Surgery scheduling using admission quotas versus using length of stay: levelling bed occupancy

Master thesis

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August 2020

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Preface

Dear readers,

This thesis concludes the Master's degree in Industrial Engineering and Management and my time of living and studying in Enschede. I look back at a great time there. I started studying Applied Physics in 2014 but switched to Industrial Engineering after ten weeks. I did never regret that decision and I am happy to call myself an industrial engineer.

I would like to thank ChipSoft for the warm welcome and especially Juul Knoben for supervising me during the process of this thesis. You always made time for me and gave extensive feedback and guidance which was highly appreciated. I want to thank the whole capacity management team for all the support they gave me and the fun that we had. I had a great time working at the office until COVID-19 became a serious issue. Afterwards, I enjoyed the virtual Friday drinks with the team. Furthermore, I would like to thank Vincent van Ham for enabling me to perform the research at the RKZ and for giving feedback whenever I asked for it.

I would like to thank Erwin Hans for the feedback and support during my thesis. Despite Erwin's, busy schedule, he was always able to give advise or answer my questions. Also thanks to Gréanne Leeftink for the feedback during the last parts of the thesis.

Last, but definitely not least. I want to thank my family and friends for support.

Enjoy reading!

Jeroen Staakman
Amsterdam, Augustus 2020

Management summary

Background

Nurses in Dutch hospitals experience a large workload. This can be explained by the high variation in bed occupancy in hospital wards. Due to the high variation, there is a regularly mismatch between the demand and supply in the wards. On one day the occupation is high and the nurses experience a large workload, the other day the occupation is low. In 2019 the RKZ already started scheduling with quotas to reduce the variation. Scheduling patients consists of two steps. Step one: assigning patients to a surgery session and step two: determining the sequence of patients in the session. After the first step a patient knows the scheduled day of the surgery. After the second step the patient knows at what time the surgery is expected to take place.

It is unclear what the effect of using the length of stay (LoS) information when scheduling patients is on the bed occupation of the subsequent wards of the RKZ. Therefore, The Red Cross Hospital (RKZ) and ChipSoft are curious whether the variation in bed occupation can be further reduced. The problem results in the following research goal:

> *To reduce variation in bed occupation in hospital wards by designing a surgery scheduling approach which uses LoS and surgery duration information and to deliver a proof of concept for the scheduling method compared to admission quotas.*

Methods

To compare both the quota scheduling method and the scheduling method based on LoS, we propose three models. One model shows the potential of the quota scheduling method which is the current scheduling method of the RKZ. The model is formulated as a small Mixed Integer Linear Program (MILP). The quota model only assigns patients to a session and does not change the sequence of the patients in the session. The LoS scheduling method uses two models. The assignment model and the sequencing model. In the assignment step we aim to fill the reserved hospital beds as much as possible. After the assignment step, a patient knows the scheduled day of the surgery. The second step, is the sequencing of the surgeries that are in the sessions. The sequencing model aims to lower the peak occupation and reduce the overtime of the ward. After the sequencing step, the patient knows the scheduled time of the surgery. We formulate the assignment model as both a MILP and a

Mixed Integer Quadratic Problem (MIQP) and we formulate the sequencing model as a MILP model.

We generate data that simulates the waiting list at the RKZ. We use this data as input for the models. Besides, we use the 2018 data of the RKZ to compare the LoS scheduling method with the realised occupation. We look into the performance of the models when the size of the waiting list changes when the weekend occupation is more important, and we compare the MILP variant of the sequencing model with the MIQP variant.

Results

To show the performance of the models we perform interventions. The first intervention is changing the size of the waiting list. We do this because, in contrary to the quota model, the LoS scheduling method uses the entire waiting list to schedule patients. We show the difference in performance when the waiting list contains more than enough patients to choose from and when the waiting list has only a limited number of patients. Besides, we show the performance of the quota model in combination with the sequencing model. The results show that we can increase the number of patients scheduled and reduce the standard deviation of the daily peak occupation during the week by 63% for the daycare department and by 32% for the clinical department when using a waiting list with a limited number of patients to choose from. When we schedule patients starting with a waiting list that contains a lot of patients the improvement is 15% for the daycare department and 72% for the clinical department. These numbers show that we can level the daily peaks in occupation for both wards which results in a more equal divided workload for the hospital staff. Using the quota model in combination with the sequencing model results in a lower variation for the clinical ward. Besides, the time that the last patient leaves the ward is two hours earlier when extending the quota model with the sequencing model. In Table 1 we show the performance of the simulation data in the models comparing the short waiting list with the long waiting list. In Figures 1 to 4 we show the performance of the LoS model using the two sizes of waiting lists.

The second intervention shows that the MIQP formulation of the objective of the assignment model outperforms the MILP formulation.

The third intervention shows the difference in performance when the Saturday and the Sunday are weighted equal to the rest of the week in the objective function. The objective that weights every day equal reduces the variation of the daily peak occupation even more. However, it results in higher fluctuation between the lowest occupation and the highest occupation over the week. An explanation for this is that when the deviation in the number of beds in the weekend is weighted heavier, patients with a longer LoS are scheduled on the Friday such that they occupy beds in the weekend. Because the RKZ does not have a lot of patients with a LoS longer than one night the patients with a LoS of one night are scheduled from Monday to Thursday.

In another experiment we compare the real RKZ occupation over the year 2018 with the occupation resulting from the LoS model. The LoS model reduces variation and reduces the maximum number of beds needed in a week.

	1 week waiting list		10 weeks waiting list	
Performance indicator	DW	CW	DW	CW
Number of patients	+13%	+3%	+10%	+14%
Mean surgery duration	-4%		-16%	
Standard deviation of the daily peak occupation	-63%	-32%	-15%	-72%
Mean occupation	+4%	+0%	+1%	+7%
Maximum beds needed	-2%	+0%	-6%	+4%

Table 1: LoS scheduling compared to quota scheduling for the Daycare Ward (DW) and the Clinical Ward (CW)

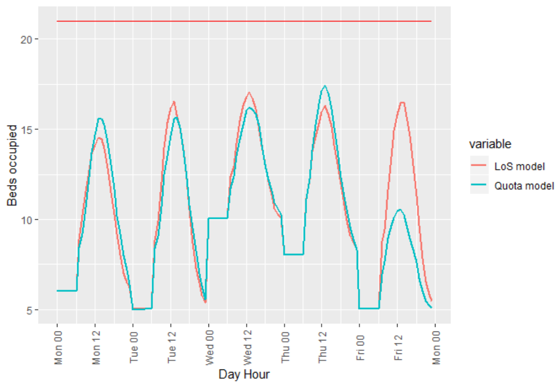

Figure 1: Ward performance A2X, 1 week of patients added to the waiting list every week

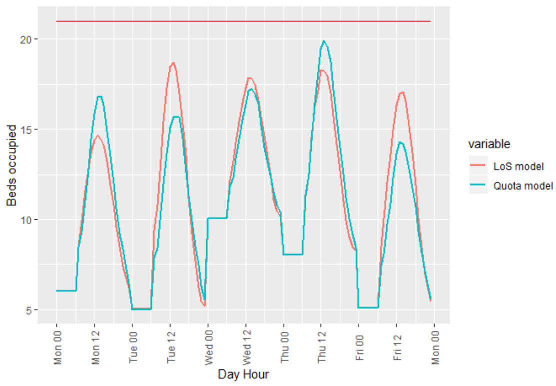

Figure 2: Ward performance A2X, Waiting list with 10 weeks of patients at the start

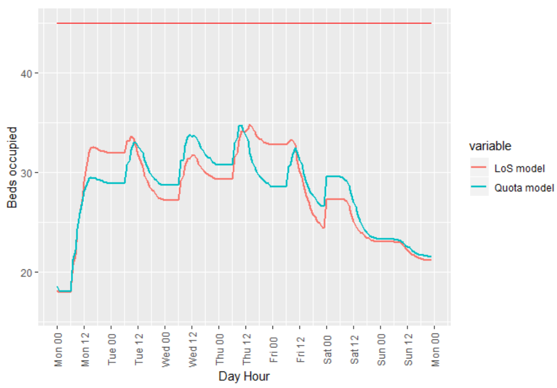

Figure 3: Ward performance A5, 1 week of patients added to the waiting list every week

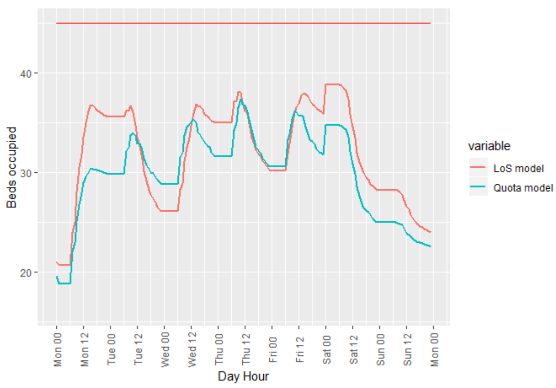

Figure 4: Ward performance A5, Waiting list with 10 weeks of patients at the start

Conclusions and recommendations

We recommend the RKZ to use scheduling based on LoS because it decreases the variation in the bed occupation which decreases the work pressure for nurses. Besides, hospital earnings can increase when the total number of patients in the ward is higher. The LoS model increases the mean occupation while the the maximum number of beds needed does not increases as much or even decreases. However, the assignment model assigns patients from the entire waiting list which can cause that a group of patients is never scheduled because another combination of patients results in a better occupation. We therefore, recommend the RKZ and ChipSoft to first follow up on those results before implementing the LoS model into their software. An suggestion would be to attach a waiting weight to each patient which becomes more important the longer the patient is on the waiting list. This should be added to the objective function. Another option is to let a planner select a group of patients that have to be assigned by the model. This reduces the flexibility of the model but ensures that planners decide which patients have surgery. Besides, we recommend to improve the predictions of the LoS for patients to obtain even better results with the models. The hospital can experiment with predicting the LoS with a model instead of letting the surgeon predict the LoS. Another option is to show the surgeon the LoS prediction based on the surgery type of the patient and let the surgeon decide if this needs to be altered.

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Acronyms

EHR Electronic Health Records.

HiX Healthcare information Exchange.

LoS Length of Stay.

MILP Mixed Integer Linear Program.

MIQP Mixed Integer Quadratic Program.

MSS Master Surgery Schedule.

OR Operating Room.

RKZ Rode Kruis Ziekenhuis (Red Cross Hospital).

SSP Surgery Scheduling Problem.

Chapter 1

Introduction

This report aims to find a method for the operational scheduling of patients in operating rooms (ORs) that reduces variability in bed occupation in subsequent wards. Chapter 1 gives an introduction to the research and the problem. Section 1.1 describes the motivation of the research and the organisational context. Section 1.2 gives the problem definition. The chapter concludes with the problem approach in section 1.3.

1.1 Background

1.1.1 Motivation of research

Personnel of Dutch hospitals went on strike at the end of 2019 to protest against the high workload and low wages. Dutch news agency NOS (2019) writes that work in the care sector is heavy, workload is high, and that there is a shortage of nurses that results in bed blockages and cancelled surgeries. CEO of the Red Cross Hospital (Rode Kruis Ziekenhuis, RKZ) Jaap van den Heuvel stated in an interview with the Dutch newspaper NRC that the workload of hospital staff has risen a lot and that, if this continues, ambulances may have to skip the RKZ if the departments are too crowded in the future (Lonkhuyzen 2019).

The RKZ uses admission quotas to schedule patients in the operating room sessions. The quotas give fixed numbers of patients that are allowed to flow out to a subsequent ward for each OR session. The quotas are determined by the capacity manager of the hospital and prevent the wards from being overloaded. The RKZ uses the quotas method because it is easy to use for the planners. The RKZ believes that it is possible to reduce the variability for the departments when the length of stay (LoS) is considered when scheduling patients in ORs.

The RKZ uses ChipSoft's electronic health records (EHR) software HiX (Healthcare information Exchange). ChipSoft offers an OR-planning tool in HiX that, next to showing the admission quotas, shows what effect the expected length of stay (LoS) of a patient has on the occupation of the subsequent ward.

ChipSoft is interested in the difference between the scheduling method the RKZ uses and a method that incorporates the LoS (length of stay). Besides, they are interested in how the method performs in hospitals of different sizes. With the result of this research, ChipSoft can give a better advice to hospitals on what method to use when scheduling patients. It is not clear for either RKZ or ChipSoft what the effect of considering the LoS is.

1.1.2 Organisational context

The Red Cross Hospital (In Dutch: Rode Kruis Hospital, or RKZ) is located in Beverwijk. Beverwijk is a city in the Netherlands, located in the province of North-Holland. Beverwijk has a population of roughly 40,000 people. It is an average size hospital. In 2018 the hospital admitted 12,567 patients and employed 1468 employees (RKZ 2018). The hospital is specialised in the treatment of burns. The operating theatre consists of six operating rooms.

ChipSoft is a Dutch software company founded in 1986. They are the market leader of electronic health records (EHR) software in the Netherlands and are steadily expanding outside of the Netherlands. ChipSoft employs over 700 people of which most work in its headquarters in Amsterdam. To make HiX usable for different types of health care organisation it has a modular buildup. Figure 1.1 shows in what types of organisations HiX is used.

The assignment is executed at both ChipSoft and the RKZ. Four days per week at the capacity management department of ChipSoft in Amsterdam and one day per week at the RKZ in Beverwijk. The capacity management department consists of around 10 employees and focuses on developing smart capacity planning solutions for HiX.

Figure 1.1: Organisations that can use HiX (ChipSoft 2019)

1.2 Problem definition

This section defines the core problem and explains the problem cluster.

1.2.1 Problem description

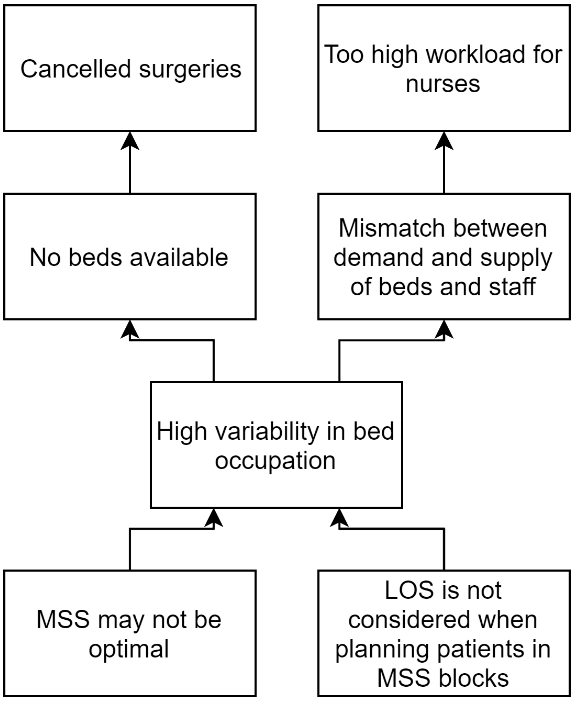

Figure 1.2: Problem cluster

Figure 1.2 shows the problem cluster. The cluster gives a simplified overview of the problems. The cluster starts with two visible problems that have their own causes.

One of the two visible problems is that a surgery is cancelled every week, which lowers the quality of care for patients and lowers the utilisation of the OR. As the operating theatre, which consists of ORs and recovery rooms, is one of the most critical and expensive resources (Guerriero and Guido 2011) it is key to keep the utilisation of ORs high. Surgeries are cancelled for many different reasons. One of the reasons is that if all the beds are occupied and there is no room for patients after surgery, a surgery can not start. Hospital beds are limited resources, mostly because the beds have to be staffed. "The costs for acquiring these beds is not substantial, however, the costs for maintaining and cleaning the beds, and the labour costs for treating the admitted patients are significantly high." (Essen et al. 2014)

The second visible problem is the high workload of nurses. Nurses have to work hard because of the administrative work that comes with patient care, the shortages of personnel and the mismatch between demand and supply of beds and staff. Nurses want to know when they have to work weeks in advance. If the prediction of the workload is too low, there will not be enough nurses and the workload of the nurses rises.

A cause for the shortage of beds and the mismatch between demand and supply is the high variability in the wards. The high variability causes that some days there are no beds available and other days there are few patients occupying the wards. Levelling this bed demand can make the staffing of nurses easier.

The MSS (Master Surgery Schedule) is a tactical planning decision where the surgical blocks get assigned to a day. LoS depends, next to many other patient characteristics, on the type of surgery. It can for example be that for one surgery this is three days, and for another surgery, it is five. If during the making of the MSS this outflow and LoS of patients is not taken into consideration the bed occupation will fluctuate.

The capacity manager of the RKZ creates four-weekly quotas which state how many patients each specialism can schedule in a specific surgery session. The quotas are based on the MSS and outflow to subsequent wards. Table 1.1 gives an example of admission quotas. The planners use the quotas to schedule patients but do not incorporate the LoS of the patient which could result in unnecessary variability.

The way surgical cases are scheduled in ORs influences the outflow of patients to the subsequent departments. The occupation level of the departments together with the staffing levels of the nurses has a direct influence on the workload for the nurses. In case there are a lot of patients in the department and the staffing levels are low the workload for the nurses is high. Next to this, having more patients than beds can lead to cancellation in the ORs. Upstream scheduling that fails to account for the patient LoS often leads to blocking (Liu et al. 2019). Reducing the variability of the bed occupation over the week results in fewer peaks in bed usage and therefore, a more divided workload and fewer cancellations.

Example of admission quota			
Department	General surgery	Orthopedic Surgery	Urology
A2X	4	4	2
A5	5	2	3

Table 1.1: Example for quotas on a Monday on week 1 for three types of surgery

In conclusion, the research will focus on the scheduling of patients on the operational level of the resource capacity planning. The MSS is considered given and the goal is to reduce variability in the wards while maintaining the OR performance.

1.2.2 The core problem

The core problem is defined as follows:

> *What is the effect of using length of stay information when scheduling patients in ORs on the variation in bed occupation in subsequent departments of the RKZ, instead of only using admission quotas.*

1.3 Problem Approach

The core problem results in the goal of this research:

> *To reduce variation in bed occupation in hospital wards by designing a surgery scheduling approach which uses LoS and surgery duration information and to deliver a proof of concept for the scheduling method compared to scheduling using admission quotas.*

The scope of the research is limited to the operational level and to two wards of the RKZ. In department A5 patients recover for a few days before they leave the hospital. A2X is the ward for day treatments.

To achieve the research goal the remainder of this report answers the following research questions.

1. How can we describe the current planning process? (Chapter 2)
2. How can we measure the performance of ORs and wards and what is the current performance? (Chapter 2)
3. What scheduling methods using surgery duration and LoS information exist in the literature? (Chapter 3)
4. How to create a scheduling method using surgery duration and LoS information specific for the RKZ? (Chapter 4)
5. How does the scheduling method using LoS information perform and what is the performance compared to scheduling with admission quotas? (Chapter 5)
6. Can the method be implemented at the RKZ? (Chapter 6)
7. Can the method be implemented at other hospitals? (Chapter 6)

Chapter 2

Context Analysis

Chapter 2 analyses the processes and resources of the RKZ that are relevant to this research. Section 2.1 shows the process of scheduling patients in ORs and shows which resources are needed. Section 2.2 describes how we measure the performance and gives the current performance. For the analysis we decide to use a full calendar year of data from the year 2018. The data set that is available at ChipSoft was extracted from HiX at the RKZ in April 2019.

2.1 Process description

This sections answers research question 1.

1. *How can we describe the current planning process?*

First, we analyse the planning and scheduling at the RKZ at each hierarchical level using the framework introduced by Hans et al. (2011). Second, the section shows a visualisation of the route that clinical patients take through the RKZ.

2.1.1 Strategic

Capacity dimension and case mix planning

The RKZ has eleven ORs with patients that flow out to different wards. Wards A5 and A2X are in scope of this research, only ORs 1 to 6 have outflow to these wards. Therefore, in this research, we consider only ORs 1 to 6. OR 1 to 6 are open 9 hours a day for elective patients. The six ORs have different starting times. Half of the ORs open at 07:50 and the other half at 08:05. This is because one anaesthesiologist works at two ORs and can only start one OR at the same time. The six ORs are almost identical, however, some specialisms prefer an OR over the others because of minor differences like an extra drain that is located in an OR. Ward A2X, the ward for day treatment is open from 07:00 - 21:00 and A5 is open 24 hours a day. The bed capacity is determined by the amount of personnel available for wards and not by the physical beds. The capacity for A2X is 21 beds and for A5, 45 beds. A2X the day treatment admits a lot more patients than A5 because patients leave the same day, that is not the case for A5. A2X has, compared to A5 almost no emergency patients at A5 this is 25%. Leeftink and Hans (2018) propose a visual representation of the case mix classification. We use this method to visualise the RKZ's case mix. Therefore, we distinguish surgery types by their COTG-code. In 2018 the RKZ had 431 different surgical types with a total of 6374 cases. For the classification we use only surgical types with 10 or more cases. This are 126 types and 5477 cases. We calculate the mean (m) and the standard deviation (s) of each surgical type. The available session time is 560 minutes (c). Figure 2.1 shows the visualisation of the case mix. Based on the figure we conclude that the RKZ has scheduling flexibility as there are more short surgeries. Besides, the coefficient of variation (s/m) shows that the uncertainty in surgery duration is moderate. The figure is similar to the case mix visualisation of a general hospital as shown in Figure 11 of the article of Leeftink and Hans (2018).

