity available. When these patients are scheduled and we still have scan time capacity available, we schedule all regular patients from previous weeks that are not scheduled yet. If we then still have scan time capacity available, we scan the regular patients of the current week. This logic is applied for all scenarios that we consider in our simulation runs. Figure 10 depicts the process that is performed for each specialty in our model during an experiment. After the processes in this flowchart are finished, the model proceeds as depicted in Figure 9 in Section 4.4. Our model must eventually generate results that enable us to draw conclusions for a full year. However, if we would run the simulation until week 52 only, then it is reasonable that the patients that arrive in the last weeks will never be scheduled. This leads to invalid results. Hence, we assume that one year in our simulation consists of 70 weeks. To generate patient arrivals for these extra 18 weeks, we use the corresponding data distributions as depicted in Table 4. In our analysis we then only use the data that is generated for weeks 1 to 52.

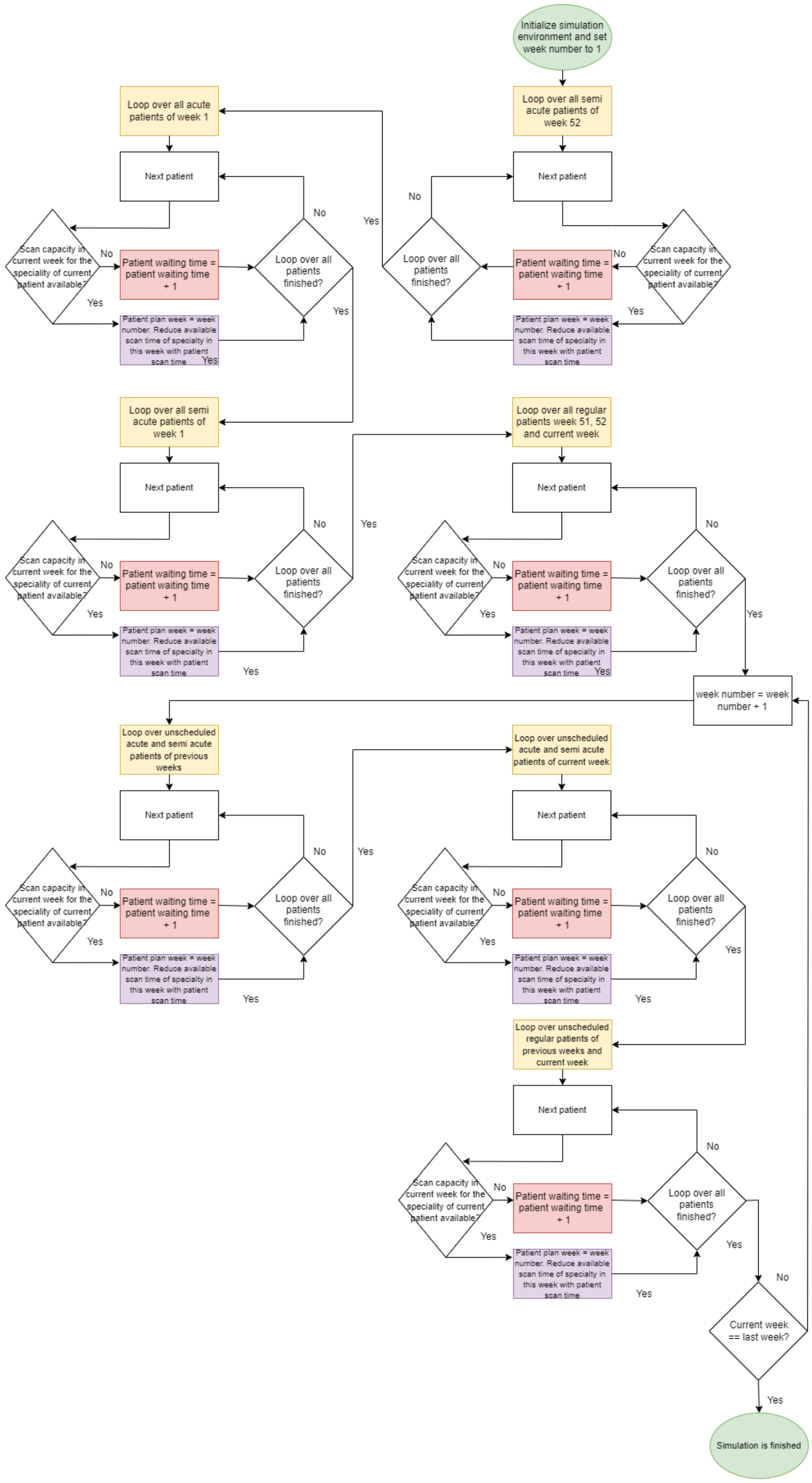

Figure 10: Flowchart of processes in a single simulation run of the model for a single specialty.

4.5 Significance level of simulation output

We describe how we constructed a model that is able to perform multiple simulation runs for a specific scenario of block scheduling with several output values, in the previous sections of this chapter. We performed several test simulation runs to observe how the model is able to generate the desired output. However, we need to perform multiple simulation runs for each scenario to increase the reliability of our results. We refer to the reliability of the results by means of the significance level. To reach a certain level of significance, we perform simulation runs until the width of the confidence interval, relative to the average output value, is sufficiently small. We use Equation 2 to evaluate if this is the case with n simulation runs for a given scenario.

$$\frac{(t_{n-1,1-\alpha/2} * \sqrt{S^2/n})}{\bar{X}} < \gamma' \tag{2}$$

We observe a trade-off between the significance level of the output and the run time of our model. Because we have different input values for all 37 scenarios, the number of simulation runs to reach a certain significance level differs for each scenario as well. To ensure that we are able to reach, for example, a significance level of 97.5% for all scenarios, we must perform a high amount of, for example 25, simulation runs. However, this involves a high amount of required run time. From our test simulation runs we know that the run time of the model increases when the number of specialties that are considered in the block schedule increases. We also know that one simulation run takes around seven minutes to complete. If we would run all our 37 scenarios 25 times with an average run time of seven minutes for each simulation run, we end up with 110 hours of actual run time. Hence, we use another approach that enables us to draw conclusions on the significance level of our simulation output. We decide to restrict the maximum run time for each scenario to one hour, which means that we can perform eight simulation runs for each scenario. This means that we have a total run time of 37 hours, which we are able to perform in three days. Based on the output of eight simulation runs for a given scenario, we are able to determine the t-value for which Equation 2 holds, and hence we know the significance level that is reached with eight simulation runs.

4.6 Conclusion

We described our simulation model setup in this chapter. From our literature review in Chapter 3 we learned that the Monte Carlo simulation technique shows potential to create insight in the impact of block scheduling for MRI resources at the Isala hospital. We gradually described how we design such a model in Chapter 4. We first provided an overview of the scenarios for which we perform simulation runs. These are based on the capacity budget of the specialties for 2022. Next, we described how we generate the input values for our simulation, and we described the desired output values of the simulation and how we determine these in our model. We also explained which user input is required to perform a simulation run. Then, we explained the logic of how patients are assigned to capacity at the Isala hospital and how we translated this logic into the appointment scheduling strategy of the model. The processes that follow each other in one simulation run are described here as well. The last section of this chapter described how we determined the number of simulation runs (eight) that we perform for each scenario and how we are able to assess the reliability of our results. We are now ready to run the model, and we elaborate on the results of the model for the different output values in our scenarios in the next chapter.

5 Analysis of model output

We describe the analysis of our model output in this chapter. First, we perform the analysis for the output that concerns the average waiting time for the different scenarios in Section 5.1. We also describe the output that we obtain about the percentage of patients that have a waiting time which is higher than the treeknorm and the remaining scan time in this section. Second, we perform the analysis for the output that concerns the penalty costs for the different scenarios in Section 5.2. Lastly, we describe the reliability of our results in Section 5.3.

5.1 Analysis of the average waiting time output

We focus on the analysis of the average waiting time output of our model in this section. We are able to create plots of the output with RStudio, where we calculate the average value for each week of all simulations runs that we have performed for each scenario. Since we have run the model for 37 scenarios, we know that we also have 37 output plots. We do not depict all these plots individually in this section, but we perform an analysis on at least one plot per scenario. In this analysis we mainly focus on the scenarios in which we account for a utilization factor of 0.96 and a scan time reduction of three minutes. We do so, because we assume that this is the most realistic scenario that occurs if block scheduling would be applied at the Isala hospital. Furthermore, we provide tables with the results for all scenarios regarding the waiting time output in Appendix C (Section 7.3) and Appendix D (Section 7.4).

5.1.1 Scenario A

We first plot the average waiting times for the scenario in which we do not fix any capacity for any specialty. This scenario corresponds with the current situation at the Isala hospital. This simulation run is basically a validation run to identify how the output of our model differs from the analysis on the waiting times that we have made in Section 2.3.2, where we observed an average waiting time for patients of 23 days. Figure 11 depicts the output for this scenario.

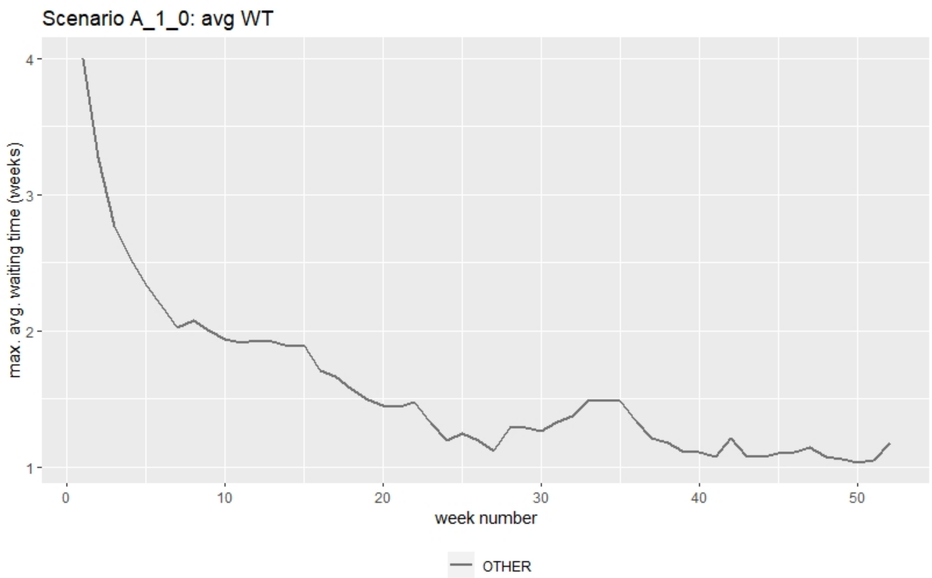

Figure 11: Plot of average waiting times in Scenario A-1-0.

We observe a rapid decrease in waiting time in the first five weeks of the year. The waiting time is higher in this period, because the simulation also needs to schedule the patients that are still in the waiting list of previous year. Furthermore, we know that week 8 and week 15 are weeks in which the total available scan times are reduced with

20%. That explains why the average waiting time until week 15 is higher than in the remainder of the year. We observe a decrease in waiting time in the other reduction weeks in the year as well: weeks 22, 29-35 and week 42. We observe from this plot that the average waiting time from our model does not approach the real average waiting time of 23 days. Two main causes for this observation exist:

1. Our model schedules patients solely based on whether or not we have remaining scan time at one of the available MRI resources. In this process of scheduling patients, we always assume that a patient is available at the appointment slot that the model assigns the patient to. However, this is not always the case in practice;

2. The Isala hospital currently works with a small amount of reserved capacity blocks already. This means that in practice more constraints need to be concerned in the appointment scheduling process than we have in our model for this scenario, where all capacity is available for each patient.

We observe an average waiting time of 12 days in the output of scenario A. However, we do not know what the real waiting times would be if we would eliminate the two causes that we described above. Therefore we proceed with the output of the model as we have it, but we must account for the fact that the output of our model is an underestimation of the real waiting times that we observe for the next scenarios. It is fair to assume that the real waiting times are higher in practice. For this scenario, we also observe that all patients were able to be scanned within four weeks. Hence, every patient receives its scan with a waiting time that is equal to or below the treeknorm.

5.1.2 Scenario B

Next we analyse the plots for scenario B. In this scenario we assigned 82 hours per week to neurology, and the remaining capacity is available for the scan requests of the remaining specialties. We illustrate this pattern in Figure 12, where we plot the data for scenario B with a utilization factor of 0.96 and a scan time reduction of 3 minutes.

