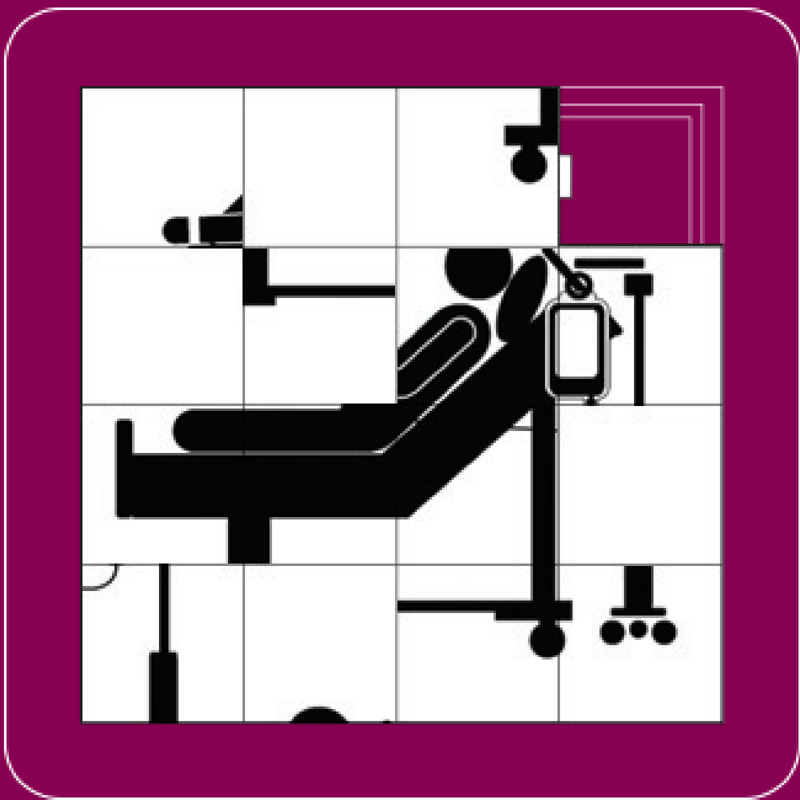
Minimising variation in hospital bed demand by improving the operating room planning

Master of Science Thesis, (Public Version)
Conducted at the St. Antonius hospital Nieuwegein/Utrecht
01-05-2014



Author:
Arvid Joran Glerum

Thesis committee:

Drs. M.B.V. Rouppe van der Voort	St. Antonius hospital
Dr. Ir. E.W. Hans	University of Twente
Dr. Ir. M.R.K. Mes	University of Twente

ZIEKENHUIS ST ANTONIUS
UNIVERSITY OF TWENTE.

Management summary

This report describes the research conducted to reduce peak fluctuations in bed demand in the St. Antonius hospital.

Problem statement & objective

The core problem is identified as the percentage of boarded patients being too high. A patient is 'boarded' on another ward when there is a bed shortage on that patient's designated ward. However, there is no bed shortage on a macro level: in the analysed period there were never more clinical patients than there were beds in the clinic. We identify variability as the root cause of boarding patients. Average bed utilisation shows that wards should have sufficient space if the variation in inflow and outflow would be reduced. Reasons for this can be natural variation but also artificial variation, the variation introduced by the hospitals own processes. We identify the scheduling of elective patients as the largest source of artificial variation in bed demand. The hospital would like to have a new planning approach to reduce this variation. Because it is not possible to remove all variation in the scheduling of elective patients we also create strategies to cope with remaining variation. To tackle the core problem we set the following goals for this research:

1. *Minimise artificial variation in bed demand by improving the OR planning.*
2. *Create strategies to cope with natural variation in bed demand.*

Approach

We identify the scheduling of elective surgical patients within the existing Master Surgery Schedule (MSS) to be the area with the best balance between practical feasibility and improvement potential. We construct two variants of a mathematical optimisation model, which advises admission planners when to schedule patient types to minimise variation in resulting bed utilisation. The new scheduling approach consists of two phases:

Phase one: determine the theoretically optimal case mix per session with a mathematical model **Phase two**: schedule patients based on the case mix prescribed by the model

The left part of Figure 0-1 shows a simplified representation of the current scheduling method and the proposed improved scheduling method is illustrated in the right part. In the old situation, sessions are filled first come first serve until there is no time left on the schedule. In the new situation planners aim to fill sessions with a predetermined mix made by our mathematical model: the case mix matrix. This matrix shows the mix and volume of patient types they should preferably schedule on each OR session.