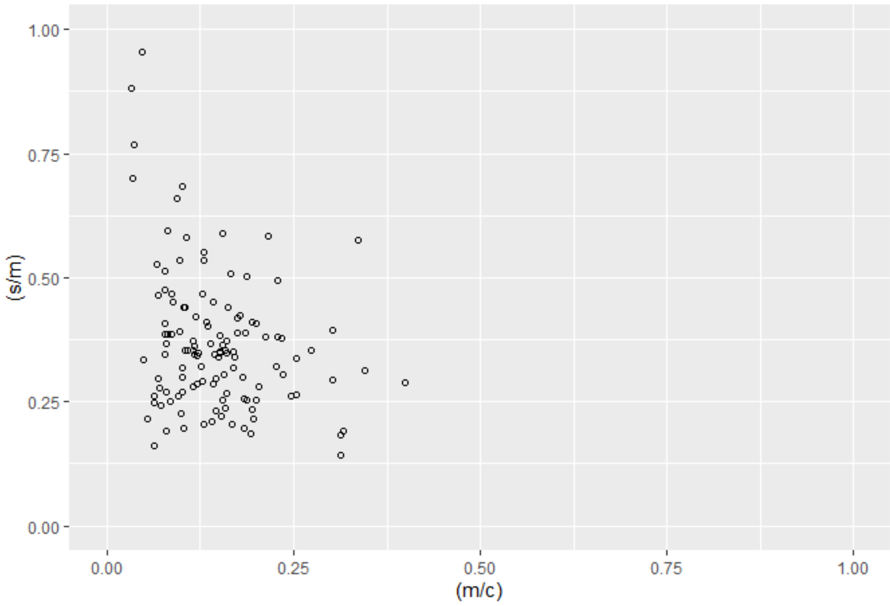

Figure 2.1: RKZ casemix (N=5477, HiX RKZ, 2018)

2.1.2 Tactical

MSS and planning quotas

The master surgery schedule of the RKZ is a four-weekly schedule which consists of 0, 1 or 2 sessions in an OR per day. The sessions states which specialism performs surgery. Each day there is a block of 2 hours planned in one of the ORs for emergency patients. The MSS is renewed every two years. Table 2.1 shows an example of a master surgery schedule for the RKZ. Each session has its own surgical group, therefore, sometimes the tables show two sessions with the same specialism. Surgical groups are groups of surgeons in a specialism that have a similar outflow to wards. Using this, the RKZ can obtain a better levelled ward occupation by optimising the MSS.

Next to the MSS the RKZ uses quotas to limit outflow to the subsequent wards. The quotas are revised more often. One surgical session can, for example, have a maximum outflow of 4 patients to ward A5 and 3 patients to ward A2X. If the quotas are reached it is not allowed to schedule a patient in the session with outflow

Week 1/4	OR 1	OR 2	OR 3	OR 4	OR 5	OR 6
Monday	CHI	ORT	CHI NCH	CHI	GYN Emergency	PLA
Tuesday	PLA	ORT	KNO Emergency	CHI CHI	CHI NCH	PLA
Wednesday	Emergency URO	ORT		CHI		PLA
Thursday	KNO URO	ORT	KAA	CHI	CHI Emergency	PLA
Friday	CHI CHI	ORT Emergency	CHI CHI	CHI	GYN	PLA

Table 2.1: Example of one week of the MSS

to one of the two wards. Because the session in the MSS have similarities in patient characteristics the quotas have an influence on the outflow of patients to wards and on the bed occupation in the wards. The quotas are revised when wards become too crowded.

The main difference between scheduling with the quotas and scheduling using the patient's LoS is that the quotas are more conservative because for every combination of patients that meet the quotas there has to be a bed in the ward. Scheduling with the patient's LoS is a more flexible option because it is a operational decision instead of a tactical decision.

2.1.3 Offline operational

Patient scheduling

The scheduling process consists of selecting a patient on the waiting list and giving him or her a surgery date and time. Scheduling at the RKZ is done centralised for 2/3 of the patients. Decentralised scheduling has the advantage that patients can directly make a new appointment. The disadvantage is that it is hard to determine how many beds are available for patients. Because scheduling is not centralised specialisms schedule their patients over a different planning horizon. This means that, for example, oral surgery schedules patients 2 months in advance, while an oncology patient can get scheduled a few weeks in advance. Here, the quotas as explained in Section 2.1.2 prevent the specialism that schedules patients first from overloading the subsequent wards.

Scheduling takes two steps. The first step is the assignment of patients to a session, which is visualised in Figure 2.2. The second step is determining the sequence of the surgeries that are scheduled in the session. This is often done the day in advance of the session. The sequence depends on patient characteristics. For example, young children are often scheduled first on the day because it can be hard to keep them sober during the day. Patients are informed of the date of the surgery after the first step which is often weeks up to months in advance. The time of the surgery is communicated to the patient one day in advance. The first step of the scheduling process (Figure 2.2) is explained below.

General practitioners forward patients to the outpatient clinic. If the specialist at the outpatient clinic decides that surgery is needed the patient will go to pre-operative screening where the patient is checked on medication and if the patient is fit enough for surgery. After a positive screening the patient is placed on the waiting list.

Figure 2.2 shows the scheduling of a patient in an OR. The planning department of the RKZ is responsible for scheduling patients in ORs. OR sessions are to be filled up to 96% of capacity which includes the planned surgery time and the cleaning time after surgeries. They do not plan to 100% because the risk of overtime will be high. Example of sessions are shown in the MSS, see Table 2.1, most of the sessions take a full or a half day.

An empty OR session is the starting point of the scheduling process. If the OR is filled less than 96% and the quotas are not met a patient is chosen from the waiting list of the specialism that has this OR session. The ORs are filled with the FIFO (first in first out) principle. If the OR session is almost filled a short surgery will be scheduled to get as close as possible to the 96%. Patients on the waiting list have different statuses P (possible to schedule), N (not possible to schedule), and V (the patient has a request and does not want to be scheduled at the moment). A patient can have the status N when the pre-operative screening is not valid anymore, the patient first has to redo the screening before he or she can be scheduled. Only patients with status P can be scheduled. When a patient is selected the planner has to check if all the materials needed for the surgery are available. If this is the case the patient is planned and the patient is called to confirm the date of surgery and to see if the patient is available that day. The process repeats itself until the OR is filled to 96% or the quotas for the wards are met.

2.1.4 Online operational

Cancellations

Table 2.2 shows the given reasons for cancelling a surgery. 333 of the 369 cancellations are given the reason "Other". Only three times the reason for cancellations is that there is no bed available. Last minute cancellations disrupt the flow in the hospital. An explanation for the high number of cancellations with the reason "Other" can be the easiness of clicking on this option.

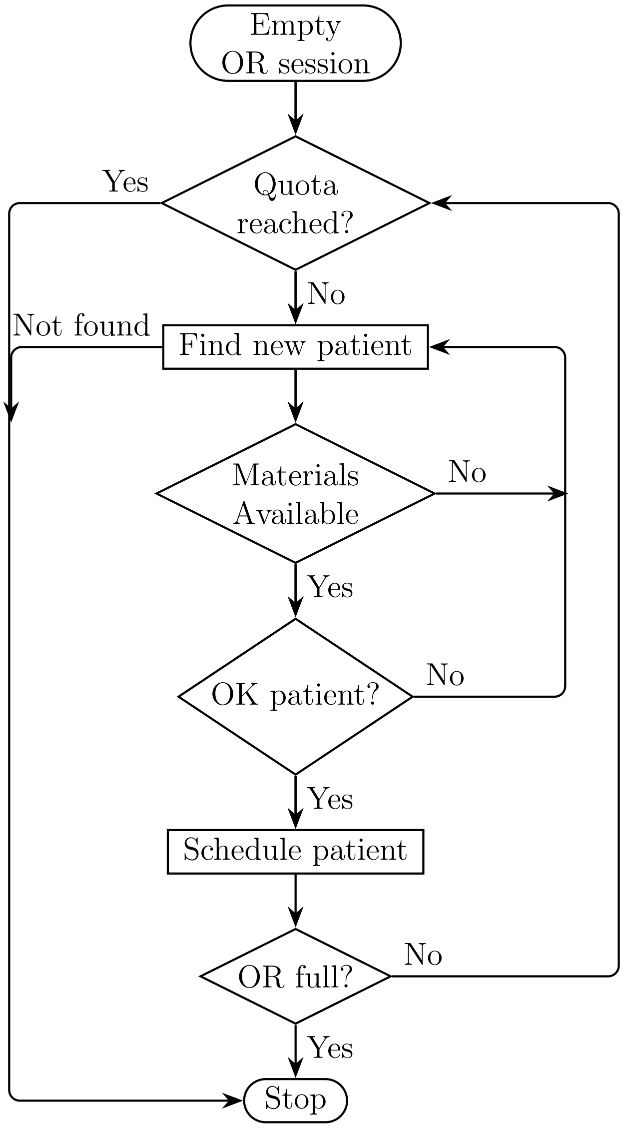

Figure 2.2: Patient assignment to OR sessions

Reason for cancellation	Number
Anaesthesia: Screening not approved	1
OR: Delay, surgery postponed	2
Patient: Did not stop medication on time	2
Beds: No bed available	3
Patient: Not sober	3
Specialist: Not available	4
Patient: Sick	5
Patient: Did not arrive	6
Patient: Own request	10
Other: Administrative	113
Other: Reschedule	220
Total:	369

Table 2.2: Reasons for cancellations (N= 11759, HiX RKZ, 2018)

Emergency coordination

The moment an emergency patient with high priority enters the hospital he or she enters the first available OR. The RKZ has no emergency ORs.

2.1.5 Clinical patient flow

Figure 2.3 shows the simplified path that clinical patients take through the hospital, this process takes place after an patient is scheduled as shown in Section 2.1.3. An elective patient is admitted to the ward before he goes into surgery. There is a chance the surgery is cancelled due to, for example, a patient not following instructions and not being sober before surgery. The emergency patient arrives at the hospital and enters the emergency department where the patient is checked and when needed the patient goes into surgery. Elective and emergency patients go to the recovery room after leaving the OR. When the patient is ready he or she is transferred to the ward. The patient is discharged when the patient is fit enough.

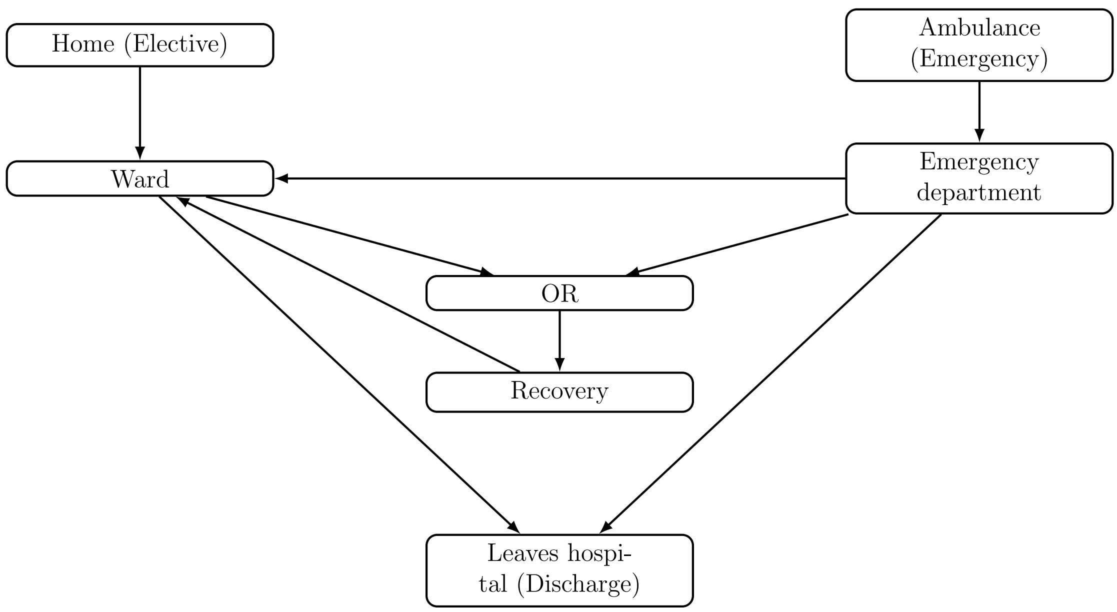

Figure 2.3: Simplified patient flow through the hospital

2.2 Performance Analysis

The following section answers research question 2:

2. *How can we measure the performance of ORs and wards and what is the current performance?*

The goal of this research is to improve the variability of the bed occupancy of the wards at the RKZ. To be able to make a comparison with the results of the interventions in Chapter 5, this section explains which performance measures are used and what the current performance is.

2.2.1 OR performance

The operating room department is one of the most expensive resources of a hospital van Essen et al. 2012. Therefore, next to only looking at the variability at the wards we take the OR performance into account. When optimising the wards we need to keep the OR performance at the same performance level.

Utilisation and overtime

ORs are opened 540 minutes per day. Excluded from the calculations are weekends and surgeries that start after 17:00. Surgeries that start after 17:00 are emergency surgeries and including these in the calculations would give an inaccurate idea of the utilisation. The changeover time between surgeries varies between 5 and 20 minutes depending of the type of surgery, this time is needed to clean the OR and get it ready for the next patient. Because the changeover time is not always recorded in HiX and because this information is not necessary for the research we ignore it.

We choose to measure surgery time as the average effective surgery time, which is the time difference between the patient arriving and leaving the OR. Van Houdenhoven et al. (2007) show that obtaining a higher utilisation accompanies a higher risk of overtime. Therefore, next to the surgery time, Table 2.3 shows the average overtime per OR. Note that the number of observations is higher than the number of patients in A5 and A2X. Next to the wards A5 and A2X, the RKZ has other wards where a part of the patients go to after surgery. Overtime is defined as the time a surgery

OR #	Surgery time	Overtime	Utilisation
1	380	8	0.70
2	408	8	0.75
3	409	10	0.76
4	452	13	0.84
5	368	10	0.68
6	443	12	0.82

Table 2.3: OR characteristics, time in minutes (N= 11759, HiX RKZ, 2018)

takes after 17:00 if the surgery started before 17:00. Note that this means that it is possible to have a surgery time that is lower than the available surgery time on that day and still have overtime. Figure 2.4 shows the average overtime of the ORs. The average overtime and its dispersion are the largest from September to November. We define OR utilisation as the total realised time patients are in surgery divided by the total available OR time. Only surgeries that start before 17:00 are included. The mean utilisation of the six ORs is 76%. Note that this number is without the changeover time and includes the emergency session time. Figure 2.5 shows the utilisation over the year. OR utilisation seems to be stable on average during the year. OR utilisation depends on the length of surgeries because changeover time is not included. If, for example, OR 5 only has short surgeries the total cleaning time will be large and there will be less time to perform surgeries, this results in a lower utilisation. In the same way an OR with only long surgery duration can show a higher utilisation

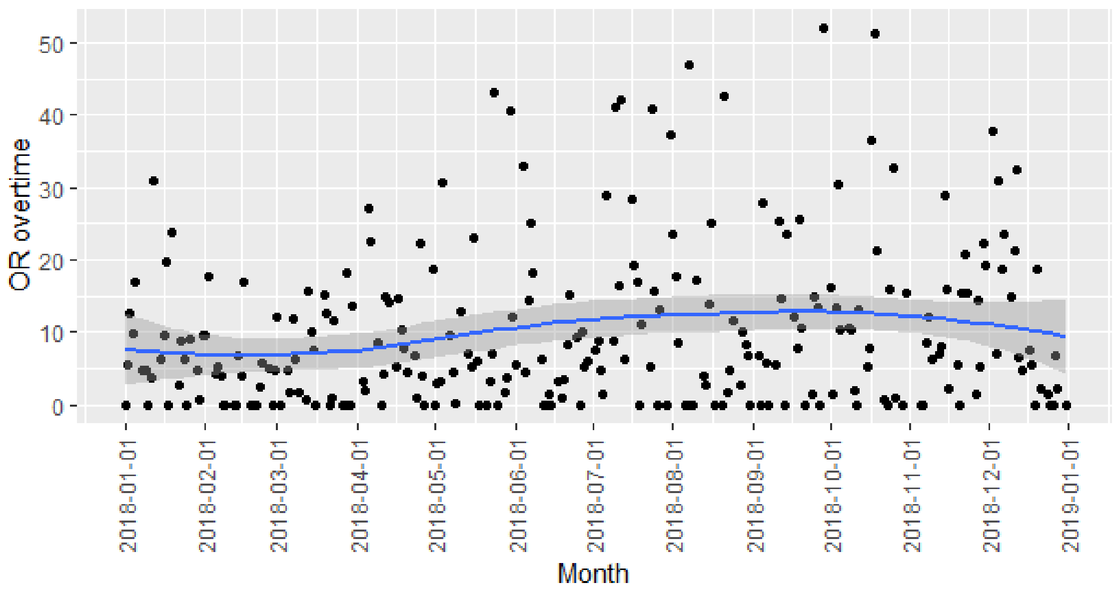

Figure 2.4: Average overtime over the year 2018 (N= 11759, HiX RKZ, 2018)

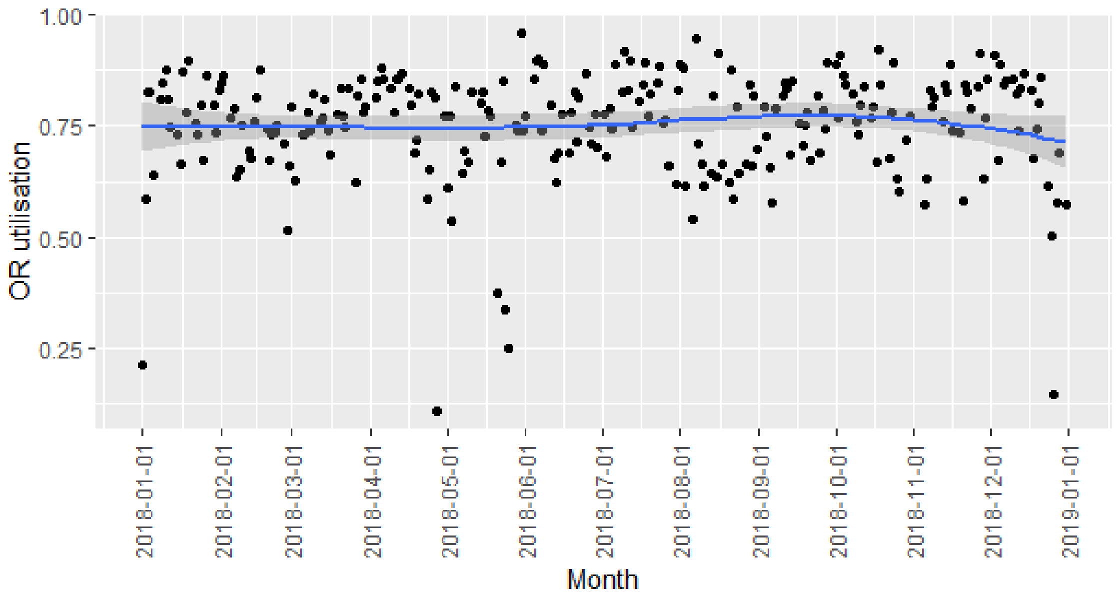

Figure 2.5: Average utilisation over the year (N= 11759, HiX RKZ, 2018)

Surgery duration

The duration of the surgery determines how many surgeries are possible in an OR day. Surgery time in combination with the LoS makes it possible to alter bed occupation patterns. If the ward occupancy is expected to be low in a week it can be useful to schedule shorter surgeries which have a longer LoS. This, of course, also works the other way around. Table 2.4 shows the realised surgery times and LoS of each specialty. Surgery duration is not an indicator for the performance because it is not influenced by scheduling.

At the RKZ the surgeon estimates the surgery duration and the planner adds time depending on the surgeon when planning the patient. On average the difference between the realised duration and the planned duration is only 0.12 minutes. The standard deviation is 25 minutes on an average surgery duration of 82 minutes.