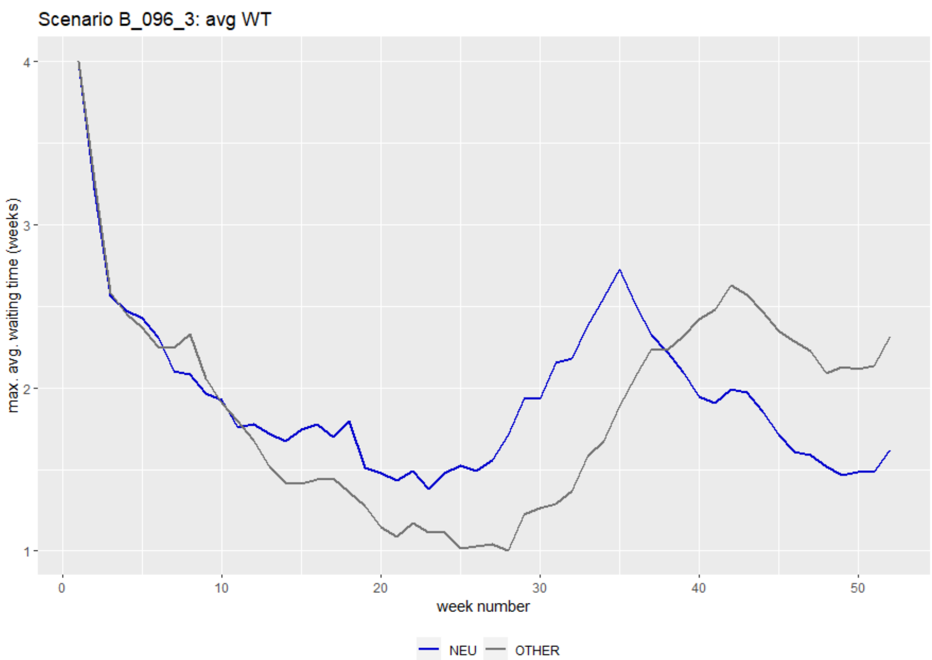

Figure 12: Plot of average waiting times in scenario B-096-3.

We immediately observe that the pattern of the average waiting time for the 'other' specialties differs from Figure 11, because of the disconnection of the scan requests for neurology patients. This is caused by the reduced amount of scan availability for all scan requests that do not concern neurology patients. We clearly see that putting restrictions on the capacity that is available for patients results in an increase in average waiting time. Furthermore, we observe an increase in waiting time for neurology patients and the other patients from week 30. For neurology this is only caused by the reduction factors that are applied in this weeks 30-35. For the patients of other specialties, however, we use other data distributions to create patients in weeks 35-39 and weeks 40-52 than we do in weeks 1-36. This explains why the pattern of the other patients differs from the pattern of the neurology patients after week 36. When we analyse the data of the percentage of patients that are scanned with a waiting time which is higher than the treeknorm, we observe that almost all patients are scheduled with a waiting time that is equal to or below the treeknorm. In week 8 we observe an average amount of 1.5% of the neurology patients that experienced a higher waiting time above the treeknorm, and in week 42 we observe an average amount of 0.3% of the other patients that experienced a waiting time above the treeknorm.

In Figure 13 we plot the data for scenario B with a utilization factor of 0.98 and zero scan time reduction, and in Figure 14 we plot the data for scenario B with a utilization factor of 0.94 and a scan time reduction of five minutes. We observe that for the scenario in which we account for the highest utilization factor and zero scan time reduction, the average waiting time is lower compared to the scenario in which we account for the lowest utilization factor and the highest scan time reduction.

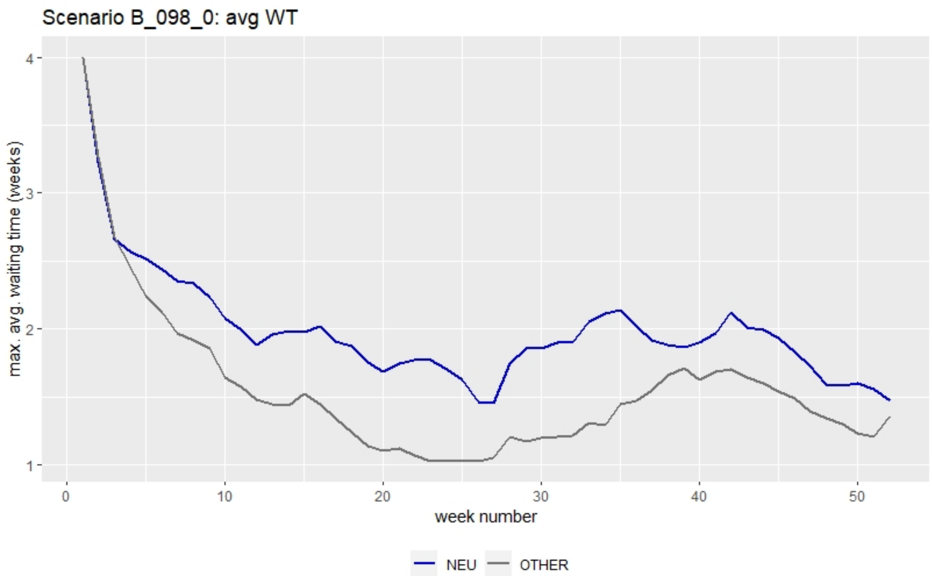

Figure 13: Plot of average waiting times in scenario B-098-0.

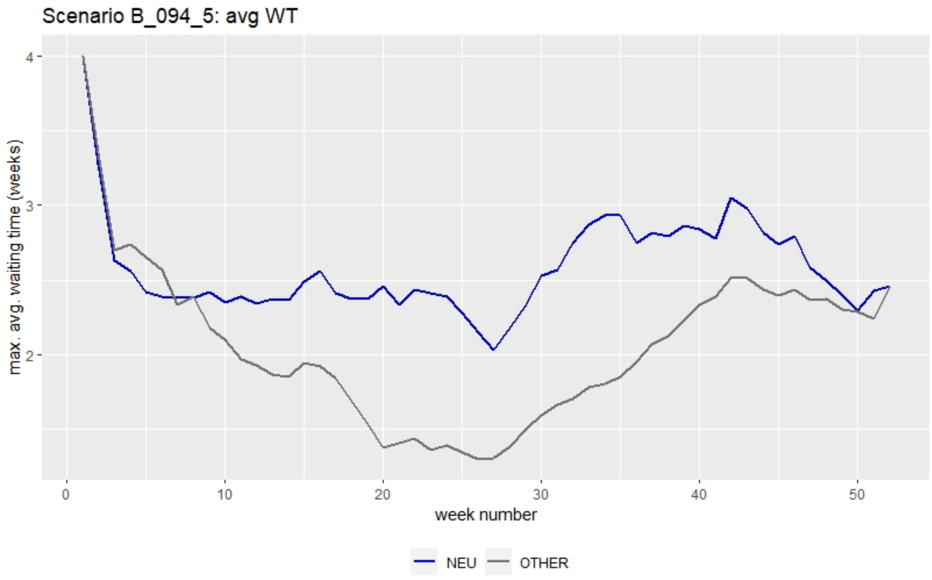

Figure 14: Plot of average waiting times in scenario B-094-5.

5.1.3 Scenario C

Next we analyse the plots for scenario C. In this scenario we assign 82 hours per week to neurology, 25 hours per week to orthopaedics and the remaining capacity is available for the scan requests of the remaining specialties. We illustrate the waiting times in Figure 15, where we plot the data for scenario C with a utilization factor of 0.96 and a scan time reduction of three minutes.

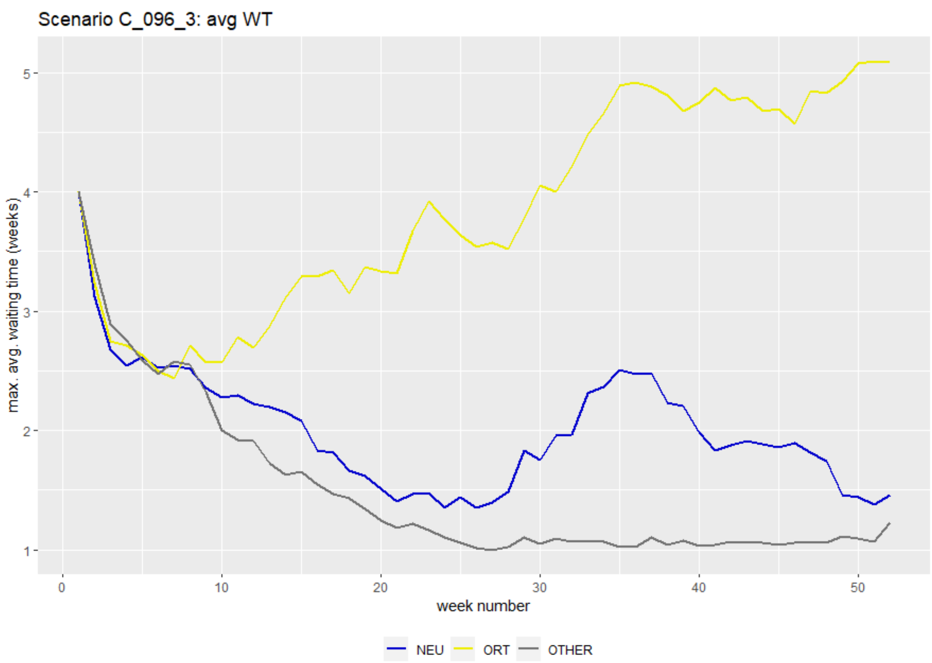

Figure 15: Plot of average waiting times in scenario C-096-3.

In the plot we observe that the waiting time for orthopaedic scan requests rapidly increases. The main cause for this is that the specialty orthopaedics performs more scans than they indicate in their budget. The available capacity in our simulation is based on the capacity budget, which is again based on the production budget that is handed in by the specialty itself. The fact that orthopaedics keeps admitting patients that require scans that they did not include in their production budget, causes this high average waiting time in case of block scheduling for orthopaedics. Furthermore, we observe that the average waiting time for patients of other specialties has decreased compared to scenario B (Figure 12), because of the disconnection of the orthopaedic patients. The last observation that we make is that the pattern of the waiting time for neurology patients follows the same pattern as we have seen in Figure 12 for scenario B. This makes sense, since we have used the same data distributions and parameters for both scenarios. When we zoom in to the waiting times for the three different scenarios that consider a decrease in scan time of three minutes, we obtain the plot in Figure 16. In this plot we observe a logical development of the data, where the average scan times are typically higher in a scenario where the utilization factor is lower.

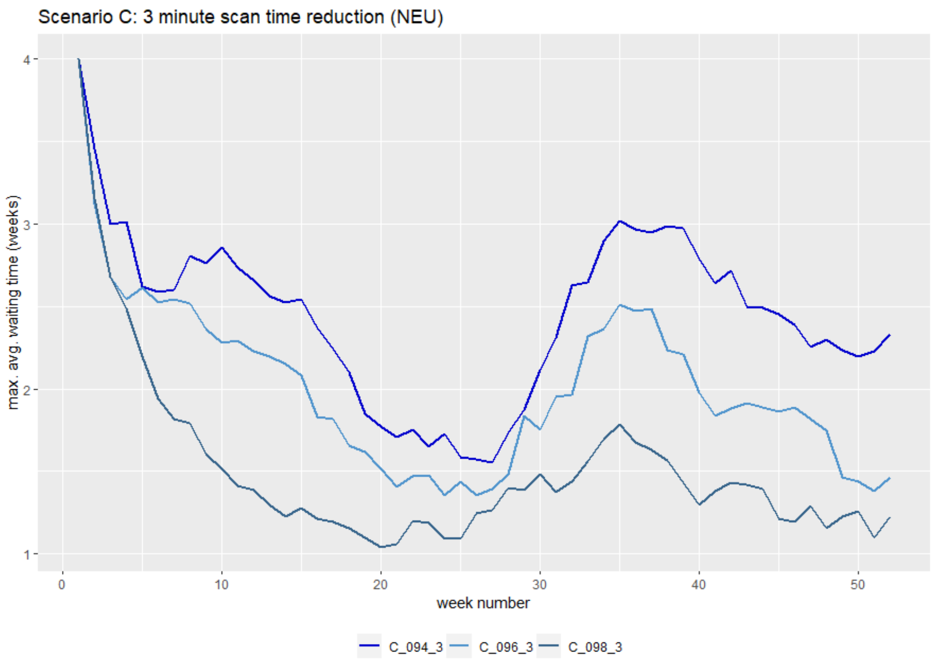

Figure 16: Plot of average waiting times for neurology in scenario C-x-3.

In scenario B where we applied a utilization factor of 0.96 and a scan time reduction of three minutes, we observed a very low percentage of scans that were performed above the treeknorm. Figure 15 already indicates that this might be different for scenario C, where we applied a utilization factor of 0.96 and a scan time reduction of three minutes. Figure 17 depicts this plot. We observe a pattern that confirms our statements in the previous paragraph about the underestimation of required capacity of orthopaedics. While the year proceeds, the capacity problems for this specialty increase as well. Furthermore, we notice that there are barely any problems for the patients from either neurology or any other specialty.