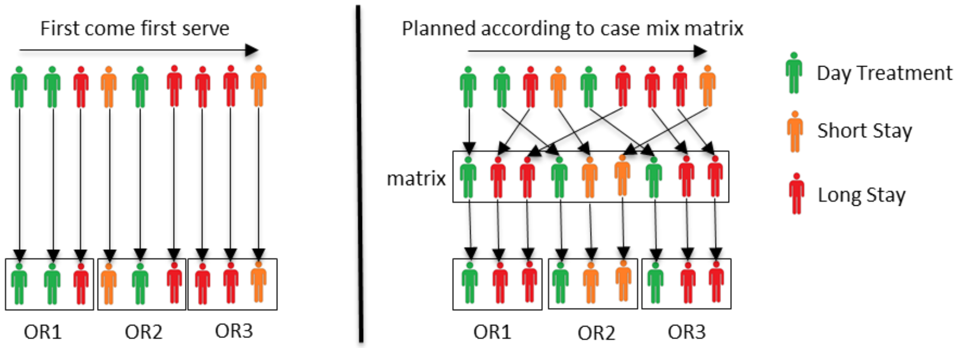


Figure 0-1 Current versus proposed situation for planning elective surgical patients

Contribution statement

The contribution of this model is that it provides an optimal, length of stay (LOS) based, patient mix per operating room (OR) session within a given an MSS. The model takes into account deterministic surgery durations and stochastic LOS distributions. The proposed planning model can be applied to other hospitals using an MSS block schedule but the interpretation of the model's results and the consequent planning guidelines are specific for the St. Antonius hospital location Utrecht.

Results

Reducing variation – In phase one, both mathematical models are able to theoretically plan patients in such a way that the bed utilisation approaches the theoretical optimum, see Figure 0-2.

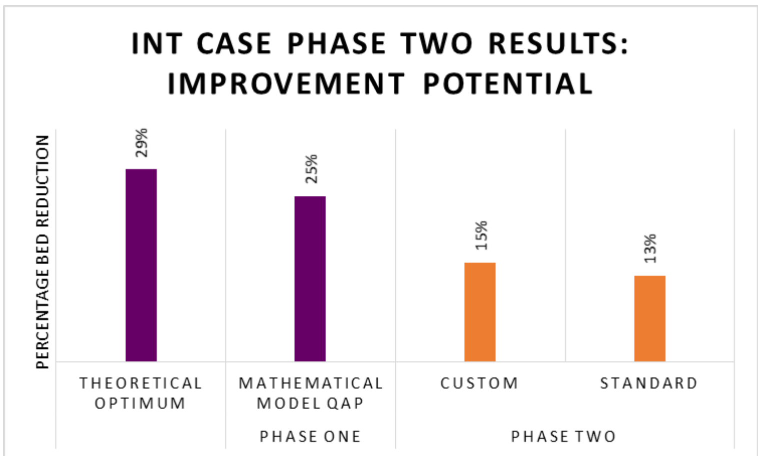


Figure 0-2 Practical improvement potential for planning elective surgical patients using case mix matrices

In phase two we find it is possible to reduce variation in bed demand by scheduling individual patients to OR sessions according to the case mix matrix. During the scheduling of patients in phase two, we find the improvement to be lower than the theoretical performance of the model. We identify patients who can only be operated on by a specific physician (strict patients), and variation in surgery duration and LOS as the largest causes of reduction in improvement potential. Figure 0-2 shows the practical phase two potential for using case mix matrices to plan elective surgical patients in the Utrecht location of the St. Antonius hospital. It can be seen that using case mix matrices from both mathematical models in scheduling elective surgical patients can lead to a 13-15% reduction in bed requirement.

Reacting to variation – Analysis shows admitting patients to a bed after surgery instead of before offers a large improvement potential for reducing peaks in bed demand. Buffer capacity offers temporary capacity to react to remaining bed demand. We conclude that length of stay improvements and flexible discharge moments have the potential to permanently free up capacity, which can be used to cope with peak demand. We identify the redistribution of beds as a possibility to decrease the percentage of boarded patients, but with little improvement potential for reacting to peak bed demand. Real time insight into the state of the system is a precondition for better coping with peak bed demand.