	Mean surgery time	SD surgery time	LoS	SD LoS	Surgery time / LoS
CHI	89	47	36.5	63.8	2.4
GYN	74	39	35.3	28.5	2.1
KAA	81	46	11.2	10.2	7.3
KNO	35	25	5.5	2.5	6.3
NCH	93	21	30.0	6.4	3.1
ORT	73	35	29.0	43.9	2.5
PLA	103	62	19.8	50.6	5.2
URO	54	24	27	46.7	2.0

Table 2.4: Surgery durations and LoS of the six ORs (N= 9103, HiX RKZ, 2018)

2.2.2 Ward performance

The goal of this research is to reduce variability in the wards of hospitals. To measure the variation of the mean occupied beds per hour in a week, we use the coefficient of variation: $CV = \sigma/\mu$. Weekends are excluded for the calculations. For A2X, the day treatment, calculations for the mean and standard deviation are done from 07:00 to 21:00. For A5 we use every hour of the day. We take the mean occupation of an hour of every weekday in a year. To clarify, we end up with 5(days) * 24 or 15(hours) = 120 values for A5 and 75 values for A2X. Table 2.5 shows the mean occupation, the standard deviation and the coefficient of variation of the two wards. Because the wards differ from each other in opening hours it is not useful to compare the wards with each other.

	Mean	Standard deviation	Coefficient of variation CV
A5	29.4	2.83	0.10
A2X	7.7	5.0	0.65

Table 2.5: Bed variation of ward A5 and A2X (N= 9103, HiX RKZ, 2018)

Bed occupation A2X

Figure 2.6 shows the occupation, the admissions and the discharges of an average weekday. the day starts at 07:00. Then the first two OR patients for the first two surgeries are admitted. If the first patient cannot go into surgery the second patient will start the day. There are also patients that do not need surgery, but for example, only need intravenous therapy (IV). Around 13:00 there is a peak in bed occupation of 14 patient on average. At 21:00 the last patients are discharged. Figure 2.7 and Table 2.6 show the bed occupation for a average week. The patterns are almost identical, only the Wednesday shows a higher peak where there are less surgical patients and more non-surgical patients. The maximum mean in Table 2.6 shows the maximum day mean of patients of Figure 2.7. The standard deviation of the daily maximum is 1.19.

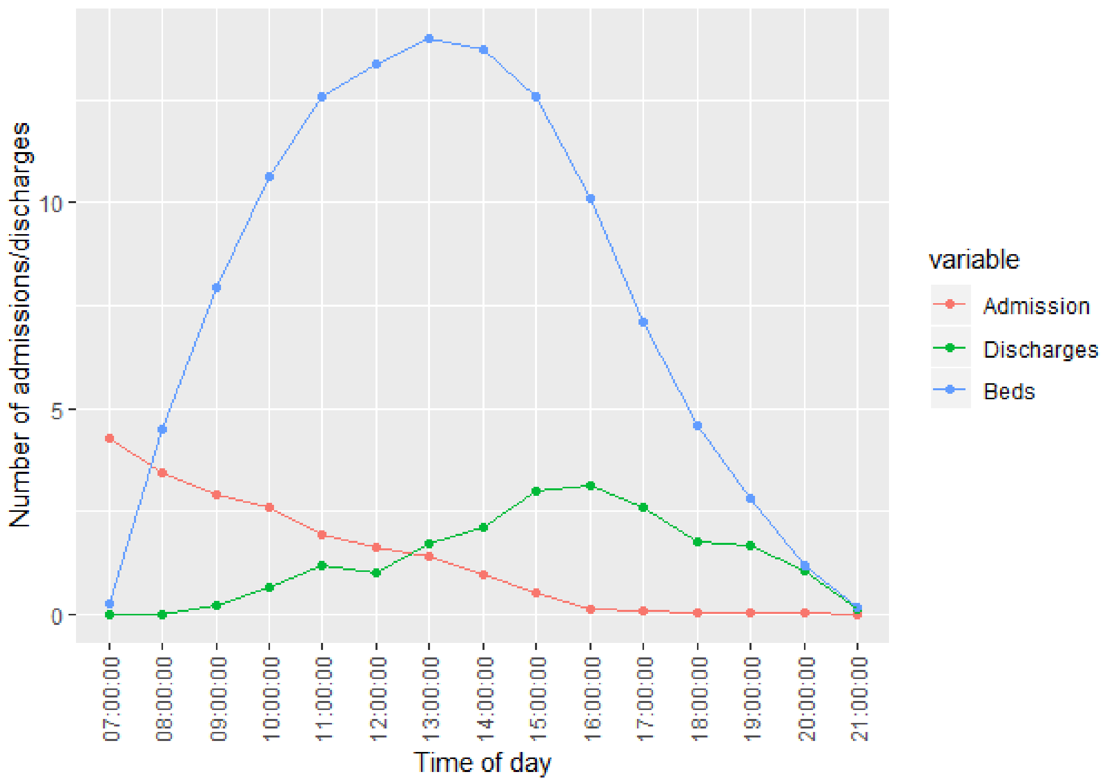

Figure 2.6: Daily occupation A2X (N= 5303, HiX RKZ, 2018)

There are different ways to look at the occupation. The RKZ counts the unique number of patients per day. The other way to calculate the occupation is to look at the average number of patients that lie in a bed during a day (07:00-21:00). Figure 2.8 shows the different methods. The average number of patients that lie in a bed during the week is stable. The number of patients that are admitted is fluctuating. Comparing all days we see that on Thursday there are a lot more patients than the other days, while the average bed occupation is not that different. That means that on Thursday patient are in the ward for a shorter time than on Tuesday. The main reason is that on Thursday there are a lot of pain-patients coming in the ward which have a short LoS.

Day	Surgical	Non surgical	Total	Max mean
Monday	6.28	1.03	7.31	13.33
Tuesday	6.90	0.83	7.73	13.67
Wednesday	5.76	1.94	7.70	15.81
Thursday	6.71	1.71	8.43	15.10
Friday	6.00	1.15	7.14	13.08

Table 2.6: A2X, average bed occupation per weekday from 06:00 - 22:00 (N= 5303, HiX RKZ, 2018)

Bed occupation A5

Figure 2.9 shows the daily pattern of an average weekday. A little before 07:00 the first patients are admitted. the peak of the day is at 10:00. Because the figure

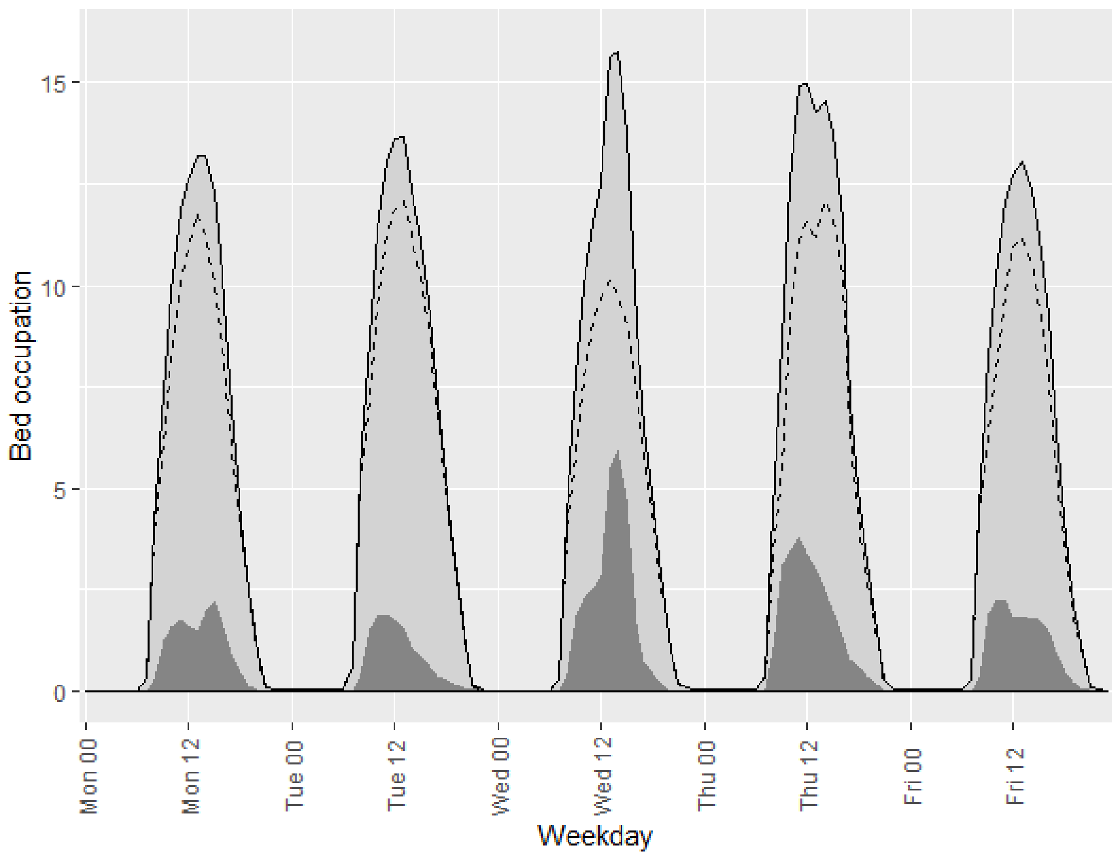

Figure 2.7: Weekly occupation A2X, dark grey showing non-surgical patients, dotted line showing the surgical patients, grey area showing all patients (N= 5303, HiX RKZ, 2018)

shows only weekdays the end of the graph does not end at the same level as the graph starts. What stands out in the figure is that the admissions seem to follow the discharges. Because Admissions and discharges have the most influence on workload for nurses. This seems to intensify the variability in workload. Figure 2.10 and Table 2.7 show the week pattern of ward A5. Monday has a lower peak, which is caused by the weekend when no elective surgeries are done. We see that the non-surgical patients which are very stable during the week caused by emergency patients. The maximum mean in Table 2.7 shows the maximum day mean of patients or the tops of Figure 2.10. We see that the fluctuations are the highest in the weekend. The standard deviation of the daily maximum is 4.15. The occupation on Monday can get higher by scheduling a lot of patients with a short surgery duration which can be seen in Figure 2.11. The figure shows the admissions per day next to the average occupation on that day. We see that on Monday already more patients are admitted to increase the bed occupation.

Figure 2.12 shows the occupation over the year the trend line. It shows that at the beginning of the year and the end of the year the occupation is the highest. A much lower occupation occurs around mid-august, due to doctors being on holiday.

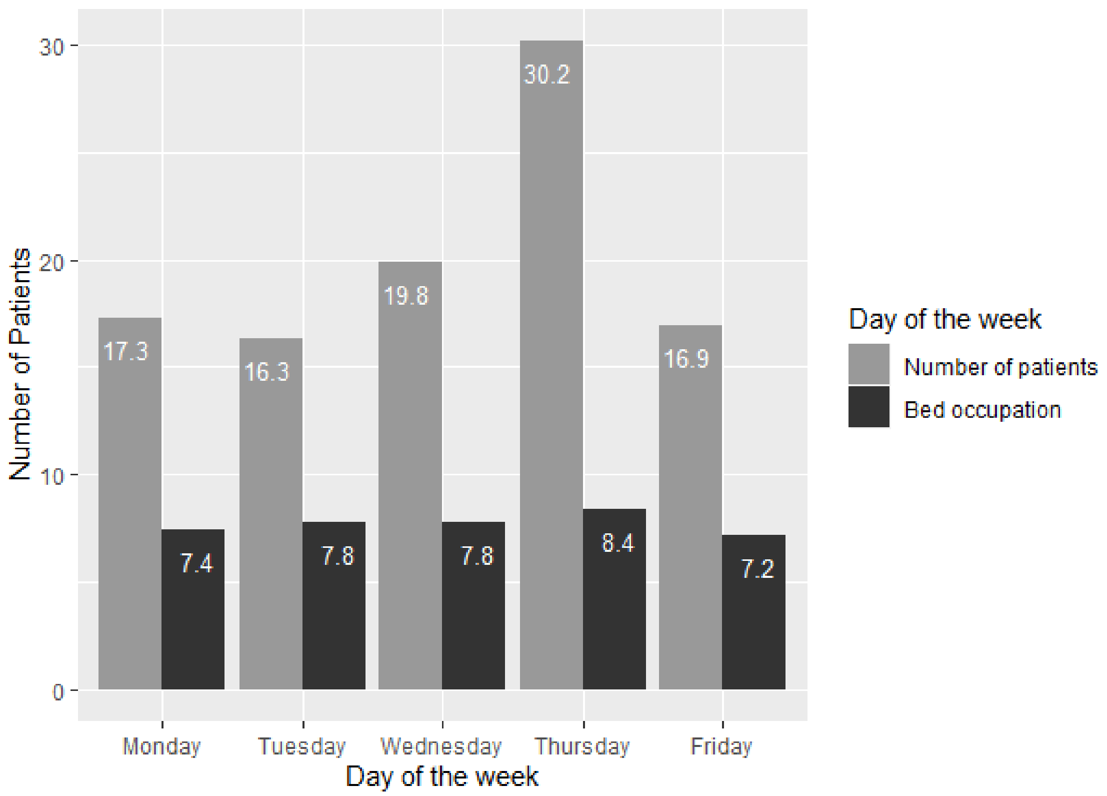

Figure 2.8: Weekly occupation measured and number of admissions A2X (N= 5303, HiX RKZ, 2018)

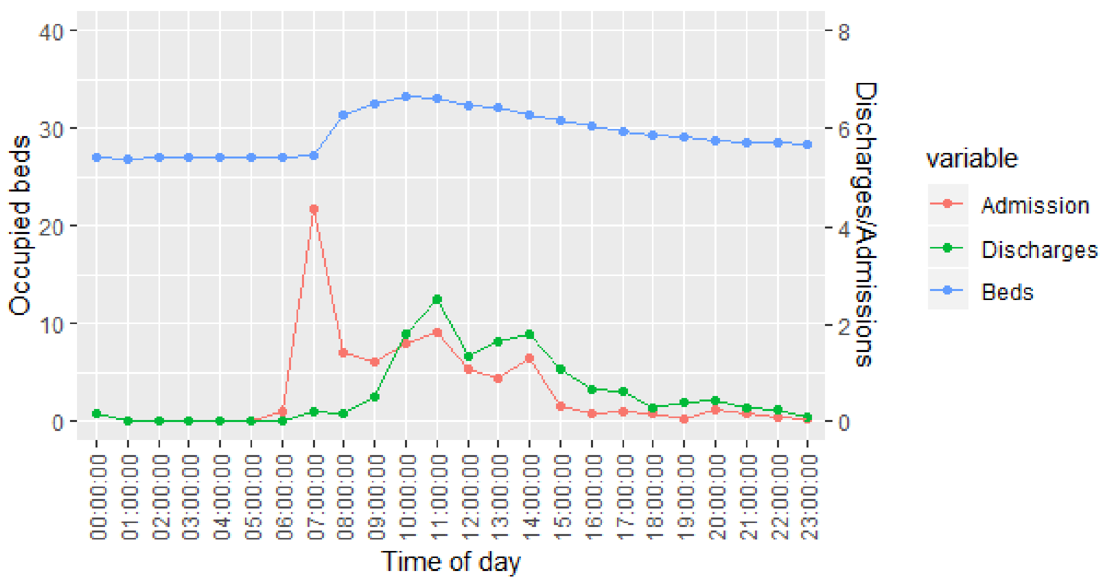

Figure 2.9: Daily occupation and admissions and discharges of A5 (N= 4528, HiX RKZ, 2018)

Length of stay

The length of stay is the time between admission and discharge of a patient. Each surgery has an expected LoS which depends mostly on the patient, the type of surgery and the medic specialists. For the research LoS is an important factor

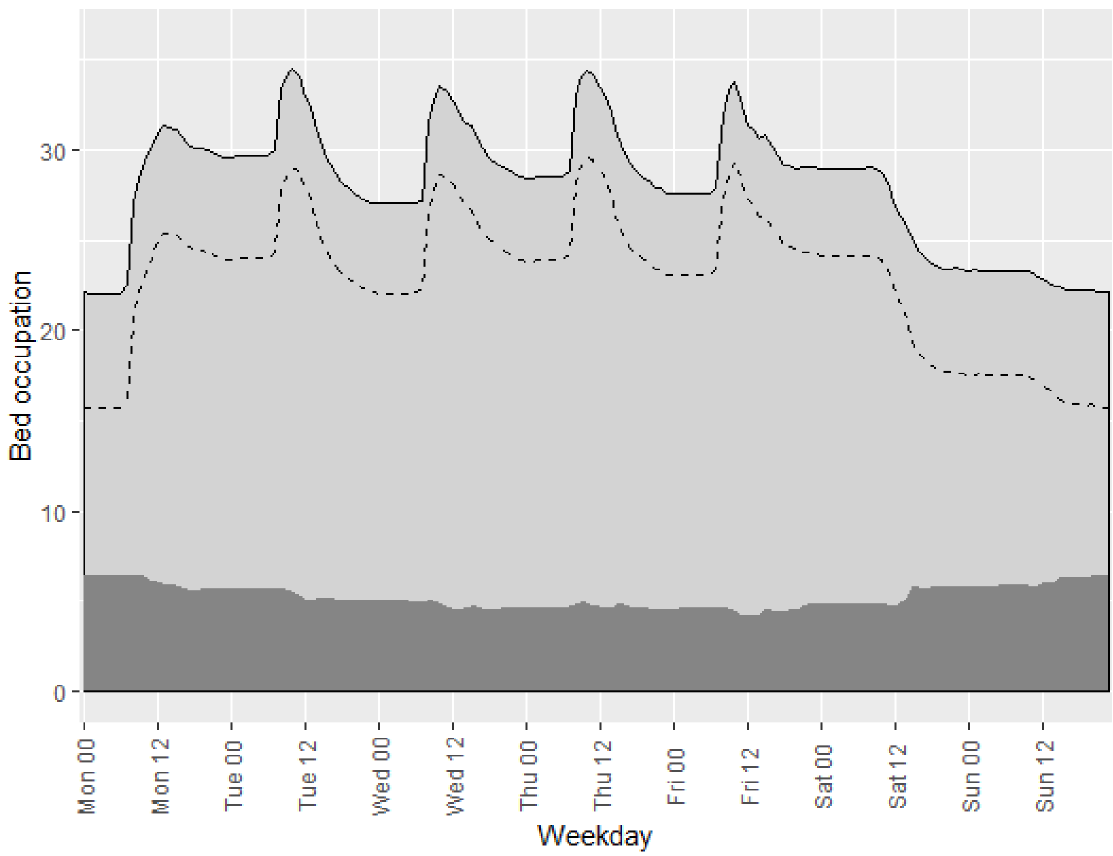

Figure 2.10: weekly occupation A5, dark grey showing non-surgical patients, dotted line showing the surgical patients, grey area showing all patients (N= 4528, HiX RKZ, 2018)

Day	Surgical	Non surgical	Total	Max mean
Monday	21.3	6.0	27.4	32.4
Tuesday	24.8	5.4	30.2	34.7
Wednesday	24.8	4.8	29.6	33.7
Thursday	25.4	4.7	30.1	34.6
Friday	25.2	4.5	29.7	34.0
Saturday	21.5	5.2	26.7	29.0
Sunday	16.8	6.0	22.8	23.4

Table 2.7: A5, average bed occupation per weekday(N= 4528, HiX RKZ, 2018)

because it relates directly to the bed occupation in the wards.

Table 2.8 shows the LoS of at ward A2X and Table 2.9 that at ward A5. Not all patients in the wards are receiving surgery. LoS is affected by the drugs the patients get administered. Influencing the LoS is outside the scope of the research. The differences are large between specialisms and wards. For example, for generic surgery (CHI) the standard deviation is large, this is the case because a lot of different surgeries fall within generic surgery.