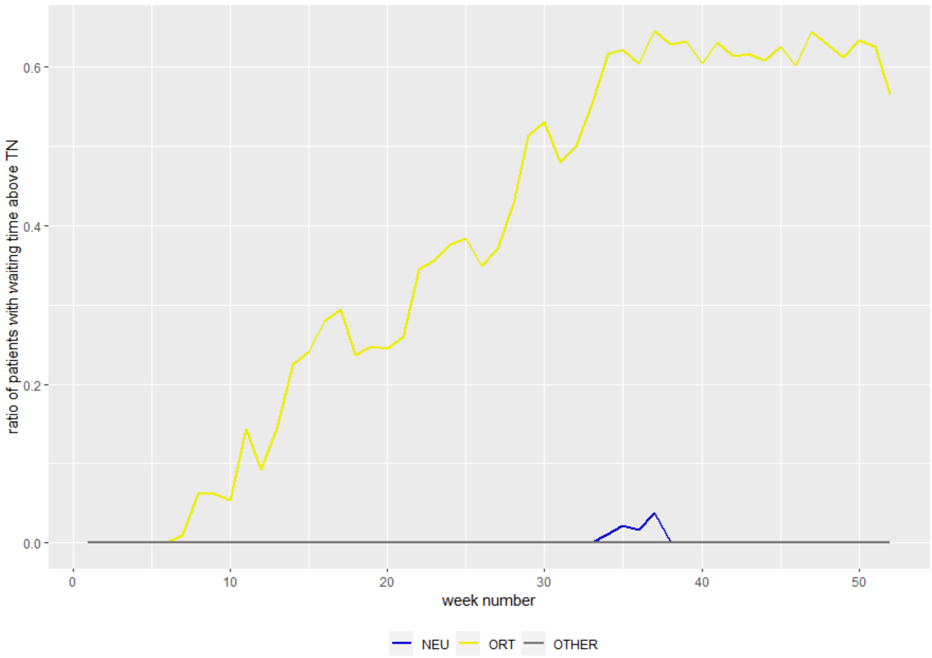

Figure 17: Plot of percentage of scans performed above the treeknorm in scenario C-096-3.

5.1.4 Scenario D

Next we analyse the plots for scenario D. In this scenario we assign 82 hours per week to neurology, 25 hours per week to orthopaedics, 19 hours per week to surgery and the remaining capacity is available for the scan requests of the remaining specialties. Figure 18 depicts the average waiting times for the specialties that are involved in this scenario.

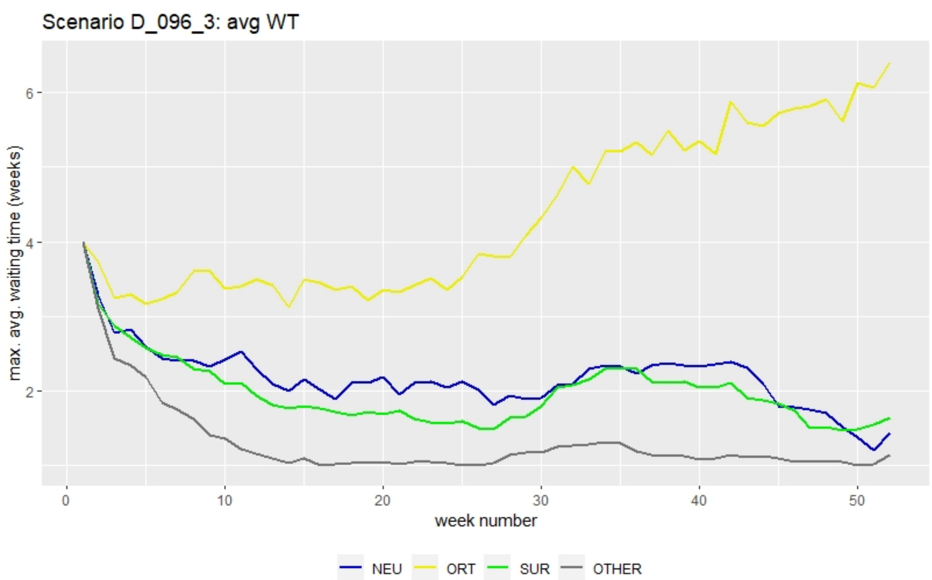

Figure 18: Plot of average waiting times in scenario D-096-3.

We observe patterns of waiting times for neurology and orthopaedics patients that we recognize from scenario B and C. We also observe that for this scenario, not many problems occur for the patients of specialty surgery or patients from any other specialty than neurology, orthopaedics or surgery. To create some more insight in how the pattern evolves for this set of fixed specialties, we also plot the data for two other scenarios, as we did in our analysis of scenario B in Section 5.1.2 as well. Figure 19 depicts the average waiting time for scenario D with a utilization factor of 0.98 and zero scan time reduction. Figure 20 depicts the average waiting time for scenario D with a utilization factor of 0.94 and a scan time reduction of five minutes. We make the same observation as for these plots in scenario B: the pattern of the average waiting time shows that the average waiting time is higher in the scenario in which we apply a utilization factor of 0.94 and a scan time reduction of five minutes. We also notice that this is the first plot in which we observe a change in the pattern of the waiting time for neurology patients. In previous plots for the waiting time of this specialty, we always observed a decrease of the average waiting time again after the last reduction week of the reduction period in weeks 29-35. However, we do not observe such a decrease in this plot.

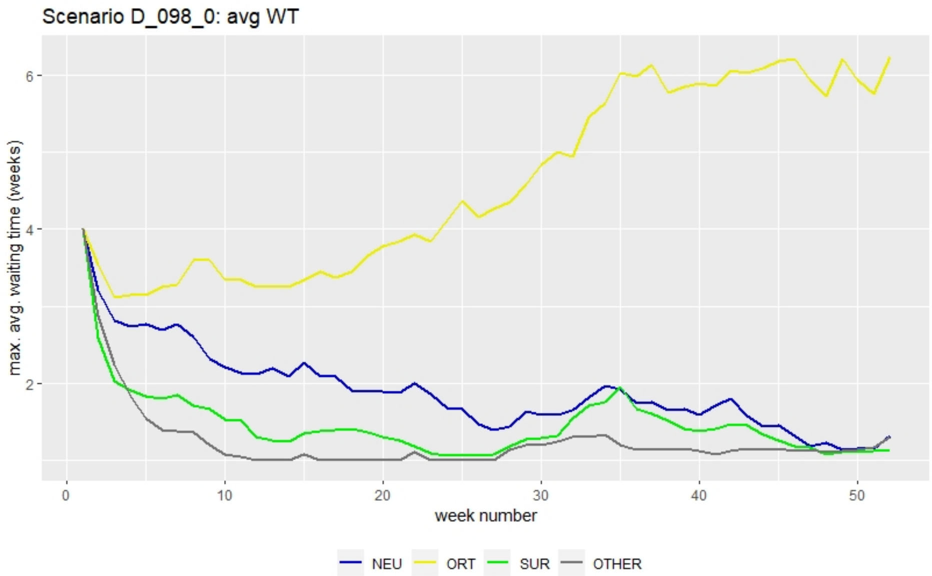

Figure 19: Plot of average waiting times in scenario D-098-0.

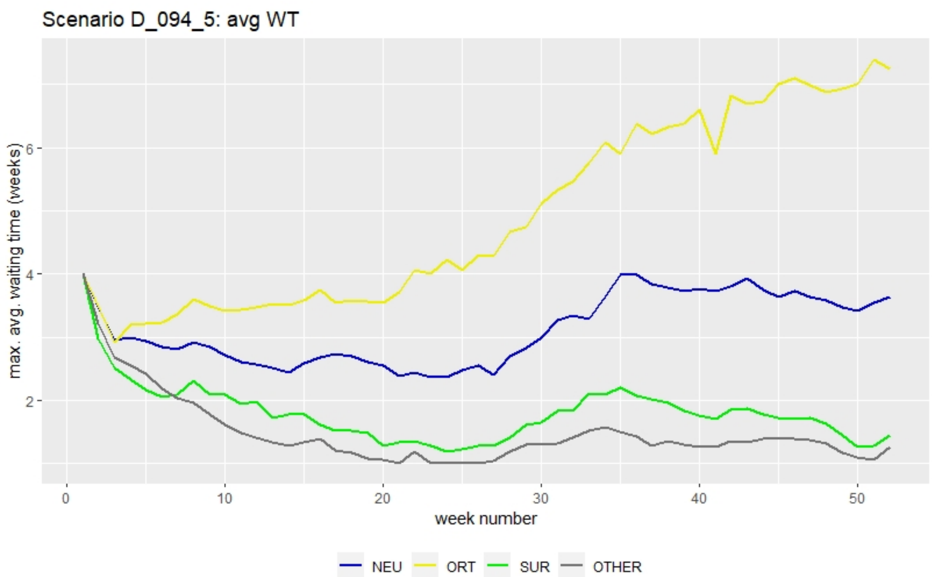

Figure 20: Plot of average waiting times in scenario D-094-5.

5.1.5 Scenario E

We now analyse scenario E. In this scenario we assign 82 hours per week to neurology, 25 hours per week to orthopaedics, 19 hours per week to surgery, 12 hours to orthopaedics and the remaining capacity is available for the scan requests of the remaining specialties. Figure 21 depicts the average waiting times for the specialties that are involved in this scenario.

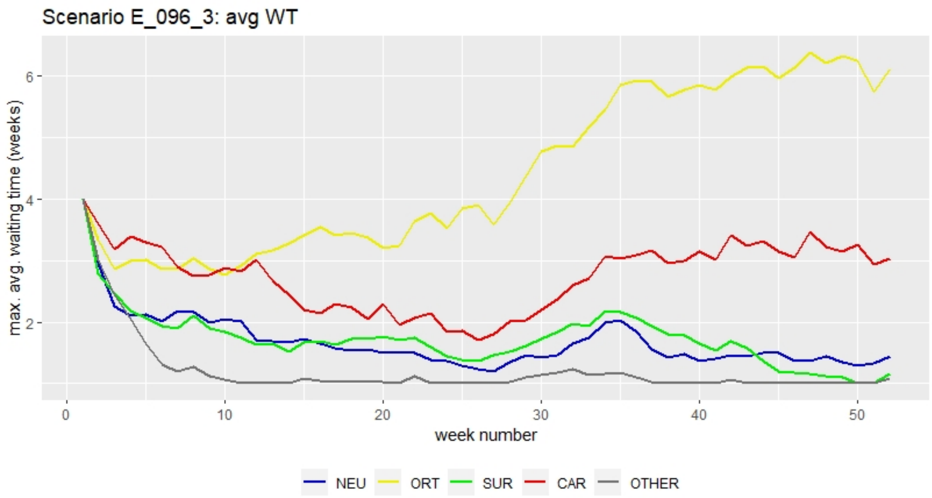

Figure 21: Plot of average waiting times in scenario E-096-3.

We notice a remarkable observation in the average waiting times of cardiology patients. We see that the increase of average waiting time that is caused by the reduction period in weeks 29-35, does not stop after week 35. We also observed this in our analysis of the average waiting times for neurology patients in scenario D, where we applied a utilization factor of 0.94 and a scan time reduction of five minutes. However, the average scan time of cardiology patients in this scenario is slightly lower. We take a closer look on the average waiting times for the scenarios in which we include cardiology in our fixed capacity and we account for a scan time reduction of three minutes. Figure 22 depicts the average waiting over the weeks in these three scenarios. We see that in the scenario with a utilization factor of 0.98, no problems occur in terms of waiting times that exceed the treeknorm for patients. On the other hand, we observe that in the scenario with a utilization factor of 0.94, patients already experience a waiting time above the treeknorm from around week 32. The last plot that we show in this section, is the ratio of patients that perceive a waiting time above the treeknorm. This plot is shown in Figure 23 and it depicts scenario E with a utilization factor of 0.96 and a scan time reduction of three minutes. From this plot we observe that we were able to schedule all patients for the specialties neurology and surgery in time. We also observe that the ratio of orthopaedics patients with a waiting time above the treeknorm increases rapidly. For this scenario, this ratio is even higher compared to scenario C (see Figure 17 in Section 5.1.3). For cardiology patients we also observe that there is a noticeable ratio of patients that perceive a waiting time that is above the treeknorm. We see that the average decreases in week 13 and starts increasing again around week 33. This is caused by the reduction factors that apply to the weeks 29-35. However, we observe that this ratio does not decrease again in the remaining weeks of the year.

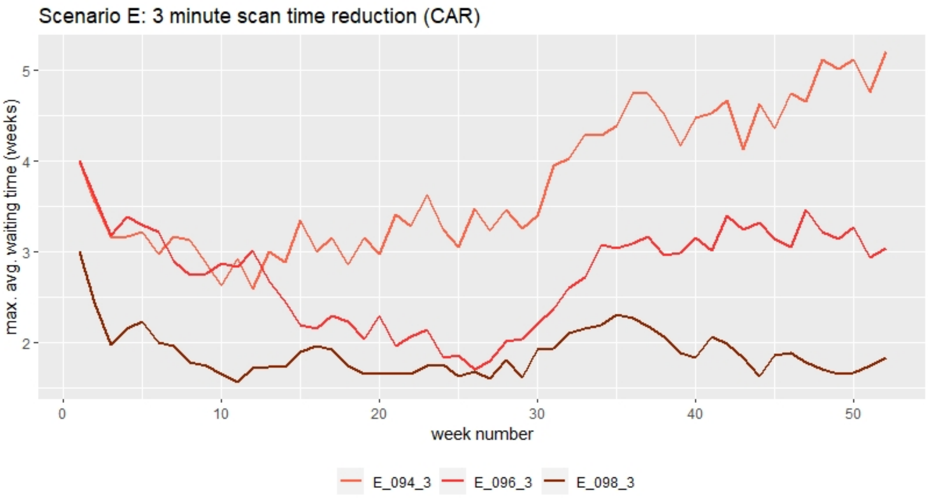

Figure 22: Plot of average waiting times for cardiology in scenario E-x-3.

