A CURE FOR THE QUEUE

Scenario based optimization at ZGT's radiology department

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Management summary

Introduction

This research took place at hospital ZGT Almelo and Hengelo in the Netherlands. We focused on the queues and overtime for the X-ray devices, named Buckys, on the radiology department of both ZGT locations. Both locations have 3 Bucky rooms, out of which 2 are in use for regular purposes and 1 for emergencies. We focused on the ones for regular use. Radiology is a so-called shared resource, which means they are used by nearly all departments in the hospital. Also, external patients, sent by their General Practitioner, visit the Bucky rooms. On the average, respectively 186 and 168 patients visit the Bucky rooms in Almelo and Hengelo per day. Capacity at each location is about 200 per day. Currently, most patients are scheduled: They have an appointment, often prior to an appointment with a specialist. About 25% of the patients arrive unscheduled on a Walk-in basis.

Problem description

Although demand does not exceed capacity on most days, ZGT has recognized a problem in their work pressure during the day. Many patients are scheduled during "peak hours", which are also the times most unscheduled patients arrive. The results are fluctuations in demand, such that capacity does not meet demand on the related time intervals. Consequently, employees experience a high work pressure at these times, while at other times the visit rate at the Buckys is very low. This means that there is both over- and underutilization. To summarize, the fluctuating demands are a nuisance for both employees and patients. The results are work pressure, long waiting times and working in overtime.

Research objective

In this research we wanted to achieve 2 goals: First, we wanted to gain insight in the source of unbalanced work pressure. Second, we wanted to improve this situation using a tailored planning solution. We answer the corresponding research question *How can ZGT improve the planning system in order to balance the work pressure at radiology?*

Approach

We found in the literature that variability in inflow is often the cause of a congested system. A congested system results into queues, waiting times and, in our case, work pressure. Therefore, we tried to reduce variability in inflow by developing a tailored planning solution.

We developed a day scheme in which we take both the number of patients that require an appointment and the pattern of arrivals of walk-in patients into consideration. The scheme shows how many patients can be scheduled per time interval of 30 minutes and how many slots need to remain open for unscheduled patients. It differs per day of the week but is the same throughout the year.

To come to this result, we made a mathematical model. For the input we determined the number of patients that require an appointment per day based on averages from historic data. The same applies for unscheduled patients, but for each time slot of 30 minutes per day. With this information we made 50 scenarios for each day of the week for each location to make the output more robust. These scenarios represent the different arrival patterns that can occur for a given day.

We made the schemes with use of an Integer Linear Programming model. For our model, we wanted to minimizing queue lengths and overtime per time interval. With the optimization software program AIMMS and solver CPLEX we developed the scheme per day and location. We also modelled the current situation to determine the performance and as the hospital wants to know the performance of a system in which all patients arrive unscheduled, we also modelled this.

Conclusion and recommendations

We modelled 3 settings: The initial design (current situation), the walk-in design and an ILP-design and determined the values for Work pressure and Overtime. We show the results in Table 1 and 2. We found that the Walk-in design performance is outperformed on each day, each location on both Work pressure and overtime by the initial design and the solution design. The performance of the solution design was best: The overtime is reduced for each day on both locations. Work pressure is also reduced for each day on both locations, except for Mondays in Almelo. We have 2 explanations for this: One cause for this is the reduction of overtime, which is compensated during the day. Also, in the initial design not all patients that arrived, were treated because the arrival pattern was uneven, such that demand did not fit within the available supply capacity. So, although the queue length is shorter in the initial design, the performance is worse because the initial design does not meet our basic requirements: Every patient should be treated. The solution design satisfies all our criteria: No patient deferrals, no untreated patients and a reduction of overtime and work pressure. Therefore, the practical value of this study is significant since it enables less work pressure for the employees at radiology, less waiting time for patients and a better overall flow through the hospital. This is relevant because the performance of the radiology department is of great importance for the process flow in the entire hospital. We also gained insight into the causes of the work pressure at the department, which can be of use for implementations in the future.

We therefore recommend using the scheme as shown in Table 6.2 and Table 6.3. Note that this scheme is tuned for the current settings of the system and needs to be revised in case one of the input parameters change. Example are a change in total arrivals, arrival patterns or the division ratio of scheduled and unscheduled patients.

Last, we want to emphasize the value for science of this study. We did a case study with a scenario-based optimization model. We developed this model for an actual case, and we tested this model with real life data. Because the model results turned out to be an effective method to solve the problem, the implementation will be done in the nearby future.

Table 1. Model results. Overtime in minutes

		Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Hengelo	Initial design	59	6	0	1	1
	Walk in design	69	44	2	2	3
	Solution design	15	3	0	0	0
Almelo	Initial design	148	52	52	12	9
	Walk in design	149	96	86	17	13
	Solution design	108	9	5	2	2

Table 2. Average Work pressure per time slot: Patients that are a surplus to the capacity

		Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Hengelo	Initial design	6	3	0	4	1
	Walk-in design	8	5	1	6	2
	Solution design	2	1	0	0	0
Almelo	Initial design	5	1	1	1	1
	Walk in design	17	5	7	6	2
	Solution design	7	1	1	1	0

Management samenvatting

Introductie

De twee locaties van Ziekenhuis Groep Twente leveren gezamenlijk jaarlijks aan ongeveer 250.000 patiënten zorg. Dit onderzoek richtte zich op de wachtrijen en overwerktijden op de röntgenafdeling van beide ZGT-locaties. De röntgenapparaten, genaamd Buckys, worden voor regulier gebruik ingezet. Daarnaast hebben beide locaties een apparaat op de spoedeisende hulp. Voor dit onderzoek hebben we ons gericht op de reguliere Buckys. Gemiddeld bezoeken respectievelijk 186 en 168 patiënten per dag de reguliere Buckys in Almelo en Hengelo. De capaciteit op beide locaties is gelijk en is maximaal 200 patiënten per dag. Momenteel krijgen de meeste patiënten een afspraak. Vaak is dit voorafgaand aan een afspraak bij een medisch specialist. Ongeveer 25% van alle patiënten bezoeken de Buckys op zogenaamde inloop basis, zonder afspraak.

Probleembeschrijving

Het aantal patiënten dat de Buckys per dag bezoekt komt vaak niet boven de maximale capaciteit van 200 uit. Toch ervaart het personeel op de afdeling een probleem in de werkdruk. Veel patiënten hebben een afspraak tijdens piekuren waardoor de vraag niet meer overeenkomt met de capaciteit die zowel machines als personeel aan kunnen. Als gevolg daarvan zijn er meer patiënten dan er verwerkt kunnen worden, terwijl op andere tijdsintervallen de vraag dusdanig laag ligt dat er weinig werk is. Er is dus sprake van zowel onderbenutting als over benutting. De werkdruk varieert hierdoor, wat hinderlijk is voor zowel personeel als patiënten. De resultaten hiervan zijn ongelijkmatige werkdruk, wachttijden en overwerken.

Onderzoeksdoel

We wilden 2 doelen behalen: Het verkrijgen van inzicht in de oorzaak van de ongebalanceerde werkdruk en het verbeteren ervan met een op maat gemaakt planningsysteem.

Aanpak

In de literatuur staat beschreven dat variabiliteit in de instroom vaak de oorzaak is van een overbelast systeem. Een overbelast systeem resulteert in wachtrijen, wachttijden en in ons geval, werkdruk. Om die reden gingen we op naar een planningsysteem dat variabiliteit in de instroom kan verminderen.

We ontwikkelden een dagschema waarin zowel het aantal patiënten dat een afspraak nodig heeft als het inloop patroon van de ongeplande patiënten overwogen werd. Het schema laat zien hoeveel patiënten er per tijdsinterval van 30 minuten ingepland moeten worden en hoeveel plekken er daarmee overblijven voor ongeplande patiënten. Het schema is op maat gemaakt voor elke dag van de week voor beide locaties en is hetzelfde gedurende het hele jaar.

Voor de ontwikkeling van dit schema maakten we een wiskundig model. Met behulp van historische data bepaalden we gemiddelde het aantal patiënten dat een afspraak behoeft per dag. Voor de ongeplande patiënten deden we hetzelfde, maar deze werden per half uur bepaald om het aankomst patroon zoveel mogelijk te benaderen. Met deze aantallen per half uur maakten we 50 scenario's die ons helpen om de werkelijkheid na te bootsen: Het gebruik van scenario's maakt het schema robuuster.

Het schema is gemaakt met behulp van Integer Linear Programming. In het model minimaliseerden we de hoeveelheid overwerk en de lengte van de wachtrijen. Hiervoor gebruikten we optimalisatieprogramma AIMMS en de solver CPLEX.

Om de resultaten te kunnen vergelijken modelleerden we tevens de huidige situatie. Daarnaast overweegt het ziekenhuis om volledig af te stappen van het gebruik van afspraken en alle patiënten op inloop te laten komen. Daarom modelleerden we ook een inloop situatie.

Conclusie en aanbevelingen

De resultaten van het modelleren van de drie situaties zoals eerder beschreven zijn te vinden in Tabel 3 en Tabel 4. We zien dat de resultaten voor de inloop situatie worden overtroffen door die van de huidige situatie en het model. De prestaties van het geoptimaliseerde model waren het best: werkdruk is voor elke dag gereduceerd. Een uitzondering hierop is de maandag in Almelo, waarvoor we twee verklaringen hebben: ten eerste neemt overwerk af, wat betekent dat meer patiënten overdag behandeld worden. Dit gaat ten koste van het aantal mensen per half uur in het systeem. Omdat de vermindering van overwerk vanwege praktische redeneren meer toegevoegde waarde heeft ten opzichte van de werkdruk gedurende dag, is dit een goede ontwikkeling. Daarnaast werden in de huidige situatie niet alle patiënten behandeld omdat er meer patiënten dan capaciteit is. Volgens de voorwaarden van het systeem het niet mogelijk is om deze patiënten allemaal te verwerken. In de praktijk wordt dit vaak opgelost door harder te werken, waardoor het aantal patiënten dat niet binnen de capaciteit past tot nul gereduceerd wordt.

De oplossing van het model voldoet aan al onze eisen: er worden geen patiënten afgewezen, er worden geen patiënten onbehandeld gelaten en het verminderd overwerk en werkdruk. Dit geeft veel praktische waarde voor het ziekenhuis: minder wachttijden, minder werkdruk en een betere doorstroom door het hele ziekenhuis. Omdat veel diagnostiek en behandelplannen beginnen bij de radiologie is dit erg relevant voor het ziekenhuis in zijn geheel. Tevens verkregen we inzicht in de oorzaken van werkdruk op de afdelingen, wat van belang kan zijn voor verder onderzoek naar dit onderwerp.

Omdat het door het model ontwikkelde schema werkdruk en overwerk reduceert, bevelen we aan om dit schema te implementeren voor de planning op de Buckys. Het schema is te zien in Tabel 6.2 en 6.3. Merk op dat dit schema volledig is toegespitst op de huidige omgeving bij de Buckys. Het dient aangepast te worden als er sprake is van een verandering in de invoerparameters. Dit kan bijvoorbeeld een verandering zijn in het totale aantal patiënten dat de afdeling bezoekt, maar ook een verandering in de ratio geplande en ongeplande patiënten of een verschuiving van pauzetijden.

Tabel 3. Model resultaten. Overwerk in minuten

		Maandag	Dinsdag	Woensdag	Donderdag	Vrijdag
Hengelo	Huidige situatie	59	6	0	1	1
	Inloop	69	44	2	2	3
	Model	15	3	0	0	0
Almelo	Huidige situatie	148	52	52	12	9
	Inloop	149	96	86	17	13
	Model	108	9	5	2	2

Tabel 4. Gemiddelde werkdruk per tijdsslot: Het overschot aan patiënten gegeven de capaciteit

		Maandag	Dinsdag	Woensdag	Donderdag	Vrijdag
Hengelo	Huidige situatie	6	3	0	4	1
	Inloop	8	5	1	6	2
	Model	2	1	0	0	0
Almelo	Huidige situatie	5	1	1	1	1
	Inloop	17	5	7	6	2
	Model	7	1	1	1	0

Voorwoord

Afgelopen maanden heb ik met veel plezier aan deze opdracht voor de ZGT gewerkt. Met het afsluiten ervan, op 27 juli 2018, heb ik de eer mijn master titel te behalen. Iets waar ik erg trots op ben en wat me erg blij maakt.

Zoals Christopher McCandless (aka Alexander Supertramp) ooit schreef, “Happiness only real when shared” wil ik graag die vreugde delen met alle fijne mensen om me heen en hen bedanken voor hun aandeel in mijn afstuderen.

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Cynthia Bergsma
25-07-2018

List of abbreviations

Abbreviation	Definition
ZGT	ZiekenhuisGroep Twente
OR	Operation Room
OC	Outpatient Clinic
ED	Emergency Department
GP	General Practitioner

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Chapter 1

1. Introduction

Over the last decades, hospitals paid more attention to efficiency in healthcare. Costs for healthcare per capita are increasing (CBS, 2015) and healthcare insurances are tightening the budgets. Therefore, hospitals try to find ways to still deliver high quality healthcare but also to fit within the cost scheme. Hospital ZiekenhuisGroep Twente (ZGT) in Hengelo and Almelo in the Netherlands experiences this tendency in everyday business. This research is about the radiology department of ZGT which experiences some problems concerning the work pressure in the X-ray department. This first chapter provides background information on this problem. First, we give some background information on ZGT in Section 1.1. Section 1.2 gives a description of the problem. Section 1.3 provides the objectives of this study, together with the research questions.

1.1. Context description

This section describes the hospital under study. Moreover, the particular department of research is explained. Section 1.1.1 describes the Hospital as a whole and Section 1.1.2 focuses on the department of this study: radiology.

1.1.1. ZGT

ZiekenhuisGroep Twente was established in 1998 when 2 hospitals were united into ZGT: the Twenteborg Hospital and Streekziekenhuis Midden-Twente ("Ziekenhuis Groep Twente," 2017). ZGT provides healthcare in 2 general hospitals, one in Almelo and one in Hengelo. Next to these general hospitals there are outpatient clinics in Goor, Geesteren, Nijverdal, Rijssen and Westerhaar (ZGT, 2018). ZGT has 220 medical specialists and 3200 employees (ZGT, 2018). Together, they treat 250.000 patients on a yearly basis. ZGT has 687 beds in total (ZGT, 2018).

ZGT made 7 promises to their patients to reach their objective to be a professional hospital. Those 7 promises are: being hospitable, respectful, competent, inspirational, trustworthy and effective, and lastly to give patients self-direction within the hospital (ZGT, 2018). To summarize, ZGT wants to create an environment that is pleasant for patients. Although these promises are part of ZGT's vision named "ZGT 2020", the hospital has endured some struggles in 2017 (ZGT, 2018). In June, the hospital announced that they have to economize € 15 million (Brok, 2017). With a turnover of € 333.8 million, this is about 4.5% of their total revenues ("ZGT Jaardocument," 2016). These financial cuts influence how the hospital acts nowadays and how they should handle their resources.

Within ZGT, there are several departments ((outpatient) clinics) that treat patients, such as cardiology, Ear-Nose-Throat and orthopaedics. Next to those are the departments that do not treat patients themselves but rather have a supportive function, such as radiology, the pharmacy and the operating rooms (ORs). Those are the shared departments within the hospital that are used by nearly all Outpatient Clinics (OCs)

1.1.2. Radiology

This study focuses on the radiology department. ZGT has a radiology department in both the hospitals in Almelo and Hengelo. Those are important resources within the hospital because nearly every (outpatient) clinic shares its use. The radiology department is fundamental when it comes to detecting and diagnosing a broad spectrum of diseases and disorders. Radiology is also fundamental for monitoring the progression of treatments. Although the resources of radiology are shared, it is a department on its own with its own planning system, employees and finances.

The type of radiation usually applied is X-radiation (X-rays or CT-scans), but also sound waves (ultrasound) and magnetic fields (MRI) are often used. The frequency of use of these devices is significant: in 2015 more than 1.5 million CT-scans and about 8.6 million X-rays were made in the Netherlands (Rijksinstituut voor Volksgezondheid en Milieu, 2018b, 2018a). During this study, the focus lies on X-rays. Both Hengelo and Almelo have 3 X-ray rooms; B2 and B3 (Almelo) and B5 and B6 (Hengelo) and a Bucky room at the emergency department (ED). Within these names, B stands for Bucky, the name of the X-ray device.

The performance of the radiology department is of great importance for the process flow in the entire hospital. They play a central role to healthcare pathways for they are significant in diagnostics. Delay in diagnostics and check-ups mean delay in the progress of treatments. Therefore, access to radiology should be smooth and waiting times for access to diagnose cannot exceed 4 weeks, according to the Treeknormen as defined by the Ministry of Health, Welfare and Sports (Ministerie van Volksgezondheid, Welzijn en Sport, 2014). ZGT wants to welcome their patients at radiology earlier than those 4 weeks. Their norm for access time is within 10 working days (2 weeks), but in general they provide access to their Bucky rooms in 2 working days ("Dashboard coördinatoren jan 2018," 2018).

1.2. Problem description

ZGT has noted that the number of visitors on the Bucky rooms highly fluctuates during the day. Demand, in terms of patients that come in, varies during the day between locations. Demand also varies between days of the week.

A single Bucky room has a maximum capacity of about 100 patients per day during office times. On the average, about 345 patients visit the Bucky rooms per day for both hospitals (data from 01-01-2017 until 31-12-2017). Evenly spread over a working day of 8 hours, this is a reasonable number. However, many patients arrive during "peak hours" and employees experience a high work pressure at some intervals during the day, while at other times the visit ratio at the Buckys is very low. This means that there is both over- and underutilization. Consequently, fluctuating demand at the radiology departments is a nuisance for both employees and patients. Having an appointment at a peak moment can lead to a waiting time of 30 minutes for patients. In the meantime, the employees must deal with the increasing impatience of the patients in the waiting room. As told by employees: "during the morning, around 8:00 until 9:00, the workflow is smooth. Around 9:00 to 10:00, a lot of visitors come in at once. So, when I go get a patient out of the waiting room around 11:00, I see a lot of people. They are looking at me, they have no place to sit because all chairs are occupied, and I can feel their frustration".

To solve this problem, ZGT already did an intervention. On the first of October 2017 they started a pilot with their orthopaedic patients. They cover 25% of all inflow at radiology. These patients can walk in at radiology without making an appointment. Section 2.1.2 gives a more detailed explanation about this pilot. With this intervention, ZGT aims to reduce the work pressure during peak hours. As told by employees, there is no significant difference in work pressure experienced yet.

In general, the hospital states that the work pressure on the radiology department is out of balance. With this study, ZGT wants to gain insight regarding the factors that cause the unbalanced work pressure at the radiology departments. Furthermore, ZGT wants to intervene on these causes such that the demand (in terms of X-ray requests), and supply (in terms of available resources that are available to handle demand) are more harmonized.

1.3. Objective and research questions

From the problem description in the previous section, the objectives for this problem are formulated in Section 1.3.1 and the research questions that support the realization of these objectives in Section 1.3.2.

1.3.1. Research objective

The research objective is twofold: First, we aim to gain insight in the origin of unbalanced work pressure at radiology. Second, we want to improve this situation using a tailored planning solution.

1.3.2. Research questions

By answering the following research question, the research objectives are realized:

How can ZGT improve the planning system in order to balance the work pressure at radiology?

To answer this question, we formulated 7 sub questions.

1. *What is the current situation at radiology?*
   1.1. *How does the department work and what are its resources?*
   1.2. *What does the process flow of radiology look like?*
   1.3. *What does the care pathway of patients look like?*
2. *What are influencing factors on the unbalanced work pressure?*
   2.1. *What does the problem bundle look like?*
3. *What are KPIs for the radiology department, and how do they perform?*

Chapter 2 analyses the current way of working at radiology. Question 1 gains insight into its processes. An overview of processes will be the result, which helps us to understand what influencing factors might be. Question 2 summarizes current challenges at the department. Question 3 determines the performance at radiology. The data gathering methods are data analysis, interviews and observational studies. In practice this means talking to radiology employees and joining them during their work such that on the spot observations can be made.

4. *What is known in the literature about planning systems on radiology departments?*
   4.1. *What is known about the effects of variability in inflow on shared resources in a hospital?*
   4.2. *What planning systems/interventions are suitable for radiology departments at hospitals?*

Chapter 3 provides theoretical background information by doing a literature study. As we already identified variability in the inflow processes at the department, Question 4.1. focuses on the effects this might cause. Question 4.2. gives an overview of planning systems that are used in other hospitals or that are otherwise applicable.

5. *How can the radiology processes be modelled?*

Chapter 4 provides a model of the radiology department. It also contains the interventions that are to be executed by the model to compare with the current situation. This shows us how the processes at radiology can be represented by a model.

6. *What are the results of the executed experiments?*

Chapter 5 provides the results of the model. A comparison between the current situation and the results of the experiments as given by the model, is described.

7. *What is the conclusion of this study, and what are the recommendations for radiology at ZGT?*

Chapter 6 gives an overall conclusion of the study. Furthermore, we give some recommendations for ZGT to improve the problem as described in Section 1.2.

Chapter 2

2. Context analysis

Chapter 1 introduced the problems experienced at ZGT's radiology. In summary, this problem comes down to a fluctuating work pressure at the Bucky department.

To solve the problem, we first gain insight in the problem by defining its causes, how the system currently performs and what performance degree is desired to improve the situation. In this chapter we identify all relevant aspects of the Bucky rooms and the radiology department in Section *2.1 System description.* We continue with a description of the flows at the department: - the inflow, process flow and arrivals process in section *2.2* System flows.