The specialists estimate the LoS of patients in whole days. They estimate this correctly in 80% of the cases. In the other cases the patient stays longer or less than

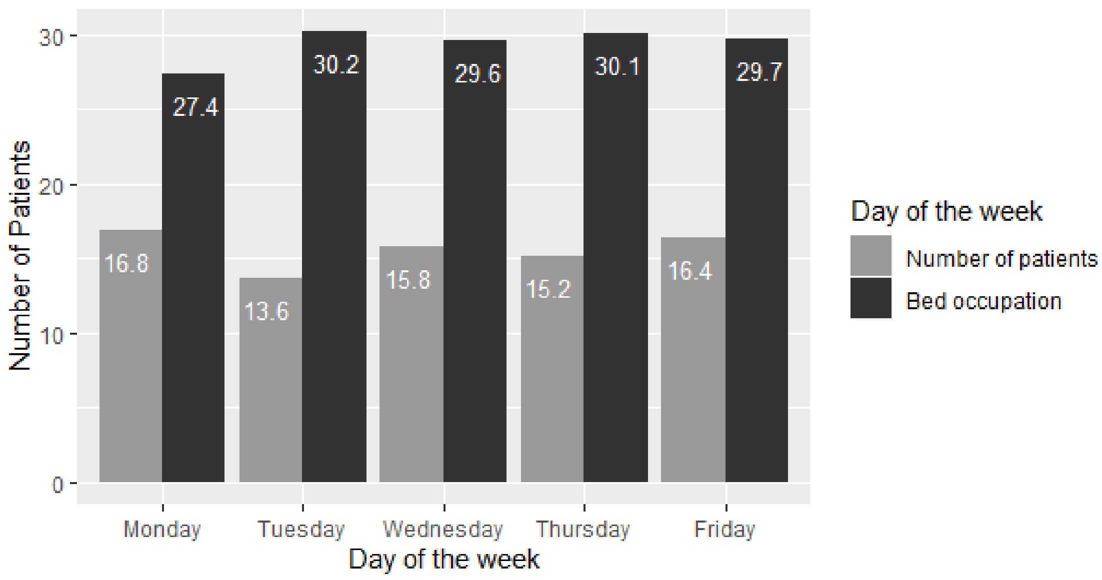

Figure 2.11: Weekly occupation and number of admissions A5 (N= 4528, HiX RKZ, 2018)

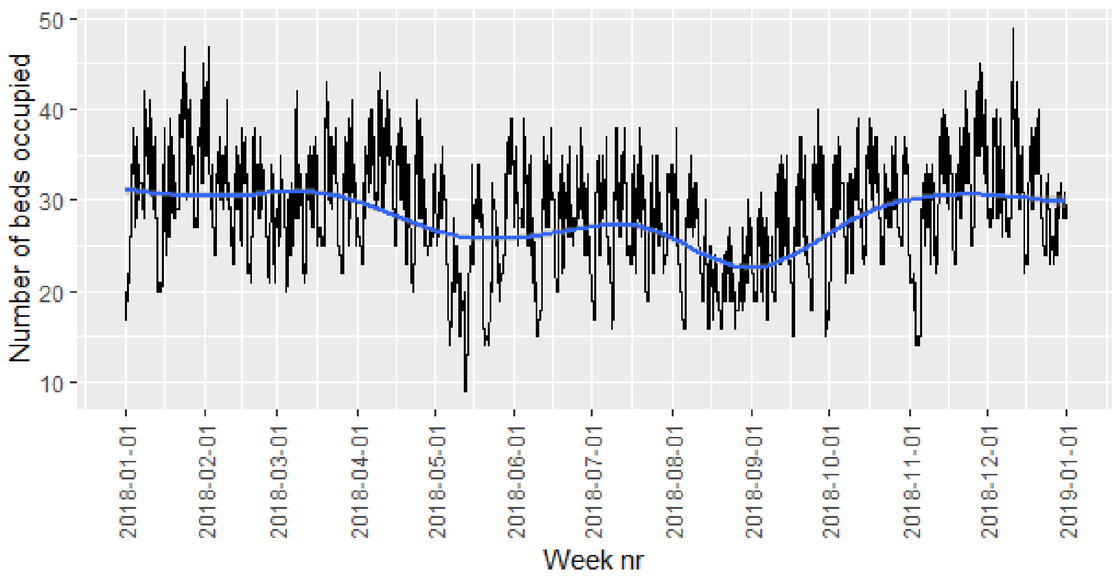

Figure 2.12: Occupation over the year for ward A5 (N= 4528, HiX RKZ, 2018)

expected. The RKZ does not estimate the daily LoS for patients going to A2X.

2.2.3 Access time specialisms

Changing the assignment of patients to ORs can result in a change in access times for patients. To make sure it does not have a negative impact on the access time of specialisms we have to keep track of the values in the current situation. Table 2.10 shows the access times of specialisms. Access time is defined as the time that a patient enters the waiting list until the time a patient gets surgery. Emergency patients are removed from calculations as they almost have no waiting time.

Specialism	Mean LoS	SD LoS
ANE	1.2	0.6
CAR	5.6	3.1
CHI	7.7	2.6
INT	5.4	2.5
KAA	5.2	2.6
KNO	6.9	1.6
LON	4.3	1.7
MDL	4.0	1.6
ORT	7.3	2.0
PLA	6.6	1.9
REU	3.8	0.9
URO	6.1	2.4

Table 2.8: LoS A2X (in hours) (N= 5527, HiX RKZ, 2018)

Specialism	Mean LoS	SD LoS
CHI	57.4	69.5
INT	49.6	46.7
KAA	17.8	12.6
NCH	26.5	11.1
ORT	43.2	38.4
PLA	30.9	41.4
URO	49.4	65.4

Table 2.9: LoS A5 (in hours) (N= 3576, HiX RKZ, 2018)

2.3 Conclusion

This chapter answers the following two research questions.

1. How can we describe the current planning process?
2. How can we measure the performance of ORs and wards and what is the current performance?

The RKZ uses quotas to schedule patients in the OR sessions of the MSS. The quotas limit the outflow to the subsequent wards. The creation of quotas is a tactical decision which limits the flexibility in selecting patients on a lower hierarchical level.

The standard deviation of the daily peak occupation is 1.2 patients for the daycare ward A2X and 4.15 patients in the clinical ward A5. In remaining of this report we aim to reduce that variation by scheduling with LoS information. The expected surgery duration that the RKZ uses to schedule patients on average is close to the realised surgery duration. The standard deviation of 25 minutes on a mean surgery duration of 82 minutes can cause unnecessary disruptions in the surgery schedule. We aim to improve the predictions in Chapter 4 when generating the input data for the models.

In ward A5 the variation originates from the elective surgical patients as the non-surgical patients are have a low variation. Figure 2.10 illustrates this. In the daycare

Specialism	Access time in days
Rheumatology	205.82
Plastic surgery	96.75
Oral surgery	73.39
Neurosurgery	46.49
Throat Nose Ear Surgery	43.96
Orthopedics	42.74
Surgery	38.82
Urology	37.43
Internal Medicine	35.19
Neurology	30.61
Gastrointestinal and liver diseases	28.91
Pain	25.50
Anesthesiology	21.77
Pediatrics	18.28
Gynecology	13.34
Cardiology	10.40
Lung medicine	8.95
Dermatology	3.50
Obstetrics	2.82
Mental health care	2.46
Intensive care	0.10

Table 2.10: Access time (days) per specialism (N= 11759, HiX RKZ, 2018)

ward A2X the variation originates from both the non-surgical as the surgical patients. Figures 2.7 illustrates this. Therefore, in this research, we aim to reduce the variation caused by elective surgical patients. The emergency and non-surgical patients are out of the scope of this research.

Chapter 3

Literature study

Extensive research exists on levelling ward occupation. However, most of the research considers the tactical planning level, only little research is done on the operational level. A recent literature review on the topic of operating room planning and surgical scheduling of Zhu (2019) shows that it is an upcoming area and more recent studies start to broaden the scope and start to consider downstream resources instead of only optimising the utilisation of an OR.

The literature study will focus on the operational level to answer the following research question:

> 3. *What scheduling methods using surgery duration and LoS information exist in the literature?*

First section 3.1 shows what articles are used for this literature study. The next four sections consider four steps that are necessary to schedule patients based on their LoS. We conclude the chapter with a recapitulation of the found methods in relation to the research questions and the applicability to the core problem.

3.1 Search method

The problem of scheduling surgeries in ORs is called the surgery scheduling problem SSP or patient scheduling problem (Zhu 2019). The search query that searches in title, abstract and keywords: "scheduling AND bed AND levelling AND (ward OR department)" results in six articles. Of those six articles, four articles, regarding optimising the MSS, are removed. Of the two remaining articles, only one considers assigning patients to surgical blocks. That is the article of Aringhieri et al. (2015) "assigning surgery cases to operating rooms: "A VNS approach for leveling ward beds occupancies". The article of Aringhieri et al. 2015 is also the only article that considers ward occupancies during the operational scheduling mentioned in the most recent literature review on the topic of OR scheduling.

Because our search results in only one article related to the research question we decide to use literature reviews on the topic of scheduling patients in ORs for a broader overview of the methods applied in different situations. We find five literature reviews occurring in the last ten years on the topic of OR scheduling and planning. We exclude one of the reviews because it is scarcely used in the six years it is available. The result are the literature reviews of Cardoen et al. (2010), May (2011), Hulshof et al. (2012) and Zhu (2019).

3.2 Length of surgical cases

We define the planned Length of a surgical case as the reserved OR time for a patient which consists of surgery time and slack time. Uncertainty in surgical case length is mostly caused by the patient's condition and the experience and skill of the surgeon (Molina-Pariente et al. 2015). Three distributions are often used to model the surgery duration the log-normal, gamma, and normal distribution (Zhu 2019). Zhu (2019) describe that considering uncertainty in the surgery duration makes OR scheduling problems quite different compared to deterministic ones. However, uncertainty or variability is often ignored in many OR scheduling problems and deterministic surgery duration are assumed. (Stepaniak et al. 2009) show that using the 3-parameter lognormal distribution gives an acceptable fit for 90% of the cases when the type of surgery is segmented by the factor surgeon. the 3-parameter lognormal distribution shows better results than the 2-parameter lognormal distribution. They show that using the mean of the 3-parameter lognormal distribution for case scheduling can result in less over- and under reserved OR time per case.

3.3 Surgical case assignment

Surgical case assignment also called Advanced scheduling or intervention assignment is the part of the scheduling process that schedules a patient from the waiting list in an OR on a specific day. Different approaches are applied to the problem of surgical case scheduling. Those include mathematical programming and optimisation techniques, rule-based heuristic approaches, and simulation(May 2011). The approaches are often focused on optimisation of the OR utilisation. Few papers consider the downstream resources during the surgical case assignment.

Jebali et al. (2006) propose a two-step approach to tackle the operating room scheduling problem. The first step consists of assigning surgeries to operating rooms. The second step deals with the sequencing of the surgeries. They determine which patients are to be operated one day in advance. The objective of the assignment step is to minimising overtime, undertime, and patient waiting time. The objectives are converted into a cost function. They create a mixed integer program and solve the program with a CPLEX solver. Hans et al. (2008) first create a list of surgeries that have to be performed on an OR-day using a First Fit dispatching rule which assigns surgeries from the top of the waiting list to the first OR it fits in. The list of surgeries for the specific day is sorted with a longest expected processing time rule, and surgeries are assigned to the first OR in which it fits. In addition to the constructive heuristic, they use local search heuristics to improve the solution by swapping different surgeries between OR-days or by moving a surgery to another OR-day. They use a random exchange methods and simulated annealing. They show that simulated annealing outperforms the random exchange methods and that regret-based random sampling is the best constructive approach. Both Jebali et al. (2006) and Hans et al. (2008) do not consider bed levelling in their approaches.

Aringhieri et al. (2015) create a model that determines the surgery date and operating room for each patient on a given planning horizon. With their model, they try to level the ward occupancies. Their mathematical program incorporates the deterministic surgery time and LOS of patients. The constraints make sure it is only possible to assign surgeries to the right specialism. Also, an option to prioritise patients is added. They count the number of days a patient will be using a bed and limit this by a number of beds reserved per specialism. The solution approach used is the Variable Neighbourhood Search (VNS) where three different neighbourhoods are described. The first exchanges a patient with a patient on another day, the second removes a patient and the third tries to add a patient that is not yet scheduled. For more general information about VNS see the article of Hansen et al. (2008)

3.4 Surgical case sequencing

Surgical case sequencing, allocation scheduling, or intervention scheduling is the step where the sequence of the surgeries is determined. Often, this step is taken one day in advance of the surgery day. The firs-come-first-serve rule is outperformed by the longest-processing-time-first rule (Hans et al. 2008). Often, other factors are relevant for the hospital like doctor preference, medical or safety reasons, patient convenient and resource restrictions (Hans et al. 2008). For daycare departments like the department at the RKZ the sequence can have a lot of impact. The surgery of a patient with an expected LoS of 6 hours has to end 6 hours before the closing of the department otherwise the patient needs to be transferred to a department where the patient can stay the night.

Jebali et al. (2006) propose two strategies to sequence the patients. The first strategy uses the assignment of surgeries to OR blocks of the first step as input and sequences the surgeries. The second strategy forgets the assignment to specific ORs and looks at the complete set of patients that was assigned to be less constrained. Their objective is to minimise overtime in the ORs and they propose a mixed integer linear program. The experiments show good results which are obtained within an hour of computation time. The article of Cardoen (2009) describes a multiple objective surgical case sequencing problem. In their problem formulation they use objectives that prioritise children and patients that need to be scheduled early, they incorporate the travel distance of patient to the hospital and they incorporate the stay in recovery after closing of the day-care center, the last objective minimises the peak in the number of beds used. Because the objectives vary in values they normalise the objectives to create an objective function. The problem is solved using mixed integer linear programming (MILP)

3.5 Determining the length of stay

Adan et al. (2009) show that using a stochastic LoS for patients results in a much better MSS than using a deterministic LoS looking at the weighted deviations between realised and targeted resource use. Their future work is the use of these tactical planning results in an operational planning environment. The paper of Aringhieri et al. (2015) that schedules patients uses a deterministic LoS in their assignment model.

3.6 Conclusion

In this chapter we answer research question 3: "What scheduling methods using surgery duration and LoS information exist in the literature?" we found little literature that considers bed levelling during the scheduling of patients. Therefore, we used other articles that do not incorporate the levelling of wards.

Few papers consider levelling of wards during the assignment step of the scheduling process. We propose to alter the model of Aringhieri et al. (2015) for the assignment step of the scheduling process. While most articles have the objective to maximise OR performance in some way our objective is to maximise bed occupation.

The sequencing step has the biggest influence on the bed occupation for the daycare department of the RKZ as LoS of patients can be divided in groups of patients with a LoS smaller than 2 hours, 2-4 hours , 4-6 hours and larger than 6 hours. Sequencing can prevent patients unnecessary needing to go to the regular ward because their expected LoS overlaps with the closing time of the daycare department. We propose the use the method of Cardoen et al. (2009) and alter it to the specific needs of the RKZ.

Chapter 4

Solution design

Chapter 3 shows that the process of scheduling patients is often split into two separate steps: the assignment step that assigns patients to an OR session on a day and the sequencing step, which gives the patient a surgery time. In this chapter, we introduce three models that we use to compare scheduling with quota with scheduling based on surgery duration and LoS: Two separate models for the assignment and sequencing step, and a model that shows the quota scheduling method that the RKZ uses. This chapter answers research question 4:

4. *How to create a scheduling method using surgery duration and LoS information specific for the RKZ?*

We describe the three models in Section 4.1, 4.2, and 4.3. Section 4.4 shows how we generate simulated patient data that serves as input for the models.

4.1 Surgical case assignment model

The surgical case assignment step consists of assigning patients from the waiting list to a specific OR session and day. The model is partly based on the article by Aringhieri et al. (2015). Below in Section 4.1.1 we first introduce the notation, parameters and variables for the model, afterwards, we describe the model in Section 4.1.2.

4.1.1 Notation

Tables 4.1, 4.2 and, 4.3 show the notation together with the sets, its indices, the parameters and, the decision variables.

Index	Description
$i \in I$	Patients
$d \in D$	Departments
$t \in \{1, ..., T\}$	Days in planning horizon
$j \in J$	Specialisms
$b \in B$	Beds
$k \in K$	OR session

Table 4.1: Sets and indices

Parameter	Description
I_d	Subset of patients that go to department d after surgery
I_j	Subset of patients that have specialism j
T	Time horizon
N_j	Maximum number of beds for specialism j during the MSS cycle
s_{tk}	Surgery time available on day t in OR session k
p_i	Surgery time of patient i
l_i	Length of stay of patient i
r_{td}	Number of beds available for patients on day t in department d
τ_{ik}	1 if patient i can be assigned to session k, 0 otherwise
C	Changeover time between surgeries

Table 4.2: Parameters

Variable	Description
x_{itk}	1 if patient i of the waiting list is assigned to day t in OR session k, else 0
o_{td}	Number of beds occupied on day t in department d
y_{td}	Deviation between the beds occupied and the beds available on day t in ward d

Table 4.3: Variables

4.1.2 Mathematical model

$$Min: \quad \sum_{t \in T, d \in D} (y_{td})^2 \qquad (0)$$

$$\begin{array}{llrcll}
s.t. & & \sum_{t \in T} \sum_{k \in K} x_{itk} & \leq & 1 & \forall i \in I & (1) \\
& & \sum_{i \in I} (p_i + C) x_{itk} & \leq & 0.96 * s_{tk} & \forall t \in T, k \in K & (2) \\
& & \sum_{i \in I_j} \sum_{t \in T} \sum_{k \in K} x_{itk}(l_i + 1) & \leq & N_j & \forall j \in J & (3) \\
& & \sum_{i \in I_d} \sum_{k \in K} \sum_{t'=t-l_i}^{t} x_{it'k} & = & o_{td} & \forall t \in T, d \in D & (4) \\
& & x_{itk} & \leq & \tau_{it} & \forall i \in I, t \in T, k \in K, & (5) \\
& & r_{td} - o_{td} & \leq & y_{td} & \forall t \in T, d \in D & (6) \\
& & x_{ikt} & \in & \{0, 1\} & \forall i \in I, k \in K, t \in T & (7) \\
& & y_{td} & \geq & 0 & \forall t \in T, d \in D & (8)
\end{array}$$

Constraints 1 make sure that patients can only be assigned once. Constraints 2 make sure that the sum of the surgery time in a session is smaller than the available surgery time in that session. To prevent overtime the available surgery time is 96% of the total surgery time in a session. Constraints 3 limit the number of patients that can be scheduled per specialism during a MSS cycle. The goal of these constraints is to prevent a specialism with a short planning horizon from overloading the department, as discusses in Chapter 2.1.3. Constraints 4 count the bed occupation for the wards on moment t by counting which patients are still using a bed after having surgery. Constraints 5 ensure that patients can only be assigned to a session with the same specialty as the patient. Constraints 6 give the deviation between the reserved beds and the assigned beds. Constraints 7 ensure binarity for the decision variables. Constraints 8 limit the bed occupation to the maximum of reserved beds for surgical patients on day t for ward d in combination with constraints 6.

The objective function minimises the squared error of the deviation between the number of beds that are reserved for surgical patients and the number of beds occupied by the surgical patients. The result is that the model aims to occupy as many reserved beds as possible.

Linear problem formulation

Alternative to the nonlinear problem shown we introduce a linear formulation of the problem. ChipSoft uses software in which it is easier to integrate a MILP model than a MIQP model. ChipSoft can base their decision to use the MILP or MIQP on the performance of the different variants which we show in Chapter 5. We obtain linearity by changing the objective function (0). Instead of the squared error, the linear model takes the sum of the errors.

$$min \sum_{t,d} y_{t,d} \qquad (0)$$

4.1.3 Solution approach

Section 4.1.2 shows the formulation of a MIQP (Mixed Integer Quadratic Program) and a MILP (Mixed Integer Linear Program). We solve the models with the software AIMMS (AIMMS-B.V. 2020) using the CPLEX solver (IBM-Corp. 2013).

4.2 Surgical case sequencing model

The second step of the scheduling process consists of sequencing the patients that are assigned to sessions in the previous step. At the end of this step, patients know the starting time of their surgery. The model has two objectives:

1. Limiting the time a patient spends at the daycare ward after the ward closes
2. Levelling the number of occupied beds during the day

The first objective reduces overtime for the daycare ward A2X and the second objective aims for a more equal bed occupation. As stated in the conclusion of Chapter 3 the sequencing step has the biggest impact on the variation of bed occupation for the daycare department A2X. Besides, overtime for ward A5 is not possible because it does not close. Therefore, in the model, we only consider the overtime and bed levelling objectives for department A2X.

The model we use is based on the model of Cardoen et al. (2009). They use the model in a freestanding ambulatory surgical centre that threats daycare patients. We made alternations and apply the model to sequence individual daycare and other surgical patients at the RKZ.

4.2.1 Notation

Tables 4.4, 4.5 and 4.6 show the notation together with the sets and its indices, the parameters, and the decision variables.