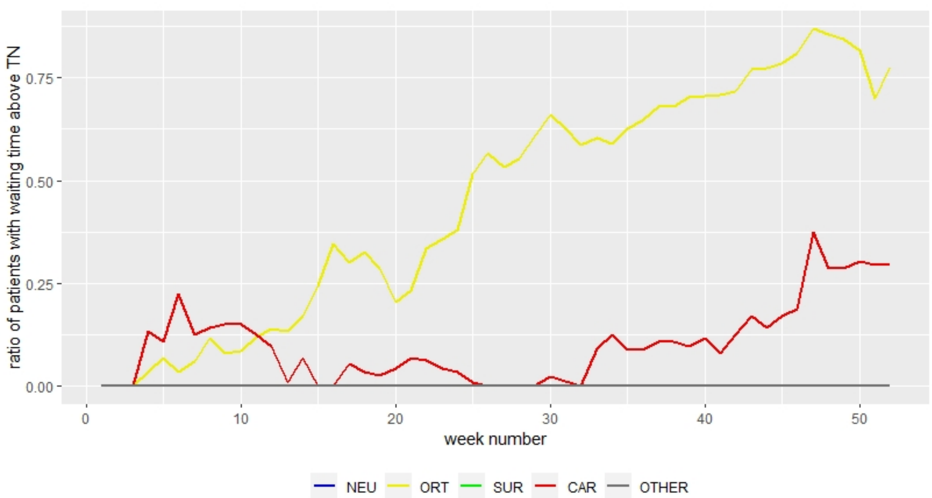

Figure 23: Plot of percentage of scans performed above the treeknorm in scenario E-096-3.

5.1.6 Remaining scan time output

W use the average remaining scan times for each scenario for validation of the average waiting time output. We expect that, for scenarios in which the average waiting times are high, the average remaining scan time is low. Table 11 in Appendix F (Section 7.6) depicts the average remaining scan time for each scenario. We clearly observe a pattern in the remaining scan times for neurology, surgery and the other specialties. It seems that, on average, the model always has some capacity left for these specialities. We also already observed that for these specialties, the average waiting times do not exceed the treeknorm of four weeks. Another observation that corresponds with the average values of the average waiting times, is the difference between the impact of the utilization factor and the scan time reduction. For both the average waiting times and the remaining scan time reduction, we observe that the impact of an increase in the utilization is higher than the impact of an increase in the scan time reduction.

5.2 Analysis of the penalty costs output

We focus our analysis on the output of the penalty costs of our model in this section. In the previous section we have mainly based our analysis on the scenarios in which we account for a utilization factor of 0.96 and three minutes of scan time reduction. We use the same scenarios in this section to analyse the results of the penalty costs output.

5.2.1 Scenario A

For this scenario, we observe that almost no penalty costs are incurred. This corresponds with the average penalty costs in this scenario that are depicted in Appendix E in Section 7.5. It also makes sense that no penalty costs are incurred in this scenario, because we observed an average waiting time of only 12 days for this scenario, which is far below the treeknorm. Because the acute and semi acute patients are scheduled first by our model, no penalty costs are assigned to these patients in our simulation output as well.

5.2.2 Scenario B

Considering the plot for scenario B with a utilization factor of 0.96 and a three minute scan time reduction, we also observe that almost no penalty costs are incurred. On average, we only observe a small amount of penalty costs in week eight for neurology and in week 42 for the group of other specialties. When we consider scenario B but then with a utilization factor of 0.94 and a five minute scan time reduction, we observe that the penalty costs increase. Figure 24 depicts this plot, where we observe an increase in the average penalty costs from week 30. Furthermore, we observe a peak in average penalty costs in week 42. These observations correspond with Figure 14, where we plotted the average waiting time for the same scenario. We observe an increase in average waiting time from week 30 and the peak in average waiting time is present in week 42. From the data frame with all output data, we also know that all penalty costs are incurred for regular patients. This means that all acute and semi acute patients were able to be scheduled in time in this scenario. When we observe the penalty costs output of scenario B with a utilization factor of 0.98 and zero scan time reduction, we observe such a low average amount of penalty costs that we consider it as being zero penalty costs.

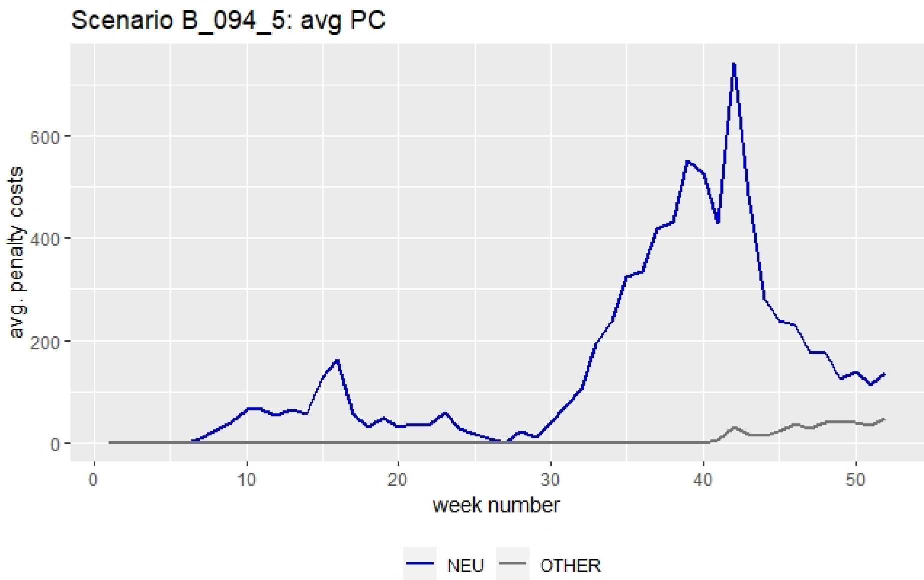

Figure 24: Plot of average penalty costs per week in scenario B-094-5.

5.2.3 Scenario C

We plot the output of scenario C in Figure 25. We observe a pattern that corresponds with the data in Figure 15, where the average waiting increases rapidly after week 30. We also know from the other previous plots with output of the specialty orthopaedics, that problems are likely to occur for this specialty in the second half of the year. We plot the penalty costs for scenario C with a scan time reduction of three minutes and the three possible utilization factors in Figure 26. Here, we see a similar pattern for all three scenarios. However, we make two remarkable observations. We observe that, from week 35, the average penalty costs per week are higher for the scenario in which we applied a higher utilization factor. We would, however, expect that the average penalty costs are higher in a situation where the utilization factor is lower. In that case, less scan time is available, patients must generally wait longer and hence the penalty costs are expected to increase. The second observation that we make is that the gap between the average penalty costs of the scenarios with a utilization factor of 0.94 with the other two scenarios is bigger than the gap between the average penalty costs of the scenarios with a reduction factor of 0.96 and 0.98.

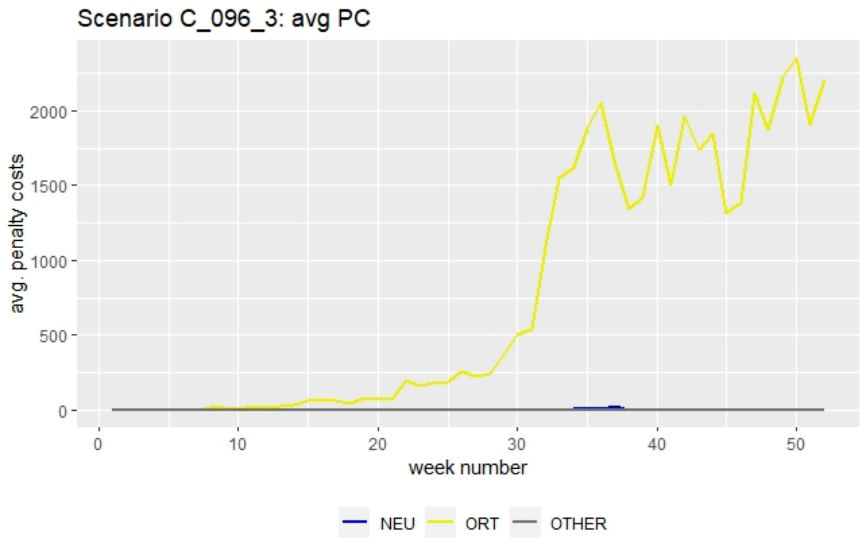

Figure 25: Plot of average penalty costs per week in scenario C-096-3.

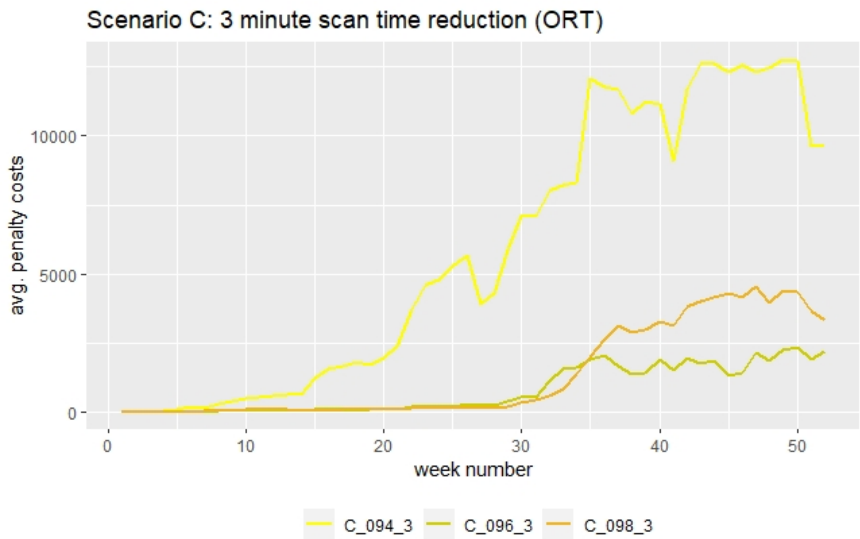

Figure 26: Plot of average penalty costs per week in for scenario C-x-3.

5.2.4 Scenario D

When we plot the output of the average penalty costs for scenario D with a utilization factor of 0.96 and a scan time reduction of three minutes, we observe a similar graph as compared to scenario C. This makes sense, since the average penalty costs per week for the specialty surgery are zero as Table 10 in Appendix E (Section 7.5) depicts. The average penalty costs of the other specialties follow the same pattern as we have observed for scenario C. However, we do observe that the peak of the average penalty costs of orthopaedics is higher in scenario D when compared to scenario C. We observe a peak in week 50 of 3,250 penalty costs for scenario D, where we observe a peak of 2,600 penalty for orthopaedics in scenario C.

5.2.5 Scenario E

In our analysis on the average waiting times for scenario E, we observed that cardiology patients perceive an average waiting time that approaches four weeks at the end of the year. When we plot the average penalty costs for this scenario, we observe the same patterns as we already did in scenarios C and D: the penalty costs of orthopaedics increase rapidly, while the penalty costs for all other specialties remain very low. We look at the penalty costs of the specialty cardiology in more detail in Figure 27. We observe that the penalty costs for the scenarios with a reduction factor of 0.96 and 0.98 are negligible. The penalty costs for the scenario in which we account for a reduction factor of 0.94 are higher. This corresponds with our observations from the average penalty costs in these scenarios.

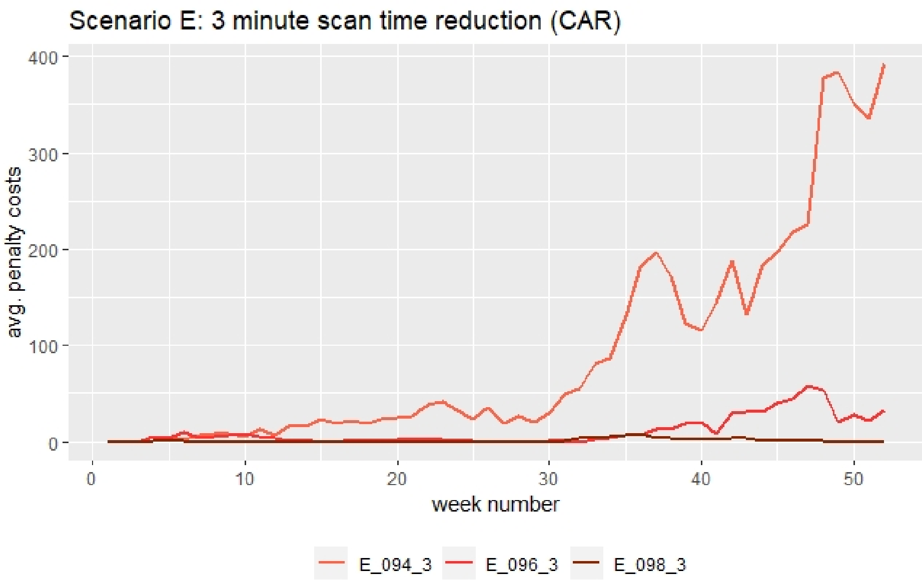

Figure 27: Plot of average penalty costs per week for scenario E-x-3.

5.3 Significance levels and validation of simulation output

In this section we evaluate the reliability of our simulation output. We first describe the significance levels that we obtain in our simulation output, and next we describe how we performed validation runs with a warm up period.