Implementation

The implementation is divided in seven steps. We start with only one specialty in step one because each specialty has *specialty-specific methods and restrictions* when it comes to scheduling patients. Starting small enables us to keep focus in fine-tuning the process for one specialty. After evaluating and improving the method for one specialty we can expand to other specialties. The seven steps:

1. **General decision rules –** extrapolate general decision rules from the case mix matrix
2. **Flexibility to adapt –**use of case mix matrices whilst adjusting for demand & MSS changes
3. **Expand to more specialties –** perform step 1 & 2 for more specialties in Utrecht location
4. **Expand to Nieuwegein location –** analyse the Nieuwegein location and implement
5. **Supporting IT system –** include support data for planning in the existing IT system
6. **Embed in IT system –** embed the planning approach completely in an IT system
7. **Planning decision making tool –** create a planning tool that schedules automatically

Management samenvatting

Dit rapport beschrijft onderzoek uitgevoerd in het St. Antonius ziekenhuis om pieken en dalen in bedbezetting te verminderen.

Probleemomschrijving & onderzoeksdoel

Als kernprobleem is geïdentificeerd dat het percentage vreemdliggers te hoog is. Een patiënt wordt een vreemdligger als deze patiënt door een beddentekort op een andere afdeling wordt gelegd dan zijn eigen. Op totaalniveau is er echter geen beddentekort: in de geanalyseerde periode waren er nooit meer patiënten in de kliniek dan bedden. We identificeren variabiliteit als de kernoorzaak achter vreemdliggers. De gemiddelde bedbezetting laat zien dat verpleegafdelingen genoeg ruimte hebben als de variatie in beddenvraag minder zou zijn. Oorzaken van variatie zijn natuurlijke variatie maar ook kunstmatige variatie, de variatie die ontstaat uit de manier waarop het ziekenhuis processen heeft ingericht. We identificeren het plannen van electieve patiënten als de grootste bron van kunstmatige variatie in beddenvraag. Het ziekenhuis wil een ander planningsconcept gaan gebruiken om deze variatie te verminderen. Omdat het niet mogelijk is alle variatie uit de planning te halen, ontwikkelen we ook strategieën om overgebleven variatie op te vangen. Om het kernprobleem aan te pakken stellen we de volgende doelen voor dit onderzoek:

1. *Het minimaliseren van kunstmatige variatie in beddenvraag door het verbeteren van de operatiekamer (OK) planning*
2. *Het ontwikkelen van strategieën hoe om te gaan met overgebleven variatie*

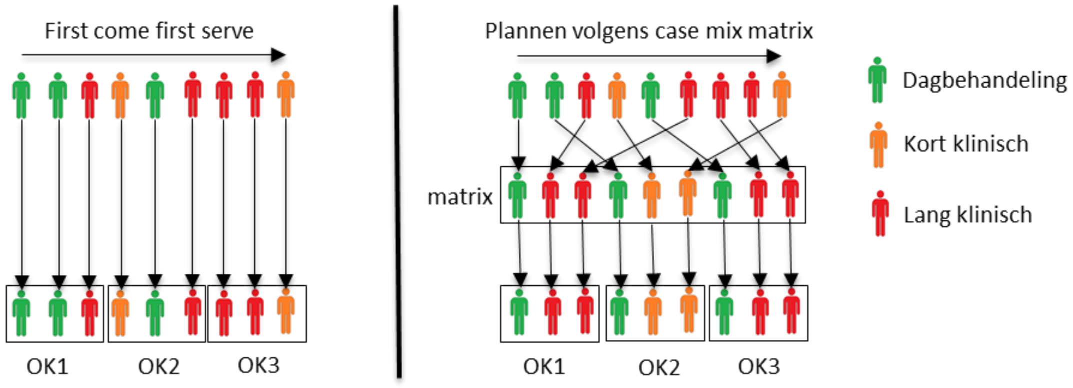
Aanpak

We erkennen het plannen van electieve patiënten op de OK, binnen het bestaande Master Surgery Schedule (MSS), als de interventie met de beste balans tussen implementeerbaarheid en verbeterpotentieel. We ontwikkelen twee varianten van een wiskundig optimalisatiemodel dat planners adviseert hoe te plannen zodat de variatie in de daaropvolgende beddenvraag vermindert. Dit nieuwe planningsconcept bestaat uit twee fasen:

Fase een: Het bepalen van een theoretisch optimale patiëntenmix per OK met een wiskundig model

Fase twee: Het daadwerkelijk inplannen van patiënten op basis van de voorkeursmix uit het model

De linker kant van Figuur 0-1 geeft een versimpelde weergave van de huidige planningsmethodiek en de voorgestelde nieuwe methode is aan de rechterkant weergegeven. In de huidige situatie worden patiënten ingepland op de eerstvolgende beschikbare OK sessie tot die sessie vol zit. In de nieuwe methode proberen planners sessies te vullen aan de hand van het volume en de mix voorgeschreven door het wiskundig model: de case mix matrix.