Index	Description
$i \in I$	Patients
$t \in \{1, ..., T\}$	Periods in day
$k \in K$	OR session
$j \in \{1, 2\}$	Objectives

Table 4.4: Sets and indices

Parameter	Description
I^{A2X}	Patients that go to A2X after surgery
I_k	Patients assigned to session k
T	Number of periods in the OR-day
p_i	Expected surgery time of patient i in periods
l_i	Expected length of stay of patient i in periods
$overtime_{it}$	Gives the overtime for patient i for each t
τ_{ik}	1 if patient i has to be operated in session k, 0 otherwise
H	number of periods that equal an hour
C	number of periods needed as changeover time
γ_{tk}	1 if session k is available at period t, o otherwise
end_k	The end time of each session k when all surgeries are performed one after another
w_j	weight of objective j

Table 4.5: Parameters

Variable	Description
x_{itk}	1 if the surgery of patient i starts at period t in OR session k, else 0
α_j	Value for objective j

Table 4.6: Variables

4.2.2 Mathematical model

$$Min: \sum_{j \in J} w_j \left(\frac{\alpha_j - Bestvalue_j}{Worstvalue_j - Bestvalue_j}\right)$$

$$
\begin{aligned}
s.t. \quad && \sum_{t \in T} \sum_{k \in K} x_{itk} &= 1 & \forall i \in I & \quad (1)\\
&& \sum_{i \in I} \sum_{t'=t-p_i-C+1}^{t} x_{it'k} &\leq 1 & \forall t \in T, k \in K & \quad (2)\\
&& \sum_{k \in K} \sum_{i \in I_{A2X}} \sum_{t \in T} overtime_{it} x_{itk} &= \alpha_1 & & \quad (3)\\
&& \sum_{k \in K} \sum_{i \in I_{A2X}} \sum_{t'=t-l_i-p_i+1}^{t+H} x_{it'k} &\leq \alpha_2 & \forall t \in T & \quad (4)\\
&& x_{itk} &\leq \tau_{ik}\gamma_{tk} & \forall i \in I, t \in T, k \in K & \quad (5)\\
&& \sum_{k \in K} \sum_{t \leq end_k - p_i - C + 1} x_{itk} &= 1 & \forall i \in I & \quad (6)
\end{aligned}
$$

Constraints 1 ensure that all patients that are assigned to sessions are scheduled. Constraints 2 prevent overlap between surgeries, one surgery can only start if the previous surgery in that session is finished and the changeover time after each surgery is incorporated. The third constraints sum the overtime of the scheduled patients in periods. The overtime of each possible x_{itk} is calculated as $overtime_{it} = t + p_i + l_i - 1 - T$ if $t + p_i + l_i - 1 > T$, 0 otherwise. If the patient leaves the bed before the end of the day there is no overtime. Otherwise, the overtime is the period the patient leaves minus the closing period of the ward. Constraints 4 count the occupied beds on period t for ward A2X. Constraints 5 ensure that patients can only be scheduled in their assigned session and at a time when the session is in operation. Constraints 6 make sure that all surgeries are performed in sequence to prevent gaps between surgeries where the surgeon and his team are idle.

The objective function is derived from the article of Cardoen et al. (2009). They propose to use a normalised objective function that originates from the field of multiple criteria decision making. The objectives (α_j) measure performance in different units. α_1 measures the overtime of ward A2X and α_2 measures the number of beds occupied in ward A2X. Therefore a summation over the two (α_j) would result in a schedule optimised over one of the two criteria. To normalise the objective function we consider the worst and best possible value of each objective:

$$\sum_{j \in J} w_j \left(\frac{\alpha_j - Bestvalue_j}{Worstvalue_j - Bestvalue_j}\right)$$

this scales the objective terms on a [0,1] scale, so that they can be compared. We set $Worstvalue_1$ and $Bestvalue_2$ to the maximum and the minimum of the overtime in the overtime matrix, $overtime_{it}$, which is calculated before solving the model. We set $Worstvalue_2$ to the number of patients which go to A2X, the worst case is that all patients occupy a bed at the same time. We define the best case, $Bestvalue_2$, as the number of patients occupying a bed when they are divided equal over the day. The weights w_j are adjustable by the hospital to prioritise objectives.

4.2.3 Solution approach

We solve the MILP with the software AIMMS (AIMMS-B.V. 2020) and use the CPLEX solver (IBM-Corp. 2013).

4.3 Quota model

In this section we introduce the quota scheduling method. Section 2.1.3 showed the quota scheduling method of the RKZ. Because the computer solves the problem, the model shows the potential of the quota scheduling method. The model is expected to create better patient combinations than the planners at the RKZ regarding the utilisation of the ORs. As input for the model, we use the quotas and the MSS of 2018 because we generate data based on the year 2018. We show the generation of the data in Section 4.4. We do not change the sequence of the patients as this only happens for a few cases at the RKZ. At the RKZ children are the first to undergo surgery. However, the children go to another ward than A2X or A5. In Chapter 5 we use the quota model to compare the two scheduling methods with each other. The model starts with the first session and fills this with patients until there is no session time left or the quotas are reached. The quota model limits itself to the first 10 A2X and first 10 A5 patients that are on the waiting list when scheduling patients as this is approximately the range of patients that the planners in the RKZ use. We formulate a MILP for every session in the MSS. The objective is to fill the session as much as possible. Below we show the formulation of the quota model.

4.3.1 Notation

Tables 4.7, 4.8 and 4.9 show the notation together with the sets and its indices, the parameters, and the decision variables.

Index	Description
$i \in I$	Patients
$d \in \{1, 2\}$	Wards A2X and A5

Table 4.7: Sets and indices

Parameter	Description
I_d	Patients that go to department d after surgery
p_i	Expected surgery time of patient i in periods
C	number of periods needed as changeover time
$SessionTime$	The amount of time in the session
$Quota_d$	The quota for department d in the session

Table 4.8: Parameters

Variable	Description
x_i	1 if the patient is assigned to the session, else 0
$Utilisation$	Gives the utilisation of the session

Table 4.9: Variables

4.3.2 Mathematical model

$$max: \quad Utilisation$$

$$\begin{aligned}
s.t. \quad Utilisation &\leq 0.96 * SessionTime && (1)\\
\sum_{i \in I} x_i * (p_i + C) &= Utilisation && (2)\\
\sum_{i \in I_d} x_i &\leq Quota_d \quad \forall d \in D && (3)
\end{aligned}$$

Constraint 1 limits the amount of surgery time in a session to 96% of the session time. The RKZ uses 96% to reduce the chance of overtime in ORs. Constraint 2 sets the utilisation of the session to the sum of the patient's surgery time including the changeover time of 10 minutes. Constraints 3 make sure that the quota of the session are considered.

4.4 Input data

In Chapter 5 we do experiments with both historical data and simulated data. The advantage of using historical data is that we can compare the results of the LoS scheduling method directly with the realised occupation. A disadvantage is that the historical data is influenced by other aspects than the scheduling method. For example, the LoS is influenced by the time a physician makes a discharge round and by the admission time of a patient. Besides, an initial daycare patient that has surgery late on the day can be sent to ward A5 instead of the daycare ward and stay the night which influences its LoS.

In this section, we show how we generate the data that is used for the simulation. The data is based on the RKZ data set that is available at ChipSoft. The data ranges from 30-06-2017 to 20-04-2019. We simulate patients coming onto the waiting list with a valid screening and who are ready to be scheduled. Subsection 4.4.1 shows the patient arrival process and the determination of the patient's surgery type and specialism. Subsection 4.4.2 shows the determination of the planned and realised surgery time. Subsection 4.4.3 shows the generation of the expected and realised LoS for patients for ward A5 and A2X. We conclude with the validation of the data set in Section 4.4.4.

4.4.1 Patient arrival process

New patients are added to the waiting list almost every day. We fit the daily arrival rate in Appendix A on the 2018 data of the RKZ. We use data of 2018 because we are using the MSS and the quotas that were used at the RKZ in 2018. The patient arrival process follows the normal distribution. We find a mean of 24.84 patients and a standard deviation of 8.26 patients. We neglect seasonal effects in the weekly arrivals. These seasonal effects are not necessary to compare the two methods of scheduling.

To determine which type of surgery the patient has to undergo we create an empirical distribution based on historical data of the RKZ. We use the COTG-codes in the HiX database to distinguish surgery types. Each COTG code belongs to one of the specialisms. We find 1706 unique COTG-codes from 30-06-2017 to 20-04-2019. Table 4.10 shows the distribution of surgical specialisms. Because CAR and ANE are placed in the session of CHI we merge these with CHI.

Specialism	Fraction
CHI	0.49
KAA	0.02
KNO	0.05
NCH	0.02
ORT	0.17
PLA	0.18
URO	0.07

Table 4.10: Patient volume distribution of specialisms (N = 6364, 2018, RKZ HiX)

4.4.2 Surgery duration distribution

The next step is to generate a planned and a realised surgery duration for the patient. The models use the planned surgery duration to schedule patients, the realised surgery duration simulates the outcome of the schedule. We choose an approach described by (Stepaniak et al. 2009). They show that the 3-parameter lognormal gives an acceptable fit for 90% of the cases when segmented by the factor surgeon. They also show that using the mean of the 3-parameter lognormal distribution for case scheduling can result in less over- and under reserved OR time per case. We use all available RKZ data, which ranges from 20-06-2017 to 20-04-2019.

We choose to split the process of generating surgery times into four groups. Group 1 consists of surgeries (COTG-codes) in combination with a surgeon that is performed ten or more times. This group contains 66% of the cases. The expected surgery duration for the first group is generated with the mean of the 3-parameter lognormal distribution for the combination of surgery and surgeon. The realised surgery duration is generated by a random number from the 3-lognormal distribution. The second group consists of the cases that could not be fitted in group 1. In group 2 we fit the 3-parameter lognormal distribution on the COTG-codes. Group 3 consists of the cases that do not fit group 1 or group 2. In group 3 we generate groups of surgery types based on their surgery duration and fit those groups on the 3-parameter lognormal distribution. Group 4 consists of cases that do not fit the other groups. For group 4 we use the empirical distribution of the COTG-codes to generate an expected and realised surgery duration.

Changeover time

Changeover time is only corrected recorded for the second half-year of 2018 at the RKZ. In most cases the changeover time is ten minutes. For the models, we assume that the changeover time is always ten minutes and we add this after each surgery.

4.4.3 Length of stay data generation

We split the generation of LoS into two parts. We generate the LoS for patients going to ward A5 differently than for patients going to ward A2X.

Expected length of stay

The physician in the RKZ estimates how many nights a patient is expected to stay in the hospital. We look for a correlation between the surgery time and the LoS of a patient. The Pearson correlation shows a score of 0.24 which indicates a weak correlation. Because of this weak correlation, we decide not to use the surgery time to generate the expected LoS. We create an empirical distribution based on the physician estimations in 2018. Figure 4.13 shows the LoS distribution that can be used for the ORT specialism. Patients with a LoS of 0 go to ward A2X

LoS	frequency
0	0.536
1	0.426
2	0.029
3	0.006
4	0.003
5	0.001

Table 4.11: Expected LoS distribution for orthopaedics (N = 1071, 2018, RKZ HiX)

The patients that have a LoS of 0 assigned will get an additional attribute which gives the expected LoS in hours. Table 4.12 shows the mean and standard deviation of the LoS of patients in ward A2X per specialism. For the expected LoS we use the mean LoS duration.

Specialism	Mean LoS in hours	SD of LoS
CHI	7.37	3.20
KAA	5.02	2.06
KNO	6.77	1.70
ORT	7.28	2.19
PLA	6.68	2.99
URO	7.11	3.76

Table 4.12: Parameters normal distribution for daily LoS per specialisms

Generation of realised length of stay

For each LoS in ward A5 we create an empirical distribution of the realised LoS. Table 4.13 gives an example of the distribution for an expected LoS of 1. The discharge time on the discharge day of the patient is assumed to be random and follows the discharge pattern as shown in Figure 2.9.

Expected LoS	Realised LoS	Frequency
1	0	0.245
1	1	0.612
1	2	0.103
1	3	0.024
1	4	0.008
1	5	0.008

Table 4.13: Empirical distribution for Expected LoS = 0

For ward A2X we create a realised Length of stay by generating times from the normal distribution. The realised LoS is influenced by the time a nurse takes a discharge round, the type of surgery, how the surgery went and by the characteristics of the patient. This makes it difficult to find a good fit for the patients' LoS distribution. We assume that each specialism follows the normal distribution. However, we correct LoS that is lower than 1 hour and set it to one hour. Table 4.12 shows the parameters of the normal distribution per specialism. ▷

4.4.4 Validation of the surgery duration and LoS generation

In this section, we validate the creation of the input data. We use a Welch Two Sample t-test to test the generation of the surgery times and the creation of the LoS. We create 52 weeks of data and compare this to the real data of 2018. Table 4.14 shows the mean of the RKZ and the simulated mean. The null hypothesis in the test is that the two means are identical. The alternative hypothesis is that the means are different. The p-values in the table show that we cannot reject the null hypothesis. The data shows that we generate surgery duration and LoS in line with the 2018 data of the RKZ.

Attribute	Real mean	Simulated mean	p-value
Expected surgery duration	80.29	81.26	0.22
Realised surgery duration	80.31	81.28	0.28
Expected LoS	0.53	0.54	0.62
Realised LoS	0.56	0.55	0.58

Table 4.14: Validation of patients attributes

4.5 Conclusion

This chapter answers research question 4 by showing a two-step approach to schedule patients based on LoS and surgery duration. Step 1, the assignment step, which assigns patients based on their LoS and surgery duration to an OR session. And step 2, the sequencing step, that aims to level the ward occupation and to reduce the overtime in ward A2X and determine a surgery sequence for patients in both wards. Besides, we create a quota model that mimics the quota method of the

RKZ. The next chapter gives the results of scheduling with LoS and compares it with scheduling using admission quotas. The simulation data generated in this chapter serves as input for the models.

Chapter 5

Results

This chapter gives an answer to research question 5:

5. *How does the scheduling method using LoS information perform and what is the performance compared to scheduling with admission quotas?*

First, we compare the models using LoS and surgery duration information with the quota model as described in Chapter 4. We experiment with different settings and different sizes of waiting lists. We use the simulated data of Section 4.4 as input for the models. Second, we show how the model performs with the 2018 data of the RKZ in comparison with the realised occupation. We run the model two times. First, with the surgery duration as estimated by the RKZ. Second, we run the model with the surgery duration estimated by the 3-parameter lognormal distribution as shown in Section 4.4.2.

5.1 LoS model versus quota model

More occupied beds result in higher earnings for the hospital. Therefore, the model does not just level the variation but also aims to occupy as many beds as possible. We use the quota model to simulate the occupation resulting from using quotas and we use the assignment model and the sequencing model of Chapter 4 together to simulate the occupation resulting from scheduling with LoS. We refer to the assignment model and the sequencing model as the LoS model. To compare the performance of the LoS model and the quota model we create three experiments. The first varies the number of patients on the waiting list. We do this to show the resulting occupation when the models have a limited amount of patients to choose from and when the amount of patients is definitely sufficient. Besides, we show the combination of the quota model with the sequencing model. The second shows the difference in performance between the MIQP and MILP formulation of the assignment step in the LoS models. Some solvers do not support MIQP models. If the performance of the MILP formulation of the assignment model gives good results the hospital can choose the MILP formulation over the MIQP formulation. The last shows the impact of altering the weight for the weekend occupation. This shows how the weekday performance changes when we also aim to maximise the occupation in the weekends. In each experiment, we simulate a full MSS cycle which is four weeks. To obtain more accurate results we perform ten replications per experiment. The models only schedule elective surgical patients. To calculate the statistics we add a fixed number of beds that are reserved for non-surgical patients or emergency patients.

5.1.1 General model settings

We run the experiments with the quadratic formulation (MIQP) of the assignment problem except for the comparison of the MILP and MIQP performance in Section 5.1.3. Expect the experiment in varying waiting list sizes the experiments are run with a waiting list that starts with one week of patients and adds one week of patients after each week to the list. In consultation with the RKZ, we reduce the focus on the weekend occupation as this impacts the occupation during the week and the RKZ prefers the more stable occupation during the week. Therefore, we multiply the deviation of beds in weekends with the factor 0.10. in Section 5.1.4 we look at the difference between using the factor 0.10 and factor 1 for the weekend variation. This results in the following objective function for the quadratic objective that we use in the experiments:

$$\sum_{t \in 1,..,5, d \in D} (y_{td})^2 + \sum_{t \in 6,7, d \in D} (0.10 * y_{td})^2$$

The sequencing part of the LoS model has the option to vary the weights between both objectives. We set the weights to 1 for both objectives such that both the closing time of the ward and the levelling of the number of occupied beds during the day have the same weight.

5.1.2 Varying waiting list size

In this section we run the quota and LoS model with different sizes of waiting lists to see the effect on the bed occupation. We do two runs. For the first run, we generate a waiting list that starts with 1 week of patients and where after each week one week of patients is added. The second run starts with a waiting list consisting of ten weeks of patients and does not add patients during the run of the model. The first run shows how the model performs with a limited number of patients and the second run shows the performance of the model when the number of patients is not a bottleneck for the LoS model. In addition, we analyse the influence of the sequencing model. We perform a run with the 10 week waiting list where the quota model assigns patients and the sequencing model sequences the patients.

Weekly addition of patients

In this experiment, the waiting list starts with one week of patients in the first week and every other week one week of patients is added to the waiting list. Patients that are not scheduled stay on the waiting list.

Table 5.1 shows the performance indicators for both methods. The LoS model shows an increase in the number of patients scheduled. although there is a slightly lower mean surgery duration, the LoS model results in a higher session utilisation. We see a reduction of the standard deviation of the daily peak occupation during the week for both A2X and A5. for A2X this is 62% and for A5 this is 33%.

Figure 5.1 shows that the bed occupation of ward A2X is more evenly spread when scheduling with the LoS model instead of the quota model. The quota model gives the impression that the quotas on the Fridays are too low. However, another explanation is that the quota model cannot make good combinations of surgeries at the end of the week. New patients arrive before Monday on the waiting list before the models start scheduling the new week. The LoS model considers all sessions in the week at the same time. The quota model considers the session one by one. The result is that some session can not be filled anymore because the patient with the right specialism for the Friday is scheduled at an earlier session in the week. Figure 5.2 shows the occupation of ward A5. The biggest difference of the LoS model compared to the quota model seems to be the high amount of admissions on Monday and Thursday. This corresponds with the slightly lower admissions on Monday and Thursday in ward A2X.

Performance indicator	Quota model		LoS model	
	A2X	A5	A2X	A5
Number of patients	205	200	231	205
Mean surgery duration	85 min		82 min	
Session utilisation	73%		75%	
SD daily max. oc. week	2.7	2.2	1.0	1.5
SD daily max. oc	2.7	3.9	1.0	4.3
Mean occupation	10.3	27.9	10.7	28.0
Max mean occupation	17.6	35.1	17.3	35.2
Closing time ward	22:55		22:12	

Table 5.1: 1 MSS cycle, addition of patients every week

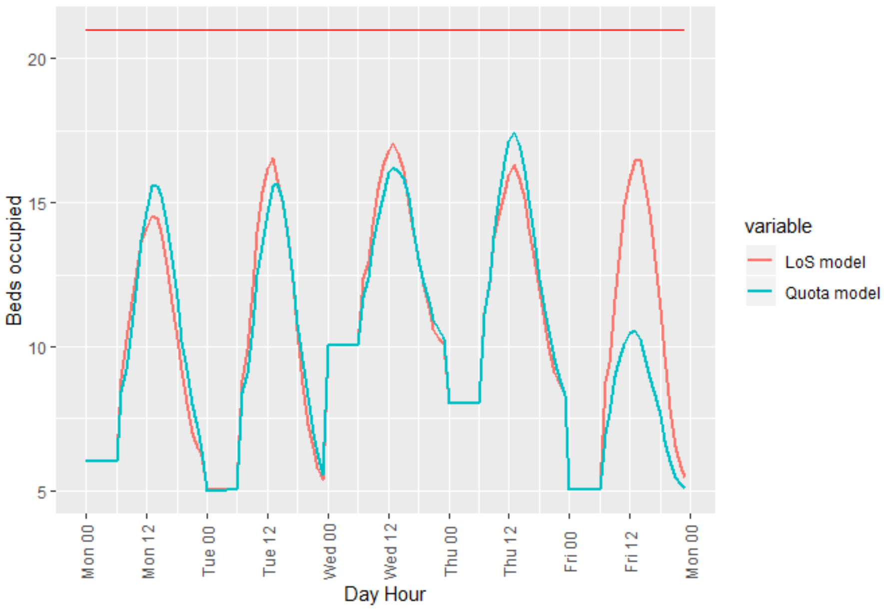

Figure 5.1: A2X 1 MSS cycle, addition of patients every week

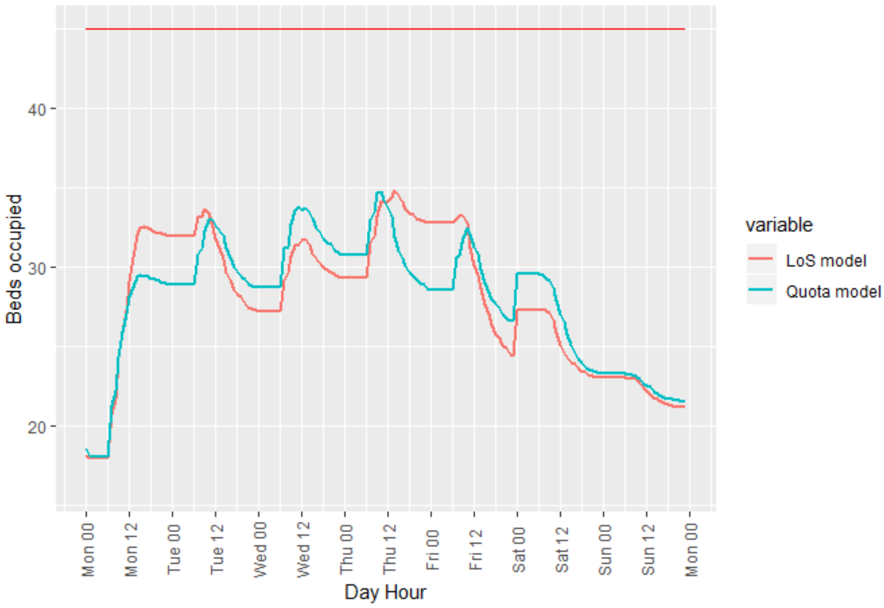

Figure 5.2: A5 1 MSS cycle, addition of patients every week

Ten week waiting list

In this experiment the models starts with 10 weeks of patients on the waiting list which the models schedule over one cycle of the MSS. The 10 weeks of patients should give an indication of how the model behaves when the size of the waiting lists is not a bottleneck. Besides, we make a comparison between the quota model, the LoS model and the combination of the quota model with the sequencing model.