5.3.1 Significance levels

As we described in Section 4.5, we determine the level of significance for each scenario based on the eight simulation runs that we have performed. Figure 28 depicts these results which are based on the average waiting time output. The average significance level over all simulation output is 95%. We observe that we reach a significance of 90% or higher for 91.34% of our output values, and a significance level of 95% or higher for 45.67% of our output values. However, we also observe nine output values with a significance level below 90%. Figure 28 shows that the significance level for the waiting time output for a given speciality fluctuates a lot because of the impact of the utilization factor and the scan time reduction. For example, we observe a difference in significance of 9% between the output for neurology patients in scenario B-094-0 and B-098-3. Furthermore, we observe that the significance levels for the category with specialties that are not included in the block schedule, shows less deviation when the number of specialties included in the block schedule increases.

Significance level with 8 replications							
Scenario	UF	STR	OTHER	NEU	ORT	SUR	CAR
A	1	0	96,0%				
B	0,94	0	96,0%	88,5%			
B	0,94	3	97,0%	93,5%			
B	0,94	5	94,0%	94,0%			
B	0,96	0	95,0%	92,5%			
B	0,96	3	94,5%	90,0%			
B	0,96	5	96,0%	92,0%			
B	0,98	0	97,5%	95,5%			
B	0,98	3	94,5%	97,5%			
B	0,98	5	97,0%	92,5%			
C	0,94	0	97,0%	92,0%	97,0%		
C	0,94	3	98,0%	89,0%	94,5%		
C	0,94	5	98,0%	94,0%	97,0%		
C	0,96	0	98,5%	96,5%	92,0%		
C	0,96	3	96,5%	96,0%	94,5%		
C	0,96	5	97,5%	96,0%	93,5%		
C	0,98	0	98,5%	96,5%	93,5%		
C	0,98	3	98,5%	97,0%	92,5%		
C	0,98	5	98,5%	94,5%	92,0%		
D	0,94	0	96,5%	93,5%	95,5%	92,0%	
D	0,94	3	95,5%	91,5%	95,5%	94,0%	
D	0,94	5	95,0%	92,0%	95,0%	94,0%	
D	0,96	0	97,0%	95,0%	94,0%	95,0%	
D	0,96	3	98,5%	95,0%	90,5%	94,5%	
D	0,96	5	97,0%	95,5%	91,0%	97,5%	
D	0,98	0	97,0%	97,0%	94,0%	94,5%	
D	0,98	3	98,0%	95,0%	90,5%	98,0%	
D	0,98	5	98,5%	93,0%	95,0%	94,0%	
E	0,94	0	99,0%	89,0%	92,0%	90,0%	89,0%
E	0,94	3	98,5%	95,0%	94,0%	95,0%	95,5%
E	0,94	5	97,5%	87,5%	92,5%	92,5%	89,5%
E	0,96	0	99,0%	94,5%	95,0%	93,0%	94,0%
E	0,96	3	99,0%	95,0%	96,0%	96,0%	93,5%
E	0,96	5	97,5%	95,5%	94,5%	96,0%	94,0%
E	0,98	0	98,0%	95,5%	89,0%	94,5%	86,5%
E	0,98	3	98,0%	95,0%	96,5%	98,0%	96,0%
E	0,98	5	98,5%	95,5%	92,5%	95,5%	88,0%

Figure 28: Significance levels for all scenarios.

5.3.2 Validation runs with warm up period

In Section 4.2.3 we described how we created a waiting list before the start of a simulation run. The patterns of the plots in Section 5.1 indicate that our waiting list approach does not result in a fully representative output pattern. In each plot we observe a steep descent in the average waiting time for the first five weeks of the year. However, with the current plots we do not know whether the waiting times over the year are converged correctly. The MRI appointment scheduling process that we simulated is a non-terminating process in reality, and hence a warm up period would have been necessary. To provide more insight in the reliability of the output patterns in Section 5.1, we perform validation runs with a warm up period of one year for each simulation run with a utilization factor of 0.96 and a scan time reduction of three minutes. Figure 29 and Figure 30 depict the output data of two years and the second year respectively for scenario C. We observe that the output data in the second year shows similar patterns compared to the first year, but without the steep decrease in the beginning of the year. We also observe a continuation of the increase of the waiting time output of orthopaedics. We use the same approach to evaluate the output patterns from scenario E. Figure 31 and Figure 32 depict the output data for which we incorporated a warm up period for scenario E. We observe similar output patterns for surgery and cardiology as we observed in our plots in Section 5.1. Again, the waiting times of cardiology show a stable pattern over the year, but the average waiting time approaches four weeks. Compared to the first year, we also observe a slight increase of the average waiting times in the second year for cardiology patients. For all output with a warm up period, we observe waiting times and patterns that correspond with the output that we analysed in Section 5.1. The average significance level of the output data with a warm up period is 95%. The average waiting time output of orthopaedics in scenario C and neurology in scenario D are the most deviating results compared to the average, with significance levels of 91% and 90% respectively. The plots of the output of the simulation runs with a warm up period for scenarios A, B and D are depicted in Appendix G (Section 7.7).

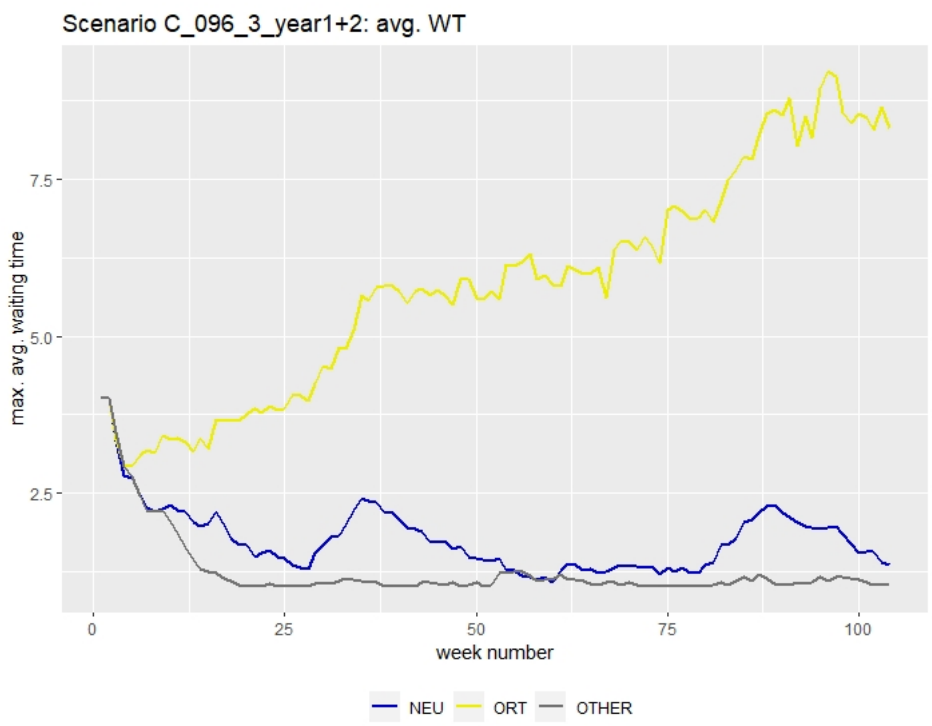

Figure 29: Plot of average waiting times for two years in scenario C-096-3 with a warm up period of one year.

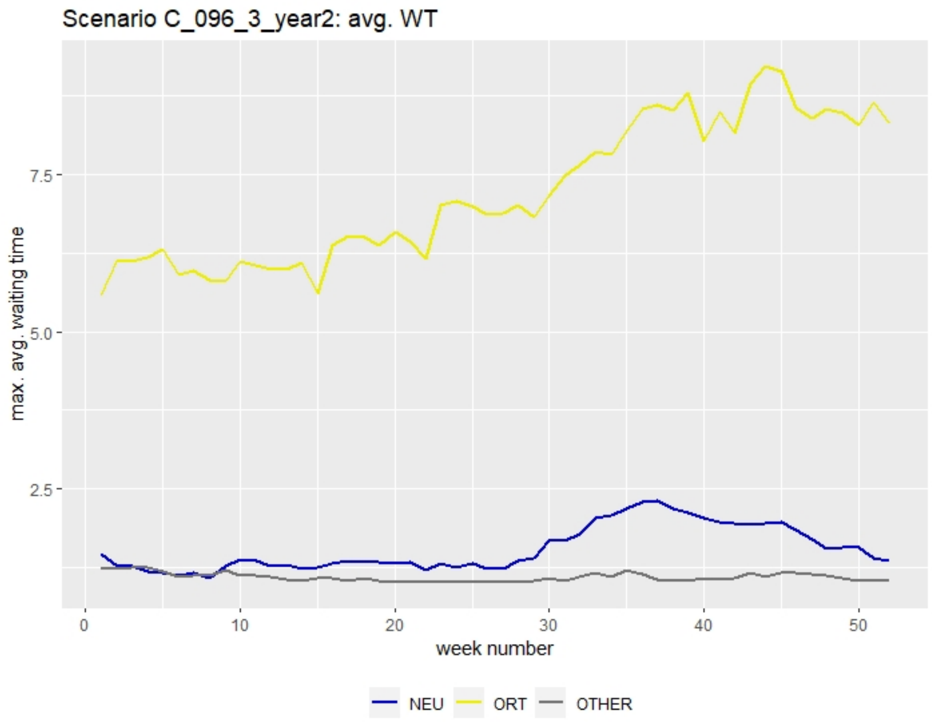

Figure 30: Plot of average waiting times for the second year in scenario C-096-3 with a warm up period of one year.

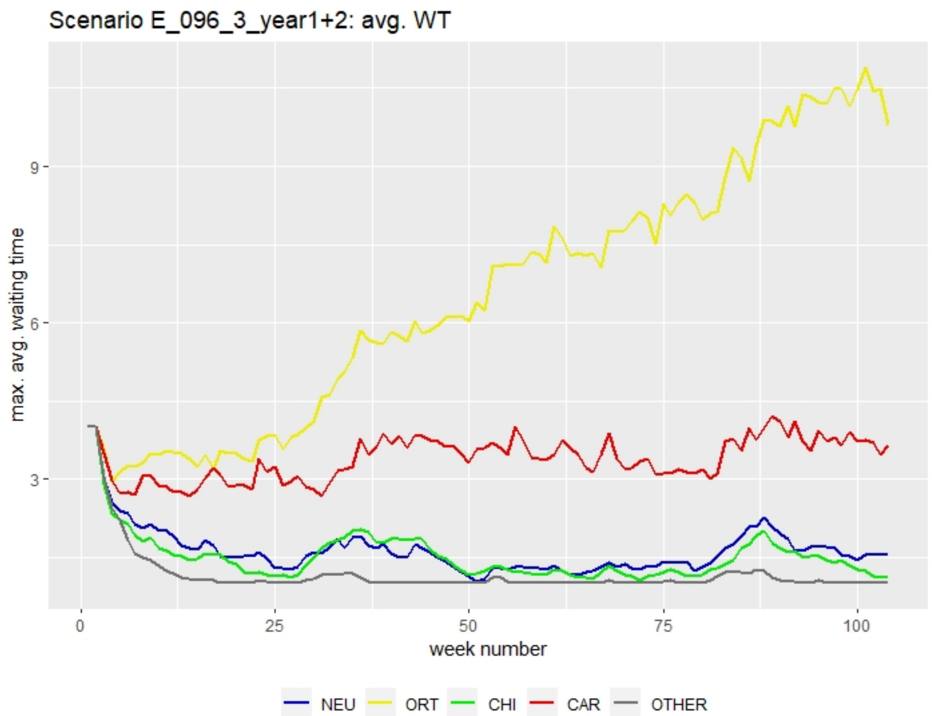

Figure 31: Plot of average waiting times for two years in scenario E-096-3 with a warm up period of one year.

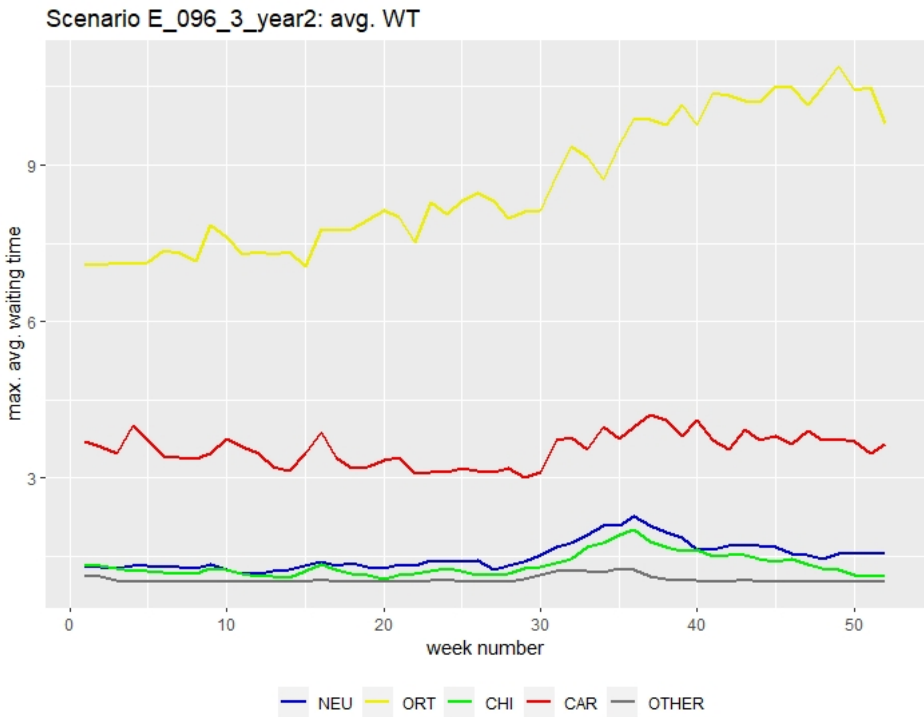

Figure 32: Plot of average waiting times for the second year in scenario E-096-3 with a warm up period of one year.