A common way to measure performance is to use Key Performance Indicators (KPIs), which we will use in Section *2.3.* System performance*.* First, we summarize all potential influencing aspects from the previous sections of this chapter. These aspects are translated to KPIs. When defining our KPIs, we keep in mind the stakeholders of our study: Patients, employees and system holders such as the management of ZGT. Our stakeholders are interested in the performance of our KPIs. In Section 2.3. we also scan all KPIs for suitability and feasibility within this study. Afterwards, we show the KPIs that are the most useful and feasible and that are therefore included in this study. Next, the current performance of these KPIs is also described. Lastly in Section 2.3, we make an overview of the problem by summarizing all influencing aspects into a problem bundle.

This chapter concludes in Section 2.4 by answering the first three research questions *"What is the current situation at radiology?", "What are influencing factors on the unbalanced work pressure?"* and *"What are KPIs for the radiology department, and how do they perform?".*

2.1. System description

This section describes the radiology department, and the Bucky rooms in particular. Radiology in ZGT has equipment to do X-ray-, ultrasound-, Computer Tomography (CT)-, Magnetic Resonance Imaging (MRI)-, mammography-, angiography-, contrast- and bone density (Dexascan) examinations. This study concerns both ZGT locations that both have their own front desks with planners.

First, we explain the resources in Section 2.1.1, namely the Buckys, employees and other properties of the department. Section 2.1.2 gives insight into the planning and control within radiology: Appointment scheduling, types of examinations, the duration of examinations and causes for exceedance of the planned duration of examinations.

We start with an overview of the total capacity of resources and processes, as shown in Table 2.1.

Table 2.1. Radiology capacity

Description	Number
Radiology technicians	108
Radiologists	17 (+ 3 in training)
Front desks	2
Buckys	6
Buckys for general use	4
Types of examinations	145

2.1.1. Resources

In this section we discuss the resources that are related to our problem, which are the Bucky rooms, the employees and the ICT system of the hospital.

Bucky rooms

ZGT has 3 rooms with an X-ray device named Bucky both in Hengelo and Almelo, which makes a total of 6 Bucky rooms. All 6 rooms are fully equipped such that all kinds of examinations can be performed. Table 2.2 displays the characteristics of ZGT's Bucky rooms.

Table 2.2. Characteristics of the Bucky rooms in ZGT

Room	Location	Use
B0	Almelo	Emergencies, 24/7
B2	Almelo	General
B3	Almelo	General
B9	Hengelo	Emergencies, 24/7
B5	Hengelo	General
B6	Hengelo	General

We focus on the general use of the Bucky rooms, so B2, B3, B5 and B6. In this report these rooms are named "Bucky room", "room", "Bucky" or its plural form. In case of referring to an emergency Bucky room, this will be explicitly stated, as we do not consider the emergency Bucky rooms B0 and B9 in this study.

Every weekday from 7:30 until 17:00 the general Bucky rooms are operational. Outside these times patients only come in for emergencies on B0 and B9. The general rooms are occasionally used outside office hours in cases such as a machine breakdown at the emergency department.

In Almelo, both rooms have their own waiting area. Figure 8.1 in the Appendix shows a map of the radiology department in Almelo. In Hengelo, both Bucky rooms use the same waiting room. Figure 8.2 in the Appendix shows the map of the radiology department in Hengelo. All Bucky rooms have 3 adjacent dressing rooms.

Employees

For every room, 2 employees are scheduled. These are radiology technicians ("laboranten") and they handle all patients who need an X-ray. Most technicians at radiology are specialized into a certain type of scan, e.g. MRI scans. All radiology employees work at the Bucky, despite their specialization.

Next to the 2 scheduled employees on each Bucky room, 2 radiology technicians are planned in a shift called circuit ("Omloop"). They handle all kinds of tasks that are not scheduled in the general planning. They also step in in case a radiology technician is required at an operation room. Radiology further consists of a daily team of 8 radiologists that make reports of each X-ray. These reports are used by doctors to plan further diagnostics and treatment. The report is made in ZGT's general ICT system named HiX (see the next section).

From 7:30 to 8:00, only 1 employee is available because the hospital wants to offer the possibility to visit the Buckys early before the consultation hours of OCs start. The same principle account after 16:30; only 1 employee is available. Generally, the shifts are over at 16:30, but in case there are patients left, they still will be treated. No patients are scheduled after 16:20. The 10 minutes remaining from 16:20 until 16:30 are preferably used for cleaning or processing some patients that are still in the waiting room. In practice, this is not often the case, so work continues after 16:30.

HiX

HiX contains all patient information, such as appointments, diagnosis and treatments. Employees of the Bucky rooms have access to HiX in which they work with a list of appointments of the current day. A separate list of patients that are already in the waiting rooms is also available. These patients are listed as “present”.

2.1.2. Planning and control of patients and resources

In this section we describe the examinations on the Buckys and their durations. We also describe patient lateness and we give some insight into the current appointment system.

As ZGT strives to be as patient friendly as possible, they handle a few rules and guidelines for planning and control of patients at the department.

1. Treat every patient: Each patient that comes to the desk gets an appointment at time of arrival. These patients are considered as walk-in patients, also known as unscheduled patients.
2. Working overtime: In case of patients left to treat at the end of the day, working overtime is preferred over rejecting or sending away patients untreated. This is avoided as much as possible.
3. Self-direction of patients: Facilitating as much ownership in the process of treatment as possible. This means patients have influence in for example their appointment time. ZGT considers applying the walk-in approach for all patients that need an X-ray.

Examinations and their duration

The process of taking an X-ray is called an examination. ZGT works with a standard duration for each type of examination. A total of 145 types of examinations can be executed on the Bucky. Every examination has a certain code, named indication or order. The indication is decided by the physician requesting the X-ray, i.e., the General Practitioner (GP).

The standard durations of examinations are mostly 5 minutes, as can be seen in Table 2.3. Table 2.3 shows the division of the different time slots the hospital uses for examinations upon the Bucky. An occurring problem is that often, if patients require more than 1 examination of 5 minutes on the Bucky, still 5 minutes are assigned (1 examination). This means for example; 3 examinations with a total required amount of time of 15 minutes, scheduled to be performed in 5 minutes. This causes schedule lateness.

Table 2.3. Time-slots and their occurrence on the average at the Bucky

Time-slot (minutes)	Percentage
5	93.4
10	6.4
15	0.1
20	0.0
30	0.0

Figure 2.1 shows the duration of appointments in minutes. The throughput time, waiting time and processing time mean respectively the total time spent at radiology from the desk until they leave, the time patients should wait until they are treated, and the time spent in the Bucky room (see also Figure 2.10. Care pathway of patients).

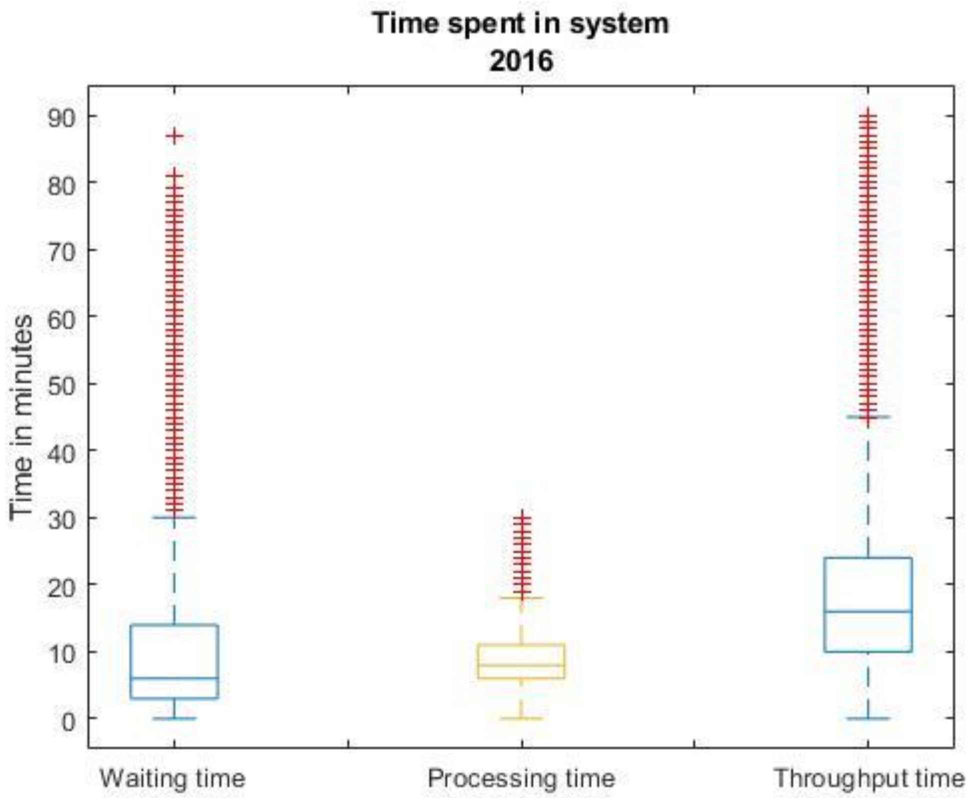

Figure 2.1. Throughput time, waiting time and processing time (n=79,747, data source: HiX, data from 2016)

Figure 2.1 shows that most processing times exceed the planned duration: The average and mean of processing time are both 8 minutes (n=79,747, Data Source HiX, data from 2016). This average should be approximately $(0.934 * 5 + 0.064 * 10 + 0.001 * 15 =)$ 5.325 minutes according to the frequency of occurrence of 5-10 and 15- minute time-slots.

Figure 2.1 shows that there are many outliers for waiting, throughput and processing times. Outliers for waiting times are included up to 90 minutes. These can be the actual waiting time, but as in the data also negative waiting times and waiting times over 12 hours are found, we assume that these outliers are some type of data inaccuracy. An explanation of one of the desk employees is that sometimes patients visit the desk before they go to another appointment and they are already marked as “present”.

We have 3 potential explanations for the outliers in processing and throughput times:

1. Bucky employees must select the patient in HiX, drag it to the “finished” list and then the system notes it as finished. Processing time, and therefore also Throughput time, can become longer in HiX than they are in reality because employees often not immediately mark the patient as “finished”, when they are finished.
2. Throughput time varies due to the patients that cannot leave radiology immediately. After the X-ray has been made, some patients must wait for the result of the X-ray in the waiting room. We explain more about this in Section 2.2 about the process flows.
3. It might be possible that the actual duration exceeds the planned duration. Because of the previously described data inefficiencies, we cannot draw conclusions on departure times. Therefore, outliers up to 90 minutes are included in Figure 2.1. Throughput time, waiting time and processing time (n=79,747, data source: HiX, data from 2016)because it might be possible that in several cases the processing or throughput time becomes large.

An explanation for processing times that are longer than the planned duration can be that radiology technicians are responsible for more than just making X-rays. They must take care of the complete process of patients from the moment they arrive in the waiting room until the end of the process. Being responsible for the complete process includes a few actions that can consume additional time:

- *Manually changing codes.* In case the indication in HiX is wrong, the radiology employee needs to manually change the description. Discovery of a wrong description happens mostly when the description does not fit with the complaints of the patient. Therefore, this is checked during the processing. Problems with indications, varying from no indications, wrong indications and incomplete indications happened 231 times in 2017. Beside these, 208 mistakes were made between left and right in 2017, i.e., a left-hand X-ray was requested when a right-hand X-ray was required.
- *Emergency department.* Employees are responsible for the transport of patients with a fracture to the Emergency department (ED) ("Spoedeisende Hulp"), hence, one of them must bring the patient. In Hengelo, the ED is quite close to radiology (approximated transport duration 5 minutes), but in Almelo this transport can take up to 10 minutes. This includes the way back to the department. The Bucky room is still operational in the meantime, but at a lower throughput rate. It is unknown how often this occurs.
- *Age.* The average and median age of the visitors of radiology are respectively 55 and 58 years. Some patients are not able to undress and dress themselves. This means the employees of radiology give the patient a helping hand. This interrupts the flow at the Bucky room and can be time consuming.

Lateness

With a schedule of more than 300 patients per day, lateness is part of daily business for planners. Patient (in)punctuality is known to impact the execution of an appointment schedule, and to cause schedule tardiness (Wachtel & Dexter, 2009). Patients that arrive too late for their appointment, get their new appointment time at the time of arrival, and therefore delay the subsequently planned patients.

Figure 2.2 shows the percentages of patients that arrive too early and late per day, and the number of minutes they are late. Earliness is displayed with a negative number of minutes. For patients that are neither early nor late (0 minutes) holds that they arrived 1) right on time or 2) they walked in (appointment time = arrival time) or 3) they arrived at the wrong location (appointment time = arrival time). Patients appearing at the wrong location happened 61 times in 2017.

Figure 2.2 shows that most patients arrive approximately on the right time, about 5 minutes early or late. Patients also arrive more than 45 minutes too late or early. This can be due to mistakes owing to patients (i.e. forgetting the appointment, traffic jams, etc), but also to planning errors made by the radiology or OC department or irregularities at the front desk of radiology.

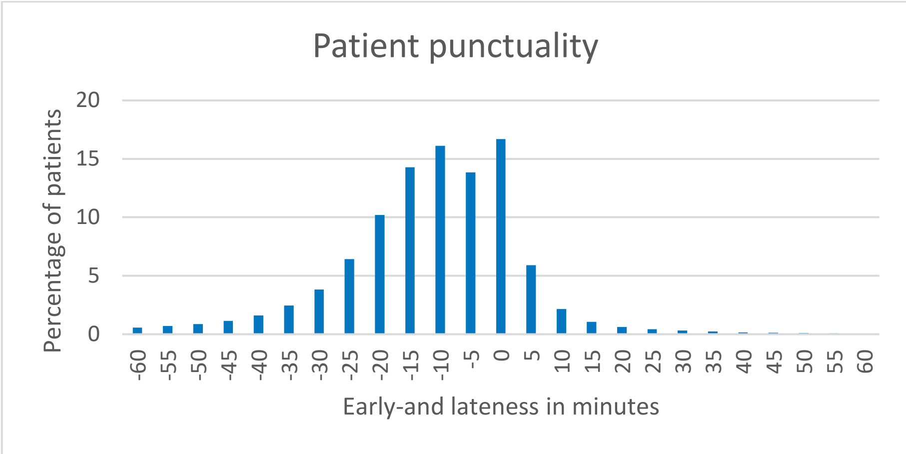

Figure 2.2. Patient punctuality in percentages (n=136325, data source: HiX, data from 2015 and 2016)

Appointment system

There are several options for patients to make an appointment at radiology:

1. They make an appointment online.
2. They call with radiology's front desk.
3. They drop by at the front desk.
4. The ward makes an appointment for the patient.

Option 1 is recently added due to the wish of ZGT to give patients the ability to have some control over their appointments. 0% of the patients used this feature in 2016. 40.5% of all patients make their appointment at radiology via the OC (option 4) or make an appointment themselves (option 2). The exact division of the remaining 59.5% over option 2 and 3 is unknown.

Until October 2017 all patients that visited the Bucky were scheduled. In order to improve the work pressure problem, a pilot was started at October first. All patients from the outpatient clinic Orthopaedics (25% of total inflow) can visit the Bucky without an appointment, in other words, can visit on a walk-in basis. Other patients are still scheduled.

Patients are treated based on appointment time. For an unscheduled patient the time of arrival applies as their appointment time. According to statements of employees, the pilot does not make any difference for the work pressure. This might be true, as can be seen in Figure 2.3, the arrivals of patients that participate in the pilot looks quite the same as the overall arrivals as shown in Figure 2.9 in Section 2.2.4.

As described earlier, ZGT wishes to give her patients more influence in the date and time of their appointments by letting them make their appointments online. They also consider giving all patients the option to visit radiology on a walk-in basis. The pilot of orthopaedics shows a few results already.

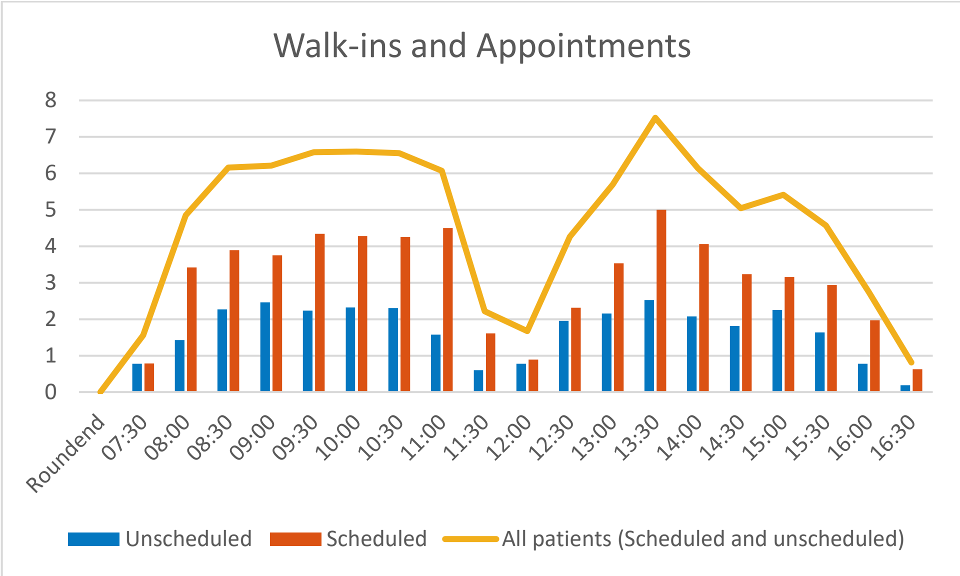

Figure 2.3. Number of walk-in patients from orthopaedics versus the scheduled patients per day (n=5833, Data source HiX, period October 2017-December 2017)

The pilot has several advantages, namely that receptionists at orthopaedics do not have to make appointments at radiology anymore. As told by a receptionist, this saves them a lot of time; Making an appointment includes several steps, taking 1 to 2 minutes on average per patient. To ease the visit for patients, they always try to combine the visit at radiology and orthopaedics (one-stop-shop). This means the appointment at radiology must be 30 minutes earlier than the appointment at orthopaedics. Because there is a limited number of time-slots available, this comes down to puzzling until an opening at both radiology and orthopaedics is found at appropriate times which also suits the patient.

In practice it comes down to the receptionists finding an opening at orthopaedics and making an appointment at radiology 30 minutes before that, regardless of availability. Over time, the puzzle of finding 2 openings changed into shifting the “problem” towards radiology by settling on an appointment and making radiology deal with it. We assume that other OCs handle their combined appointments in the same way. Patients must be at their successive appointment with their doctor on a specific time. In the hospital, this appointment is prioritised over radiology’s work. Therefore, radiology employees have to ensure the patient is not delayed.

2.2. System flows

In this section we describe the flows through radiology, starting with a basic description of the process at radiology in Section 2.2.1, followed by the inflow (2.2.2), which describes where patients come from. An explanation of all inflows is given. Subsequently, the care pathway and process flow of the department (2.2.3) are explained. We conclude with the arrival processes of patients in Section 2.2.4.

2.2.1. Primary process flow

The general process at radiology is shown in Figure 2.4, these are the steps taken by the different patient groups.

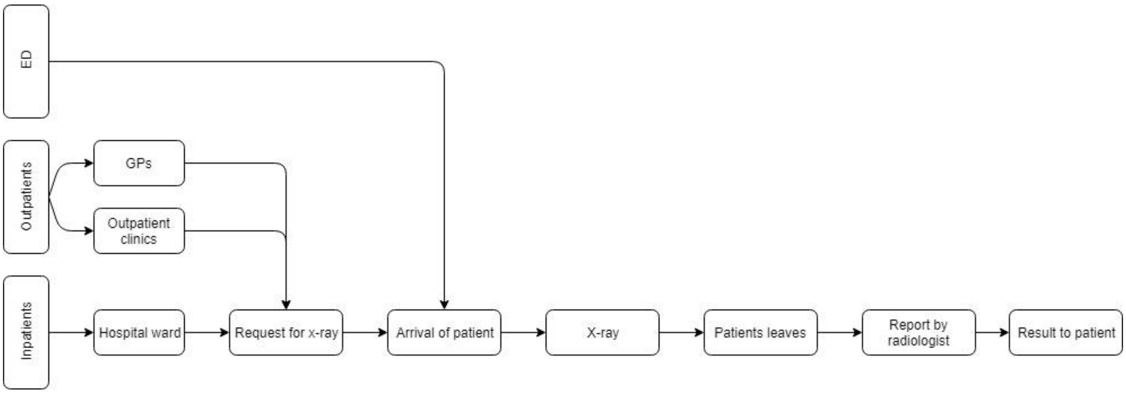

Figure 2.4. Primary process at radiology

2.2.2. Inflow

Patients are sent to the radiology department by 1) their general practitioner, 2) an (outpatient/day-care) clinic in the hospital, or 3) the emergency department. Figure 2.5 shows the flow of patients into the radiology department. We will continue this section by explaining all inflow streams.