Table 5.2 shows the performance indicators for both methods and both wards. Like the experiment above where we use one week of patients the LoS model again schedules more patients than the quota model. The LoS model also shows a decrease in the standard deviation of the daily maximum during the week. Because the LoS model can choose from a waiting list containing 10 weeks of patients it assigns surgeries with a lower surgery duration to sessions than the quota model. This is caused by the objective of the LoS model that aims to fill as many beds as possible. The LoS model uses all available patients to find a solution. The quota model only uses the first 10 A2X and first 10 A5 patients to select patients from. After scheduling the patients the waiting list of the quota model contains 6727 patients with an average expected surgery duration of 78 minutes, the waiting list of the LoS model contains 6146 patients with an average expected surgery duration of 91 minutes. Hospitals earn more money with full hospital beds. However, not scheduling the group of patients with a long surgery duration is not desirable.

Figure 5.3 and Figure 5.4 show the occupation of both wards. We see that the model tries to assign more patients to a bed in ward A5 on Monday compared to the quota model. The result is that fewer patients are assigned to a bed in ward A2X on the same day. Ward A5 shows a low occupation after Tuesday which is the result of assigning a lot of patients to Monday with a LoS of 1 night. Those patients leave the hospital on Tuesday. Besides, the model increases admissions on Friday to obtain occupied beds on Saturday and Sunday. Which results in a higher occupation during the weekend than the quota model.

Next to the quota and the LoS model Table 5.2 shows the result of running the sequencing model with output of the quota model. The sequencing model does not lower the standard deviations of the daily maximum occupations for ward A2X. However, it lowers the standard deviation in ward A5. The objectives of the sequencing model are only considering ward A2X and not ward A5. Note that the mean occupation of the quota model and the quota including sequencing differs for ward A5. The reason is that the discharges at ward A5 follow the discharge distribution shown in Figure 2.9. Figures 5.5, 5.6, and 5.7 show the occupation of the quota model in comparison to the quota model in combination with the sequencing model. For the daycare ward A2X we see that the daily maximum occupation is higher for the run with the sequencing model. This is a result of the sequencing model aiming to close the ward with as little overtime as possible. Figure 5.7 shows the mean daily pattern. It shows that the quota model spreads the patients over more time. The quota model does not consider the overtime of the wards. At the RKZ, daycare patients that are scheduled late are sent to the clinical ward A5 to spend the night. Ward A2X can be closed at 21:00 in that case. Figure 5.6 shows that the sequencing model results in lower peaks for the clinical ward A5.

Performance indicator	Quota model		Quota + Sequencing		LoS model	
	A2X	A5	A2X	A5	A2X	A5
Number of patients	251	245	251	245	275	279
Mean surgery duration	86 min		86 min		72 min	
Session utilisation	89%		89%		85%	
SD daily max. oc. week	2.0	2.5	2.0	2.1	1.7	0.7
SD daily max. oc.	2.0	4.1	2.0	3.8	1.7	3.6
Mean occupation	11.1	29.8	11.1	29.5	11.2	31.9
Max mean occupation	20.1	37.2	20.9	35.3	18.9	38.8
Closing time ward	23:38		21:40		22:10	

Table 5.2: 1 MSS cycle, waiting list with 10 weeks of patients

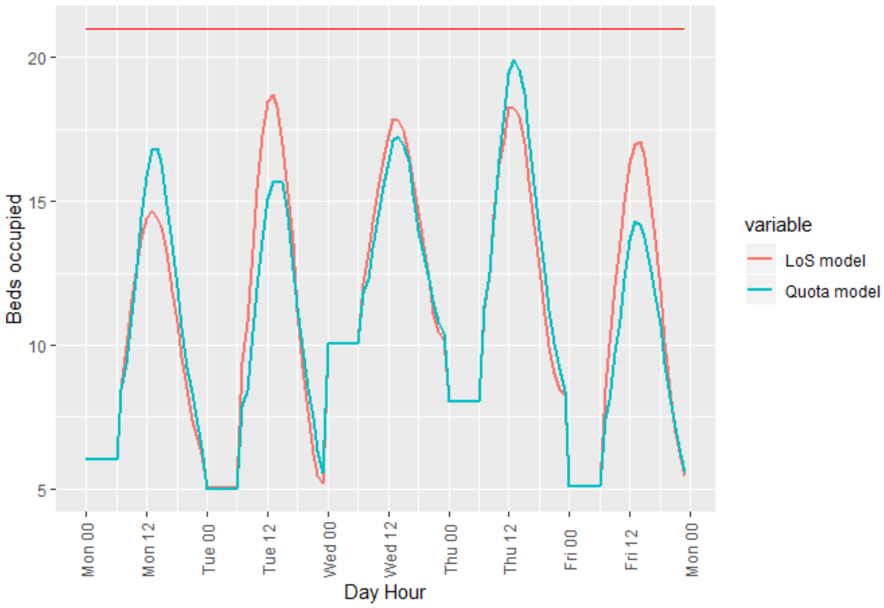

Figure 5.3: A2X 1 MSS cycle, waiting list with 10 weeks of patients

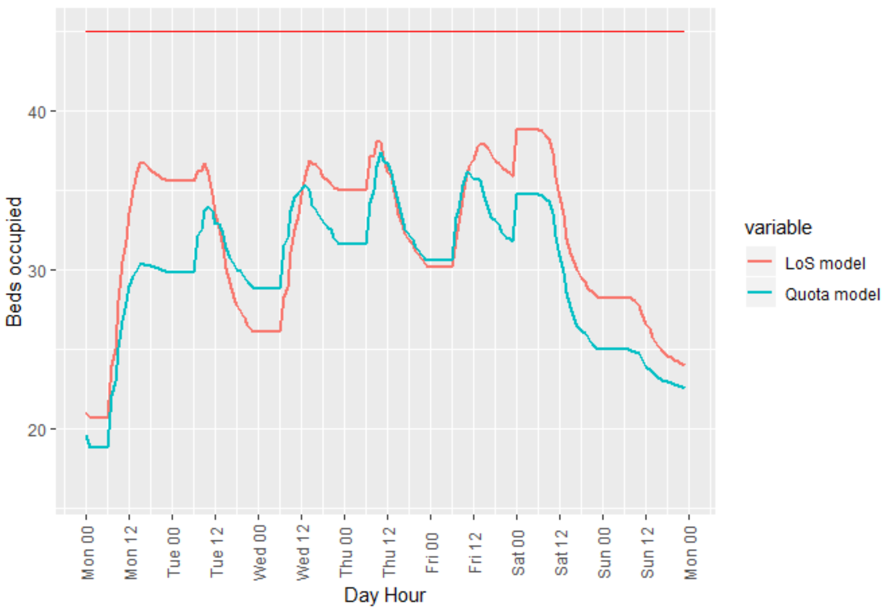

Figure 5.4: A5 1 MSS cycle, waiting list with 10 weeks of patients

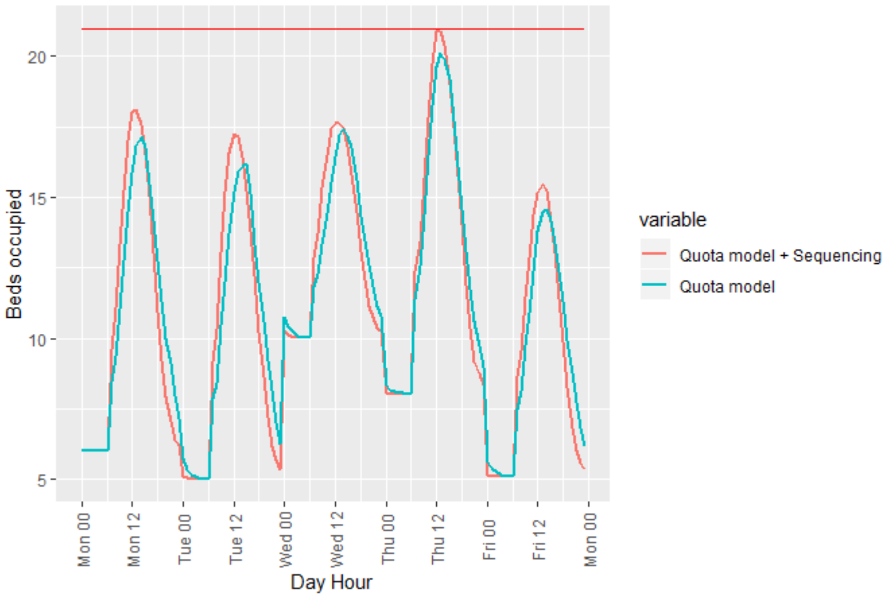

Figure 5.5: A2X, 1 MSS cycle, waiting list with 10 weeks of patients, quota model + sequencing model

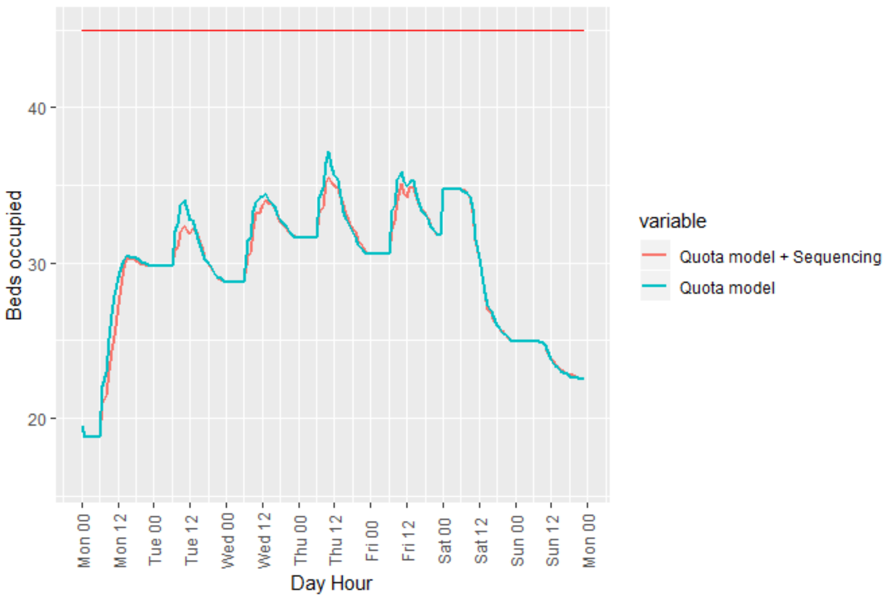

Figure 5.6: A5, 1 MSS cycle, waiting list with 10 weeks of patients, quota model + sequencing model

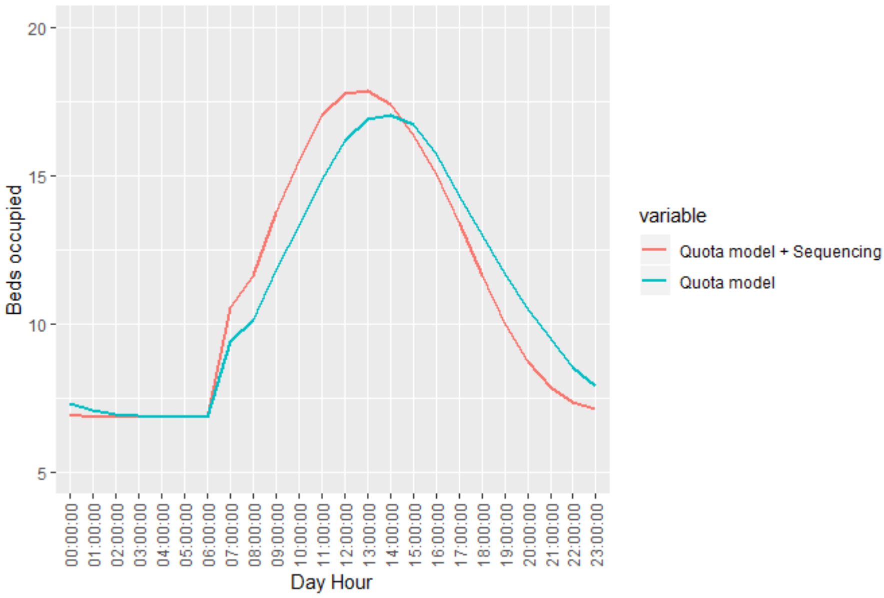

Figure 5.7: A2X daily occupation, 1 MSS cycle, waiting list with 10 weeks of patients, quota model + sequencing model

5.1.3 MIQP compared with MILP

In this section we compare the performance of the two different objective formulations for the assignment problem as shown in Section 4.1.2. Both objectives aim to fill the beds as much as possible. However, the difference is that the linear model does not consider the amount of deviation per day where the quadratic formulation does. For example, the MIQP model prefers an outcome that has a deviation of two patients on Monday and two patients on Tuesday over an outcome where there is a deviation on Monday is four patients and the deviation is zero patients on Tuesday. The MILP model does not make a distinction for those outcomes. We run this experiment to see whether the MILP model still gives good enough results.

Table 5.3 shows the difference performance indicators. We see that the MILP performs slightly better on ward A2X compared to the MIQP model but performs worse on ward A5 regarding the standard deviation of the daily maximums during the week. The MIQP variant shows a higher utilisation of the session time. Solving the MILP got interrupted during the sequencing step after three replications. The assignment model assigned only patients to one ward and none to the other for one day in the week. As a result, the sequencing model could not calculate the best and worse values for the objective function. Therefore, we show only the data of the first three replications.

Figure 5.8 shows the performance of the MILP in ward A2X compared to the quota model. Figure 5.1 shows the MIQP performance of the LoS model. Figure 5.9 shows the MILP performance compared with the quotas and Figure 5.2 shows the MIQP performance. The MILP variant shows an almost similar occupation for ward A5 compared with the quota model. Where the big difference is the occupation on Friday. The MILP model shows a higher occupation in ward A2X and a lower occupation in A5.

Performance indicator	Quota model		MILP LoS model		MIQP LoS model	
	A2X	A5	A2X	A5	A2X	A5
Number of patients	205	200	237	196	231	205
Mean surgery duration	85 min		81 min		82 min	
Session utilisation	73%		73%		75%	
SD daily max. oc. week	2.7	2.2	0.9	2.3	1.0	1.5
SD daily max. oc.	2.6	3.9	0.9	4.7	1.0	4.3
Mean occupation	10.3	27.9	10.8	27.8	10.7	28.0
Max mean occupation	17.6	35.1	17.6	35.8	17.3	35.2
Closing time ward	22:55		21:54		22:12	

Table 5.3: 1 MSS cycle, addition of patients every week

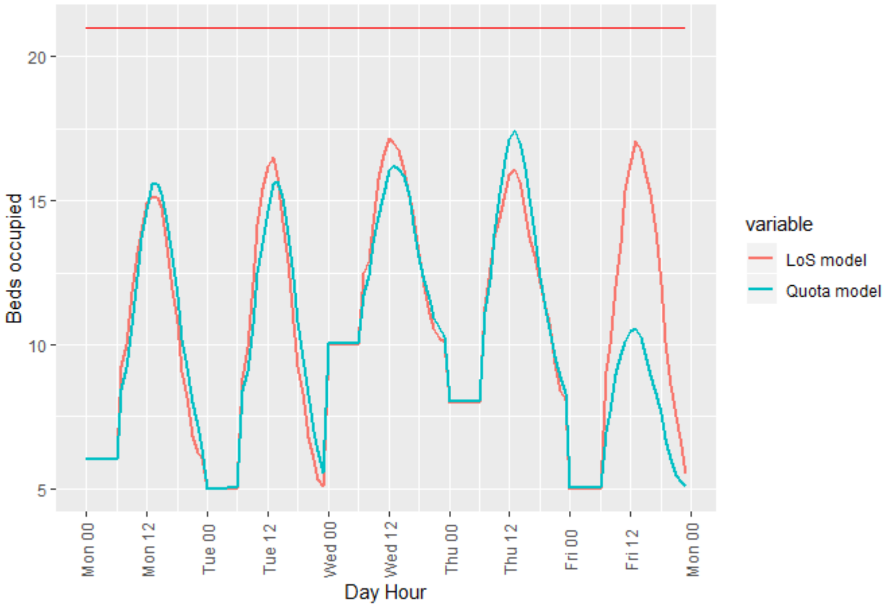

Figure 5.8: MILP vs quotas, A2X 1 MSS cycle, addition of patients every week

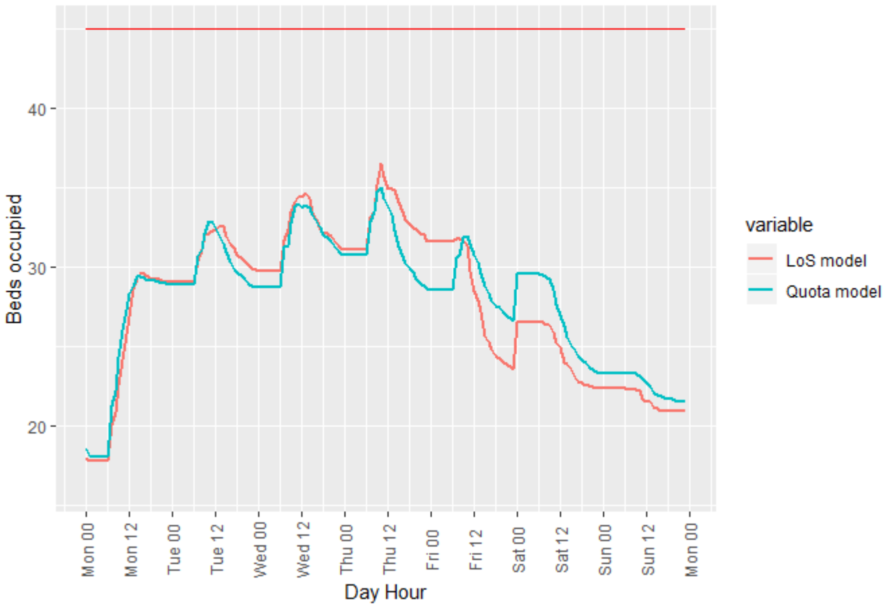

Figure 5.9: MILP vs quotas, A5 1 MSS cycle, addition of patients every week

5.1.4 Changing the weekend weight

In this section we alter the weights in the objective function for deviating from the number of reserved beds in the weekends. Equations 5.1 and 5.2 show the different objectives. We want to know what the influence is of altering the weight for the weekend on the occupation during the week.

$$Min : \sum_{t \in 1,..,5, d \in D} (y_{td})^2 + \sum_{t \in 6,7, d \in D} (0.10 * y_{td})^2 \tag{5.1}$$

$$Min : \sum_{t \in 1,..,7, d \in D} (y_{td})^2 \tag{5.2}$$

Table 5.4 shows the performance of both objective functions. We see that there is a difference in the standard deviation of the resulting bed occupation. Objective 5.2 performs better on both the standard deviation of the daily maximums during the weekdays and during the week including the weekend. The improvement of the standard deviation over the whole week of ward A5 is unsurprising because we aim to reduce the variation over the whole week with objective 5.2. However, Objective 5.2 also lowers the standard deviation of the peaks during the weeks. The model using Objective 5.2 schedules the most patients on Friday to realise a higher occupation during the weekend. The result is that fewer patients are scheduled from Monday to Thursday. Objective 5.2 results in higher fluctuation between the lowest occupation and the highest occupation over the week as can be seen in Figure 5.11. An explanation for this is that when the deviation in the number of beds in the weekend is weighted heavier. Patients with a longer LoS are scheduled on the Friday such that they occupy beds in the weekend. Because the RKZ does not have a lot of patients with a LoS longer than one night all other patients are scheduled from Monday to Thursday. Patient that are scheduled on Monday also occupy a bed on Tuesday in the model. If the same number of beds are available on Monday and Tuesday and all beds are filled on Monday. This means that no patients can be scheduled on Tuesday. Resulting in a big low when patients are discharged on the Tuesday. On Wednesday the process starts again by filling the Wednesday and Thursday with patients with a LoS of one night.

Figures 5.10 and 5.11 show the bed occupation of the model using the objective function shown in Equation 5.2 and the occupation with the quota model.