5.4 Conclusion

In this chapter we described the observations that we obtain from our simulation output. We first performed the analysis for the output of scenario A to obtain an indication to what extent our output data corresponds with reality. From this we observe that our output data is an underestimation. This is the case because we ignore patient preferences in appointment scheduling and the current capacity blocks in our simulation. Next, we analysed the output of the average waiting time values, where we also evaluated the output of the ratio of patients that is treated with a waiting time above the treeknorm and the remaining scan time. From our output data we observe that orthopaedics suffers from a fixed amount of capacity. The values of all output are the worst for this specialty. We observe output patterns that show a non-ending increase in average waiting time. For neurology and surgery, however, we observe promising patterns when we consider the available scan capacity for these specialties and the arrival of scan requests that are based on historical data. Although the output data is an underestimation of the real waiting time, we observe patterns in which the waiting time stabilizes throughout the year. The output of the penalty costs mainly confirms the observations that we made from the average waiting time output. Because we did not apply a warm up period in our initial output plots, we made some validation simulation runs in which we did include a warm up period. From these validation plots, we observe that the output patterns and the average waiting times are similar to the output of the simulation runs in which we did not include a warm up period. We observe an average significance level of simulation output of 95% for the plots without a warm up period, as well as for the plots with a warm up period. In the next chapter we provide the conclusions that follow from our research.

6 Conclusions on the research

We conclude our research in this chapter. We first describe the insights for science that are revealed by our research. Next, we elaborate on the limitations and points of discussion of our research. Lastly, we describe the insights for practice. Here we provide recommendations to the Isala hospital on how block scheduling can be applied for MRI resources, based on the output and analysis of our simulations.

6.1 Conclusions: insights for science

Our simulation study proposes a generic approach to create a model that is able to predict the impact of block scheduling for MRI resources. We gathered inspiration from multiple possible modeling techniques that are applied in the field of block scheduling for healthcare departments. We designed the model such that additional specialties can be added to the existing model, and also the sequencing of adding specialties can be changed. Furthermore, the same approach can be used to predict the impact of block scheduling for other diagnostic resources, such as CT scans. The approach that is described in Chapter 4 may serve as a source of inspiration for any other individual that is interested in creating such a model themselves. We mainly evaluated the impact of block scheduling by the average waiting times for the different scenarios that we have constructed. However, we created other KPIs for our analysis as well. We considered the average ratio of patients that is treated above the treeknorm, the remaining scan time, and the penalty costs per scenario. We recall the main research question of this research, before we elaborate on the conclusions of our research that follow from the outcomes that we present in Chapter 5.

Which model can be designed that predicts the impact of different scenarios of block scheduling for MRI resources on the waiting time for patients?

1. With our research we proved that the Monte Carlo simulation technique is suitable to model potential consequences of an implemented block schedule for specialties that use MRI resources. All specialties that are interesting for anyone to consider in a block schedule, are able to be included in the model that we constructed. Possible expected consequences of block scheduling can be modeled in a similar approach as we did in our research.

2. We assumed the pure block scheduling strategy in this research. This means that specialties have to schedule the scan requests in their own capacity, without any flexibility. Our research shows that block scheduling only works for a specialty that proposes a realistic production budget. For specialties that structurally underestimate the scans that are going to perform next year, the waiting times increase rapidly. On the other hand, specialties do not have to exceed their assigned capacity to meet the patient arrivals, if an accurate estimation of the required capacity can be calculated based on the production budget. For these specialties, the waiting time stabilizes and peaks in waiting time correspond to weeks in which less scan capacity is available.

3. In research where patients are assigned to capacity, it is better to use a warm up period than to use a waiting list that corresponds with reality to calculate the correct output patterns. The waiting list approach results in output that is not fully representative, because waiting times are not fully converged yet. Although the run time of simulations with a warm up period is higher than simulations with the waiting time approach, this output shows more accurate results for a full year.

6.2 Limitations

During this research, several assumptions and decisions resulted in a set of limitations and points of discussion:

1. After we finished running the simulation for all scenarios with our waiting list approach, we decided to run some validation scenarios with a warm up period. From these validation scenarios, we concluded that the patterns of the average waiting times with the waiting list approach are representative, but not for a full year. With the waiting list approach we obtain a good indication of how the patterns of the average waiting time evolve, but especially for the first few weeks this is not the case. We therefore recommend to always use such a warm up period for non-terminating simulations in similar research topics. Furthermore, for the scenarios that we did not perform the validation runs with a warm up period for, we do not know to what extent the waiting time approach is representative. We assume that it is comparably, but it would have been better if we generated all our initial output with a warm up period.

2. Our output values have different significance levels. It would be better to make more simulation runs for each scenario, and then decide for each scenario how many simulation runs result in the desired significance level. This would lead to a fairer analysis of the results.

3. We assumed a limitation of the available scan times per week. We did not incorporate the possibility to scan patients in the evening or during the weekends, while this does happen in practice. We made this assumption because we also excluded all inpatient scan requests in our research. Discussions with the board of the SCC and healthcare logistics team, and some basic calculations provided the basis for these assumptions. However, the outcomes of the average waiting times in scenario A of our model, indicate that this assumption leads to an overestimation of the available scan time. The outcomes of the model would have been more realistic if we made a more accurate calculation on the balance between the inpatient scan requests, and the scans that are performed in the evenings and during the weekends.

4. The patient status in our model is static. This means that, once the patient status is assigned, it does not change while running the simulation. The appointment scheduling process of our model corresponds with the scheduling procedures for MRI scans at the Isala hospital. However, we would have made a better approximation of the real appointment scheduling process if we would have incorporated a dynamic patient status. If, for example, a regular patient is already waiting for a scan for six weeks, this patient will be scheduled before a newly arrived semi acute patient in practice. This means that the status of a patient that has a regular status and a certain (high) current waiting time, is changed while running the simulation. Our model does not account for such situations. If we would incorporate a dynamic patient status and change the appointment scheduling procedures accordingly, we expect some differences in output. In that case, the average waiting times decrease and the penalty costs do either remain the same or increase. The regular patients that already perceive a high waiting time are treated earlier (which decreases the average waiting times), but it is more likely that a semi acute (or even an acute) patient cannot be scanned in the corresponding week. The penalty costs of not scanning such a patient in time are higher than the penalty costs for not scanning a regular patient in time. However, there will also be less regular patients with very high penalty costs because they are scheduled earlier because of a changed status.

5. For convenience, we use average scan times for the specialties and scenarios that we consider in this research. We apply scan time reductions for the specialties that receive fixed capacity and we deduct these values from the average scan times of the specialties. However, in practice, it is not always possible to have a scan time reduction of five minutes for a specific scan. Therefore, it is better to interpret this absolute scan time reduction in minutes as a relative decrease in average scan time. In our research, the average scan times of almost specialties and scenarios are around 30 minutes. Therefore, a scan time reduction of 3 minutes refers

to a reduction of around 10% and a scan time reduction of 5 minutes refers to a reduction of around 16%. The average scan time of cardiology is 55 minutes. Here, a 3 minute scan time reduction refers to a reduction of around 5% and a 5 minute scan time reduction refers to a reduction of around 9%.

6. To generate patient arrivals in our simulation we first analysed the data of scan requests of 2019. We only used this data because more recent data is not fully representative for normal hospital operations, because of the influence of Covid-19. We were not able to access less recent data, because of organizational changes. This results in that the patterns of the scan request data can be biased for some unknown reason. This means that the patterns that are present in the data of 2019, can also be not representative for the true average scan requests per week in a certain year. Furthermore, based on this analysis, we generate requested scan hours per week in our model. Next, we generate a number of patients for the corresponding week by dividing the generated hours of scan time by the average scan time of the corresponding speciality or scenario. In this method, we actually allow ourselves to generate patients based on continuous distributions. However, we could also have analysed the number scan requests that are handed in each week, and multiply this by the average scan time of the corresponding specialty or scenario. With that method, we maybe would have been able to create patient arrivals based on, for example, the Poisson distribution or the Binomial distribution. We have no exact information on how the model would react if we would use such distributions. However, we consider the distributions that we used as a good approximation for the actual amount of requested scan hours per week.

7. The run time of an average run of our simulation run is seven minutes. These runs are performed on a device with a HP intel i5 (8th gen.) processor. The run time of a single simulation run decreases if a device with an i7 or even an i9 processor is used. This run time radically limited the number of runs which we were able to perform for our scenarios.

6.3 Conclusions: insights for practice

Based on the results of our research we can conclude on several on several insights for practice. We combine these insights in our final conclusions and recommendations for the Isala hospital:

1. The average waiting times increase when specialties are incorporated in a block schedule if the strict appointment scheduling rules are applied as we did in our model. In our model, the average waiting times for specialties with realistic production budgets multiply with factor 1,7. The average waiting times for specialties that are assigned too few capacity, increase with factor 3 to 6 on average. However, as we propose in our limitations, the waiting times decrease when a dynamic patient status would have been involved, which is actually the case in practice.

2. The values for the output of our simulations are the worst for orthopaedics. Although our average waiting time output is an underestimation, we already observe a waiting time that exceeds the treeknorm for regular patients around week 26. The main cause for this, is that this specialty hands in an unrealistic production budget each year. The main cause for this, again, is the limitation that the production budget of this specialty is not allowed to grow anymore. In a situation without block scheduling for orthopaedics, it is still possible to exceed the production budget and perform scans for these patients. However, if the Isala hospital would fix the capacity for orthopaedics based on the capacity budget of 2022 in a block schedule, the fixed capacity would not be sufficient to schedule the scan requests that will be handed in throughout the year. We recommend to not apply block scheduling for orthopaedics in the current situation.

3. The output for neurology and surgery show promising results. This is mainly caused by the realistic production budget of these specialties. This results in stable waiting times for these specialties throughout the year. Although we not explicitly modeled the scenario in which we only fix capacity for neurology and surgery,

we recommend to start discussing the implementation of block scheduling with the stakeholders of these two specialties. In our results we also observe that scenarios with a higher level of remaining utilization and lower scan time reduction, have a lower average waiting time than scenarios with a lower level of remaining utilization and higher scan time reduction. From this we conclude that the utilization factor has a bigger impact on the output than the scan time reduction. Fortunately, the Isala hospital can influence both factors simultaneously when block scheduling is applied.

4. We obtain precarious results for the specialty cardiology in our research. We recommend to start the process of implementing block scheduling for neurology and surgery first. Dependent on the progress of this process, cardiology can be considered as well.

5. The scan requests of the specialties neurology and surgery comprise around 45% of the total scan request for MRI resources. If the Isala hospital would decentralize its planning responsibilities because of block scheduling for these two specialties, it can also be possible to reduce the workforce at the central planning department with 1 FTE.

According to our literature review in Chapter 3, the SCC 'Medical Imaging' must abide to the following guidelines when block scheduling will be implemented:

1. The blocks that are allocated to a specialty must be monitored and reevaluated systematically.

2. Data upon which decisions regarding block time must be valid and representative for the demand requirements for the concerning specialties.

3. Clearly define the KPIs upon which the impact and/or performance of block scheduling will be assessed.

4. Do not block more than 85% of the total weekly available scan time.

5. Balance the assigned capacity evenly over the week. Otherwise, problems can occur in, for example, availability of laboratory technicians.

6. Involvement of stakeholders is really important when changing operations within healthcare organizations. When block scheduling is applied, all stakeholders that are involved in the MRI appointment scheduling process must be made clear why the decision is made and which expected benefits are involved.

7. Involvement of stakeholders is also really important to trigger behavioural change in healthcare organizations. Hence, the perceived benefits of block scheduling also need to be enlightened to the laboratory technicians, since they are responsible for a possible scan time reduction.

We refer to Chapter 3 for a more detailed description and the references of the above described guidelines.

7 Appendices

7.1 Appendix A: Simulation scenarios

Table 7: Simulation scenarios.