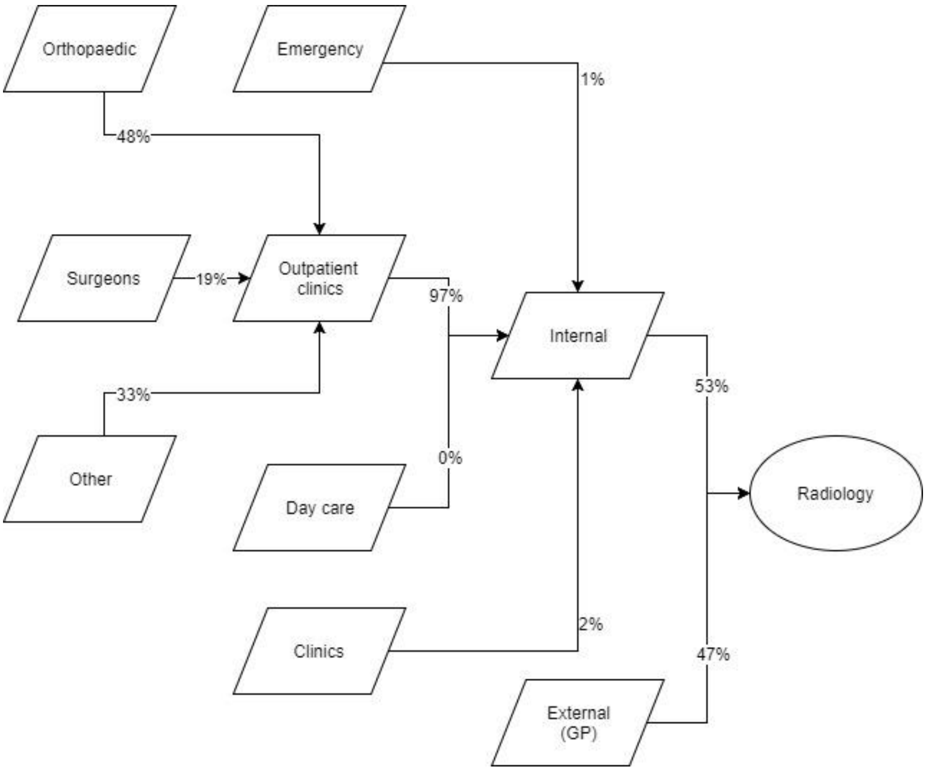

Figure 2.5. Patient inflow at radiology (n=149052, Data source HiX, period January 2015 - December 2016)

Emergency

Patients that visit the ED are not treated in the general Bucky rooms. However, some ED patients are found in the data, we assume this is due to unavailability of the emergency Bucky. This applies for 1% out of the internal referrals, so this input is considered negligible.

Outpatient Clinics

About 50% of the patients that visit radiology are sent by an outpatient clinic such as orthopaedics. Most patients get an appointment at radiology about 30 minutes before their appointment at the outpatient clinic (one-stop-shop). This means that if the OCs plan no appointments during a lunchbreak, the demand at radiology decreases too.

A relevant factor of patients having an appointment right after their Bucky visit is that there exists some time pressure for Bucky employees. In case processing times exceed 30 minutes, the result will be lateness through the complete hospital if patients appear too late at their next appointment.

Clinics

A clinical patient is hospitalized. An internal message indicates the need for an appointment for an X-ray for a hospitalized patient. If the appointment is within 30 minutes of the current time, the radiology department requests the ward to bring in the patient. If the appointment is in >30 minutes, the ward itself takes care of the patient being at radiology at the right time.

General practitioner

47% of all inputs are from the GP. These referrals are an important source of income, because those X-rays are not part of a DBC but can be directly invoiced to insurance companies. In general, patients make an appointment themselves after they received a referral letter for an X-ray. In case the GP marks the condition as an emergency, ZGT strives to help the patients within 1 hour.

Because most patients visit the GP after 8:00, the most likely time for them to come to radiology is starting from 9:00. Patients from the GP for which is suspected that they have a fracture are sent right away without making an appointment. This influences the work pressure and occurs deviation from the planning. This is shown in Figure 2.6, which shows the arrival times of patients during the day, together with their type of origin (GP, Orthopaedics or another OC).

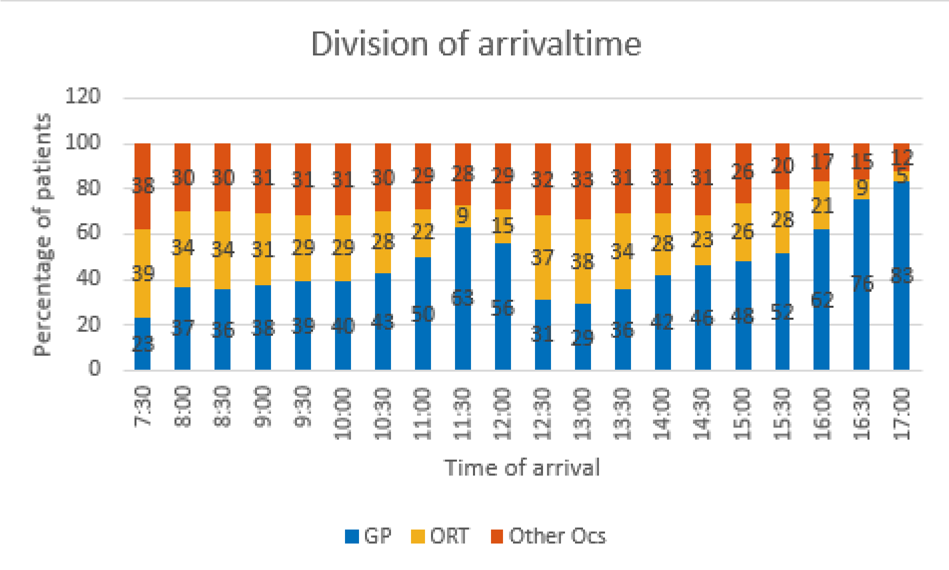

Figure 2.6. Division of arrival time at the Bucky (n=149052, Data source HiX, data from 2015 and 2016)

Figure 2.6 shows that the percentage of arrivals of specific patient types fluctuates during the day. With the OCs having lunchbreaks around 12:00, we see the percentage of GP patients increase. Also, the number of OC patients is high (67%) at 7:30 because OCs start their consultation schedule at 8:00. At 17:00 only 17% of the patients come from OCs, which is due to the end of the OCs consultation hours at 17:00.

2.2.3. Process flow

Figure 2.7 displays the actions of employees at radiology and the steps taken by patients. In this section, we describe the processes in this flowchart.

Once a patient is referred to radiology they make an appointment themselves or get an appointment via their ward. The patient arrives at the front desk and its time of arrival is registered into HiX. In case of an orthopaedic patient that is participating in the pilot the time of arrival is noted as both appointment time and time of arrival. The patient is "present" and can, from that moment on, be assigned to a specific Bucky room. The patient is sent to the waiting room.

When employees are ready, they assign a patient to their room. 1 out of the 2 technicians is working with the patient currently in the Bucky room, while the other assigns a new patient to their room and gets prepared for this patient. They do this by reading the indication and by summoning the patient to the dressing room. Assigning is done mostly randomly between the 2 rooms. The sequence of selection is based on appointment time.

Sometimes they prepare for more than 1 patient at a time and they might call 2 or even 3 patients out of the waiting room. Those patients can already get changed and prepared in 1 of the 3 dressing rooms. This is up to the employees and depends on personal preferences and circumstances. Therefore, this step is named "Bucky fully assigned?". There is no standard number of patients that should be in the dressing rooms. If the Bucky is fully occupied employees first handle the patients in the Bucky and dressing rooms. If the technicians are prepared for a new patient (Bucky fully assigned? → no), they sent 1, 2 or even 3 patients from the waiting room to the dressing rooms.

If the Bucky is empty, a patient enters the Bucky room and the X-ray is made. The X-ray is checked on correctness by the technicians. When everything went well, the patient is finished and can leave. The technicians mark the patient as "finished" in HiX and the X-ray will be analysed by a radiologist. Radiology technicians are not allowed to diagnose, but in case of an obvious fracture there is no need to wait for the radiologist to check the X-ray. The patient is taken to the ED, where the fracture will be treated. If the technicians suspect a fracture and this corresponds with the complaints of the patient, the patient is marked as "urgent". Being urgent means after the X-ray they are marked with a black box in the "Finished" list in the system. That way radiologists can see that those patients are waiting in the waiting room for results. The radiologists need to analyse these X-rays within 30 minutes. The Bucky employees should inform the patient of the diagnosis. In case of a fracture, they bring the patient to the ED.

After this process of finishing, the next patient from the dressing room is requested into the Bucky room. When the dressing room is empty, the process starts again and a patient from the waiting room is selected. If there are no more patients marked as "present", in other words there are no patients in the waiting room, the process starts again with the arrival of a patient.

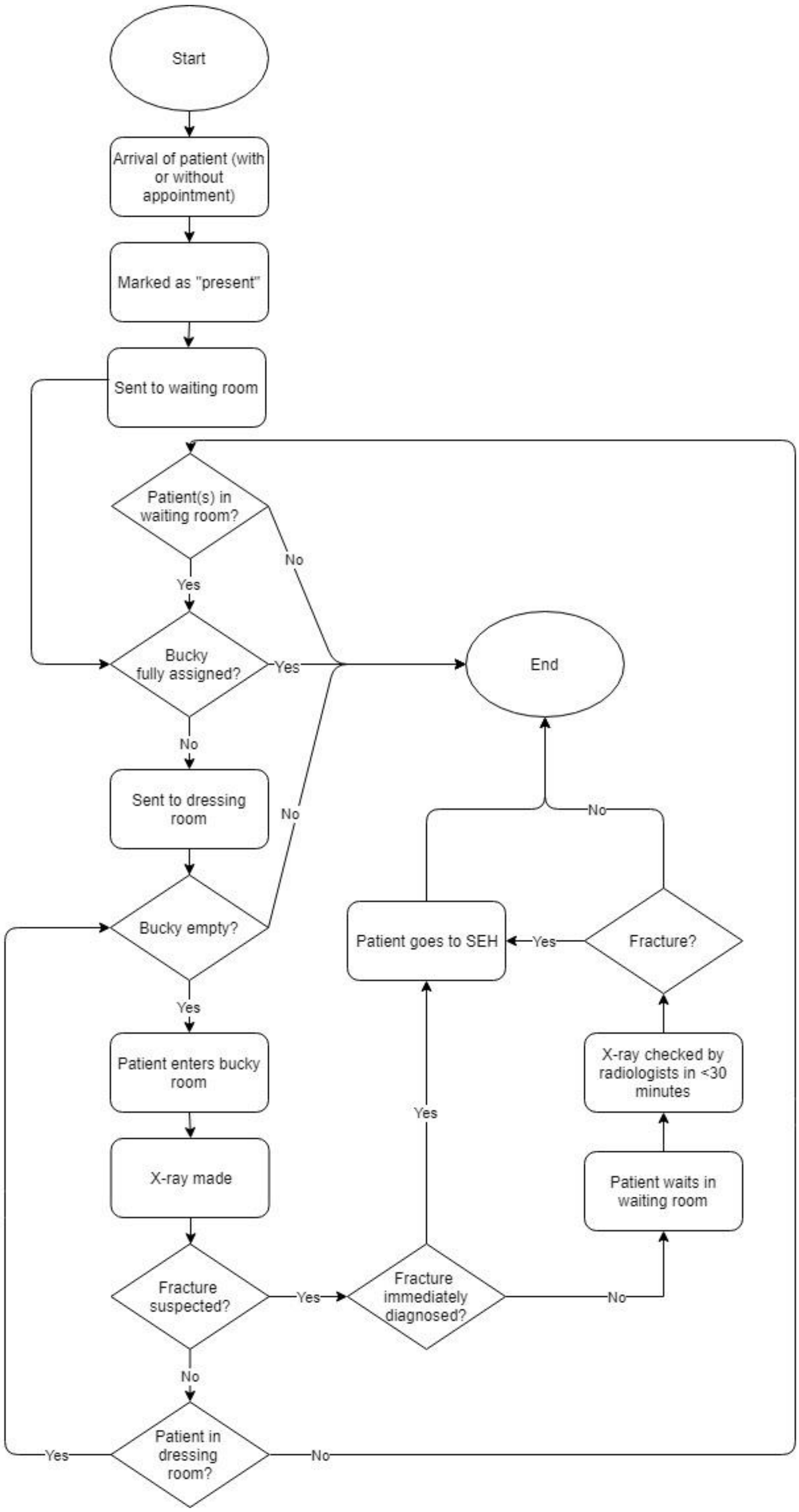

Figure 2.7. Total process flow at radiology

2.2.4. Arrival process

ZGT's 4 Bucky rooms treat an average of 333 patients per day. The number of patients treated at the Bucky rooms are also described as "demand" or "production" in this study. A total of 333 patients, means an average demand of 85 patients per Bucky room per day.

There are some differences between weekdays (Monday to Friday). Demand tends to be lower on Fridays compared to other days, whereas Thursdays have the highest variation in patient numbers per day. This is shown in Figure 2.8. Differences in arrivals between weekdays are often seen in hospitals. This might be relevant because variation in arrivals can influence variability in work pressure. There are also differences between both locations in terms of production per day, which is also shown in Figure 2.8. This can be explained by the fact that ZGT Almelo is slightly bigger than ZGT Hengelo. Also, ZGT Almelo serves inhabitants of a larger region than ZGT Hengelo as MST Enschede and MST Oldenzaal are relatively close to Hengelo.

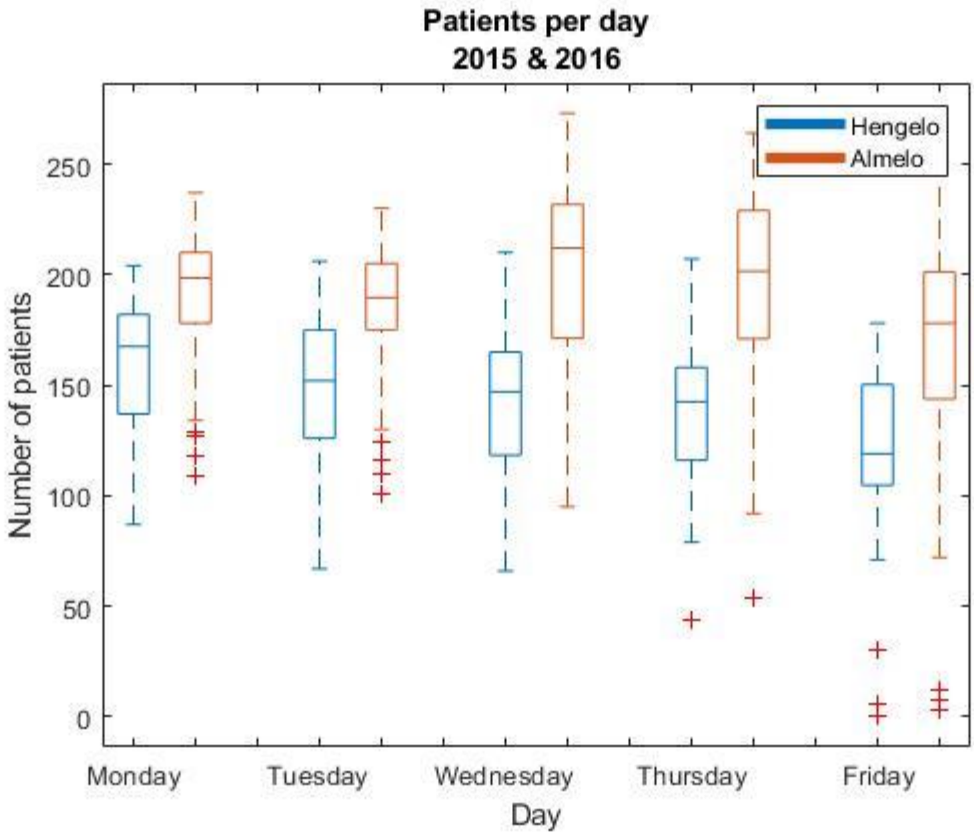

Figure 2.8. Boxplot on patients per week day. Differences between Almelo and Hengelo (n=149052, Data source HiX, period January 2015 - December 2016)

Next to variation between weekdays and location, ZGT also deals with disparity during the day. Figure 2.9 shows how many patients arrive on average on a certain time. The available number of employees is also plotted in Figure 2.9. As can be seen, on several times during the day, the average number of patients (demand) does not match with the available number of employees (supply). This is due to underutilization of the system on some time intervals during the day and overutilization on other intervals. This is as expected because this is how Bucky employees experience their working day.

Supply is calculated based on production numbers in historic data (2015 and 2016), and upon 2 employees per room, taking lunch and coffee breaks into consideration. During breaks, 2 out of 4 employees leave the Bucky room. The remaining employees split up and both handle a

Bucky room on their own. That way, both Bucky rooms are still operational, but at a slightly lower throughput rate.

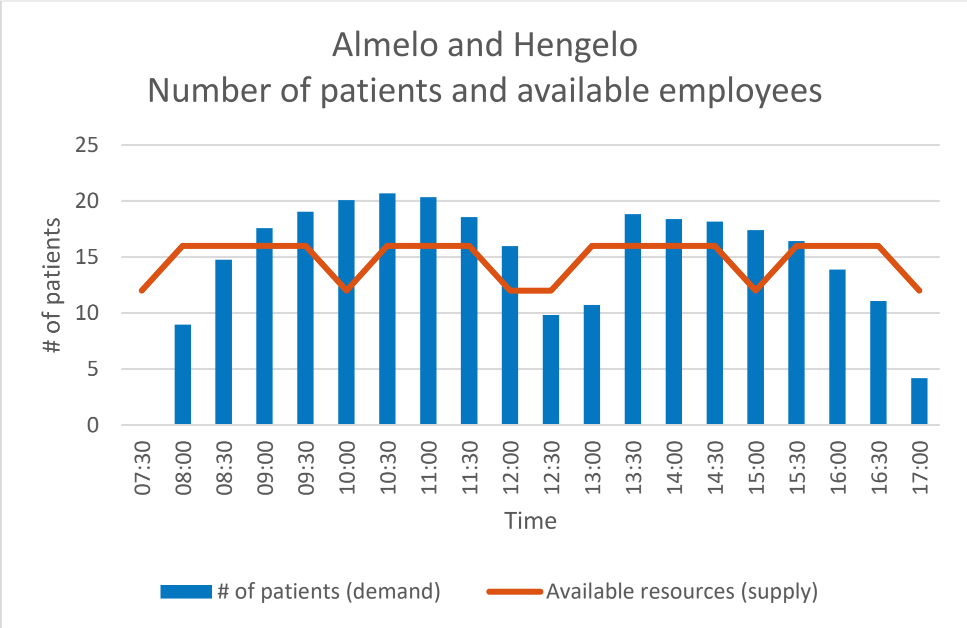

Figure 2.9. Mismatch between demand and supply (n=149,052, Data source HiX, January 2015 - December 2016)

2.3. System performance

As we want to gain insight into the current performance and the desired performance of the Bucky rooms, we describe in this section what we exactly want to measure. We quantify the aspects that are defined during this chapter (2.3.1). We select the ones that are most relevant for this study in Section 2.3.2: those that are most relevant in terms of current performance and the degree of performance we want to attain. Lastly, we summarize all KPIs in the problem cluster in Section 0.

2.3.1. All KPIs

In this section, all aspects that are described in this chapter are transformed into performance indicators. That way we can measure the current performance of the department, what indicators to focus on to improve our problem and what level of performance we would like to achieve. We distinguish our KPIs for our stakeholders, - patients, employees and management. We start with the KPIs for employees. For employees we define KPI Work pressure. ZGTs patients are interested in KPIs as access time, waiting time and throughput time. For management we define System KPIs such as overtime, number of rejections, production level, lateness and duration of examinations.

Employee KPIs

According to employees, the number of patients waiting in the waiting rooms directly influence their work pressure. They see these patients physically when they enter the waiting room, but also see a list of patients that are currently “present” and in the waiting room in their HiX schedule of the day.

Therefore, we define *work pressure*, which is also our first KPI, as number of patients that are in the waiting room. To be more precise, we define it as the number of patients that add up to the number of patients that can be processed.

To measure work pressure, we focus on the number of patients that are in the waiting room during certain time intervals. Radiology employees identified the work pressure rating as shown in Table 2.4. Using this rating, we can give a daily score to work pressure and check the degree of work pressure during certain parts of the day.

Table 2.4. KPIs for employees

Number	KPI	Definition	Requirements
1	Work pressure	Number of patients in waiting room that cannot be processed in a certain time interval. In other words: Patients that are marked "present" in HiX - capacity	Minimize

Patient KPIs

Concerning arrivals of patients, three aspects are important. First, to provide quick diagnostics, *access times* should be low: equal to or less than 2 working days because radiology has made this a restriction for the department. Quick diagnostics are also important for the overall performance of a hospital since it is often the first step in a care pathway.

We also take time spent at radiology in consideration. Figure 2.10 shows the processes for a patient and explains how waiting times relate to the total time spent in the system.

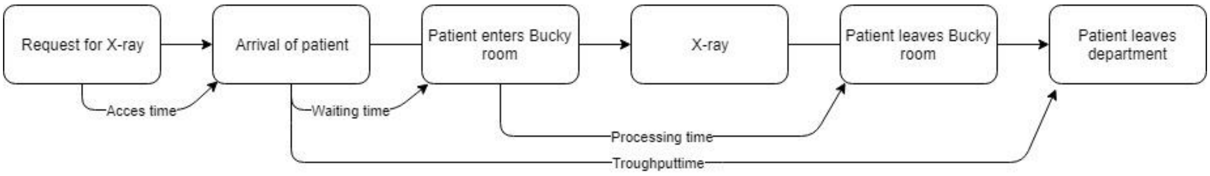

Figure 2.10. Care pathway of patients

Waiting time should be minimized for the comfort of patients. The third KPI is therefore about *waiting times*.

The fourth KPI is about *throughput time*. Since most patients are told to visit radiology 30 minutes before their successive appointment, throughput time should not exceed 30 minutes. As processing time is mostly between 5 to 10 minutes, the radiology department strives for waiting times that do not exceed 20 minutes. The three KPIs and their requirements are listed in

Table 2.5.

Table 2.5. KPIs for patients

Number	KPI	Definition	Requirements
2	Access time	Time between request and appointment	d < 2 working days
3	Waiting time ratio	Percentage of patients that involuntarily must wait longer than 20 minutes. In case of an early arrival of the patient (before appointment time), the appointment time applies.	t < 20 minutes
4	Throughput time	Time between arrival and end of process at radiology	t < 30 minutes

Managerial KPIs

Since strategic and managerial decision-making is mostly about global performance, we consider the overall performance of the Bucky rooms in our KPIs. First, the Bucky rooms are open until 17:00, which means that there should be no patients left to treat after that time. This results into system KPI, *Overtime*. Overtime measures the number Minutes worked after regular hours. For practical reasons it is important that overtime is minimized as working overtime is related to high costs.