Performance indicator	Quota model		Objective 5.1		Objective 5.2	
	A2X	A5	A2X	A5	A2X	A5
Number of patients	205	200	231	205	227	206
Mean surgery duration	85 min		82 min		82 min	
Session utilisation	73%		75%		75%	
SD daily max. oc. week	2.7	2.2	1.0	1.5	0.5	0.5
SD daily max. oc.	2.7	3.9	1.0	4.3	0.5	2.8
Mean occupation	10.3	27.9	10.7	28.0	10.7	27.9
Max mean occupation	17.6	35.1	17.3	35.2	17.0	34.3
Closing time ward	22:55		22:12		22:05	

Table 5.4: 1 MSS cycle, comparing Objectives 5.1 and 5.2

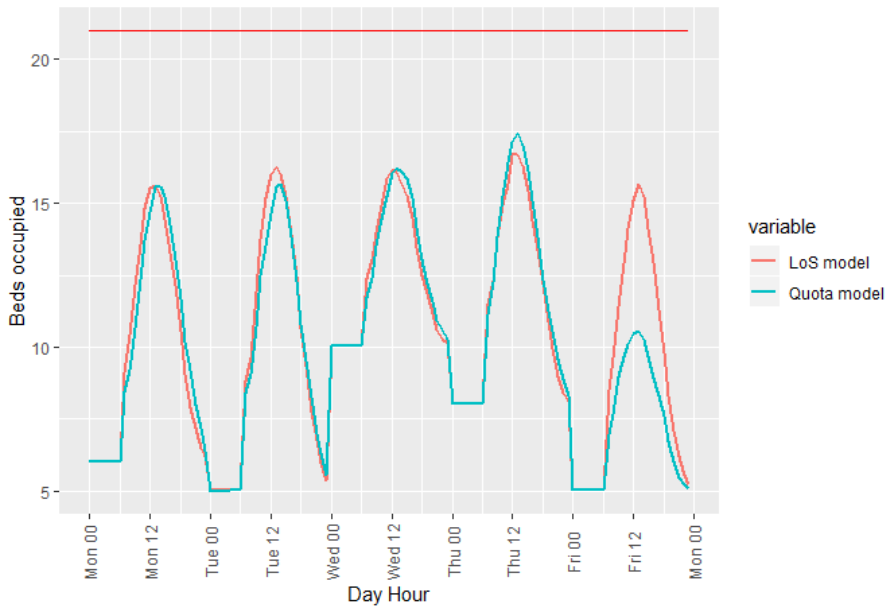

Figure 5.10: Using Objective 5.2 , A2X 1 MSS cycle, addition of patients every week

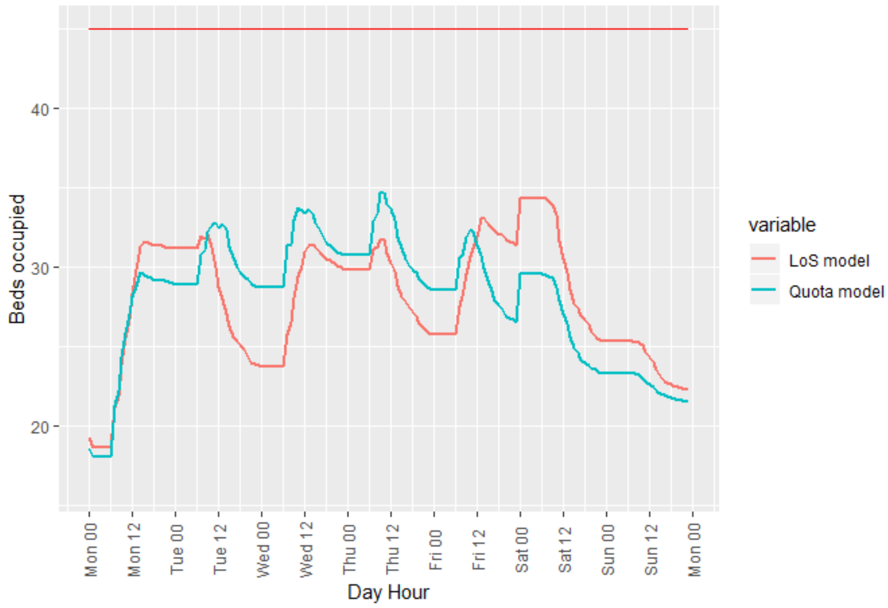

Figure 5.11: Using Objective 5.2, A5 1 MSS cycle, addition of patients every week

5.2 The RKZ data set

In this section we show the bed occupation obtained for surgical patients of the RKZ in the year 2018 and compare it with the resulting bed occupation when scheduling with LoS and surgery duration. Besides, we show the difference from scheduling with the expected surgery duration of the RKZ and the expected surgery duration created with the 3-parameter lognormal distribution as shown in Section 4.4.2. The RKZ started using quotas in 2019. This section does not show the difference between scheduling with quotas and scheduling with LoS and surgery duration information. This section does show the improvement potential compared to the scheduling method that the RKZ used in 2018.

5.2.1 Data

As input for the model, we use surgeries that were performed in the year 2018. We use surgeries where the patients were sent to either ward A2X or ward A5. We remove records with a negative surgery duration or incomplete LoS. The expected LoS of specialism "NCH" is changed to 1 if the expected LoS was 0 because those patients are always sent to the clinical ward A5.

We determine the maximum number of bed-days that a specialism can use by finding the historical bed division. The fraction is multiplied with the number of beds that are available in a MSS cycle. Table 5.5 shows the number of reserved beds for both wards together. We set a maximum to the number of beds to prevent one specialism occupying most of the beds and leaving no room for the other specialisms.

5.2.2 Assumptions

This approach relies on a number assumptions which should be considered before making conclusions about the performance of the LoS model. At the end of this

Specialism	Fraction	Max beds
CHI	0.51	531
KAA	0.02	17
KNO	0.03	32
NCH	0.03	28
ORT	0.18	191
PLA	0.16	168
URO	0.08	79

Table 5.5: Bed reserved per specialism per MSS cycle

section, we show what kind of impact we expect each assumption has on the LoS model.

First of all, the data contains only patients that were put on the waiting list and scheduled in real life. This limits the model to find better combinations of patients that could obtain lower variability in occupation. Second, the model does not consider cancellations and we assume that we know for sure that a patient is coming to the hospital. Third, patients occupy a bed exactly one hour before the time of surgery. This means that when there is a delay due to patients having longer surgeries than expected, the next patient arrives later than scheduled. The opposite also holds, when a surgery can start earlier than expected the patient will still be there one hour before the surgery. The fourth assumption is that staff is never a bottleneck. This means that we can occupy all beds during a holiday in the model. The fifth assumption is to discharge patients following the same discharge distribution as Figure 2.9. LoS of patients in A2X is generated as described in Section 4.4.3. The sixth assumption of the model is that only 1 patient arrives for the first surgery slot. In the real data two patients arrive for the first surgery slot to have a backup in case a surgery has to be cancelled. The last assumption is that we only consider the elective surgical patients and the other patients are added with a fixed number. The variation in bed occupation is measured over the total occupation. In the real situation, there is also variation in the non-surgical and emergency patients. The assumptions and their expected impact are shown in Table 5.6.

Assumption	Impact
1. Only planned patients used	+
2. Cancellations ignored	--
3. Patient always in bed 1 hour in front of surgery	+
4. Staff is never a bottleneck	-
5. Discharges follow a distribution.	0
6. No backup patient in the morning	-
7. Fixed number of non-surgical and emergency patient added	--

Table 5.6: Estimated impact of assumptions on LoS approach in real life, (++, +, 0, -, --), a "+" means that the model would perform better in practice

5.2.3 Experimental settings

We run the LoS models described in Chapter 4 for 52 weeks. Every new week patients are added to the waiting list from which the model can choose. The patients enter the waiting list the same week as in the real data. The assignment model handles one week of patients at the same time and is repeated 52 weeks before the data is used as input for the sequencing model. The sequencing model runs for every surgery day. We use the objective function shown in Equation 5.1. We set both weights of the objectives of the sequencing model to 1.

5.2.4 Model results

Table 5.7 shows the results for both the model using the expected surgery duration as predicted by the RKZ and the model using the predicted expected surgery duration as shown in Section 4.4.2. The performance of the model using the surgery duration predicted with the 3-parameter lognormal distribution is lower than the performance of the surgery duration as predicted by the RKZ. Therefore, we will only compare the results of the model using the RKZ prediction with the results of the real occupation. In Section 5.2.4 we compare both predictions of the surgery duration in more detail.

Table 5.7 shows that the LoS model schedules 8 patients less per MSS cycle than the RKZ model. The model cannot schedule more patients because the waiting list only consists of patients that had surgery in 2018. The patients still on the waiting list of the LoS model have an expected duration of 90 minutes. The model reduces the standard deviation of the daily maximums during the week with 27% for ward A2X and with 53% for ward A5. We reduce the maximum number of beds needed for ward A2X with almost 2 patients while the mean occupation is somewhat similar. The mean occupation for ward A2X is higher in the LoS model than the occupation of the real data. This means that there is an error in the prediction of LoS in ward A2X. The closing time of the ward emphasises that. This can be explained by the factor that in the RKZ the nurses send the patients home when the ward is going to close which influences the LoS. In the model, the LoS is not influenced by the closing time of the ward.

Performance indicator	Real RKZ occupation		LoS model with exp. duration RKZ		LoS model with 3-par. lnorm exp. duration	
	A2X	A5	A2X	A5	A2X	A5
Number of patients	248	198	241	197	239	198
Mean surgery duration	82 min		81 min		81 min	
SD daily max. oc. week	1.5	1.7	1.1	0.8	1.3	0.9
SD daily max. oc.	1.5	3.4	1.1	3.5	1.3	3.4
Mean occupation	10.5	29.4	10.9	28.9	10.8	29.0
Max mean occupation	19.7	35.4	17.9	34.5	17.7	34.4

Table 5.7: Comparison RKZ data and model output using the surgery duration of the RKZ and the surgery duration of the 3-parameter log normal distribution

Figures 5.12 and 5.13 show the performance of the LoS model. We see a difference in the occupation on Monday and the occupation in the weekend. The model tends to schedule more patients on Monday then on Friday in ward A5. Ward A2X shows a reduction of patient admissions on Monday. Figure 5.14 shows the average daily occupation of ward A2X, the daycare ward. It shows that more patients arrive at 07:00 in the LoS model than at the RKZ. The figure shows the lower peak of the LoS model at 13:00 and shows that patients stay longer in the ward.

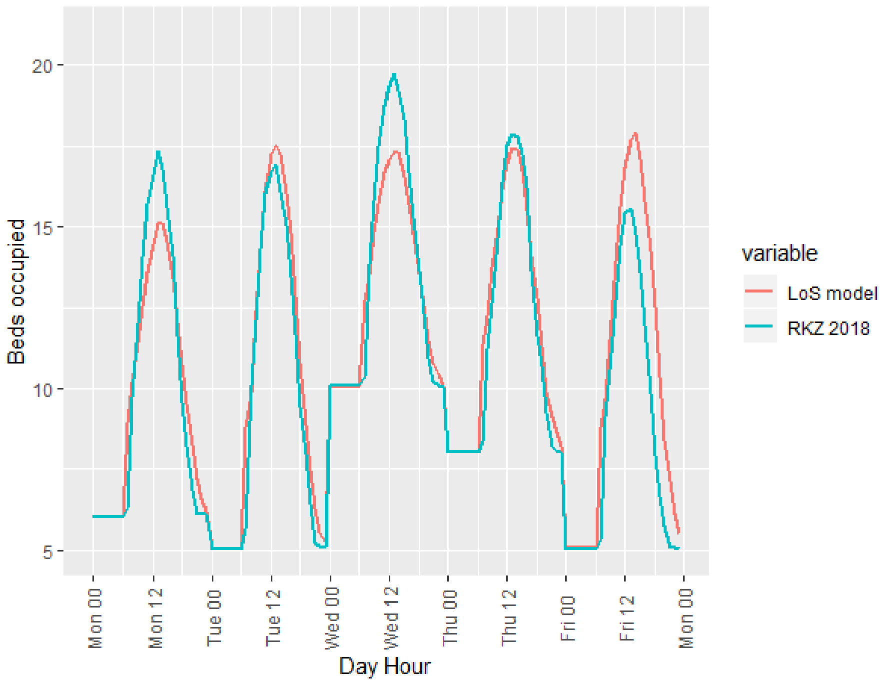

Figure 5.12: A2X 1 MSS cycle, addition of patients every week, performance of the LoS model using the RKZ data

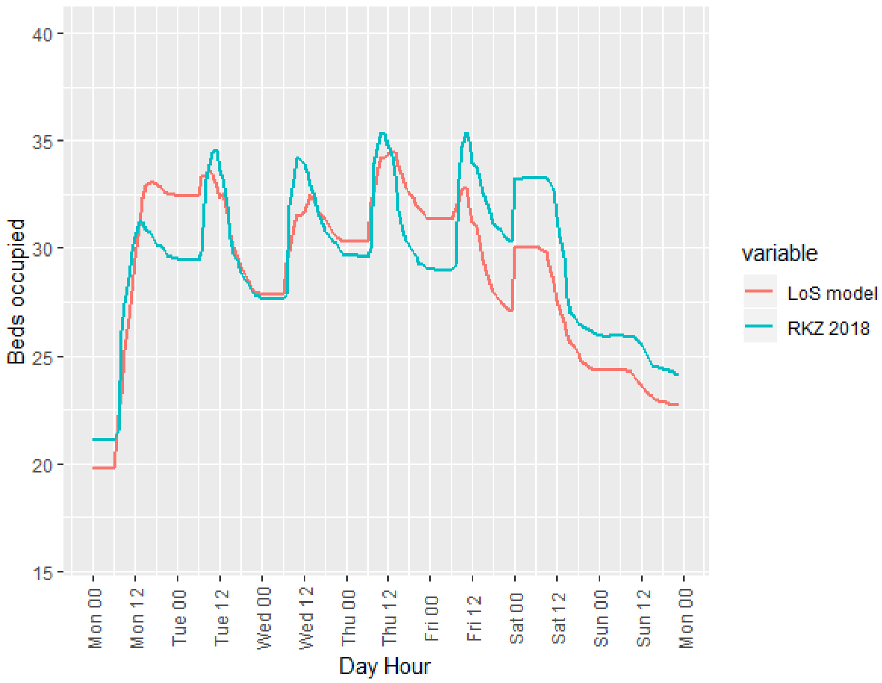

Figure 5.13: A5 1 MSS cycle, addition of patients every week, performance of the LoS model using the RKZ data

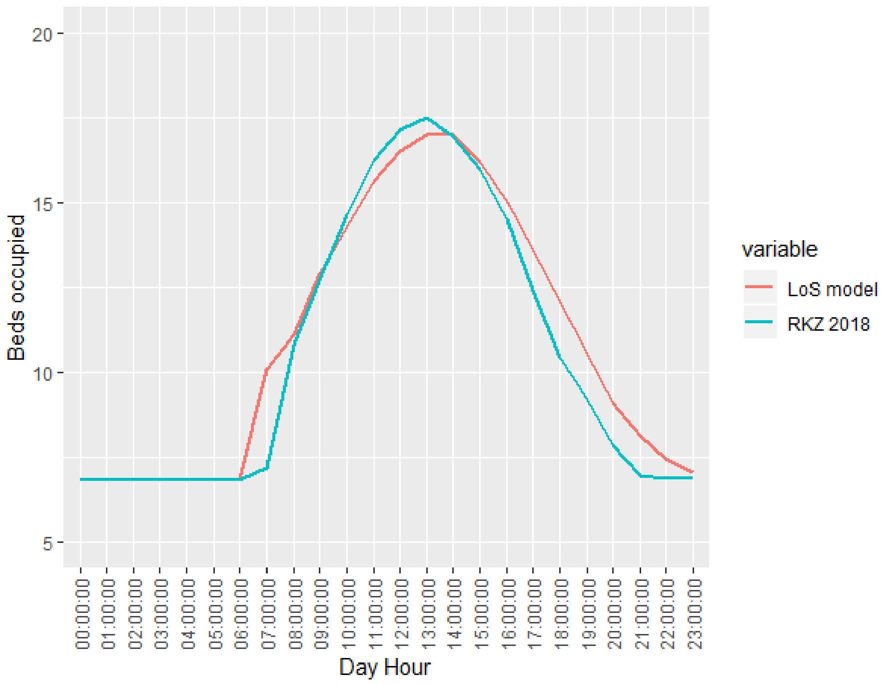

Figure 5.14: RKZ data vs LoS model with expected surgery duration of the RKZ. Day occupation of A2X

Performance of the surgery duration predictions

Table 5.8 shows the performance of the predictions of the surgery duration of the RKZ and those of the 3-parameter lognormal distribution. The table shows that the

RKZ has a more accurate prediction of the surgery duration than the predictions as described in Section 4.4.2. The predictions at the RKZ are made by the surgeon and the planner and can contain more aspects than the 3-parameter lognormal estimation which uses the COTG-code and the surgeon to estimate the duration. Besides the estimation of surgery duration in Section 4.4.2 uses less than 2 years of data. Table 5.7 shows the performance of the models for both estimations of surgery duration.

	Mean deviation	standard deviation
Expected duration RKZ	-0.12	25.24
3-parameter log normal distribution	0.30	28.03

Table 5.8: Prediction of surgery duration: RKZ versus 3-parameter log normal

5.3 Conclusion

Section 5.1 shows that we can reduce the standard deviation of the daily peak occupation during the week by scheduling using the LoS model. Besides we increase the number of patients scheduled and the mean occupation of the wards. The Los model prefers to schedule patients with a lower LoS to be able to schedule more patients in ORs and to occupy more beds. The result is that patients with a higher expected surgery duration stay on the waiting list. The MILP variant of the assignment model performs worse than the quota model and results in unrealistic schedules. Changing the weekend weight improves the standard deviation of the daily maximum occupied beds during the weekdays but also when the weekend is included. This is an unexpected result and shows that optimising the bed occupation in the assignment step does not result in optimal peak occupations in the result.

Section 5.2 shows the comparison of the realised bed occupation of elective surgical patients in 2018 with the bed occupation resulting from the LoS model. We show that the predictions of the surgery duration using the 3-parameter lognormal distribution performs worse than the predictions of the RKZ. The LoS model reduces the variation in the daily peak occupations during the week and reduces the maximum number of beds needed for ward A2X.

Chapter 6

Implementation and use

Chapter 5 shows that scheduling with quotas improves the variation of the bed occupation for the RKZ. The method schedules more patients and in most cases the maximum amount of beds needed is lower. In this chapter we show what the RKZ, ChipSoft, and other hospitals can do with the results of this report. We show what conditions a hospital has to meet to be able to use the LoS model and how they can implement the scheduling method based on LoS and surgery duration. We give answer to the following two research questions:

6. *Can the method be implemented at the RKZ?*
7. *Can the method be implemented at other hospitals?*

Section 6.1 shows the requirements for hospitals to be able to implement a scheduling method using LoS. Section 6.2 shows the possible implementation and use for hospitals in general. Section 6.3 shows the use specific for ChipSoft. Section 6.4 shows the implementation plan for hospitals. The use for hospitals in Section 6.2 and the implementation plan in Section 6.4 is also relevant for ChipSoft.

6.1 Conditions for use and implementation

Using the LoS method described in this report requires that hospitals meet a number of conditions. First of all, a hospital should have an accurate prediction of the LoS and the surgery duration of a patient. The quality of these predictions is important for the performance of the models. Second, the hospital should have an IT system that gives insight in the bed occupation to monitor the LoS method. Last, the staff of the hospital should be willing to change the way of scheduling patients. Scheduling with LoS means that there are more aspect to consider when scheduling patients. The hospital planners should know how the new method works. Besides, when a hospital chooses to automatically schedule patients the method takes over part of the work of the hospital's planners.

6.2 Use for hospitals

Hospitals can use the results and models described in this report to improve their scheduling process. The research aims to improve the bed occupation in the RKZ. However, the results can be generalised for other hospitals.

6.2.1 Assessing the impact of scheduling with quotas or LoS

Hospitals that consider switching to scheduling with quotas or scheduling based on LoS can use the models described in this report to find which method results in an improvement of the bed occupation. In this report we showed how changing from scheduling with quota to scheduling with LoS impacts the RKZ. However, hospitals with another patient mix can show different results. The variation in LoS for hospitals has an influence on the performance of the LoS model. Therefore hospitals should assess the impact of the scheduling methods themselves.

A hospital should first experiment with the model as shown in Section 5.2 to get an insight if an improvement in bed occupation is possible using the LoS scheduling method. If the first step indicates that improvement is possible the second step is to check what the difference is in scheduling with quotas and scheduling with LoS using the experiments in Section 5.1. When using simulated data the hospital removes the external factors and the results show only the difference between the two scheduling methods. If the result for scheduling with LoS is positive the hospital can use the implementation plan in Section 6.4 to integrate scheduling based on LoS information.

6.2.2 The sequencing model

A hospital can choose to only use the sequencing model of this report to sequence the patients assigned to a session. Often hospitals create the sequence a short time before the surgery day. If a hospital has the length of stay information for daycare patients the hospital can reduce the maximum amount of beds needed or decrease the overtime. It is possible to extend the sequencing model shown in Section 4.2 with prioritisation for groups of patients. Cardoen et al. (2009) show two constraints that can be added to the model to schedule children and other patients with priority early in a session.