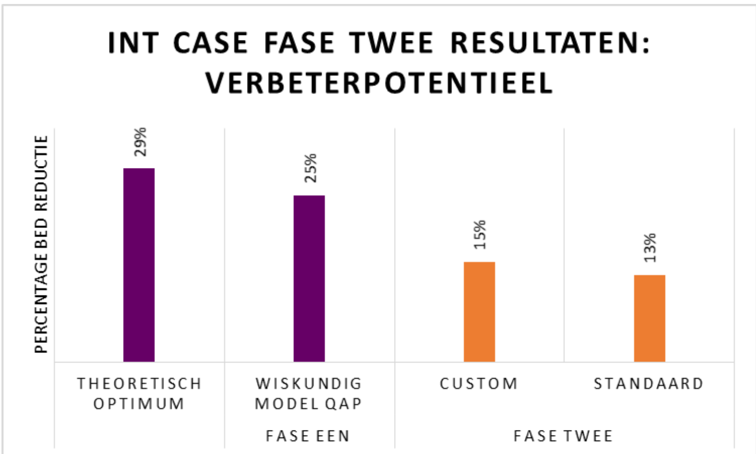
Figuur 0-1 huidige versus voorgestelde planningsmethodiek voor electieve patiënten op de OK

Contributie statement

De contributie van dit model is dat het een optimale mix van patiënten geeft, gebaseerd op ligduur, binnen een bestaand MSS. Het model gebruikt deterministische operatieduur en een stochastische ligduurverdeling. Het voorgestelde planningsmodel kan ook gebruikt worden in andere ziekenhuizen die een MSS blok schema gebruiken, maar de interpretatie van de modeluitkomsten in dit onderzoek richten zich specifiek op de Utrecht locatie van het St. Antonius ziekenhuis.

Resultaten

Variatie verminderen – In de eerste fase zijn beide modellen in staat om patiënten theoretisch zo te plannen dat de bedbezetting in de buurt komt van het theoretisch optimum, zie Figuur 0-2.



Figuur 0-2 Verbeterpotentieel in fase 1 en 2 voor alle negen snijdende specialismen op locatie Utrecht van het St. Antonius ziekenhuis

In fase twee is het mogelijk patiënten in te plannen volgens de case mix matrices voortkomend uit beide modelvarianten. De reductie in benodigde bedden is echter minder in fase twee dan de theoretische reductie in fase een. We erkennen patiënten die slechts door een specialist geopereerd kunnen worden (strikte patiënten), en variatie in operatieduur en ligduur als de grootste oorzaken voor deze vermindering. Figuur 0-2 laat zien dat het plannen volgens matrices van beide wiskundige modellen een winstpotentieel oplevert van 13-15% beddenreductie.

Opvangen van variatie – Analyse laat zien dat patiënten pas na een operatie opnemen in een bed een aanzienlijke reductie in beddenvraag kan opleveren. Tijdelijke buffercapaciteit kan gebruikt worden om de daarna overgebleven variatie op te vangen. We concluderen dat ligduurverbetering en flexibele ontslagprocedures de potentie hebben om permanent meer vrije capaciteit te creëren, wat gebruikt kan worden om pieken op te vangen. Het herverdelen van bedden over de afdelingen kan het aantal vreemdliggers verminderen maar zal op totaalniveau geen extra capaciteit opleveren. Een realtime overzicht van de huidige staat van het beddenhuis is een randvoorwaarde om variatie beter op te kunnen vangen.

Implementatie

De implementatie is onderverdeeld in zeven stappen. We starten de implementatie bij slechts een specialisme omdat elk specialisme specifieke planningsrestricties en methoden heeft. Door het klein te houden kunnen we de implementatie hierop aanpassen. Na het evalueren en verbeteren van de methode voor een specialisme kan er uitgebreid worden naar andere specialismen. De zeven stappen:

1 **Algemene beslisregels –** gebruik algemene beslisregels uit de case mix matrices
2 **Flexibiliteit inbouwen –** gebruik matrices met bijsturen voor verandering in vraag & MSS
3 **Meer specialismen –** herhaal stap 1 & 2 voor meer snijdende specialismen in Utrecht
4 **Uitbreiden naar Nieuwegein –** analyseer de Nieuwegein locatie en breid uit.
5 **Ondersteunend IT systeem –** ondersteunende data inbouwen in bestaand IT systeem
6 **Inbedden in IT systeem –** volledig inbedden van planningsmethodiek in IT system
7 **Planning beslistool –** ontwikkel een beslistool om de methode heen die automatisch plant

Acknowledgements

Upon reading this, you have stumbled upon the final results of my long, vibrant and especially unforgettable time as a student. Over the course of my time as a student, I have seen two studies, three universities in as many countries, failed courses, thankfully a lot more passed courses, low grades, high grades and perhaps most important: many, many inspiring people that I am proud to call my friends now. The thesis that lies before you in a way reflects how I see myself as a person, in that it is very practice based and solution oriented but with a central role for the exact side of science.