Then, ZGT has a policy of not rejecting patients. The sixth KPI *Rejections* measures the number of patients that are rejected at the desk.

Arrivals of patients, and therefore the punctuality of patients, are related to our problem of unbalanced work pressure. Patient punctuality directly relates to the total time spent at radiology, as for example arriving too early might increase waiting time. Arriving too late results into more patients that must be treated in a specific time interval and therefore increasing throughput time for all patients in that interval. Also, impunctuality resulting into arriving at the wrong time, wrong location or without appointment, still means the patient has access to radiology. We therefore identify KPI seven, *Lateness*.

As eighth, we take the duration time of examinations into account. In 0 about examination duration we described how much the actual duration of examinations exceeds the planned duration. Because this influence the throughput times of the Bucky rooms, we identify the KPI *Duration time*. The actual processing time at the Bucky rooms should match the planned duration of the examination.

All corresponding KPIs are listed in Table 2.6.

Table 2.6. KPIs for management

Number	KPI	Definition	Requirements
5	Overtime	Minutes worked after regular hours	Minimize
6	Rejections ratio	Rating for patients that get deferred once arrived at the desk	x = 0
7	Lateness	The number of minutes patients are early or late	Minimize t
8	Duration time	The absolute difference between the actual duration and the planned duration of an examination	Actual duration $t_a \approx$ planned duration t_p

2.3.2. Included KPIs and KPI overview

In the previous section we described all factors that are influencing our problem and their corresponding KPIs. We identified 3 stakeholders – patients, employees, and management. For these stakeholders we classified a total of 8 KPIs: *Work pressure, Access time, Waiting time ratio, Throughput time, Overtime, Rejections ratio, Lateness and Duration time*. These KPIs require data to measure them. However, for some KPIs no data or data or insufficient quality is available. These data types can be collected by performing observations, but the added value of doing these time-consuming observations during this study is not high enough. Therefore, some KPIs are excluded. These KPIs are:

- Access time
- Throughput time
- Lateness
- Duration time

KPIs *Throughput time* and *Duration time* are excluded due to the following data insufficiency:

The exact departure time is unknown. Departure times are collected in HiX, but the available times do not match the exact departure time as patients should be switched manually to “finished”. The time a patient is switched to “finished” is the departure time. In practice, this happens often after at least one more patient is processed, bundling the administrative proceedings of several patients into one.

KPIs *Throughput time* and *Duration time*, since both rely on departure time of patients, therefore these are excluded.

Access time is excluded as we assume capacity is sufficient, and therefore patients get either an appointment at their desired time or can walk in. Until now, no problems concerning access time occurred at the department. We assume access time in case of a scheduled patient to be satisfactorily, as in the current situation no complaints are known. In case of unscheduled patients, access time is 0.

We also exclude *patient lateness*. For this study we consider this a factor that cannot be influenced. Therefore, we assume that patients arrive on the right time for their appointment.

This gives the following KPIs:

KPI 1. Work pressure.
As the work pressure rates the number of patients that are additional to the capacity of a time interval, this should be approximately 0. Because work pressure depends on the arrivals of unscheduled patients, which is not affectable, we try to minimize work pressure.

Table 2.7. KPI 1: Work pressure

KPI	Definition	Current performance	
1. Work pressure	*Average queue length per day*	*Hengelo:* *Monday: 5.8* *Tuesday: 3.2* *Wednesday: 0.4* *Thursday: 3.6* *Friday: 0.6*	*Almelo:* *Monday: 4.6* *Tuesday: 0.9* *Wednesday: 1.3* *Thursday: 0.6* *Friday: 0.6*

KPI 2. Waiting time ratio.
$$Waiting\ time\ ratio = \frac{n_{t>20}}{n_{all}}$$

$t_{waiting\ time}$ = *time of being summoned to dressing room – arrival time*

Since the time of arrival and the time a patient is assigned to a Bucky room are known, we can measure the waiting time. Our definition of "waiting time" is from arriving at the desk until being assigned to a room. This should be less than or equal to 20 minutes. Potential waiting in the dressing room is not taken into consideration because these times are unknown. The measurement value for waiting time is the percentage of patients that must wait longer than 20 minutes.

Table 2.8. KPI 2. Waiting time ratio

KPI	Definition	Current performance
2. Waiting time ratio	*Patients that wait longer than 20 minutes*	*Waiting time ratio = unknown*

KPI 3. Overtime.

Because patients cannot be left untreated, working overtime might occur. We try to minimize working overtime.

Table 2.9. KPI 3. Overtime

KPI		Definition	Current performance	
3.	*Overtime*	*Minutes worked after regular hours*	*Hengelo*	*Almelo*
			Monday: 59	*Monday: 20*
			Tuesday: 6	*Tuesday: 7*
			Wednesday: 0	*Wednesday: 7*
			Thursday: 1	*Thursday: 2*
			Friday: 1	*Friday: 1*

KPI 4. Rejections ratio.

$Rejections\ ratio = \frac{n_{rejected}}{n_{all}}$ $n_{rejected}$ = *# of deferred patients*

The number of deferred patients at the desk is not collected in HiX, but since this is a rule, we assume this number currently is 0. Therefore, we use this is a restriction into our study. As no rejections are allowed we assume this number to be 0.

Table 2.10. KPI 4. Rejections ratio

KPI		Definition	Current performance
4.	*Rejections*	*Rating for patients that get deferred*	*Rejections ratio = unknown ≈ 0*

2.3.3. Problem cluster

Figure 2.11 visualizes the relations between the factors as described in this section, and what their symptoms are. The factors resulting into the symptoms as noticed on the work floor like an unbalanced work pressure, concludes into a core problem. Figure 2.11 is a summary of the factors and the occurring problems as experienced at the radiology department of ZGT.

As described in Section 2.5., some factors are not considered for this study. For example, the input flow at radiology from outpatient clinics and the GP might be affectable. However, this is out of the scope of this study, and therefore left for further research. The same accounts for some symptoms. The scope of this study is to reduce fluctuations in demand in order to balance work pressure. We therefore do not specifically consider symptoms like the waiting times exceeding 20 minutes, lateness of patients at other departments, stress, dissatisfied patients and long Bucky lead-times. On the contrary, although this is not the objective of this study, we expect these symptoms to improve to some degree as the main problem recuperates.

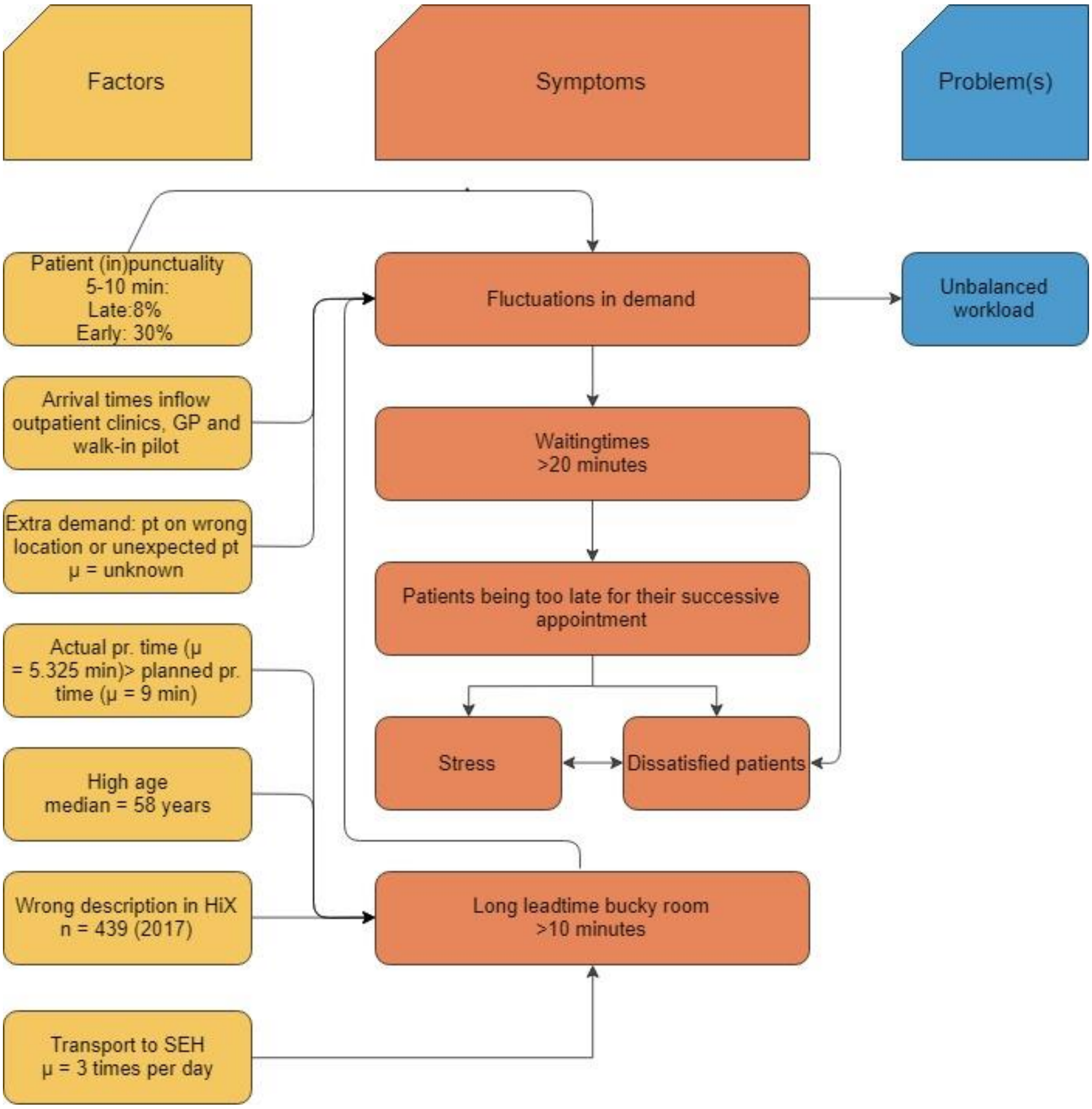

Figure 2.11. Problem Bundle

2.4. Conclusion

In this chapter we discussed the radiology department at ZGT and the context for our study. In Section 2.1. we described all resources and flows at radiology, enabling us to answer the question *"What is the current situation at radiology?"*. ZGT has 4 Bucky rooms that are for general use during work-days. 2 employees are scheduled upon a Bucky room every day from 7:30 until 17:00 and at each location, 2 "Circuit" employees are scheduled for several unscheduled issues. We described the process flow, which can be summarized to the primary process as shown in Figure 2.4. The care pathway of patients is shown in Figure 2.7, which also gives a more detailed insight in the process flow of the department.

We identified several influencing factors, so we summarize the answer to sub-question 2 *"What are influencing factors on the unbalanced work pressure?"*.

The current way of planning causes inefficiencies because:

1) Patient are (in)punctual: 11% of patients arrive too late for their appointment, 30% arrives 5 to 10 minutes early, influencing work pressure as they are in the waiting room.
2) Additional proceedings for Bucky employees that are time consuming, like bringing patients to the ED and manually changing codes in HiX
3) The arrival pattern of unscheduled patients is similar to the arrival pattern of scheduled patients. This causes the unbalanced work pressure. This increases work pressure at peaks between 9:00 and 1:00 and 13:30 and 15:30.
4) Duration of examinations in theory (median = 8 minutes, average = 8 minutes) exceed the planned duration (average 5.325 minutes). It is difficult to make a waterproof statement about this aspect as departure times as shown by HiX are not quite reliable.
5) Flows from the GP and OCs set the pace for the arrivals at the Bucky rooms.

These aspects give insight into our problem and prove its existence; the work pressure is unbalanced during the day. The relations between the factors, their symptoms and the resulting problem is visualized in the problem bundle in Figure 2.11. The demand fluctuation during the day, causes work pressure. We define work pressure as the number of patients that are currently listed in HiX as "Present" that are adjacent to capacity. We summarize these fluctuations in demand as variability. To measure the current degree of performance and variability at the Bucky rooms, we identified the KPIs in Table 2.11. With this table, we answer research question 3 "*What are KPIs for the radiology department, and how do they perform?"*

Table 2.11. KPI Summary

KPI	Definition	Current performance	
		Hengelo	Almelo
1. Work pressure	*Average queue length per day*	*Monday: 5.8* *Tuesday: 3.2* *Wednesday: 0.4* *Thursday: 3.6* *Friday: 0.6*	*Monday: 4.6* *Tuesday: 0.9* *Wednesday: 1.3* *Thursday: 0.6* *Friday: 0.6*
2. Waiting time ratio	*Percentage of patients that involuntary wait longer than 20 minutes*	*Waiting time ratio = unknown*	
3. Overtime	*Minutes worked after regular hours*	*Monday: 59* *Tuesday: 6* *Wednesday: 0* *Thursday: 1* *Friday: 1*	*Monday: 20* *Tuesday: 7* *Wednesday: 7* *Thursday: 2* *Friday: 1*
4. Rejections	*Rating for patients that get deferred*	*Rejections ratio = unknown ≈ 0*	

Chapter 3

3. Literature review

The problem as described in Chapter 2 can be summarized as high fluctuations in work pressure at radiology. In other words, the system of demand and supply is out of balance. Background information on this problem helps us to identify potential improvements, which is the goal of this literature review. First, we discuss capacity management in Section 3.1, in which capacity is meant in terms of employees, time and devices. Next, we focus on aspects of variability within inflow processes in the hospital in Section 3.2. The words “inflow” and “arrivals” are used interchangeably within this chapter. We review how the effects of these aspects can be improved in Section 3.3. We do this by analysing interventions, appointment systems, that are suitable for our context. From the suitable interventions we continue to the Solution approach in Section 3.4 Continuously we describe our research methodology, the intervention that is most suitable for our problem, in Section 3.5 We refer to our problem as the Bucky problem. We describe the means of evaluation in Section 3.6. and we conclude this chapter in 3.7.

The literature used for this section is collected mostly with use of the search engine Scopus and by being redirected from references in relevant literature. To give some insight into the quest trough Scopus we added the search query in the Appendix in Table 8.2. Next to this, we searched through relevant literature as found with the query as shown in Table 8.2. and reading relevant graduation reports from colleague master students that did a case study in the same Hospital environment with related topics.

3.1. Capacity management

According to Hall (2006), patient flow represents the ability of the healthcare system to serve patients quickly and efficiently as they move through stages of care. The study on finding a balanced system is also known as capacity management.

Large parts of demand for resources within hospitals are unscheduled. As a result, there is a permanent mismatch between the demand for a treatment and the available capacity (Creemers & Lambrecht, 2010). The consequence is an everlasting search for the right trade-off between processing times (including waiting times) and capacity, resulting in the right amount of utilization and a smooth patient flow. As is well known in capacity management, a higher utilization results in longer waiting times (Slack, Chambers, & Johnston, 2010).

Adding to that, existence of waiting times starts by variability in the arrival process: This is one of the main properties as derived from queueing theory (Morton & Bevan, 2008). The arrival process, and therefore also the demand, is set by arrivals of patients. Because arrival times of patients are generally not uniformly distributed but vary during the day, arrivals and their variability influence the processes’ utilization.

3.2. Variability

Variability exists naturally in systems. High variances in hospitals are associated with small increases in total inpatient costs (Baker, Phibbs, Guarino, Supina, & Reynolds, 2004). One of the consequences of variability in demand is that the system might become congested and that waiting times increases (Morton & Bevan, 2008).

Hospital capacities and resources are determined at an aggregate level planning (Vissers, Bertrand, & Vries, 2001), but often difficulties are faced at an operational level. These difficulties occur because it is common to plan and control hospital capacities through simple deterministic approaches using average patient flow, average processing times and average demand (Harper, 2002). So, planning relies on long-term approaches while variability in demand influences planning in short term (Munavalli, Rao, Srinivasan, Manjunath, & Merode, 2017). This discrepancy between planning and reality leads to long waiting times and under-utilization of resources (Munavalli et al., 2017). When this occurs at diagnostic resources like radiology this can become a tight bottleneck in patient flows (Haraden & Resar, 2004). As variability in demand and arrivals affects the productivity in a healthcare system, this is a major concern for the hospital as a whole (Baker et al., 2004).

3.3. Appointment systems

As Bhattacharjee and Ray (2016) state it "Appointment systems for scheduling patients to a hospital facility play an important role in controlling and synchronizing the arrival of patients with resource availability thereby reducing the waiting time of patients and increasing the utilization of resources". In other words, appointment systems play a major role in the performance of a department.

The performance of an appointment system relies on environmental and decision-related factors, in which environmental factors include unpunctuality of patients and walk-ins. Decision related factors are appointment policies and the number of resources that are made available. Many appointment systems made modifications to deal with environmental factors, such as reservation of slots for specific use (Bhattacharjee & Ray, 2016). Use of an appointment-based system is a standard way to reduce the effects of variability in arrival time. Often a standard processing time is used per appointment. In the literature processing time is also referred to as flow time.

We distinguish for each solution system scheduled patients and unscheduled patients, e.g. walk-in patients or patients that appear at the wrong location. Scheduling and non-scheduling both have advantages. Using pre-scheduled appointments might be useful in case of long travelling times for patients, for planning considerations or to spread work pressure. On the contrary, scheduling can yield potentially long access times to a resource (Kortbeek et al., 2014). For using the unscheduled approach accounts that access time approaches 0, giving the resource a high level of accessibility and a feeling of participation for patients. It makes a resource deal with potentially high arrival variations on the other hand (Kortbeek et al., 2014).

In this section we discuss systems that are suitable for departments like radiology and more specific, the Bucky rooms. These systems are a guideline on how to divide available system capacity on our 2 patient groups: Scheduled and non-scheduled patients. For this overview studies on scheduling on outpatient clinics as well as radiology departments are used as both are comparable with our situation.

3.3.1. Individual block fixed interval rule (IBFI)

A single patient is assigned to an appointment slot and all slots have an equal length (Bhattacharjee & Ray, 2016). This approach is not suitable for walk-in based departments, so all patients must be scheduled. The situation at the Bucky at ZGT before the pilot with walk-ins is comparable to this appointment system.

3.3.2. Sequential appointment scheduling considering walk-in patients

This method fixes appointments for patients that announce their arrival beforehand, while remaining time-slots are available for unscheduled patients (Yan, Tang, & Jiang, 2014). This makes it applicable for walk-in departments. It is assumed that arrivals of unscheduled patients compensate for no-shows, which are assumed to have a certain probability to occur. Yan et al. state that it is more efficient to use overbooking instead of letting unscheduled patients compensate for no-shows, mostly when the probability of no-shows increases. However, this approach focuses mostly on costs. It takes waiting costs (time) into account, but still promotes overbooking to overcome no-shows, which might increase work pressure at certain time intervals.

3.3.3. Delay scheduling

Delay scheduling is applicable for walk-in based departments and can be used to control unscheduled patient flows while the ability to walk-in remains (Reilly, Marathe, & Fries, 1978). Previous works showed that it allows work-load shifting, which means work-load is replaced from a certain time interval to another (more suitable) time interval: Patients arrive and are allocated an "delay-time"; the time they must wait until their appointment starts, also known as their waiting time (Reilly et al., 1978). A patient can either accept or reject the delay-time. In case of rejection, the patient returns at another moment.

3.3.4. Cyclic Appointment Schedules

This method offers both walk-in and scheduled services and is invented by Kortbeek et al. (2014). It is suitable for outpatient clinics and diagnostic facilities. Cyclic Appointment Schedules (CAS) relies on the fact that demand for both scheduled and unscheduled patients is often cyclic, e.g. follows a certain pattern and therefore, the resulting appointment schemes are also cyclic (Kortbeek et al., 2014). A cycle length can vary between several days and month(s).

CAS first uses an iterative approach in which the total number of patients for each day of the cycle is determined (Kortbeek et al., 2014). Capacity is determined considering a maximum number of access days. Then, it develops the best day schedule for each cycle day. A day has a fixed number of time-slots. With use of queue length probabilities that are a result from the first stage, the number of scheduled patients are distributed over a day. The number of patients that are to be rejected that day, is minimized.

So, with use of 2 models, CAS balances the waiting time for unscheduled patients and the access time for scheduled patients. Service always takes 1 time-slot. If a patient cannot be treated within x time-slots from arrival, it will be rejected. CAS allows no overtime.

3.3.5. Closed-form approach

Qu, Rardin, Williams, & Willis (2007), developed an approach to determine a division on percentages of scheduled and non-scheduled patients. They found that the optimal percentage to allocate for walk-in patients is mainly depended on the ratio of average demand for non-scheduled appointments and the ratio of patients that show up for pre-scheduled appointments.

3.3.6. Off-peak scheduling

When predicting a pattern of arrivals of unscheduled patients, remaining time-slots can be filled with pre-scheduled appointments. This allows work-load shifting and therefore reduction of work pressure. Such systems are described by (Gupta & Denton, 2008).

3.4. Solution approach

The 6 ways of appointment scheduling found in the literature are interventions suitable for improvement of the Bucky problem. We found appointment systems that are suitable for complex systems, such as CAS, and found relatively simplistic systems, such as the Individual Block Fixed Interval Rule. We also found methods to divide available system capacity of our 2 patient groups. These groups both occupy a fraction of all available time slots. In this section we describe the intervention selected for the Bucky problem.

The division of scheduled and unscheduled patients is predetermined by the hospital. ZGT wants to either allow a whole patient group to visit unscheduled or applies scheduling to a complete patient group. Orthopaedics is a rather large OC, but as most other inflow from OCs to radiology is scattered (see Table 8.1 in the Appendix), these OCs either are all scheduled or unscheduled. For this study, all patients from the GP and OCs other than orthopaedics are scheduled. Unlike the arrival rates of orthopaedic patients, which are known because of the pilot, there is no data is available upon the arrival rates of these patients.