6.2.3 Optimise the quotas of a hospital

The model in Section 4.3 fills MSS sessions based on the chosen quotas. These quotas can be altered and hospitals can experiment with other quotas to assess the resulting bed occupation. A heuristic can help find the best quotas for a given MSS and patient mix. The hospital needs to generate data that is representative for the current patient mix that can be used in the models.

6.3 Implementation and use for ChipSoft

Most of the hospitals in the Netherlands are running the software HiX of ChipSoft. An implementation of the model based on LoS and surgery duration into HiX gives the hospital the option to use the models for their scheduling process. To implement the models into HiX, ChipSoft should look into a good way to integrate the MIQP and MILP models. The running time of the models depends on the type of solver, this is also a decision that needs to be considered. In this section, we show what ChipSoft could do with the assignment and sequencing model.

6.3.1 Integration with OR planning tool

ChipSoft offers an OR planning tool for hospitals. This tool enables the hospital to drag patients from the waiting list to an OR session and get insight into the occupation of the wards, the remaining session time and, if the hospital uses quotas, the remaining quotas.

Automatic planning

The OR planning tool of ChipSoft can be extended with the LoS models described in this report to automate the scheduling process. To schedule patients in a fully automated way the models need, for example, to be extended with constraints regarding the OR equipment and the patient's preference for a surgeon.

Sequencing

ChipSoft can choose to implement the sequencing model in their electronic health record system. The hospital fills the OR sessions with the OR planning tool and a short time in advance of the surgery day the hospital runs the sequencing model from within HiX to create a sequence that optimises the hospital's preferences.

6.4 Implementation plan for hospitals

This section shows a step by step implementation plan for hospitals that consider to introduce scheduling based on LoS and surgery duration information. This step assumes that the hospital meets the conditions as discussed in Section 6.1.

1. Prepare the models

In the first step the hospital needs to alter the models such that they coincide with the hospitals' resources. The number of wards, the number of ORs and the number of beds should be included in the model. Additionally, the hospital can choose to extend the models and include prioritisation for patient groups in the sequencing model.

2. Data gathering and data cleaning

In this step, we gather the data that is needed in the third step. We need to replicate the waiting list for a period that is representative for the present. Besides we need to create a session table that serves as input of the model.

3. Comparing the LoS model with the real occupation

Using the waiting list generated in step 2. The third step is to run the model with the historic waiting list. If the result shows improvement it is worth continuing with the implementation.

4. Creating simulation data

For step 5 in the implementation plan, we need to have simulation data that is representative for the current patient mix. Hospitals can follow the steps described in Section 4.4.

5. Experimenting with the model

In this step, the hospital should experiment with the model. For example, as shown in Section 5.1. However other experiments are possible. The hospital should think about the weights in the sequencing model that determine the preference for levelling the bed occupation or closing the ward on time. When additional objectives are added to the sequencing model these weights should also be considered.

6. Implementation in the IT system

When the configuration of the model is chosen the model can be implemented in the IT system. The IT system should have a link between the system and a solver that can handle large MIQP and MILP models.

6. Use the tool as an automatic scheduling system

In the previous steps, the hospital showed that scheduling with LoS improves the scheduling process. The hospital can now start using the scheduling tool. They can decide when to schedule the patients with the assignment model. This can be for example four weeks in advance. When patients are cancelled or removed the other patients in the model should be fixed in the model to find a new patient to take the place of the removed patient. The sequencing step can be done a short time in advance of the surgery date. This limits the probability of cancellations and changes in the sequence.

Chapter 7

Conclusions and recommendations

This chapter summarises the most important findings of the research. Besides, we show recommendations for the RKZ and ChipSoft and we propose topics for future research.

7.1 Conclusions

First, we recapitulate the goal of the research that we introduced in Chapter 1. Second, we summarise the answers to the research questions we introduced in Chapter 1

The goal of this research is

> *To reduce variation in bed occupation in hospital wards by designing a surgery scheduling approach which uses LoS and surgery duration information and to deliver a proof of concept for the scheduling method compared to admission quotas.*

Chapter 2.2 shows the RKZ's current scheduling process and current performance of the ORs and wards. We identify the occupation patterns of ward the clinical department A5 and the day department A2X. We decide to focus the research on the variation caused by elective surgical patients.

In Chapter 3 we do a literature study on scheduling methods using surgery duration and LoS information. We find that the scheduling process is often split into two steps: the assignment step and the sequencing step. We find two main articles which we use as inspiration for the assignment model and sequencing model described in Chapter 4.

Chapter 4 introduces three models. We introduce the assignment model and the sequencing model that together form the LoS model. We also introduce a quota model that mimics the scheduling process of the RKZ. We formulate the assignment model in a MILP and a MIQP variant. Besides we show how we generate simulation data that the models use as input in Chapter 5.

In Chapter 5 we show the performance of the models that are described in Chapter 4. We compare the performance of the LoS model with the quota model using simulated data. Besides we compare the model output of the RKZ data of 2018 with the realised occupation in 2018. The results show that we can reduce the standard deviation of the daily peak occupation during the week with 63% for ward A2X and with 32% for ward A5 when starting with an empty waiting list and adding one week of patients to the waiting list every week. When we schedule patients with a waiting list that consists of 10 weeks of patients the improvement is 15% for ward A2X and 72% for ward A5. Table 7.1 shows the main findings. The table shows that we can increase the number of patients and reduce the variation while slightly increasing the maximum number of beds needed for ward A5. More patients and a higher mean occupation mean that the hospital can increase earnings. However, we also see that the LoS model has a preference for patients with a short surgery duration. The mean surgery duration of patients scheduled decreases which means that the patients with a longer surgery duration stay on the waiting list. This is undesirable behaviour of the model and should be solved before implementing the model. In Section 7.2 we show potential solutions. Figures 7.1 to 7.4 show the difference of the quota model with the two LoS approaches. The real improvement for scheduling with LoS compared to scheduling with quotas should lie between the values shown in Table 7.1. The RKZ has a waiting list with a lot of patients on which patients are added every week.

	1 week waiting list		10 weeks waiting list	
Performance indicator	A2X	A5	A2X	A5
Number of patients	+13%	+3%	+10%	+14%
Mean surgery duration	-4%		-16%	
Standard deviation of the daily peak occupation	-63%	-32%	-15%	-72%
Mean occupation	+4%	+0%	+1%	+7%
Maximum beds needed	-2%	+0%	-6%	+4%

Table 7.1: Performance of LoS scheduling in relation to quota scheduling

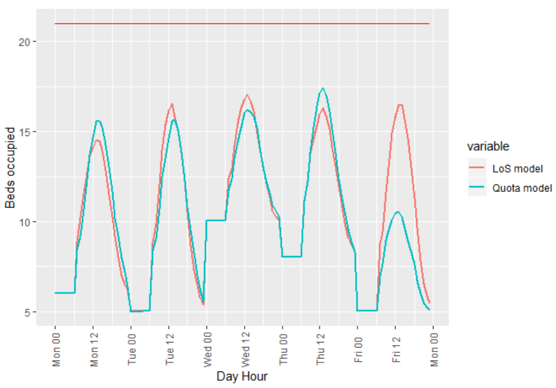

Figure 7.1: A2X, 1 week of patients added to the waiting list every week

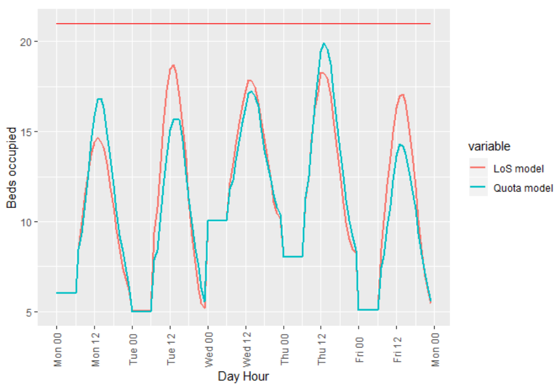

Figure 7.2: A2X, Waiting list with 10 weeks of patients at the start

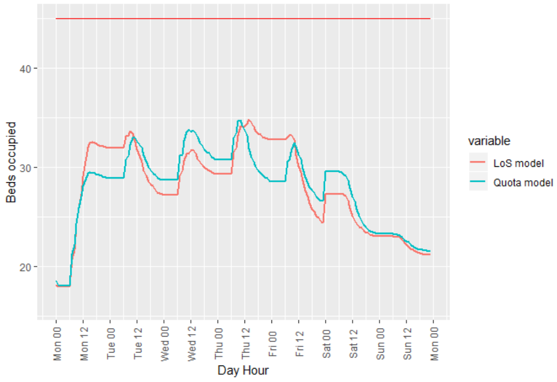

Figure 7.3: A5, 1 week of patients added to the waiting list every week

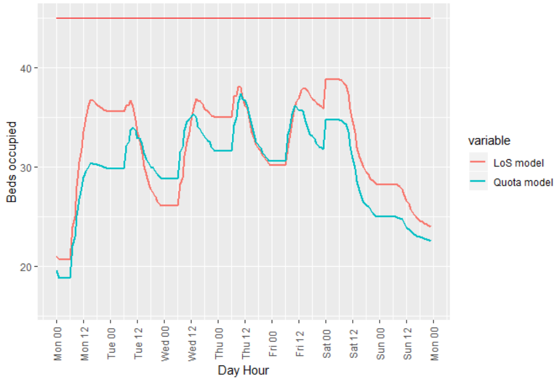

Figure 7.4: A5, Waiting list with 10 weeks of patients at the start

Chapter 6 shows different ways how hospitals and ChipSoft can use and implement the findings in this report. ChipSoft can integrate the LoS models with the OR planner to facilitate the automatic scheduling of patients. Hospitals can use the research to assess the potential improvement of scheduling with LoS or scheduling with quotas, they can alternate and integrate the sequencing model in their IT system. Besides, the quota model gives them the option to experiment with selecting other quotas without affecting the hospital's bed occupation. This enables them to improve the hospital's quotas.

7.1.1 Contribution to theory and practice

In this report we use two models to schedule the patients based on LoS and surgery duration. The first model assigns a date to each surgery. The second model sequences the surgeries in each OR session. Scheduling approaches in the literature often focus on optimising the performance of the ORs without considering the downstream resources. We extend the model of assigning patients of Aringhieri et al. (2015) to fit the RKZ and formulate the model as an MILP and MIQP. In addition we sequence the patients with a model that is based on the sequencing model found in the article of Cardoen et al. (2009). They use the model to find the best sequence for surgical types for daycare patients. We use the model to sequence individual patients. With this report we show the difference between the quota scheduling method and the method using LoS. Besides, we show that, when scheduling with LoS and depending on the OR time and available beds, the model has a preference for surgeries with a short duration compared to the quota model.

Chapter 2 gives the RKZ insight in the current state of the performance of different resources. These insights can point the RKZ in the direction of possible improvements. Next to this, the remaining of the report shows how changing the scheduling method of the RKZ can improve performance of the wards and reduce fluctuations in the maximum daily occupations. Scheduling using LoS can give them more flexibility when scheduling patients. The quota model which we formulate as a MILP gives hospitals the possibility to optimise the quotas in the MSS. The research gives ChipSoft a basis to advise hospitals on the change of the scheduling method. Besides, ChipSoft can integrate the LoS models in their products to make them available for a lot of hospitals. The assignment model could help to select the right patients to fill sessions and the sequencing model can be implemented in combination with the LoS or with the quota model to improve the sequence of the patients.

7.2 Recommendations and Future research

7.2.1 Improving the assignment model

The assignment model shown in Section 4.1.2 aims to fill the available beds as full as possible. However, the model assumes that a patient with a LoS of one night occupies a bed for two days while in practice this is not the case. A patient is admitted in the ward at 09:16 on average and discharged at 15:21 which means that a patient does not occupy a bed for the full two days. Therefore the model is too conservative in assigning beds to patients and there is potential room for improvement. Because the model assigns patients with a los of one night to two days the model cannot schedule a patient in that bed the next day. This results a occupation shown in Figure 5.11. The large reduction of beds after the Tuesday can be reduces by assuming that a part of the beds will be empty in the afternoon for the patients that are scheduled on Monday with a LoS of one night. More research has to be done to find a method to increase the bed occupation with this information. A potential solution is to schedule patients on half days instead of whole days.

Chapter 5 shows that patients with longer surgery duration are not scheduled because the model schedules as many patients as possible to increase bed occupation. We recommend that the hospital finds a solution to this problem before implementing the LoS models. One way of tackling this problem would be to add a constraint to the assignment model that the mean surgery duration of the scheduled patients has to lie between acceptable ranges. Extending the objective function of the assignment model can be another option. Patients would get a weight which increases if they are waiting longer for a surgery. The weights of the patients can be incorporated in the objective function. Another solution may be to increase the available OR time. The RKZ does not use all the available OR sessions during the week. If the bottleneck would be the number of available beds the model would not need to schedule surgeries with a short surgery time.

7.2.2 Improve LoS predictions

The focus of the RKZ is not on the estimation of the patients LoS because the LoS information is not used at the moment. If the RKZ predicts those values better the performance of the LoS model increases.

7.2.3 Increase the number of schedulable patients

When the RKZ chooses to schedule using LoS the method could be improved by creating a bigger pool of patients. This can be obtained by also allowing to schedule patients that have not had a screening yet. The screening then should be done after scheduling the patient and before the surgery. However, the hospital should look into the increase in cancellations due to scheduling unscreened patients.

7.2.4 Validate the models with recent data

For this research, we used the 2018 data of the RKZ. The RKZ did not use admission quotas during that period. The comparison of the RKZ occupation and the outcome of the LoS models with the 2018 data as shown in Section 5.2 would compare the LoS method with the occupation realised with scheduling with quotas. Besides, the results of the simulation data of the quota model shown in Section 5.1 should show a similar pattern to the RKZ occupation when quotas are used.

7.2.5 Estimating surgery durations

In Section 4.4.2 we show how we predict surgery durations using the 3-parameter lognormal distribution with a combination of the surgery type (COTG code) and the surgeon. We used less than two years of data to predict these durations and the performance is worse than the current predictions of the RKZ. The predictions can be improved when more data is available.

7.2.6 Research into reduction of the LoS of daycare patients

It may be worth looking into the reduction of LoS of the daycare patients. Their LoS in influenced by the medication they get administered. Shorter LoS can result in a bed being used by two patients on a day instead of one. This can reduce the peak occupation or increase the OR utilisation.

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Appendices

Appendix A

Fitting the patient arrival process

We want to find the best distribution fit for the patient arrival process. We identify possible distributions by plotting a Cullen and Frey graph in the software R. Figure A.1 shows the plot. The blue dot indicates that based on the kurtosis and square of skewness of the data more distributions are possible. We use the Chi-square test and the Akaike information criterion to find the best fit on the data.

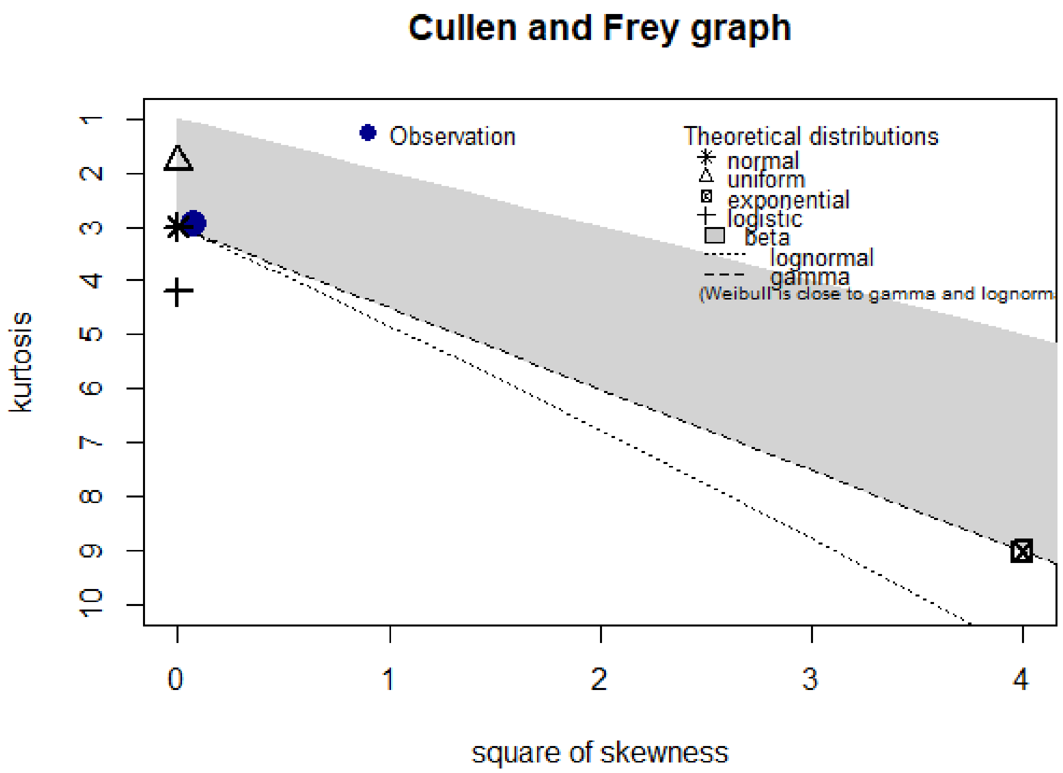

Figure A.1: Cullen and Frey graph of the daily patient arrival

We test the normal, log normal, and gamma distribution. The Akaike information criterion (AIC) estimates the out-of-sample prediction error and helps identifying the quality of the fit. A lower AIC score is better. Table A.1 shows the test information.

We use a significance level of 0.05. Both the Normal and the Gamma distribution have a good fit. Be choose the Normal distribution because the AIC score is lower and the p-value is higher. Figure A.2 shows the fit of the distribution. The Q-Q plot and the P-P plot support our choice for the normal distribution. The mean

Distribution	p-value	AIC
Normal	0.164	1804
Log-normal	0.0015	1864
Gamma	0.105	1821

Table A.1: Chi-square test and AIC criterion

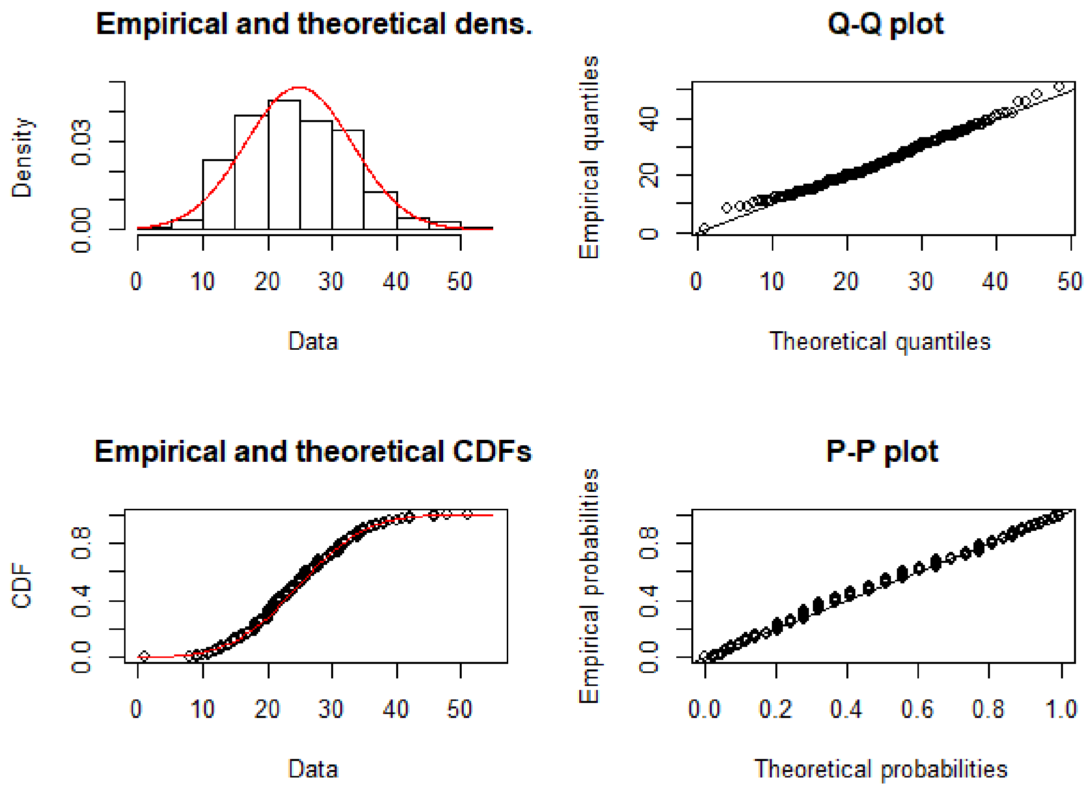

Figure A.2: Data plots over normal distribution for patient arrival

of the data is 24.8 and the standard deviation 8.26 patients per day. For the model we use patient per week.