Scenario	Utilization factor	Scan time reduction
A	1	0
B	0.94	0
B	0.94	3
B	0.94	5
B	0.96	0
B	0.96	3
B	0.96	5
B	0.98	0
B	0.98	3
B	0.98	5
C	0.94	0
C	0.94	3
C	0.94	5
C	0.96	0
C	0.96	3
C	0.96	5
C	0.98	0
C	0.98	3
C	0.98	5
D	0.94	0
D	0.94	3
D	0.94	5
D	0.96	0
D	0.96	3
D	0.96	5
D	0.98	0
D	0.98	3
D	0.98	5
E	0.94	0
E	0.94	3
E	0.94	5
E	0.96	0
E	0.96	3
E	0.96	5
E	0.98	0
E	0.98	3
E	0.98	5

7.2 Appendix B: Logic flowchart waiting list

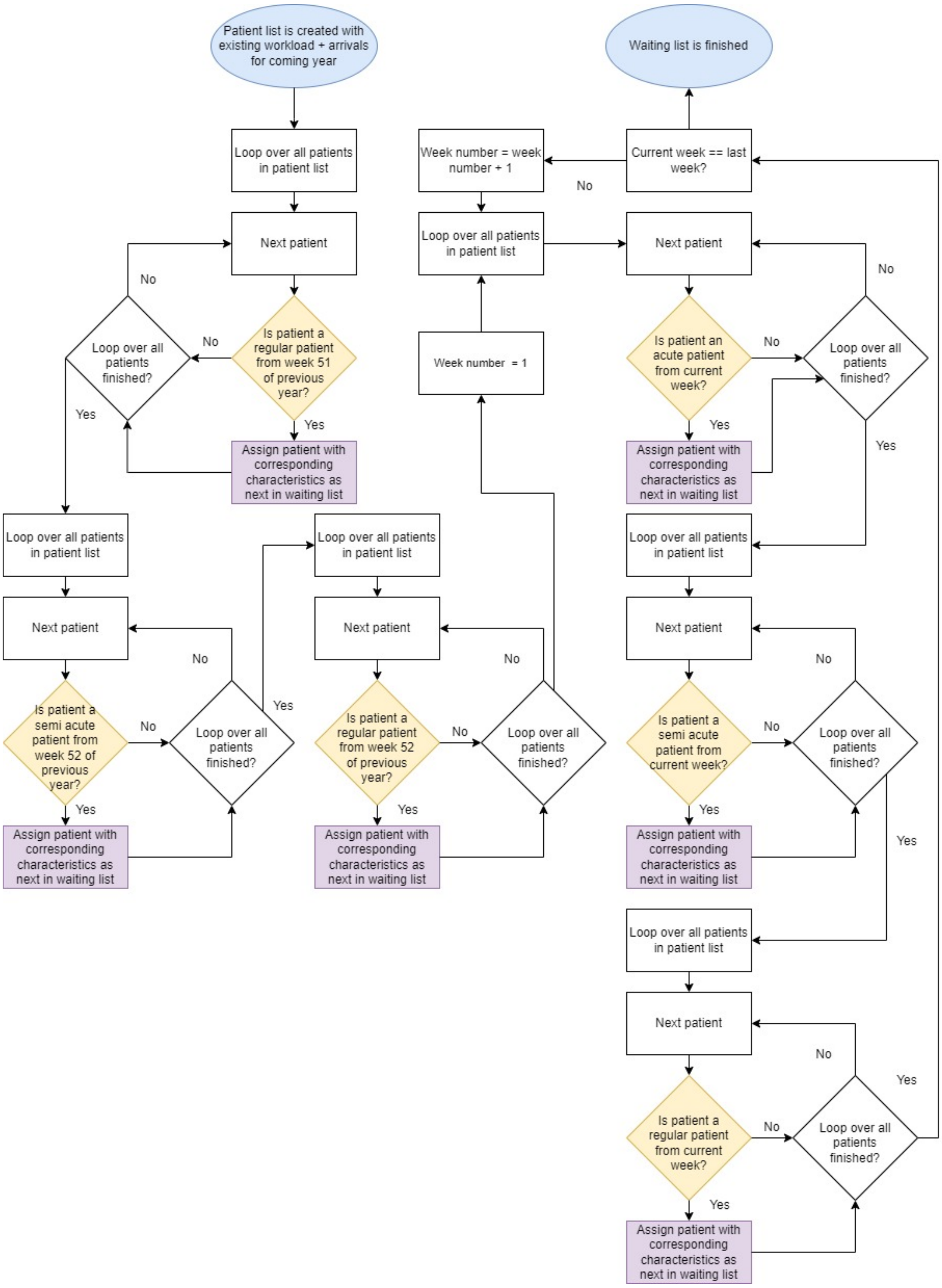

Figure 33: Flowchart of processes to create the waiting list from the patient list.

7.3 Appendix C: Detailed model output: average waiting time

Table 8 below depicts the average waiting time in days for each scenario. In the headers of the table we refer to the utilization factor (UF), the scan time (ST) reduction, and the waiting time (WT) for the specialties.

Table 8: Average waiting time output for all scenarios.

Scenario	UF	ST reduction	WT NEU	WT ORT	WT SUR	WT CAR	WT Other
A	1	0					12.0
B	0.94	0	16.5				15.8
B	0.94	3	19.1				13.0
B	0.94	5	18.2				14.0
B	0.96	0	14.9				12.2
B	0.96	3	13.1				13.1
B	0.96	5	14.7				12.5
B	0.98	0	12.9				10.4
B	0.98	3	11.7				10.7
B	0.98	5	13.5				12.0
C	0.94	0	16.9	42.8			10.1
C	0.94	3	16.9	55.0			9.9
C	0.94	5	18.9	40.9			9.6
C	0.96	0	12.0	35.7			9.4
C	0.96	3	13.5	30.8			10.0
C	0.96	5	11.9	32.5			9.2
C	0.98	0	11.6	35.4			9.1
C	0.98	3	10.4	33.8			9.8
C	0.98	5	12.8	31.7			9.0
D	0.94	0	19.6	44.1	12.2		9.5
D	0.94	3	15.7	45.9	11.3		9.7
D	0.94	5	22.3	40.1	12.0		9.9
D	0.96	0	12.7	34.0	12.3		9.0
D	0.96	3	14.1	34.3	13.3		9.0
D	0.96	5	12.3	31.4	11.1		9.2
D	0.98	0	12.8	35.2	10.0		8.7
D	0.98	3	13.6	39.8	11.4		9.0
D	0.98	5	12.5	30.9	9.7		9.1
E	0.94	0	16.8	44.2	12.8	20.4	8.4
E	0.94	3	15.5	44.0	11.3	29.6	8.6
E	0.94	5	18.3	36.2	15.4	26.5	8.7
E	0.96	0	18.6	31.4	11.2	22.0	8.4
E	0.96	3	11.4	34.9	11.4	19.9	8.4
E	0.96	5	8.1	18.4	7.8	18.8	5.4
E	0.98	0	11.6	31.0	10.9	20.0	8.3
E	0.98	3	11.5	34.0	8.8	16.5	7.8
E	0.98	5	11.6	33.8	9.3	22.2	8.2

7.4 Appendix D: Detailed model output: ratio of waiting time above TN

Table 9 below depicts the average ratio of patients that perceives a waiting time above the treeknorm. In the headers of the table we refer to the utilization factor (UF), the scan time (ST) reduction, and the specialties.

Table 9: Average ratio of patients with waiting time above TN for all scenarios.

Scenario	**UF**	**ST reduction**	**NEU**	**ORT**	**SUR**	**CAR**	**Other**
A	1	0					0
B	0.94	0	0.05				0
B	0.94	3	0.07				0
B	0.94	5	0.16				0
B	0.96	0	0.03				0
B	0.96	3	0				0
B	0.96	5	0.02				0
B	0.98	0	0				0
B	0.98	3	0				0
B	0.98	5	0.05				0
C	0.94	0	0.10	0.59			0
C	0.94	3	0.07	0.76			0
C	0.94	5	0.07	0.60			0
C	0.96	0	0	0.59			0
C	0.96	3	0	0.43			0
C	0.96	5	0	0.45			0
C	0.98	0	0	0.52			0
C	0.98	3	0	0.50			0
C	0.98	5	0.01	0.43			0
D	0.94	0	0.14	0.58	0		0
D	0.94	3	0.05	0.71	0		0
D	0.94	5	0.25	0.75	0		0
D	0.96	0	0	0.46	0		0
D	0.96	3	0	0.47	0		0
D	0.96	5	0	0.44	0		0
D	0.98	0	0	0.50	0		0
D	0.98	3	0.04	0.55	0		0
D	0.98	5	0	0.55	0		0
E	0.94	0	0	0.40	0	0.15	0
E	0.94	3	0	0.38	0	0.03	0
E	0.94	5	0.6	0.52	0	0.24	0
E	0.96	0	0.08	0.45	0	0.21	0
E	0.96	3	0	0.53	0	0.13	0
E	0.96	5	0	0.23	0	0.29	0
E	0.98	0	0	0.38	0	0.15	0
E	0.98	3	0	0.40	0	0.03	0
E	0.98	5	0	0.51	0	0.24	0

7.5 Appendix E: Detailed model output: penalty costs

Table 10 below depicts the average penalty costs for each scenario over all weeks in the year. In the headers of the table we refer to the utilization factor (UF), the scan time (ST) reduction, and the penalty costs (PC) of the specialties.

Table 10: Average penalty costs for each specialty for all scenarios.

Scenario	UF	ST reduction	PC NEU	PC ORT	PC SUR	PC CAR	PC Other
A	1	0					0
B	0.94	0	24.7				1.3
B	0.94	3	44.5				0
B	0.94	5	167.7				7.1
B	0.96	0	19.8				0
B	0.96	3	1.6				0
B	0.96	5	0				0
B	0.98	0	2.1				0
B	0.98	3	0				0
B	0.98	5	72.1				0
C	0.94	0	94.5	4476.4			0
C	0.94	3	44.1	7288.1			0
C	0.94	5	48.2	4678.38			0
C	0.96	0	0	2052.0			0
C	0.96	3	1.2	1674.6			0
C	0.96	5	0	1958.8			0
C	0.98	0	0	2497.9			0
C	0.98	3	0	2262.6			0
C	0.98	5	9.2	2320.7			0
D	0.94	0	95.8	4063.4	0		0
D	0.94	3	40.3	5076.4	0		0
D	0.94	5	409.9	3845.6	0		0
D	0.96	0	0	2048.0	0		0
D	0.96	3	4.5	2214.6	0		0
D	0.96	5	0.2	1894.3	0		0
D	0.98	0	0	1854.1	0		0
D	0.98	3	23.2	4039.6	0		0
D	0.98	5	5.0	989.3	0		0
E	0.94	0	86.9	12.5	0	111.9	0
E	0.94	3	10.4	40.7	0	234.7	0
E	0.94	5	267.3	53.2	0	191.8	0
E	0.96	0	64.5	1332.5	0	43.2	0
E	0.96	3	0	2358.3	0	18.2	0
E	0.96	5	0	1222.2	0	71.9	0
E	0.98	0	0	1442.3	0	97.9	0
E	0.98	3	0	2452.6	0	1.1	0
E	0.98	5	0	2570.5	0	44.7	0

7.6 Appendix F: Detailed model output: remaining scan time

Table 11 below depicts the average remaining scan time in minutes for each scenario. In the headers of the table we refer to the utilization factor (UF), the scan time (ST) reduction, and the remaining scan time (RST) for the specialties.

Table 11: Average remaining scan time output for all scenarios.

Scenario	UF	ST reduction	RST NEU	RST ORT	RST SUR	RST CAR	RST Other
A	1	0					837.7
B	0.94	0	91.4				122.1
B	0.94	3	35.4				217.1
B	0.94	5	92.2				177.8
B	0.96	0	99.2				287.7
B	0.96	3	215.1				295.1
B	0.96	5	120.0				339.8
B	0.98	0	240.4				468.0
B	0.98	3	286.1				437.9
B	0.98	5	172.0				394.2
C	0.94	0	82.1	0			421.8
C	0.94	3	98.3	0			483.5
C	0.94	5	58.3	0			401.5
C	0.96	0	233.8	0			583.5
C	0.96	3	195.1	0			545.9
C	0.96	5	234.7	0			537.5
C	0.98	0	263.4	0			665.6
C	0.98	3	349.7	5.2			693.9
C	0.98	5	248.1	5.4			665.5
D	0.94	0	43.7	0	50.8		332.3
D	0.94	3	112.3	0	50.6		365.3
D	0.94	5	47.8	0	34.9		379.5
D	0.96	0	213.9	0	46.3		492.4
D	0.96	3	143.1	0	50.6		533.2
D	0.96	5	221.8	4.9	69.2		445.4
D	0.98	0	187.4	0	92.8		573.4
D	0.98	3	249.4	0	100.9		596.7
D	0.98	5	259.6	0	73.6		530.2
E	0.94	0	119.0	0	63.8	6.2	593.6
E	0.94	3	91.1	0	52.8	2.9	560.0
E	0.94	5	125.6	1.1	39.6	0	529.3
E	0.96	0	72.3	0	62.7	10.6	638.6
E	0.96	3	205.0	4.3	66.7	6.9	653.5
E	0.96	5	142.3	3.0	36.6	0	416.0
E	0.98	0	292.2	0	80.2	19.0	738.7
E	0.98	3	183.0	0	66.7	7.1	576.0
E	0.98	5	292.2	0	97.7	4.9	726.1

7.7 Appendix G: Output plots of average waiting time with warm up period

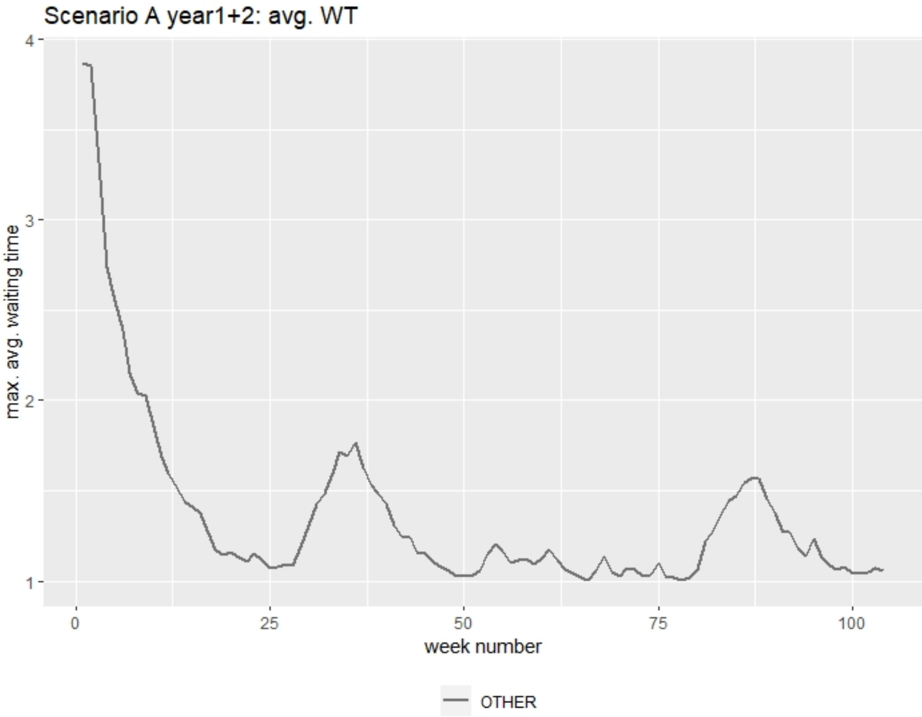

Figure 34: Plot of average waiting times for two years in scenario A with a warm up period of one year.