3.5. Method

To synchronize the arrivals of patients with resource availability we use Section 3.3. as inspiration. We select our intervention based on several objectives. We found that variability in inflow adds variability to the system. Although studying the causes of variability might yield a lot of improvement possibilities, especially for the flow from the OCs, influencing inflows requires input from multiple departments. We do not have access to these inputs currently. Therefore, the causes of variability are out of scope for this study. We thus focus on the effects of variability in demand.

The first goal is to reduce work pressure and overtime. The secondary goals are waiting times. As patients will never be rejected, overtime is a relevant last aspect in our intervention. As ZGT wants to offer the ability of walk-ins at the Bucky, we only consider interventions that permit this option. We also want to allow scheduling. We give a small summary of all found methods with their pros and cons.

We found the *Individual block fixed interval rule*, that only allows scheduled patients in a fixed time-slot. *Sequential appointment scheduling* fixes time-slots for scheduled patients, the remaining slots are available for unscheduled patients. It does not take the arrival pattern of unscheduled patients into account. *Delay scheduling* allows patients to visit on a walk-in basis but has a risk of potentially long waiting times. Patients can either accept their delay time or leave, which is inapplicable for our problem as patients often have a sequential appointment. *CAS* is a fancy method that takes several aspects into consideration but is unnecessary complicated for our problem which has the same amount of capacity on each day of the cycle. It also allows no overtime and works with rejections, making it inapplicable. The *Closed-form approach* by Qu et al (2007) might be helpful in case we want to optimize the division of unscheduled and scheduled patients. However, as ZGT does want to be the policy of either scheduling or allowing walk-ins for each patient in a certain patient group to be the same, this is not feasible. Applying the Closed-form approach might include the situation in which a part of an OC, i.e. 30% must schedule their appointments, whereas the other 70% can visit unscheduled. This is not an option, see Section 3.4. Lastly, *Off-peak scheduling* is applicable to the Bucky problem. It is an evident way of improving the problem, but it does not take different scenarios for unscheduled arrivals into account.

The described interventions provide us with insight and inspiration for a solution method. The desired result is a schedule that meets the following requirements. The schedule:

- Distinguishes between weekdays
- Is the same for each weekday
- Allows scheduled and unscheduled patients and distinguishes between slots reserved for scheduled patients and unscheduled patients

As for our method to come to this result, we want it to:

- Be adjustable in case new fractions of scheduled and unscheduled patients are required
- Takes resource availability into account: lower availability during coffee and lunch-breaks
- Minimizes work pressure during the day, considering peak moments of both the OCs and the walk-in patients

As all appointment systems and methods as described in Section 3.3 do not completely cover these aspects, we will combine some of the described methods and adjust them to create an intervention that meets all requirements.

Linear Programming is a tool for solving optimization problems; minimizing a linear function of decision variables that must satisfy a set of constraints (Winston, 2004). When decision variables can only take integer values (we can only schedule an integer number of patients), we speak of Integer Linear Programming (ILP). ILP can help us to find an optimal allocation of all scheduled and unscheduled patients over all time slots given a certain division of these patients.

We also want to take the arrival times of unscheduled patients into account combined with the peak moments of scheduled patients due to the planning of OCs. Therefore, we add a scenario-based aspect to the ILP. We consider several scenario's, with a fixed probability of occurrence, in which the number of arrivals on a certain time interval varies.

3.6. Evaluation

In order to evaluate a proposed intervention appropriately, the system with its inputs, processes and outputs needs to be represented (Bhattacharjee & Ray, 2016). This can either be done in practice, with analytic queueing models or discrete-event simulation based. Trial and error in practice is often not feasible because processes cannot be disturbed for practical reasons. Also, testing in practice can be costly and requires time to end up in a certain steady state of performance.

As for analysing the performance analytical, (Bhattacharjee & Ray, 2016) state that integrating all characteristics of an appointment system can become fairly challenging. For the Bucky problem features like the varying duration time, both scheduled and unscheduled patients and different arrival patterns make analysing the performance rather difficult.

As summarized by (Carter, 2002), "Approximately 10 percent to 15 percent of the papers in our database describe applications involving simulation. Obviously, one of the major issues in health care is waiting times, and most health care queueing problems are too complex to be analysed theoretically. Therefore, simulation is a popular alternative". On the other hand, building a simulation model can be quite time-consuming (Law, 2007). Therefore, we suggest another option: Keeping track of the current performance of the Bucky for a certain time-period, in order to compare with a shadow log in which the performance of the proposed intervention is tracked over the same time-period.

3.7. Conclusion

We found that a high system utilization goes along with long waiting times. The existence of waiting times can be found in variability in the arrival process. As variability naturally exists in systems, it causes problems at an operational level. Due to the use of simplistic deterministic approaches to determine capacities, these problems can be recovered in low utilization of resources at certain time intervals, resulting into high utilization at other intervals. This is the answer to research question 4.1. *What is known about the effects of variability in inflow on shared resources in a hospital?* The effects of variability in inflow are long waiting times and varying system utilization, meaning also variance in work pressure. We do not take the causes of variability into consideration as this is out of the scope of this study. We thus focus on the effects of variability and how to handle them. We therefore studied appointment systems as a solution system.

When looking for solution methods we found that resources in hospitals must deal with environmental and decision-related factors such as respectively patient unpunctuality or unscheduled arrivals and decision-making on appointment schedules. Some factors are settled already: ZGT wants to allow unscheduled patients and does not reject in case of unpunctuality. Therefore, we focus on the decisions related with appointment schedules. Also, the division on which patients must be scheduled and which patients can walk in is already settled: Only orthopaedic patients can walk in currently. Appointment schedules are a common way to improve performance of hospital departments. We then identified 6 approaches that are to some extent applicable for the Bucky rooms of our study.

We found that appointment systems are distinctive in the fact that some allow unscheduled patients whereas others do not. The answer to research question 4.2. *What planning systems/interventions are suitable for radiology departments at hospitals?* is summarized in Table 3.1.

Table 3.1. Summary of planning systems suitable for radiology departments

System	Description
Individual block fixed interval rule	Every patient in a single time slot. Scheduled
Sequential appointment scheduling	Schedule required time slots. Remaining time slots open for unscheduled
Delay scheduling	Patients arrive unscheduled and are allocated a delay-time; time until their appointment starts. Patient can accept and wait or reject and leave
Cyclic Appointment Schedules	Provides a schedule for each day in a cycle (certain period). Allows scheduling and walk-ins
Closed-form approach	Optimizes the fraction of scheduled and unscheduled patients in a system
Off-peak scheduling	Schedule patients when walk-in demand is low

The answer to the overarching research question of this chapter, 4. *What is known in the literature about planning systems on radiology departments?* is that there are lots of studies on planning systems in hospitals, but that some creative adjustments might be necessary to create the just right intervention. Our conclusion is that none of the systems found is directly applicable to the Bucky problem. As all 6 do not specifically meet our requirements, we combine and adjust the methods to meet our goals. We want the result of the intervention to be a day schedule for each day of the week and that allows both scheduled and unscheduled patients. The method that leads us to that day schedule must be able to take resource availability into account, must be adjustable and must minimize the work pressure during a day. To reach these goals, Integer Linear Programming is selected in which we reflect several scenarios with a fixed probability of occurrence. In these scenarios the number of arrivals on a certain time interval varies. To evaluate the day-schedule we will use a shadow log during a certain period to compare the results of the intervention to the results of the current appointment system.

Chapter 4

4. Model Description

Chapter 3 provided a literature review on our problem aspects and set the foundation for the development of a model that helps us improve the problem. This mathematical model is described in more detail in this chapter, chapter 4. This chapter also contains the interventions that are to be executed by the model to compare them with the current situation. This shows us how the processes at radiology can be represented by a model. This chapter provides the answer to research question 5: *How can the radiology processes be modelled?*

This chapter starts with the problem definition of the study in Section 4.1. In Section 4.2 we give a basic introduction to the model with its workings, inputs, assumptions and limitations, such that the mathematical model as described in Section 4 is more easily understood. In Section 4.3 we therefore describe the more in-depth aspects of the model, like its formulation and how it is validated. We conclude the chapter with the conclusion in Section 4.4.

4.1. Problem definition

We start this chapter with a recap of the problem definition as shown in Chapter 1. With this mathematical model we want to reach the second objective of our study:

> *First, we aim to gain insight in the origin of unbalanced work pressure at radiology. Second, we want to improve this situation using a tailored planning solution.*

Therefore, we are looking for an answer to the research question: *How can ZGT improve the planning system in order to balance the work pressure at radiology?*

In this section we refer to "Work pressure" as queue length, because this is the measurement used in the model. Using this substitute is in the sections related to the model makes the interpretation of the model more exact. In the other Sections that are not related to the model, we use the more practical and descriptive term "Work pressure".

4.2. Introduction of the model

This section introduces the model. It describes the conceptual model in 4.2.1 and its input requirements in section 4.2.2. The assumptions made for building this model and its limitations are listed in section 4.2.4.

The model is based upon the literature found in Section 3 and is centred around the KPIs as described in Section 2. The KPIs lead to the model requirements. Because KPIs are important in the foundation for the model, we give a small recap. Our KPIs are:

1. Work pressure
2. Waiting time
3. Overtime
4. Rejections

As already described in Section 2, we define the KPI *Work pressure* as the number of patients that are in the system during a given time interval, additional to the number of patients that can be processed during that time interval. In other words, these patients are "extra" and therefore are the source for queues as the number of patients exceeds the capacity.

We want a minimum amount of *Waiting time* for the patients in the system. This KPI is related with the KPI *Work pressure.* Because work pressure is equally balanced during the day, the occurrence of queues is minimized and with that, also Waiting time.

The definition of overtime is the number of patients that still must be processed at the end of a shift. In case of queues during the day, it is very likely that Overtime occurs. Given these KPIs, we develop the model.

Lastly, the number of *Rejections* should be 0. Therefore, the model does not allow patients to be rejected. In case of more patients than available capacity, employees continue working after the end of their shift, leading the model to the KPI *Overtime.*

4.2.1. Conceptual model

This section describes the basic concepts of the model. Since radiology works with a daily schedule for the Buckys, the result of the model should also be a schedule. We distinguish in 2 types of patients, namely *scheduled* and *unscheduled* patients.

Unscheduled patients are the patients that currently participate in the pilot, the patients from orthopaedics. They can visit the Bucky at a walk-in basis. These are 25% of the total number of patients that are processed by the Buckys.

Scheduled patients are all other patients. These patients get an appointment, weeks to days ahead.

As described in Section 3.4 the division of scheduled and unscheduled patients is predetermined by the hospital. Because the hospital considers applying walk-ins for each patient that visits the Bucky, we test this setting too to compare it with the current situation and the proposed solution approach.

The desired result is a day scheme. Because the scheduled patients can be planned, we want to create a day scheme that shows when to schedule them. This scheme takes the arrival times of unscheduled patients into account. The scheme should be developed in such a way that the risk of queues is minimized and that all patients are processed at the end of the working day. Thus, we want to achieve this by smartly scheduling patients that require an appointment, leaving time slots available at time intervals that unscheduled patients are expected. The scheme differs per day of the week but is the same for e.g. each Monday of the year.

Experiments with 3 settings:

1. The initial design (the current situation), to explore the current performance of the system.
2. A complete walk in setting. All patients arrive unscheduled. As input we use an extension of the inputs as described in Section 4.2.2.
3. The pilot setting, with the orthopaedic patients that visit the Bucky unscheduled (25% of inflow) to develop a solution. As input we use the input as described in section 4.2.2.

Objective. The model should measure the KPIs within the solution approach; *Rejections, Work pressure* and *Overtime*. The number of rejections is defined by the hospital and should be 0. Therefore, we add this as a constraint to the model. So, the objective of the model becomes minimizing the other KPIs, *Work pressure* and *Overtime*. In mathematical models these aspects are often referred to as decision variables (DVs). Including these DVs in our model, our objective function becomes: *Minimize (Work pressure + Overtime).*

Software package AIMMS (Advanced Interactive Multidimensional Modelling System) is used to build the model. AIMMS is developed for building decision support applications and solving scheduling problems (AIMMS, 2018) and it enables the user to build a mathematical model in a straightforward user interface and provides the use of various solvers to optimize the model, such as CPLEX (IBM), CP-Optimizer (IBM) or Gurobi (Gurobi Optimization).

Solver IBM ILOG CPLEX is used to solve the problem. CPLEX version 12.8 is implemented in AIMMS and is known as one of the best solvers. It is also free for academic use.

4.2.2. Input requirements

For the model to develop a scheme, it needs input in terms of arrivals per time interval. Also, other specifications of the real-world situation need to be defined in the model in order to create a valid solution. This section describes the input requirements of the model: The arrival process, the capacity of the system, the weights for the components of the objective function.

For the arrival process we distinguish again between scheduled and unscheduled patients. As the number of unscheduled patients is not known beforehand, we add *scenarios* to the model to make it more robust.

The available capacity varies per time slot. An examination takes 5 minutes, so, per time slot of 30 minutes 6 patients can be processed. Because each location has 2 Buckys, so the processing numbers double. Table 8.3 in the Appendix shows the capacity per time slot. Capacity is 4 in time slot 1 and 20 to 24. This is because at those times only 1 employee is available. At time slot 6, 10, 11 and 15, Bucky employees have their lunch breaks, therefore capacity is 8 patients per 30 minutes. (for a more detailed description: See 0). Capacity is based upon the assumption that either: Each examination takes exactly 5 minutes or average duration of examinations on a day is 5 minutes. The duration time is fixed by the hospital.

The planning horizon is defined for days and time of the day. The desired scheme contains the number of scheduled patients per time slot per day. Scenarios with different arrivals are defined per day and per time slot. Therefore, we identify the following indices:

d: Day of the week d. d = [Monday, Tuesday, Wednesday, Thursday, Friday]

t: Time slot t with a duration of 30 minutes during day d. Each t equals a predefined time, (see Table 8.3 in the Appendix).
t = [1,2…24]

The arrival process of scheduled patients is used as 1 value. Scheduled patients are assumed to know their appointment time beforehand, e.g. weeks or days ahead. Scheduled patients often have a preferred appointment time, as described in Section 2. An explanation for this is the One-stop-shop principle. Therefore, the appointments of scheduled patients are inserted in the model as average number of arrivals per day. The arrival rates are drawn from historic data from the period 1-1-2018 until 31-05-2018. Historic data shows that these arrival rates are static: in 2017, the arrival pattern was similar. Therefore, the average arrivals per 30 minutes of patients with an appointment are rounded and inserted once into the model.

Arrival process of unscheduled patients are non-static**.** For unscheduled patients the arrival pattern differs. The pilot started on 1-10-2017 and the arrival rates were not stable in the first 3 months: The percentages of unscheduled patients were in October 13%, in November 20% and the percentage approached 25% in December. In the subsequent months, January until May 2018, the system became more stabilised. Still, the arrivals of patients are unannounced and therefore cannot be scheduled. Nevertheless, some historic data on unscheduled arrivals is known, giving us an *expected* number of arrivals per time slot per day. The expected number of arrivals are a guideline to base our model on. Since this number can still vary, we introduce scenarios in our model. See Section 4.2.3.

4.2.3. Scenarios

The average number of unscheduled arrivals is known but since we consider historic data, this number varies. To create a more robust day schedule, multiple scenarios are therefore considered. For example, the average number of unscheduled arrivals on Monday in Hengelo at 10:30 is 4.42. As we consider the historic data of 2018, arrivals for each Monday at 10:30 vary from 2 to 10, making an average of 4.42. To create the most realistic model, we do not take a rounded version of the average, say 4 or 5 because this yields the best result in case the arrivals are indeed 4 or 5 but not if arrivals are 10 or 2. Arrivals of 2 and 10 are not as likely to happen as 4, but therefore we use the Poisson random number generator.

The Poisson distribution is used to generate random arrivals for each time interval of 30 minutes given the average, in the Poisson distribution announced as parameter Lambda (λ).

When using λ=4.42, the random generator produces numbers varying around 4: Approximately between 1 and 10, with a more likely chance on producing 4 or 5 than 1 or 10.

To do this, the average arrivals on a time interval of 30 minutes is calculated from historic data (01-01-2018 until 31-05-2018). We generate random numbers for each time slot and each day, with the average number of unscheduled arrivals as drawn from data as parameter λ. Thus, the scenarios contain the expected number of *unscheduled patients* on all time intervals during a working day.

MATLAB is used to generate the scenarios. An example of a scenario is shown in the Appendix in Table 8.4. This table shows the arrivals on Mondays. These arrivals are drawn with the Poisson random generator in MATLAB with parameter λ per time slot. λ is the average number of arrivals per day per time slot, drawn from historic data in the period 01-01-2018 until 31-05-2018.

Probabilities of occurrence of each scenario are equal. While generating the scenarios the Poisson distribution already takes the likeliness of occurrence of each expected number of arrivals into account, as the expected arrivals are based on λ and vary around λ. Therefore, it is not necessary to include a higher or lower probability on a certain scenario.

The number of scenarios is based on 2 aspects: Computation time and the degree in which the scenarios approach the reality. This comes down to a trade-off between computation time and added value. For each time slot we calculated the difference between the average number of patients as derived from historic data and the average number of patients within the scenarios. In principle, the more scenarios, the smaller the difference between the historic data and the scenarios. Also, computation time influenced our decision.

We took a sample, Tuesday in Almelo. The average difference between historic and generated data and the maximum absolute difference for all time slots (24) are given in Table 4.1. We see a decrease in absolute differences when the number of scenarios increase. More scenarios, and therefore a smaller gap between the real data and the generated data might give a better model performance, but an increase in scenarios means an increase in computation time. AIMMS, the software used for solving the model, was not able to solve the tests to optimality. Therefore, we interrupted the solver if the objective function did not increase anymore, resulting in the approximated/estimated computation time in Table 4.1.

Table 4.1. Scenario characteristics

Number of scenarios	Average of absolute difference for all time slots |historic – generated|	Maximum absolute difference per time slot |historic – generated|	Approximated/estimated computation time to optimality
20	0.24	0.83	6
50	0.14	0.56	20
100	0.08	0.28	∞
200	0.07	0.26	∞

We see in Table 4.1 that with an increase of scenarios also computation time increases. Some experiments with different amounts of scenarios were performed to create insight into required computation time and improvement of the solution proportional with the increase of required computation time. Computation time depends on aspects such as the number of arrivals per day: As this approached its limit (max day capacity is 200 without working in overtime) the problem becomes bigger and more difficult to solve, with as a result an excessive required time to solve the problem to optimality. For example: After 13.5 hours, AIMMS was not able to solve the model to optimality for Monday in Almelo with 25 scenarios.

As for added value, we see that Average of absolute difference for all time slots in 4.1 nearly improves when we double the scenarios from 100 to 200. We wanted to reach a predetermined goal of an absolute difference of <1 per time slot between the historic data average and the data generated by the Poisson random generator. This was the case for all days on all locations with approximately 50 scenarios. Because we were looking for a right trade-off between model accuracy and computation time, we settled with an average absolute difference for all time slots of <0.2, which was the case with 50 scenarios. Therefore, we decided to use 50 scenarios.

4.2.4. Model assumptions and limitations

We were not able to include all aspects of the real-life system in the model. Chapter 2 describes some aspects that influence work pressure in a negative way. Although it might be helpful to include all those aspects when modelling a system, this is not always possible nor feasible. To make a simplified version of the real-life system within the available time, some assumptions are made, and some simplifications are applied:

- No no-shows: Each patient that has an appointment e.g. is scheduled, shows up
- No rejections: Every patient that visits the Bucky, does not leave without treatment
- Waiting time = queue length, as the system uses a First Come First Serve (FCFS) policy.
- Patient groups are clustered: Although patient groups vary, the patients are clustered into 2 groups: Scheduled and unscheduled.
- In case of a no-show, the slot is automatically open for unscheduled patients
- Each examination takes 5 minutes.

Next to the assumptions we also describe some important drawbacks of the model:

- Preferences for an appointment time for scheduled patients are not entirely included. Depending on the output of the model, the scheme, a certain number of patients can be scheduled within a time slot. In case the maximum level is reached, a patient cannot visit the Bucky at its preferred time.
- Variation in examination duration is not included, each examination takes 5 minutes as is prescribed by the hospital.

- No examinations with a standard duration of 10 minutes are included in the model: We assume these patients count as 2 unscheduled arrivals. Depending on the preference of the hospital, it is also a possibility to decide to oblige an appointment for those that require more than 5 minutes within the Bucky room.
- No time is reserved for bringing patients to the ED.
- The arrival pattern of the Walk-in design is based on a fraction of the total number of patients. The pattern is not the actual pattern but just an approximation.

4.3. Mathematical model

In this section we transform the conceptual model of Section 4.2.1 into a mathematical model. We start with the notation of the model in Section 4.3.1, followed by the formulation of the model in mathematical terms in Section 4.3.2. While already spent some time on modelling, some changes are made in the model. These are described in Section 4.3.3. Then we define the weights for the objective function in Section 4.3.4. In Section 4.3.5 we describe how the model is verified and validated.

4.3.1. Notation

We start the declaration of the model with the notation as shown in Table 4.2. Time slots t match with time periods of 30 minutes, starting at 7:30 in the morning (t1) and ending at 19:00 (t24). For the complete table of time slots and corresponding times see Table 8.3 in the Appendix. We include this broad amount of time slots to be able to track the performance of the model in terms of overtime.

Table 4.2. Notation

Index and set	Definition
$t \in T$	Time slots in regular time and in overtime, respectively T^r and T^o with $t \in T = T^r \cup T^o$.
$s \in S$	Scenarios {s1..s50}
$l \in L$	Locations {Almelo, Hengelo}
$d \in D$	Days {Monday, Tuesday, Wednesday, Thursday, Friday}

Parameter	Definition
$up_{l,d,t}^{s}$	Number of expected arrivals of unscheduled patients in scenario s, on location l and day d in time slot t.
$sp_{l,d}$	Number of scheduled patients on location l and day d
$c_{l,t}$	Capacity of location l in time slot t (number of patients) The same for each day d

Variable	Definition
$RS_{l,d,t}$	Number of slots Reserved for Scheduled patients on location l and day d in time slot t
$Q_{l,d,t}^{s}$	Expected queue length per day in scenario s on location l and day d at the end of time slot t: The number of patients that are a surplus to capacity.
$P_{l,d,t}^{s}$	Expected number of patients Processed in scenario s on location l on day d in time slot t
$V_{l,d,t}^{s}$	Auxiliary variable. Difference between the number of patients in the system in scenario s on location l on day d in time slot t and the capacity.
$M1$	Large number compared to $V_{l,d,t}^{s}$
$M2$	Large number compared to the patients in the system and the capacity
$Y_{l,d,t}^{s}$	Auxiliary binary variable {0,1} to determine the number of processed patients in scenario s on location l on day d in time slot t

4.3.2. Formulation

Minimize the queue length and the number of patients processed in overtime:

$$Min \sum_{l \in L} \sum_{s \in S} \sum_{d \in D} \left(\sum_{t \in T} Q^s_{l,d,t} + \sum_{t \in T^o} P^s_{l,d,t} \right)$$

S.t.

$\sum_{t \in T} RS_{l,d,t} = sp_{l,d}$	$\forall l \in L, \forall d \in D$	4.1
$RS_{l,d,t} \leq c_{l,t}$	$\forall l \in L, \forall d \in D, \forall t \in T^r$	4.2
$RS_{l,d,t} \leq 8$	$\forall l \in L, \forall d \in D, t = 18$	4.3
$RS_{l,d,t} = 0$	$\forall l \in L, \forall d \in D, t \in T^o$	4.4
$Q^s_{l,d,t} \geq RS_{l,d,t} + up^s_{l,d,t} - c_{l,t}$	$\forall l \in L, \forall d \in D, \forall s \in S, t = 1$	4.5
$Q^s_{l,d,t} \geq Q^s_{l,d,t-1} + RS_{l,d,t} + up^s_{l,d,t} - c_{l,t}$	$\forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T$	4.6
$V^s_{l,d,t} = Q^s_{l,d,t-1} + RS_{l,d,t} + up^s_{l,d,t} - c_{l,t}$	$\forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^o$	4.7
$Y^s_{l,d,t} * M1 \geq V^s_{l,d,t}$	$\forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^o$	4.8
$P^s_{l,d,t} \geq Q^s_{l,d,t-1} + RS_{l,d,t} + up^s_{l,d,t} - Y^s_{l,d,t} * M2$	$\forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^o$	4.9
$P^s_{l,d,t} \geq c_{l,t} - (1 - Y^s_{l,d,t}) * M2$	$\forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^o$	4.10
$RS_{l,d,t}, Q^s_{l,d,t}, P^s_{l,d,t} \in Z_{\geq 0}$	$\forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T$	4.11
$Y^s_{l,d,t} \in \{0,1\}$	$\forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^o$	4.12
$V^s_{l,d,t} \in Z$	$\forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^o$	4.13

The objective is to minimize both queue length (during the whole day) and overtime. Constraint 4.1 makes sure all patients that require an appointment, actually get scheduled: The total number of Reserved Slots equals the total number of patients that require an appointment. The number of Reserved Slots per time slot cannot exceed the available capacity in that time slot. This is assured with constraint 4.2. Time slot 18 is from 16:00 until 16:30. Because most of the employees leave at 16:30, planning occurs according to the rule that after 16:20 no patients are scheduled anymore. Therefore, constraint 4.3 makes sure no more than 8 patients can be scheduled (instead of 12 at full capacity). Constraint 4.4 makes sure no scheduling is done after 16:30 in overtime, although there is still capacity for unscheduled patients.

We use constraint 4.5 and 4.6 to determine the queue length. The queue length equals:

$$Q^s_{l,d,t} = \mathrm{Max}\,\{0, Q^s_{l,d,t-1} + RS_{l,d,t} + up^s_{l,d,t} - c_{l,t}\} \qquad 4.14$$

which means that the queue length is the maximum of either 0, or the queue of the previous time slot plus the number of scheduled patients (Reserved slots) plus the unscheduled arrivals minus the capacity. For time slot 1, there is no queue yet, so the queue of the previous time slot is not included.

Because this "Max" formulation does not fit within the common ILP formulation, we transformed this formulation to constraint 4.5, 4.6 and 4.11 to determine the queue length.

The queue length at t=1 (4.5) equals the scheduled patients and the patients that arrived unscheduled, minus the capacity at time slot 1. In case this will become a negative number, constraint 4.11 applies: queue length will then become 0.

The same holds for the queue length at the other time slots (4.6), except for the fact that the queue length of the previous time slot is also added. These are determined with constraint 4.6.

Note that queue lengths are determined for all time slots as these are not only used in regular time but are also used to determine overtime.

Constraints 4.9 and 4.10 determine the number of processed patients, P, by taking either the number of patients in the system or the capacity. If the number of patients exceed capacity, the number of processed patients will at most become the capacity. This is because no more patients can be processed than there is capacity. In case there are less patients than capacity, the value for P will equal the number of patients. We only apply constraint 4.10 and 4.11 for the time set Overtime because we only want to minimize the patients processed in overtime and not during the day.

Variable P denotes the number of patients that are treated for each scenario, location, day and time slot. P equals

$$P^{s}_{l,d,t} = Min(Q^{s}_{l,d,t-1} + RS_{l,d,t} + up^{s}_{l,d,t}, \qquad c_{l,t}) \qquad 4.15$$

So, P is the minimum of either the queue of the previous time slot plus the number of scheduled patients (Reserved slots) plus the unscheduled arrivals , or the capacity. The maximum number of patients that can be treated is either the number that is present if this is lower than capacity, or the capacity because no more patients than available capacity can be treated.

Because this “Min” formulation also does not meet the ILP formulation requirements, we use constraints 4.7, 4.8, 4.9 and 4.10. to determine the number of processed patients.

Constraints 4.7 and 4.8 are auxiliary variables to determine the number of processed patients. Variable V in constraint 4.7 determines the difference between the number of patients in the system and the capacity. Constraint 4.7 sets the value V, which is used in constraint 4.8. Constraint 4.7 and 4.8 are useful for the optimality of the model because they set a predetermined value for Y. Depending on the outcome, this eliminates options for constraints 4.9 and 4.10 to calculate: Less iterations have to be made.

Constraint 4.11 makes sure that all variables except the auxiliary variables Y and V are non-negative and integer. Constraint 4.12 states that auxiliary variable Y is a Binary and thus can only become 0 or 1. In auxiliary variable V the number of patients can be less than capacity or exceed capacity. Therefore, V can become both a negative or positive integer, which is stated by constraint 4.13.

4.3.3. Model improvements on the go

While working on this model, we first used equation 4.14 and 4.15 in our model in AIMMS. Although the formulation in 4.14 and 4.15 yields the desired results and is a correct way of formulating, it does not meet the LP or ILP formulation requirement and therefore has some drawbacks: It takes a lot of computation time to solve the model to optimality.

Instead of an LP model it is a type of Constraint Programming (CP or COP). Therefore, these equations are later replaced by constraints 4.5 and 4.6 (instead of equation 4.14) and by constraints 4.7 until 4.10 (instead of equation 4.15).

One of the benefits of replacing the constraints by constraint that are applied for ILPs is that instead of the solver CPOptimizer 12.7 (by IBM) the high-quality solver CPLEX could be used. This yields an enormous decrease of computation time: Approximately several hours for the CPOptimizer versus several seconds for CPLEX.

4.3.4. Objective function weights

Our aim is to minimize the variables queue length and overtime. So, four each time slot, the queue length is determined by adding the queue length of the previous time slot, the unscheduled arrivals and the scheduled patients and then subtracting the capacity of the time slot (see Equation 4.5 and 4.6). So, in case of queues, the value for queue length, equals the queue length. This means the value of Work pressure is its own value times 1. Thus, the objective function weight is 1.

Overtime is also included in the objective function. Work pressure can be reduced if the patients are evenly divided over all 24 slots. In some cases, this can result into working overtime: The definition of the variable Overtime equals the number of patients processed in overtime. Overtime is a result of the combination of queues during the day, arrivals in overtime and a decreased capacity in the overtime. Working overtime is for practical reasons less favourable than queues during the day, so this is minimized. The value of Overtime is therefore its own value times 2.

As the system must deal with queues one way or another, it is most beneficial to "schedule" queues at the end of the day: That way, there is a lower work pressure during the day. This is undesired because employees do not want to deal with an excess of patients at the end of their working day. To determine the function weights, we will perform sensitivity analysis on these parameters in Section 5.1.

4.3.5. Verification and validation

The model should represent the system as it is used in Hengelo and Almelo. Therefore, we verify and validate the model such that we can be sure it is an actual representation of reality. The difference between validation and verification is well described by Law (2007) and is shown in Figure 4.1 by Mes (2015).

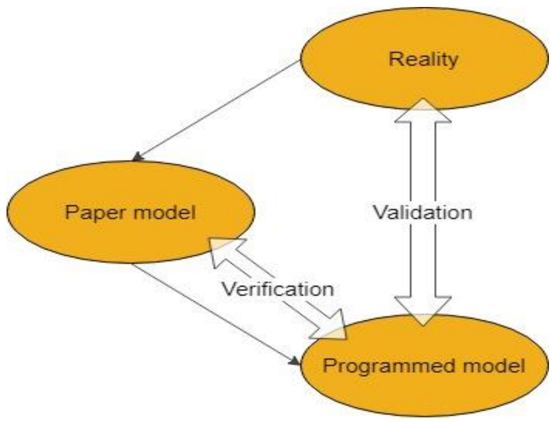

Figure 4.1. Verification and validation (Mes, 2015)

We assume that the conceptual model corresponds with reality. For this, often check-up moments were planned with stakeholders and experts, such as the coordinator of the Bucky department. In these meetings all assumptions and decisions made until then, were validated.

Second, after transforming the paper model into a programmed model, the programmed model was verified with the paper model and validated with reality.

Verification is done by checking the correctness of every new added aspect of the model. While programming, every step is checked and if considered necessary, checked by hand-made calculation. For example, checking if the input in the model corresponds with the actual input can be done by just walking through the number and see if they are equal. Another example is for queue lengths. This is an important variable in the model and therefore it is important that it is calculated correctly. Therefore, queue length correctness is frequently checked by making calculations by hand for sample time slots.

For validation, we first want to make sure that input data corresponds with the actual arrivals of patients. For the scheduled patients, the input in number of patients per time slot equals the actual average number of patients per time slot: This can be checked for each day and time slot.

For the unscheduled patients, validation is done by taking the average per time slot, over all arrivals in all scenarios: $\frac{\sum_{s=1}^{S} UP_{l,d,t}^{s}}{S}$. For example, taking the arrivals of all scenarios at t1 (7:30). This should correspond with the initial λ of t1, the input for the Poisson random number generator and the average number of unscheduled arrivals from historic data. We allowed small deviations from the initial average, ranging from 0.01 to 0.05.

For validation of the rest of the model, a presentation with stakeholders was organised as it was not possible to determine queue lengths and overtime based on historic data (see 2.3.2 on data limitations). During this meeting the basic workings of the model were shared and checked upon correctness with experts. Also, the current situation was produced with the model (for details: 4.3.6). Queue lengths and overtime of the current situation were provided during the presentation and according to experts, the results corresponds with the actual situation.

4.3.6. Adjustments for the initial design

To determine the current performance of the system the queue length and overtime also needs to be determined. The model is slightly adjusted for this purpose, as the goal is not to find the best number of patients to schedule in a time slot, but just to find a value for the objective function for the current situation. Currently, unscheduled patients get an appointment at the time of arrivals. The scheduled patients are fixed. The current approach is to add the unscheduled patients to the planning. Therefore, we did the same to determine the objective value for the initial design and to determine Q_l and O_l for both locations. We introduce a new parameter, namely a, which stands for all arrivals. The notation for this model is as follows:

$$a_{l,d,t}^{s} = sp_{l,d,t} + up_{l,d,t}^{s} \qquad \forall l \in L, \forall d \in D, \forall t \in T, s \in S \qquad 4.16$$

$$Q_{l,d,t}^{s} \geq RS_{l,d,t} + up_{l,d,t}^{s} - c_{l,t} \qquad \forall l \in L, \forall d \in D, \forall s \in S, t = 1 \qquad 4.17$$

$$Q_{l,d,t}^{s} \geq Q_{l,d,t-1}^{s} + RS_{l,d,t} + up_{l,d,t}^{s} - c_{l,t} \qquad \forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T \qquad 4.18$$

$$Q_l = \frac{\sum_{d \in D} \sum_{t \in T^r} \sum_{s \in S} Q_{l,d,t}^{s}}{|S|} \qquad \forall l \in L \qquad 4.19$$

$$P_{l,d,t}^{s} \geq Q_{l,d,t-1}^{s} + a_{l,d,t}^{s} - Y_{l,d,t}^{s} * M2 \qquad \forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^{o} \qquad 4.20$$

$$P_{l,d,t}^{s} \geq c_{l,t} - (1 - Y_{l,d,t}^{s}) * M2 \qquad \forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^{o} \qquad 4.21$$

$$V_{l,d,t}^{s} = Q_{l,d,t-1}^{s} + a_{l,d,t}^{s} - c_{l,t} \qquad \forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^{o} \qquad 4.22$$

$$Y_{l,d,t}^{s} * M1 \geq V_{l,d,t}^{s} \qquad \forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^{o} \qquad 4.23$$

$$O_l = \frac{\sum_{d \in D} \sum_{t \in T^o} \sum_{s \in S} P_{l,d,t}^{s}}{|S|} \qquad \forall l \in L \qquad 4.24$$

$$Q_{l,d,t}^{s}, P_{l,d,t}^{s} \in Z_{\geq 0} \qquad \forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T \qquad 4.25$$

$$Y_{l,d,t}^{s} \in \{0,1\} \qquad \forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^{o} \qquad 4.26$$

$$V_{l,d,t}^{s} \in Z \qquad \forall l \in L, \forall d \in D, \forall s \in S, \forall t \in T^{o} \qquad 4.27$$

4.3.7. Adjustments for the walk-in design

To determine the performance of a situation in which all patients arrive unscheduled, we need to adjust our model. Our goal is not to find the best number of patients to schedule, but to find the queue lengths and overtime. Then, we can compare the 3 settings on the same KPIs.

We expanded the current number of patients that arrive unscheduled, $up^{s}_{l,d,t}$. In the data, this is about 25%. For each day, we found the total amount of patients, for which we used the ratio scheduled/unscheduled to determine the new value of $up^{s}_{l,d,t}$: The number of patients in case 100% arrives unscheduled.

We did not use the total arrivals $sp_{l,d,t} + up^{s}_{l,d,t}$ because $sp_{l,d,t}$ is currently scheduled and does not follow a natural walk-in arrival pattern as $UP^{s}_{l,d,t}$ does. Therefore, we determined the 100% numbers out of the ratio scheduled/unscheduled.

We want to determine Q_l and O_l. We use the model as described in 4.3.6, but the definition of a changes: $a^{s}_{l,d,t} = up^{s}_{l,d,t}$

4.4. Conclusion

In this chapter we combined the information of the system we gathered in chapter 2 and the knowledge on appointment systems as obtained in chapter 3 to model the system. With this information we answer our research question 5: *How can the radiology processes be modelled?*

Our KPIs, *Rejections, waiting time, Work pressure* and *Overtime* are used to determine the basics of the model. Because deferring patients is not allowed, KPI *Rejections* was used as a hard constraint in our model. *Waiting time* for patients corresponds with queue length, which is the definition of KPI *Work pressure*. Therefore, KPIs Work pressure and Overtime are used in the model as variables to minimize to achieve our desired result: A blueprint for planners that tells how many patients to schedule in a time slot. This scheme differs for each day of the week. We solve the model to determine the scheme given the model constraints and capacity per time slot.

To make the scheme more robust to various numbers of unscheduled patients, scenarios in which the expected number of arriving unscheduled patients vary are used. These are generated randomly with use of a Poisson distribution with input parameter λ: the average number of unscheduled arrivals per time slot per day. The number of scheduled patients per time slot are based on the average per time slot per day and are fixed. The model is verified and validated by doing calculations by hand, meetings with experts and data checks with historic data. We found that the workings and the output of the model correspond with the experiences of the employees.

Chapter 5

5. Results

This chapter provides the results of the model as described in Chapter 4 in terms of work pressure and overtime. We will refer to work pressure in this section as "queue length" as this is how it was measured in the model. We give overtime in terms of minutes that are worked after 17:00. We give the results for both locations and all 3 settings: Initial design, walk-in design and solution design.

We start with the results of a sensitivity analysis in Section 5.1. Then, we describe the overtime results for all settings and locations in Section 5.2. We continue with the work pressure (queue) results in Section 5.3 and conclude this Chapter in Section 5.4.

5.1. Sensitivity analysis

We analysed the sensitivity of the model to gain insight in the factors that influence the performance measures. We have 2 factors in our model: Overtime and queue length. We did a sensitivity analysis on these factors. To be more precise, we did a sensitivity analysis on their function weights to see how these influences the performance of the results.

For practical reasons we decided that preventing overtime has a higher priority than preventing queue forming. Therefore, the function weights for overtime are equal or higher than the function weight for queue lengths.

As sample we used Monday in Hengelo with an average of 186 patient arrivals per day. We took this day because it is a busy day, but still has space left to optimize: In other words, the day capacity is not exceeded. We used 50 scenarios, and our input parameters for each experiment setting were the same. AIMMS solved the model to optimality. We did several experiments with the function weight for overtime varying from 1 to 1000 but this did not influence the performance of the model. We therefore conclude that the model is not sensitive for changes in the function weights. This is because the model is solved to optimality and therefore no additional changes that might improve the solution can be made if the weights vary. Also varying the function weight for Queue length did not change the results.

5.2. Overtime

In the objective function overtime is measured as the number of patients that are processed after regular working hours. To make this term a bit more tangible and applicable, we will transform the number of patients that are processed in overtime to time worked overtime. So, overtime is described in terms of time worked after 17:00, assuming again that processing takes 5 minutes per patient.

3 out of 4 employees are finished working at 16:30 and the remaining employee works to treat patients that are still in the waiting room until 17:00. Capacity after 16:30 decreases from 12 to 4 patients per 30 minutes because there is only 1 employee left. In Table 5.1 we summarize the results of all 3 settings for location Hengelo.

Table 5.1. Model results. Average overtime in minutes in Hengelo per day for each setting

	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Initial design	59	6	0	1	1
Walk in design	69	44	2	2	3
Solution design	15	3	0	0	0

Outstanding are Mondays: In the initial design and the Walk-in design Mondays are related with approximately an hour of overwork. This is as we expected, because Mondays are busy according to statements of employees and this effect is also a reflection of the average number of arrivals on Mondays. These are the highest compared to other days in Hengelo: 186 on Mondays versus 181, 151, 171 and 149 respectively on Tuesdays, Wednesdays, Thursdays and Fridays.

So, the number of arrivals is high and additional to that, the arrival numbers vary per scenario. The given numbers above are averages per day, which means there exists some variation in the number of patients. Unscheduled arrivals on Mondays vary from 44 to 77 over all scenarios with an average of 60, while scheduled patients are fixed at 130. A simple calculation tells us that the cases with (77+130) 207 patients per day does not fit within the capacity of 200. Therefore, the number of patients per day is a good explanation for the overtime.

A second explanation is that the arrival patterns (both scheduled and unscheduled patients) are irregular with peaks during the day and therefore demand does not fit the capacity, causing overtime. This also explains the even higher overtime on Monday, and the value of 44 minutes overtime on Tuesday in the walk-in design: In this design, the walk-in pattern is expanded from 25% to 100% with no scheduled patients, making the arrival pattern even more unbalanced.

With Figure 5.1 we show the effects of both explanations in more detail. Average overtime on Mondays in the initial design is 59 minutes, but the boxplots show outliers up to 150 minutes. These can not only be caused by a higher demand than supply but is caused by a combination of both factors: More demand than supply and an uneven arrival pattern, with more arrivals at the end of the day than at the beginning of the day.

On Mondays and Tuesdays, we see a reduction of average overtime in Table 5.1 in the solution design. Furthermore, we see less dispersion of the amount of overtime in the solution design compared to the initial and walk-in design.

The overtimes on Wednesdays and Fridays are low as demand is also lower on these days. For Thursdays, we explain in Section 5.3 why overtimes are low; this is related to queue lengths.