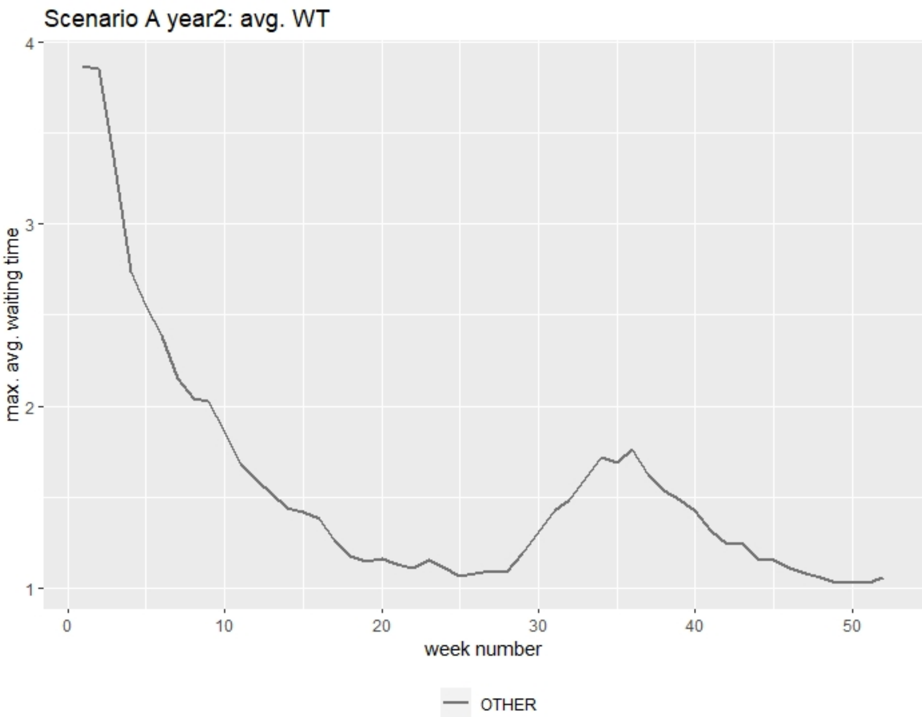

Figure 35: Plot of average waiting times for the second year in scenario A with a warm up period of one year.

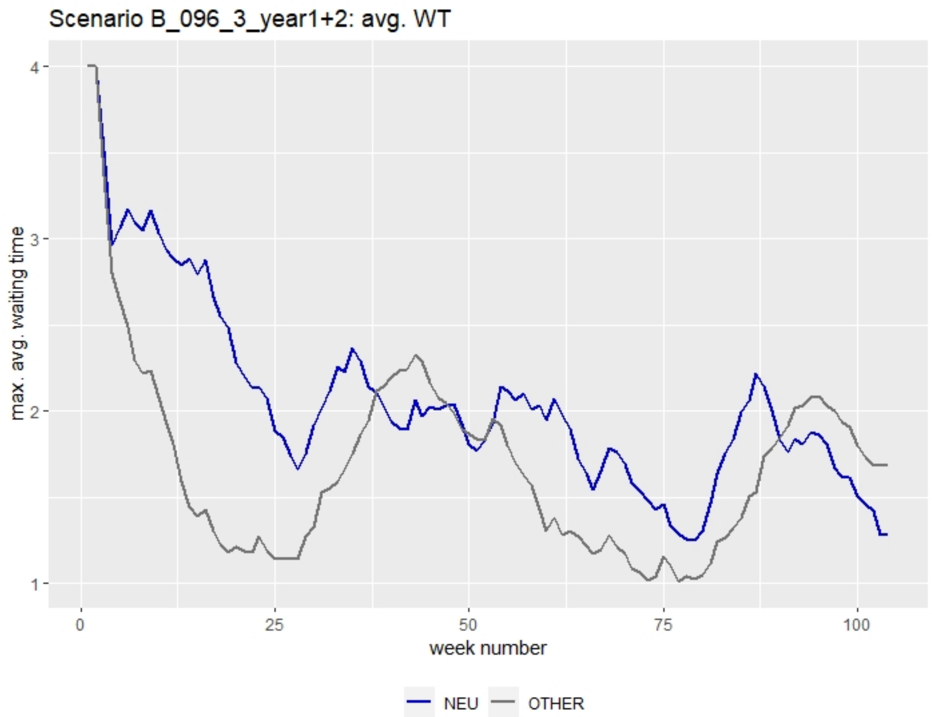

Figure 36: Plot of average waiting times for two years in scenario B-096-3 with a warm up period of one year.

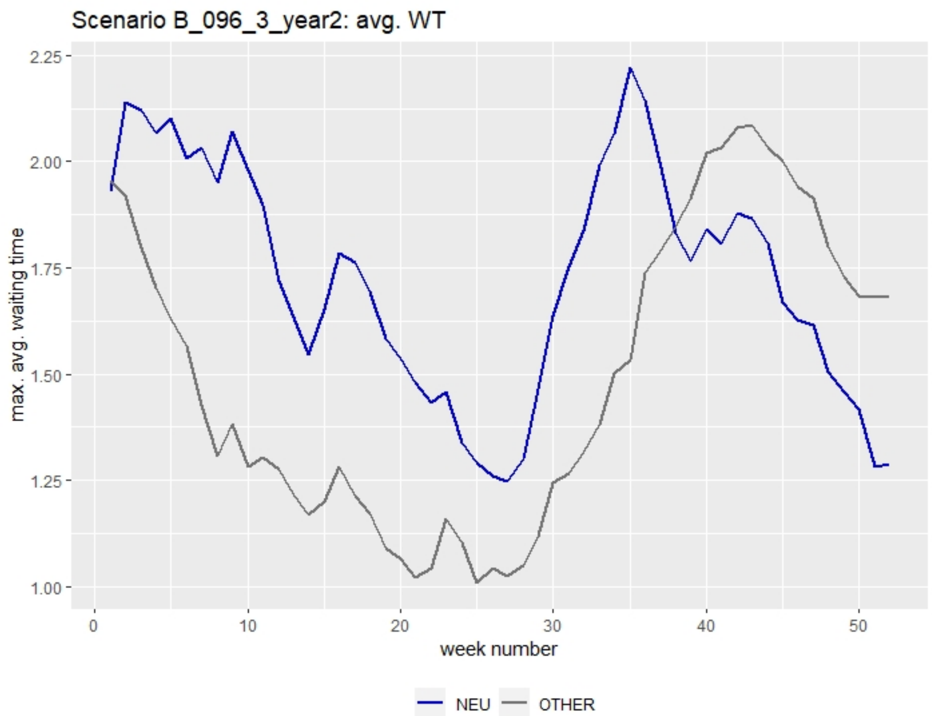

Figure 37: Plot of average waiting times for the second year in scenario B-096-3 with a warm up period of one year.

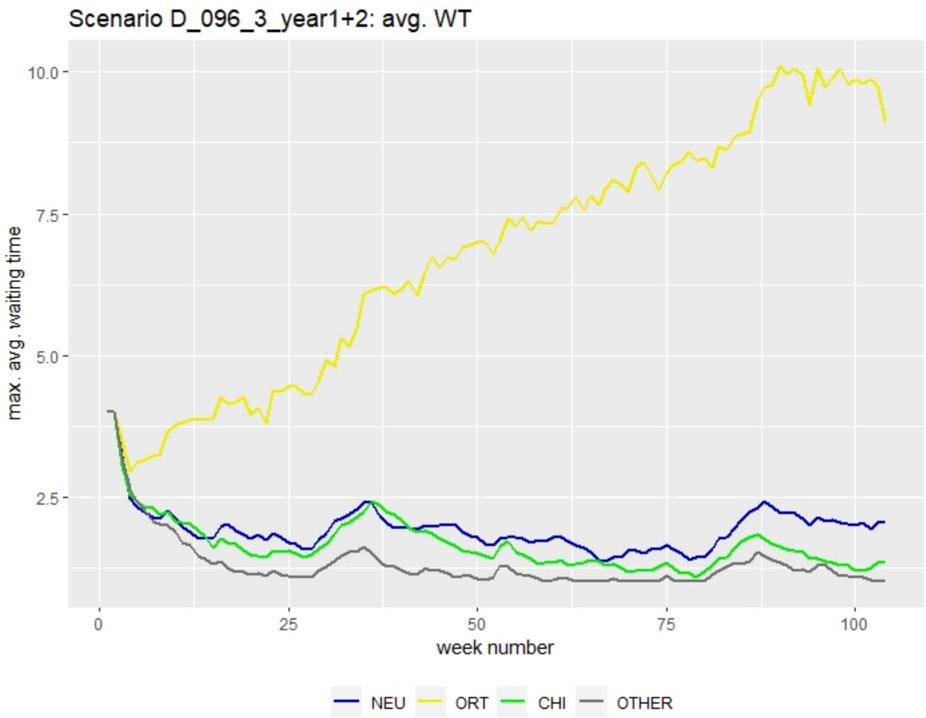

Figure 38: Plot of average waiting times for two years in scenario D-096-3 with a warm up period of one year.

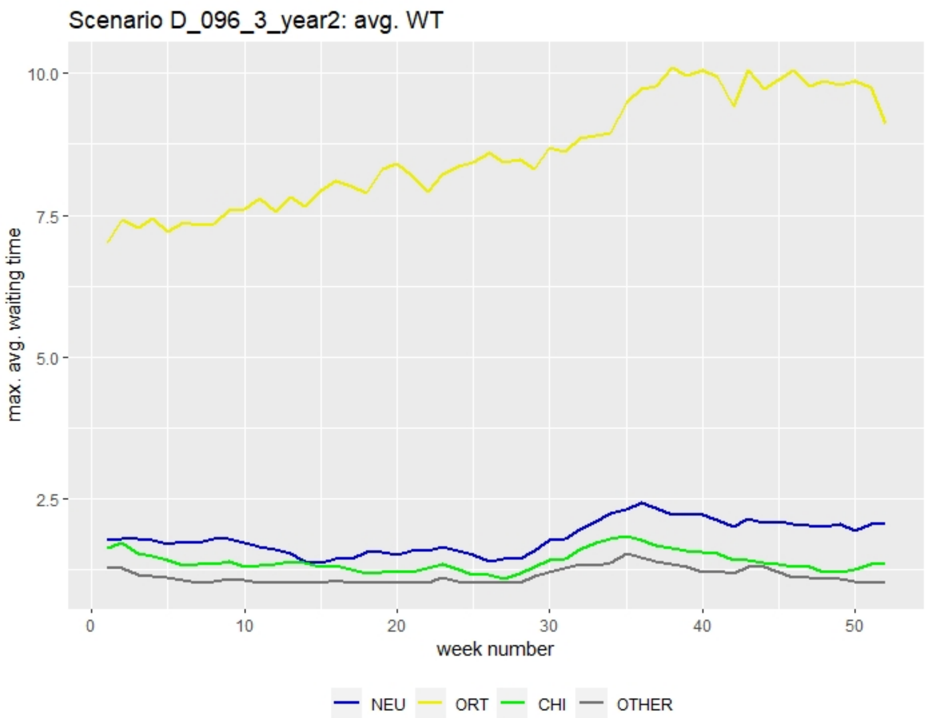

Figure 39: Plot of average waiting times for the second year in scenario D-096-3 with a warm up period of one year.

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