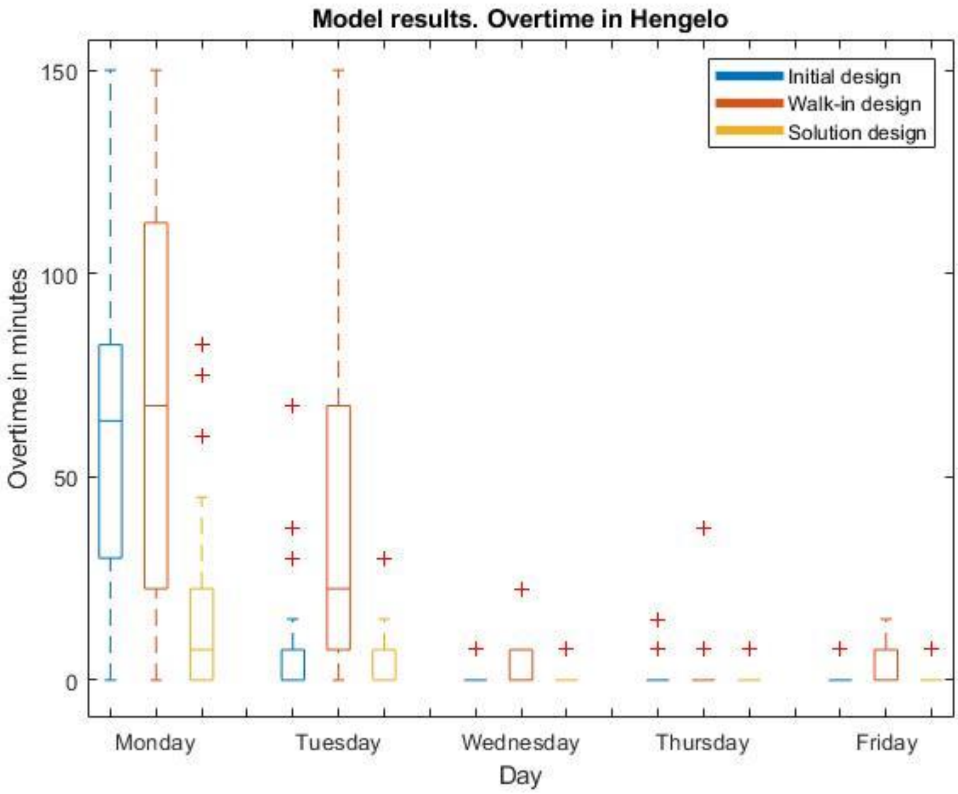

Figure 5.1. Model results. Overtime in Hengelo in minutes

We also determined average overtimes per day for Almelo, which we show per day per setting in minutes in Table 5.2. The first aspect that is notable is that Almelo has more overtime to handle than Hengelo. Average total arrivals for Almelo are 212 (Monday), 186 (Tuesday), 188 (Wednesday), 179 (Thursday) and 160 on Fridays. Almelo must handle more patients than Hengelo per day, which is the cause of the higher amount of overtime.

Table 5.2. Model results. Average overtime in minutes in Almelo per day for each setting

	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Initial design	148	52	52	12	9
Walk in design	149	96	86	17	13
Solution design	108	9	5	2	2

In Figure 5.2 we show the boxplots corresponding to the overtime in Almelo per setting per day. Again, outliers up to 150 minutes are remarkable. For Mondays these outliers are no surprise, because in some scenarios and in historic data, demand exceeds supply with more than 23 patients. Since supply after 16:30 decreases from 12 to 4 patients per 30 minutes, it is evident that in these cases it takes more than 2.5 hours to treat all remaining patients if only 1 employee is still working. In practice, this amount of working overtime does not occur as often more employees stay to process all patients in case of these excesses. In the cases with more than 216 patients per day, not all patients were processed in the model, even not after an overtime of 2 hours.

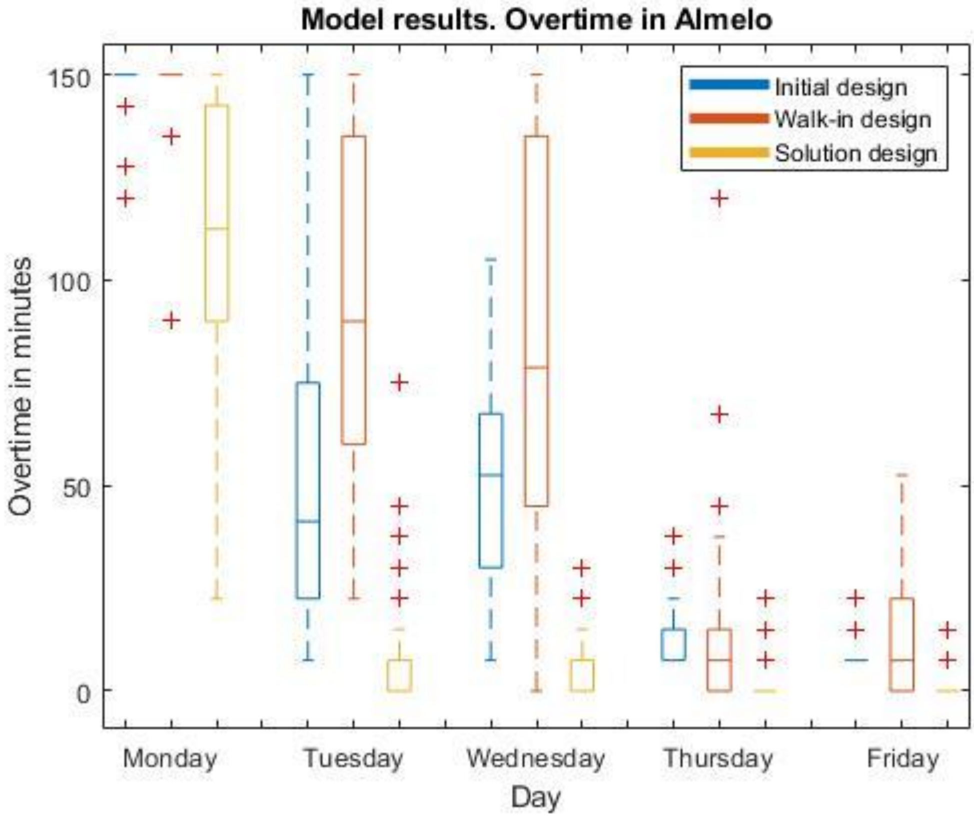

Figure 5.2. Model results. Overtime in Almelo in minutes

We also see that the overtimes for the walk-in design are often higher than the overtimes of the other settings. We expected this to happen as we expanded the arrival pattern from 25% to 100%, this is caused by the irregularities of the arrival pattern and the missing benefits from scheduling patients during off-peaks.

Unlike Hengelo, Wednesday is a busy day in Almelo with an average of 190 patients. The same principle of demand exceeding capacity as explained for Hengelo applies here. This causes waiting time in all settings. Thursdays (179 patients) and Fridays (163 patients) are relatively quit days, which explains the lack of excessive overtime on these days.

5.3. Work pressure

In this section we describe the results for the work pressure for all 3 settings. We refer to Work pressure as queue length in this section, as this is the definition of work pressure in our model.

Queue length is modelled for each location, each scenario, each day and each time slot, which means we have a lot of data on queue lengths. As this is not representable, we will use the average queue length of a day and boxplots with all queue lengths per time slot to display our results.

We start with Hengelo. In Table 5.3 we show the average queue lengths for each day in Hengelo. Once more, we see the trend the busiest day Monday. An average queue length of about 6 in the initial design. Considering that queue length defines the number of patients that are an overabundance to the capacity, this is a remarkable number: 6 patients per 30 minutes that cannot be processed. As Mondays were stated as busy days by the Bucky employees, this is as we had expected. We explain this phenomenon with the total number of patients that arrive. As already shown in the Overtime section 5.2, demand often exceeds supply on Mondays, making it impossible to fit in all patients during the day. Also, the irregular arrival pattern plays its part in building up queues: During peak hours, about 7 patients can come in at once, which has its impact on queueing.

Table 5.3. Model results. Average queue length per day in Hengelo for each setting

	Monday	Tuesday	Wednesday	Thursday	Friday
Initial design	5.9	3.2	0.4	3.6	0.6
Walk-in design	7.8	4.8	1.0	5.5	1.5
Solution design	1.8	0.7	0.1	0.4	0.1

In Figure 5.2 we also see that queue lengths on Tuesdays and Thursdays in the initial design are, relatively to the arrivals, quite high. We also see dispersion of the queue lengths for these days: it varies from 0 to 25. Arrivals on Thursdays are 171 patients on the average. The queue lengths of Tuesdays and Thursday are approximately 3 and 4 per time slot. This is mostly due to the balance between queue lengths and overtime. In Figure 5.1 and Table 5.1 we see that overtime in Hengelo on Tuesdays and Thursdays in the initial design barely occurs. This is compensated during the day: Building up queues makes the system able to not become idle. So, in the off-peak moments, queues are resolved. This makes sure that in case capacity is sufficient, which is the case on Thursdays, overtime barely occurs but queues do exist. We see a reduction of queue length in the solution design, which is because patients are scheduled more efficient to prevent the appearance of queues. The relation between queues and overtime is described in section 5.1. Sensitivity analysis.

Lastly, the initial and walk-in design on Fridays knows some moments that queue length exceeds 15 patients in a time slot. This is due to the uneven arrival pattern of patients as 41% of the patients on Fridays in Hengelo visit the Bucky unscheduled: the queue lengths of the walk-in design emphasize this.

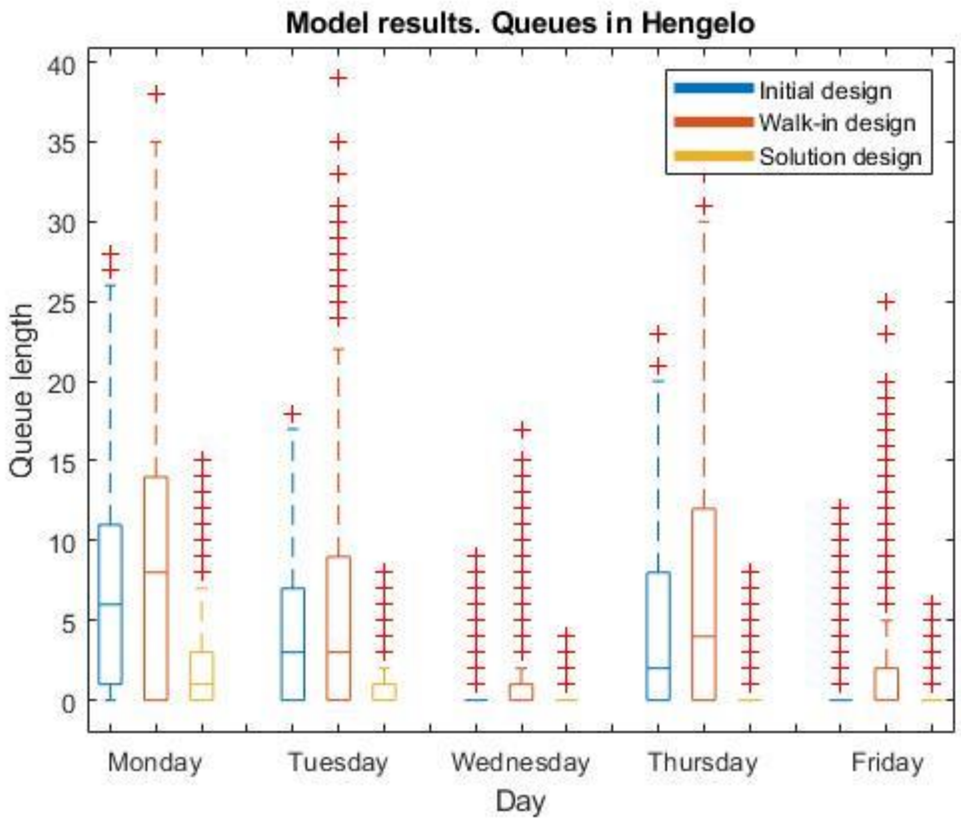

Figure 5.3. Model results. Queue length in Hengelo in numbers of patients

At last, we want to emphasize the differences between the days of the week. An unbalance seems to exist: On Mondays, employees must deal with more queues compared to Wednesdays or Fridays.

We continue to the queues in Almelo as shown in Table 5.4 and Figure 5.4.

Table 5.4. Model results. Average queue length per day in Almelo for each setting

	Monday	Tuesday	Wednesday	Thursday	Friday
Initial design	4.6	0.9	1.3	0.6	0.6
Walk in design	16.9	4.7	7.4	5.6	2.2
Solution design	6.5	0.7	0.9	0.6	0.1

The first aspect that attracts attention is that on Mondays, the initial design performs better than the solution design: an average of about 5 patients in the initial design versus 7 in the solution design. This was expected to happen for 2 reasons:

First, in the current design not all patients were processed. This happened apart from the scenarios in which the arrivals exceeded capacity, which was the case in 8 scenarios. In the initial design, on the average 6 patients per Monday could not be treated due to an uneven demand pattern and apart from the cases in which demand exceeded capacity. The value for overtime stops increasing at the absolute maximum allowed time of 19:00, but the patients that are not processed do not count for overtime anymore and do not influence queue length. In the solution design it also occurred that patients were not treated, but this was only in the 8 cases that the total demand exceeded capacity. In all other scenarios, all patients were treated, but this has a higher queue length as result.

Second, we have a reduction of an average of 6 minutes in overtime. As described in the Section 5.1 about the sensitivity analysis, a trade-off is made between overtime and queue length. As overtime reduces, we can expect an increase in queue length.

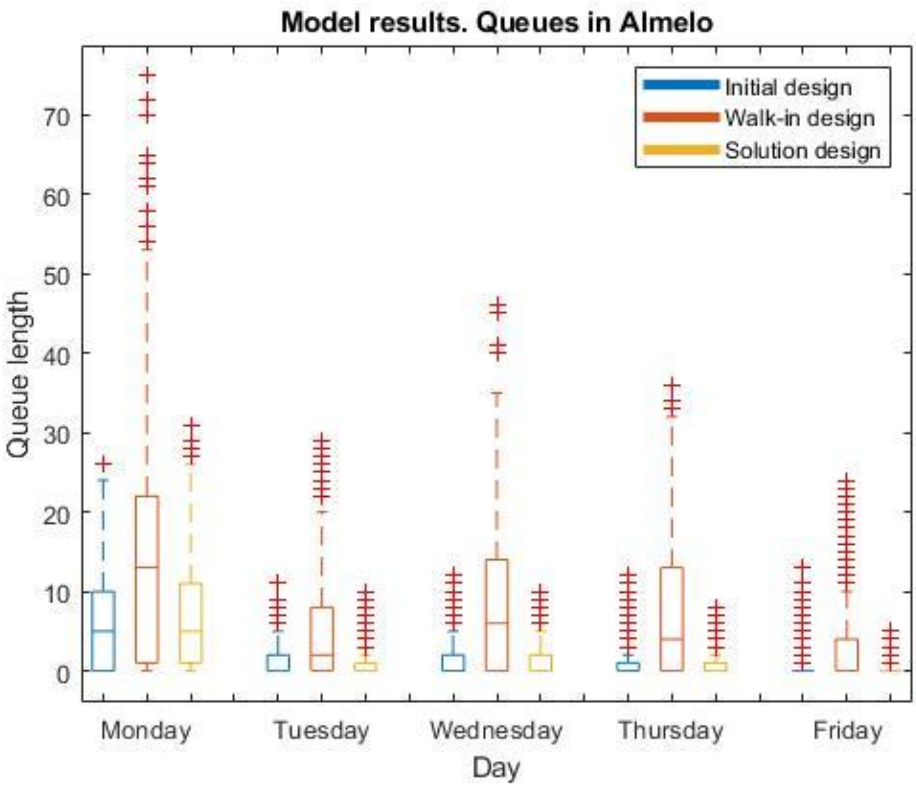

Figure 5.4. Model results. Queue length in Almelo in numbers of patients

We also see a decrease in queue length in the solution design for each day. We expected this to happen as our solution model planned the scheduled patients in such a way all patients are more evenly divided over the day to prevent queue forming.

The walk-in design performs worse than both other settings on each day. This is caused by the same principle as in Hengelo: variability in the arrivals of patients cause congestion of the system and therefore are a cause for queues.

5.4. Conclusion

In this section we conclude chapter 5 and answer the corresponding research question

What are the results of the executed experiments?

First, we did a sensitivity analysis to determine the effect of the function weights in the objective as described in Section 4.3.4. For practical reasons the overtime value cannot become lower than the value for queue length.

We did several experiments to test the sensitivity of the objective function weights of the model. Our zero measurement (experiment 0) has the function weight ratio 1:2 for respectively "Queue length" : "Overtime". We varied the function weight for Overtime from 1 to 1000 but this did not influence the amount of overtime and the queue lengths. We therefore concluded that the model is not sensitive for changes in function weight.

We then tested 3 model settings: The initial design; the way the system currently works, the Walk-in design, in which all patients arrive unscheduled and the solution design, with the results of the model as proposed in section 4.

We found results for each setting, for each day on each location. First, we can state that the walk-in design was outperformed in queue length and overtime by the initial and the solution design. Except for Mondays in Almelo, the solution design performed best in terms of queues and overtime for each day and location.

Queue lengths on Mondays in Almelo are longer in the solution design compared to the initial design. One cause for this is the reduction of overtime; the model makes a trade between these aspects.

Also, in the initial design not all patients that arrived, were treated. In case the demand exceeds capacity, this is reasonable. However, in the initial design this happened because the arrival patterns of patients were uneven. An uneven arrival patterns has as a result that it is not possible to process all demand if it approaches the maximum supply: For this to happen, demand needs to be evenly spread during the day, which is not the case with an uneven arrival pattern. This resulted in an average of 6 untreated patients per Monday. In the solution design, patients were left untreated in case demand exceeded supply. So, although the queue length is shorter in the initial design, the performance is worse as the initial design does not meet our basic requirements: Every patient should be treated.

From this we conclude that the performance of the solution design is the best in terms of overtime and queue length. It not only reduces both on the average, but also reduced the disparity.

In general, we can state that Mondays are busier than other days at both locations. An explanation for this phenomenon can be that patients often postpone their GP visit from weekends until the Monday. Therefore, Mondays must deal with more patients than the other days with an increase in overtime and queues as a result. Sometimes demand exceeds supply, making it impossible to treat all patients.

Chapter 6

6. Conclusion and recommendations

This chapter gives an overall conclusion of the study based on the results in Chapter 5. Furthermore, we give some recommendations for ZGT to improve the problem as described in Section 1.2. In this section we answer the last research question, namely: *What is the conclusion of this study, and what are the recommendations for radiology at ZGT?*

6.1. Conclusion

The main research goal was to reduce work pressure initiated by an unbalanced workload. We did this by gaining insight into the causes of unbalanced workload and looked for a tailored planning solution. The solution system is generated by the literature on planning systems. Our goal was to minimize Work pressure (in terms of queue lengths per time slot: The patients that are a surplus to capacity) and overtime (the number of minutes worked after regular time) in 3 settings: The initial design, the Walk-in design and the Solution design.

We found that the Walk-in design was outperformed by the Initial and Solution design in both overtime and work pressure. Accordingly, we found 2 causes for the experienced work pressure: Demand that exceeds the maximum supply (Mondays, both locations) and variability in the arrival patterns of unscheduled patients: Arrivals patters are uneven such that these fluctuations cannot be counterbalanced. Although this might be compensated during the day by working harder, this is a relevant aspect of the existence of work-pressure in ZGT.

Because of the Walk-in characteristics (25% of inflow) of the department, we cannot influence the arrival times of the unscheduled patients. Therefore, our Solution design (Table 6.2 and Table 6.3) is aimed at the scheduled patients. It optimizes the schedule such that minimize overtime and work pressure are minimized. With this solution design we developed a daily scheme for each day of the week for both locations. In this scheme for each time-period of 30 minutes is defined how many patients should be scheduled and how many slots should remain open for unscheduled patients. We present this scheme in Table 6.2 and Table 6.3

The solution design performed better on all aspects than the initial design. Except for Work pressure in Almelo on Mondays, in both locations on all days, both Overtime and Work pressure reduced. The reductions are shown in Table 6.1. Work pressure on Mondays in Almelo increased because in the initial design, on the average 6 patients per day were deferred due to capacity limitations. In general, the demand is unevenly spread over the week.

Table 6.1. Improvements in solution design versus initial design: Δ Overtime and Δ Work pressure

Reduction	Location	Mo	Tu	We	Thu	Fri
Δ Overtime:	Hengelo	44	3	0	1	1
Minutes worked after regular hours	Almelo	40	43	47	10	7
Δ Work pressure:	Hengelo	4.1	2.5	0.3	3.2	0.5
Patients surplus to capacity per time slot (Average)	Almelo	-1.9	0.2	0.4	0.0	0.5

The volatility of the model depends on the input parameters like the arrival ratio of scheduled and unscheduled patients, the arrival pattern of unscheduled patients and the total number of patients. The model is specified for the current settings and a change in the input parameters will very likely influence the performance of the model in a bad manner. For example, if the arrival pattern of unscheduled patients changes and more patients come in during the lunch break, this can have potentially large impacts on the queue lengths of the rest of the day.

6.2. Recommendations

In all aspects, the solution design performs best. Therefore, we represent in this section the corresponding scheme for the solution design as shown in Table 6.2 and

Table 6.3. The day scheme states that for example on Mondays in Hengelo at 7:30 it is best to schedule 4 patients. This means there is, considering capacity at 7:30 (4 patients) no place left for unscheduled patients, but as we see in the historic data, rarely unscheduled patients arrive during this slot. Table 6.2 and Table 6.3 shows the day scheme for Hengelo and Almelo.

Because the solution design performs better than the current design, we recommend using the day schedules as presented in Table 6.2 and Table 6.3. We recommend using this scheme as it takes the arrival pattern of unscheduled patients into account, which is not the case in the current design. This ensures a more evenly spread work pressure during the day.

Furthermore, we recommend allowing workload shifting during days. Re-plan patients with non-urgent appointments away from Mondays (both locations) to days with a lower workload in order to decrease capacity on Mondays. This is an action on operational level and depends on the workload division for the current week.

Note that this solution is specified for the current settings of the system, in which about 25% of all inflow is unscheduled. The arrival rates are drawn from data over the period 01-01-2018 until 31-05-2018. Depending on seasonal changes, the input parameters can change and therefore change the performance of the model. Therefore, we recommend updating the schemes every three months.

For the implementation and evaluation of the solution we would like to advice to start using the scheme and adjust according to findings on the work floor. For example, if it turns out that still queues exist during peak hours due to the timing of coffee and lunch breaks, running the model again with adjustment in capacity might be useful.

6.3. Limitations of the study

The limitations in this study are as follows:

- We did not consider the variation in appointment duration. This has impact on the performance of the proposed solution as the throughput times directly influence the queue length.
- No patient preferences in the model are considered.
- We did not consider seasonal changes in demand.
- Because the model was improved on the go by developing the just right constraints, the number of scenarios could have been higher. This is not a major problem because the generated scenarios still approach the real-life situation because their average values differ <1 from the historic data per time slot, which is an accurate approximation. The number of scenarios could be increased for a successive study.

6.4. Future research

We suggest including the processing/throughput times for further research. As described earlier, this is an important factor for the performance of the solution. Also, some experimentations with the best mix of scheduled and unscheduled patients might yield profit for the department in terms of work pressure or overtimes.

Table 6.2. Model output.
Day scheme for Hengelo with the optimal number of scheduled patients per time slot per day

	Monday	Tuesday	Wednesday	Thursday	Friday
07:30	4	3	1	2	2
08:00	11	10	9	9	7
08:30	9	8	8	7	7
09:00	7	9	7	6	5
09:30	7	6	6	7	4
10:00	2	4	3	2	0
10:30	7	8	6	6	3
11:00	8	8	7	6	5
11:30	10	9	9	9	7
12:00	7	6	4	5	5
12:30	5	5	3	3	2
13:00	7	7	7	6	7
13:30	7	8	6	7	5
14:00	7	8	8	7	6
14:30	4	4	3	5	3
15:00	8	8	7	10	5
15:30	12	10	7	11	6
16:00	8	8	8	8	8
16:30	0	0	0	0	0
17:00	0	0	0	0	0

Table 6.3. Model output.
Day scheme for Almelo with the optimal number of scheduled patients per time slot per day

	Monday	Tuesday	Wednesday	Thursday	Friday
07:30	4	4	4	3	3
08:00	12	11	11	9	8
08:30	11	10	10	9	9
09:00	10	9	10	8	9
09:30	9	10	10	7	7
10:00	5	6	4	4	3
10:30	10	9	8	7	7
11:00	9	9	10	8	6
11:30	8	9	9	8	7
12:00	7	6	7	6	5
12:30	7	5	5	5	4
13:00	11	10	10	9	9
13:30	12	10	10	8	9
14:00	12	9	9	9	8
14:30	8	6	6	5	5
15:00	12	9	10	10	9
15:30	12	12	12	11	9
16:00	8	8	8	8	8
16:30	0	0	0	0	0
17:00	0	0	0	0	0

7

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8

8. Appendix

8.1. Waiting room Almelo

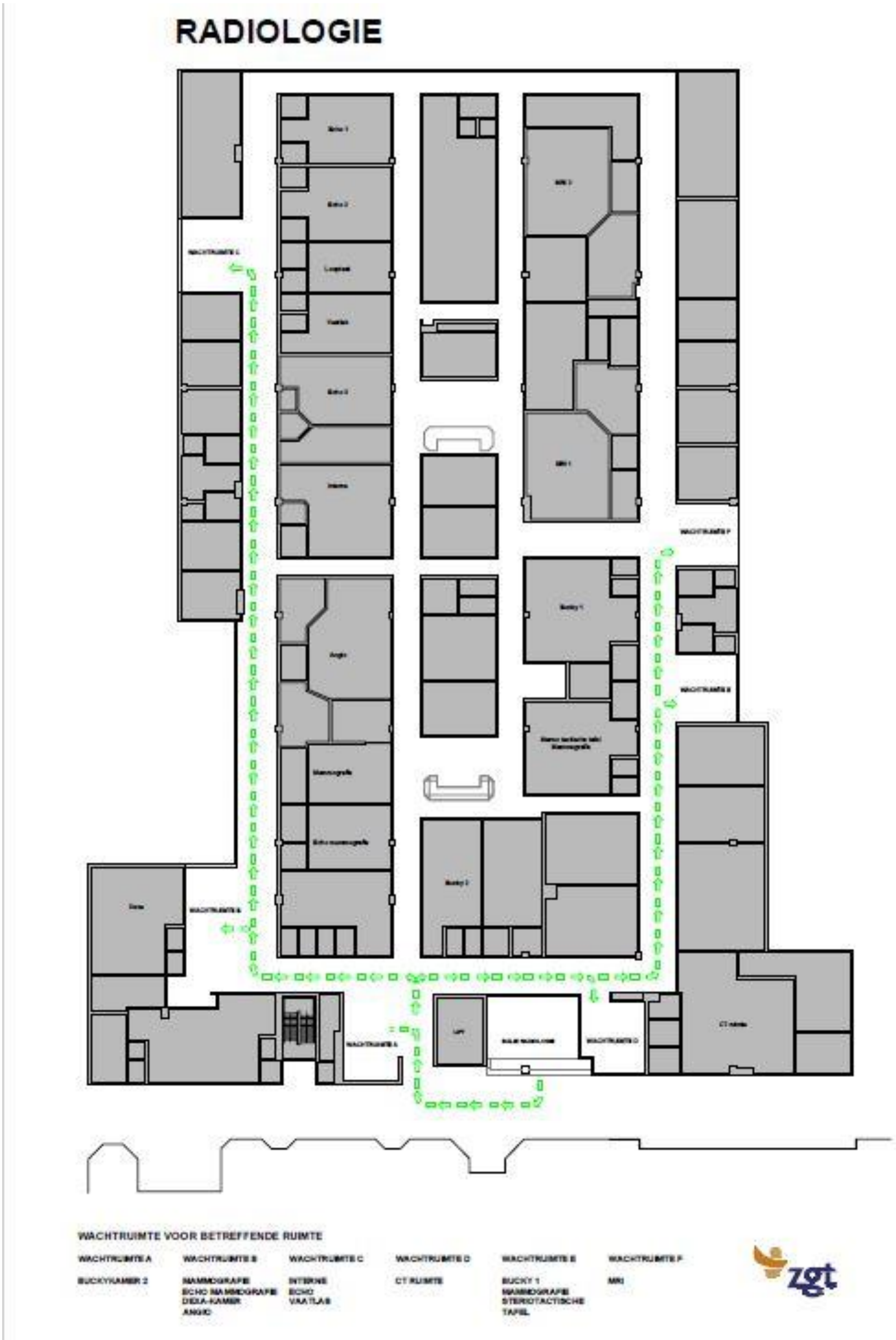

Figure 8.1. Waiting room Almelo

8.2. Waiting room Hengelo

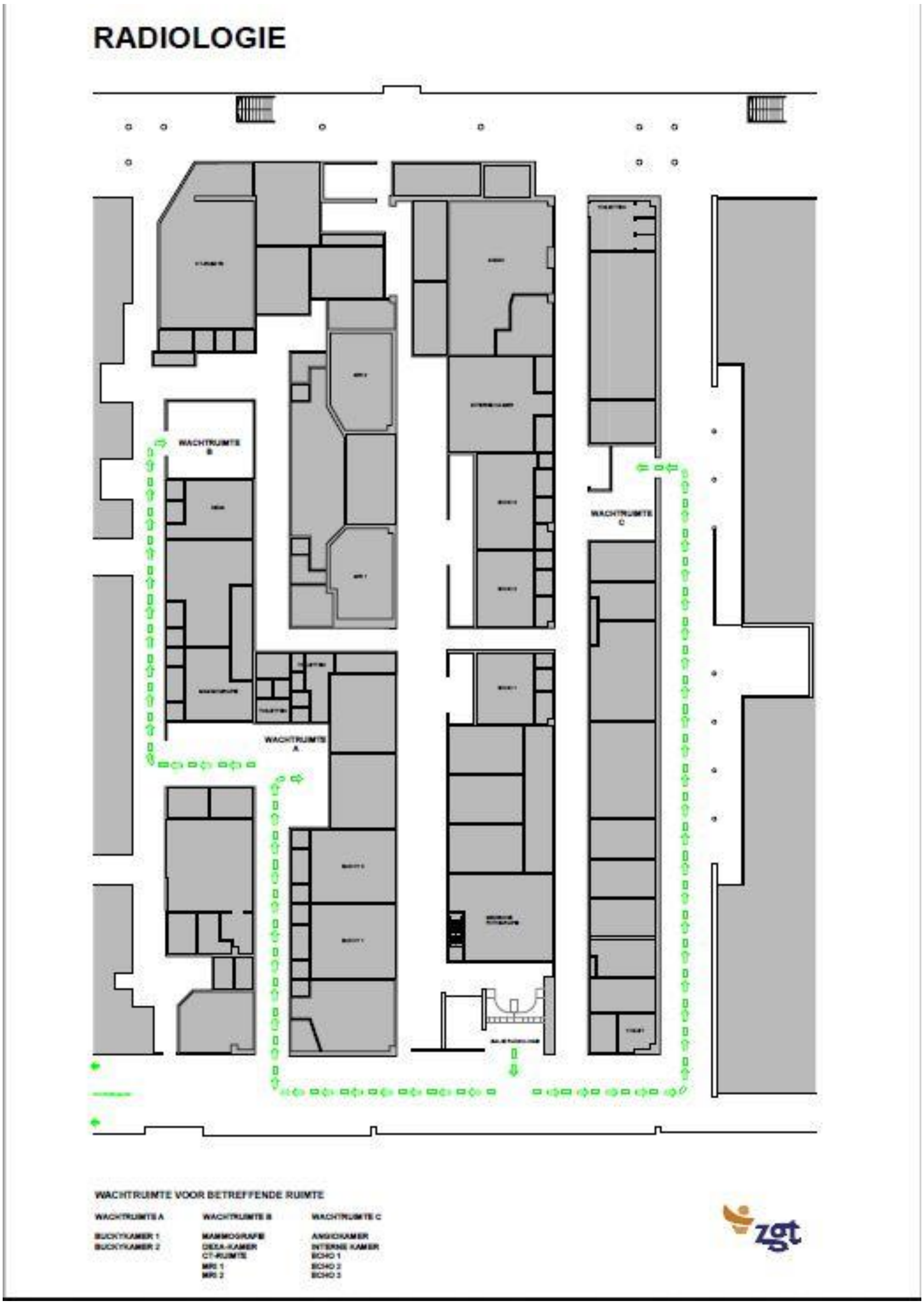

Figure 8.2. Waiting room Hengelo

8.3. All referrals to radiology and their frequency

Table 8.1. All referrals to radiology and their frequency

Specialty	Frequency	Percentage	Description
HUI	41555	47.6	GP
ORT	22381	25.6	Orthopaedics
CHI	8655	9.9	Surgeon
LON	4604	5.3	Pulmonologist
REU	3306	3.8	Rheumatology
CAR	1373	1.6	Cardiologist
INT	1308	1.5	Internist
URO	1020	1.2	Urologist
PLA	666	0.8	Plastic surgeon
NEU	534	0.6	Neurologist
KIN	461	0.5	Paediatrician
GAS	241	0.3	Gastroenterologist
PIJ	178	0.2	Pain clinic
KGR	165	0.2	Clinical geriatrician
SPO	165	0.2	-
DER	152	0.2	Dermatologist
VHA	133	0.2	Internal GP
REV	88	0.1	Revalidation
JEU	86	0.1	Paediatrician
KNO	84	0.1	Ear nose throat
DIV	39	0.0	Diverse
GYN	30	0.0	Gynaecologist
ANA	22	0.0	Anaesthesiologist
RAD	12	0.0	Radiology
OOG	11	0.0	Ophthalmologist
OVS	11	0.0	-
BED	10	0.0	-
ABG	5	0.0	Medical doctor
DIE	4	0.0	-
SEH	2	0.0	ED
PSY	2	0.0	Psychology
KLP	1	0.0	-
SON	1	0.0	External specialist
VER	1	0.0	-
ALL	1	0.0	Allergist
Total	87307	100.0	

8.4. Search query

Table 8.2. Search query for literature review

Date	Data base	Query	# of hits	Viewed	# of articles used
16/03/2018	Scopus	(TITLE-ABS-KEY (capacity AND management)) AND (hospital*)	28772		0
16/03/2018	Scopus	(TITLE-ABS-KEY (capacity AND management)) AND ((hospital*)) AND (radiology)	1260		0
16/03/2018	Scopus	(TITLE-ABS-KEY (capacity AND management)) AND (((hospital *)) AND (radiology)) AND (x-ray)	177		0
16/03/2018	Scopus	(TITLE-ABS-KEY (capacity AND management)) AND (hospital*) AND (bucky)	0		0
17/03/2018	Scopus	TITLE-ABS-KEY (variability AND hospitals)	15051		0
17/03/2018	Scopus	(TITLE-ABS-KEY (variability AND hospitals)) AND (((factors)) AND (radiology)) AND (planning)	31		1
17/03/2018	Scopus	TITLE-ABS-KEY (variability AND hospitals AND arrival)	109		0
17/03/2017	Scopus	(TITLE-ABS-KEY (variability AND hospitals AND arrival)) AND (radiology)	7		1
19/03/2018	Scopus	(TITLE-ABS-KEY (variability AND hospitals AND interventions)) AND ((radiology)) AND (planning)	8		0
19/03/2018	Scopus	(TITLE-ABS-KEY (hospital AND planning AND appointments)) AND (capacity)	136		0
19/03/2018	Scopus	(TITLE-ABS-KEY (hospital AND planning AND appointments)) AND ((capacity)) AND (arrival*)	12		1
19/04/2018	Scopus	Kortbeek	x		x
22/04/2018	Scopus	(TITLE-ABS-KEY (hospital AND shared AND resources)) AND (variability)	22		0

22/04/2018	Scopus	(TITLE-ABS-KEY (hospital AND shared AND resources)) AND (inflow)	0		0
22/04/2018	Scopus	(TITLE-ABS-KEY (hospital AND ancillary)) AND (arrival*)	23		0
22/04/2018	Scopus	(TITLE-ABS-KEY (hospital AND resources)) AND (((arrival*)) AND (variability)) AND (ancillary)	1		0
22/04/2018	Scopus	(TITLE-ABS-KEY (hospital AND resources)) AND (((arrival*)) AND (variability)) AND (shared)	4	2	
24/04/2018	Scopus	(TITLE-ABS-KEY (hospital AND variability AND radiology)) AND (arrival*)	2	1	1
15/05/2018	Scopus	(TITLE-ABS-KEY (hospital AND resources AND arrival AND effect)) AND (variability)	9	1	1
21/05/2018	Scopus	TITLE-ABS-KEY (outpatient AND scheduling AND in AND healthcare: AND a AND review AND of AND literature)	5	2	2

8.5. Capacity per time slot

Table 8.3 Capacity per time slot

Time slot	Time	Capacity
1	07:30	4
2	08:00	12
3	08:30	12
4	09:00	12
5	09:30	12
6	10:00	8
7	10:30	12
8	11:00	12
9	11:30	12
10	12:00	8
11	12:30	8
12	13:00	12
13	13:30	12
14	14:00	12
15	14:30	8
16	15:00	12
17	15:30	12
18	16:00	12
19	16:30	8
20	17:00	4
21	17:30	4
22	18:00	4
23	18:30	4
24	19:00	4

Table 8.4. Example of scenarios: Scenario 1 to 4 on Monday

Time slot	Average arrivals from	Average Poisson arrivals	s1 Unscheduled arrivals	s2 Unscheduled arrivals	s3 Unscheduled arrivals	s4 Unscheduled arrivals
1	0.84211	0.78000	0	0	1	1
2	1.31579	1.36000	3	0	3	1
3	2.47368	2.64000	2	3	1	4
4	3.47368	4.24000	4	2	5	0
5	4.89474	4.74000	2	6	3	4
6	4.52632	4.70000	3	4	5	2
7	4.42105	4.76000	3	4	6	4
8	2.89474	3.32000	0	4	3	2
9	2.10526	2.12000	3	3	2	1
10	1.26316	1.06000	0	0	0	1
11	2.05263	2.32000	1	0	3	3
12	4.15789	4.24000	6	2	2	3
13	4.57895	5.04000	3	5	6	5
14	4.89474	4.88000	6	8	2	4
15	3.36842	3.42000	2	4	7	4
16	4.42105	4.60000	4	5	6	4
17	2.94737	2.86000	3	3	0	2
18	2.00000	2.10000	3	1	4	2
19	0.68421	0.76000	1	2	2	2
20	0.21053	0.26000	0	0	0	0
21	0.00000	0.00000	0	0	0	0
22	0.00000	0.00000	0	0	0	0
23	0.00000	0.00000	0	0	0	0
24	0.00000	0.00000	0	0	0	0
Unscheduled arrivals per s	58	60	49	56	61	49
Scheduled arrivals per s			130	130	130	130
Total arrivals (S+U) per s			179	186	191	179

8.7. Input initial design Hengelo and Almelo

Table 8.5. Input initial design Hengelo

Time-slot	Time	Monday	Tuesday	Wednesday	Thursday	Friday	Time-slot	Time	Monday	Tuesday	Wednesday	Thursday	Friday
t1	**07:30**	3	3	3	2	3	**t13**	**13:30**	14	11	9	10	8
t2	**08:00**	5	6	5	6	6	**t14**	**14:00**	15	11	9	11	8
t3	**08:30**	8	9	7	8	8	**t15**	**14:30**	11	11	9	8	7
t4	**09:00**	12	13	11	13	12	**t16**	**15:00**	13	10	9	7	9
t5	**09:30**	13	13	11	13	11	**t17**	**15:30**	10	9	8	7	6
t6	**10:00**	12	11	10	12	9	**t18**	**16:00**	8	7	6	6	5
t7	**10:30**	14	12	10	14	11	**t19**	**16:30**	3	3	2	3	3
t8	**11:00**	15	15	13	15	14	**t20**	**17:00**	0	0	0	0	0
t9	**11:30**	10	10	9	10	8	**t21**	**17:30**	0	0	0	0	0
t10	**12:00**	7	9	6	6	6	**t22**	**18:00**	0	0	0	0	0
t11	**12:30**	7	8	7	9	6	**t23**	**18:30**	0	0	0	0	0
t12	**13:00**	10	9	9	9	7	**t24**	**19:00**	0	0	0	0	0
				Total average					190	180	153	169	147

Table 8.6. Input initial design Almelo.

Time-slot	Time	Monday	Tuesday	Wednesday	Thursday	Friday	Time-slot	Time	Monday	Tuesday	Wednesday	Thursday	Friday
t1	**07:30**	2	3	3	4	4	**t13**	**13:30**	15	11	12	12	9
t2	**08:00**	5	5	5	7	6	**t14**	**14:00**	15	13	14	13	9
t3	**08:30**	8	8	8	9	9	**t15**	**14:30**	15	12	13	10	9
t4	**09:00**	11	12	12	12	10	**t16**	**15:00**	13	12	10	8	8
t5	**09:30**	11	8	10	12	9	**t17**	**15:30**	14	9	10	9	9
t6	**10:00**	11	10	10	10	9	**t18**	**16:00**	10	9	8	8	8
t7	**10:30**	16	11	14	10	13	**t19**	**16:30**	5	4	4	3	2
t8	**11:00**	15	15	16	14	16	**t20**	**17:00**	0	2	1	1	1
t9	**11:30**	13	14	13	14	12	**t21**	**17:30**	0	0	0	0	0
t10	**12:00**	9	9	7	7	6	**t22**	**18:00**	0	0	0	0	0
t11	**12:30**	8	9	8	7	6	**t23**	**18:30**	0	0	0	0	0
t12	**13:00**	13	10	10	8	8	**t24**	**19:00**	0	0	0	0	0
				Total average					209	186	188	178	163

8.8. Combined model output Hengelo

Table 8.7. Model results. Day scheme for Hengelo with scheduled and unscheduled patients

	Monday		Tuesday		Wednesday		Thursday		Friday	
	S	**U**	**S**	**U**	**S**	**U**	**S**	**U**	**S**	**U**
07:30	4	0	3	1	1	3	2	2	2	2
08:00	11	1	10	2	9	3	9	3	7	5
08:30	9	3	8	4	8	4	7	5	7	5
09:00	7	5	9	3	7	5	6	6	5	7
09:30	7	5	6	6	6	6	7	5	4	8
10:00	2	6	4	4	3	5	2	6	0	8
10:30	7	5	8	4	6	6	6	6	3	9
11:00	8	4	8	4	7	5	6	6	5	7
11:30	10	2	9	3	9	3	9	3	7	5
12:00	7	1	6	2	4	4	5	3	5	3
12:30	5	3	5	3	3	5	3	5	2	6
13:00	7	5	7	5	7	5	6	6	7	5
13:30	7	5	8	4	6	6	7	5	5	7
14:00	7	5	8	4	8	4	7	5	6	6
14:30	4	4	4	4	3	5	5	3	3	5
15:00	8	4	8	4	7	5	10	2	5	7
15:30	12	0	10	2	7	5	11	1	6	6
16:00	8	4	8	4	8	4	8	4	8	4
16:30	0	8	0	8	0	8	0	8	0	8
17:00	0	4	0	4	0	4	0	4	0	4

8.9. Combined model output Almelo

Table 8.8. Model results. Day scheme for Almelo with scheduled and unscheduled patients

	Monday		**Tuesday**		**Wednesday**		**Thursday**		**Friday**	
	S	**U**	**S**	**U**	**S**	**U**	**S**	**U**	**S**	**U**
07:30	4	0	4	0	4	0	3	1	3	1
08:00	12	0	11	1	11	1	9	3	8	4
08:30	11	1	10	2	10	2	9	3	9	3
09:00	10	2	9	3	10	2	8	4	9	3
09:30	9	3	10	2	10	2	7	5	7	5
10:00	5	3	6	2	4	4	4	4	3	5
10:30	10	2	9	3	8	4	7	5	7	5
11:00	9	3	9	3	10	2	8	4	6	6
11:30	8	4	9	3	9	3	8	4	7	5
12:00	7	1	6	2	7	1	6	2	5	3
12:30	7	1	5	3	5	3	5	3	4	4
13:00	11	1	10	2	10	2	9	3	9	3
13:30	12	0	10	2	10	2	8	4	9	3
14:00	12	0	9	3	9	3	9	3	8	4
14:30	8	0	6	2	6	2	5	3	5	3
15:00	12	0	9	3	10	2	10	2	9	3
15:30	12	0	12	0	12	0	11	1	9	3
16:00	8	4	8	4	8	4	8	4	8	4
16:30	0	8	0	8	0	8	0	8	0	8
17:00	0	4	0	4	0	4	0	4	0	4