Unlike most IEM students, I actually started studying health care, professionally flunking way too difficult math courses and acing health care related courses in the field of biomedical engineering. Although I finally figured out my area of expertise was more problem solver than theoretical thinker, it did spark my interest in healthcare. This insight about myself, is something my mother already told me a long time ago. It just goes to show: always listen to your mother. Just as it is recommendable to listen to Erwin Hans, at least most of the time that is, when he is not cracking jokes. This because I wouldn't be sitting here without meeting Erwin for my bachelor thesis. Not even three weeks after meeting him, I was on an airplane headed towards an Australian adventure full of wonderful people. Anneke and Erwin are pretty much solely responsible for my interest in healthcare as it is now, both spiders in an international web of healthcare researchers. This web also brought me to an exchange semester in Munich, without a doubt one of the best decisions I have made in the last few years. Of course, when looking for a master assignment it were the same connections that got me talking with Marc at the St. Antonius hospital, where he invited me to do my MSc research. Marc is a highly enthusiastic and motivating mentor for me, for which I am very grateful. Our different backgrounds have led to many challenging discussions, and I like to believe it was a great learning experience for us both. Without doubt the last six months have been a blast: friendly colleagues, challenging assignments and a very synergetic vibe on logistical topics with Marc and Renee. I would like to thank Erwin, Marc and Renee for all the laughs and their close involvement and assistance in getting this thesis finished. I would like to thank Martijn for the flexibility to step in as the second committee member at a late stage. I would like to thank my friends for all the highlights, not in the least those to come. I would like to thank Nichon, Gerjan and my mother Irma for being a wonderful family, I hope you will accept an MSc degree as a wedding present mom. And finally, I would have loved for my father to have been here for this moment, but I like to think he knows anyway.

Arvid Glerum, Utrecht 2014

Table of contents

Management summary i

Management samenvatting iv

Acknowledgements vii

Table of contents viii

Table of concepts .... - 1 -

1 Introduction .... - 2 -

1.1 Background .... - 3 -

1.2 Problem Description .... - 3 -

1.3 Research goal .... - 4 -

1.4 Scope .... - 4 -

1.5 Methodology .... - 5 -

1.6 Research questions .... - 6 -

2 Situational analysis .... - 7 -

2.1 Process description .... - 7 -

2.2 Control structure .... - 11 -

2.3 Stakeholders .... - 14 -

2.4 Performance indicators .... - 16 -

2.5 Current performance of the system .... - 19 -

2.6 Conclusion .... - 23 -

3 Literature research .... - 24 -

3.1 Variability in health care processes and patient flow .... - 24 -

3.2 Managing variability .... - 26 -

3.3 OM literature about OR scheduling .... - 27 -

3.4 Statistical process control & control charts .... - 30 -

4 Selection of improvement interventions .... - 31 -

5 Intervention 1: Approach for levelling incoming bed demand .... - 34 -

5.1 Conceptual model .... - 34 -

5.2 Formal model description .... - 35 -

5.3 Model output - 40 -
5.4 Validating the technical model - 41 -
5.5 Limitations of the approach - 41 -
6 Intervention 1: Experimental settings & results - 43 -
6.1 Experimental design - 43 -
6.2 ORT case study phase one - 49 -
6.3 ORT case study phase two - 54 -
6.4 INT case study - 60 -
6.5 Conclusions - 67 -
7 Interventions for reacting to incoming bed demand - 69 -
7.1 Intervention 2: Admitting patients after surgery - 69 -
7.2 Intervention 3: Use buffer capacity during peak demand - 73 -
7.3 Intervention 4: Length of stay improvements - 74 -
7.4 Intervention 5: redistribution of beds - 74 -
7.5 Intervention 6: Insight in the "state of the system" - 75 -
7.6 Conclusion - 76 -
8 Implementation - 77 -
9 Conclusion & Recommendations - 81 -
9.1 Conclusions - 81 -
9.2 Recommendations - 83 -
Bibliography I
Appendix A – Analysis Day Treatment (U008) IV
Appendix B – Analysis Clinical Ward 4a (U402) IV
Appendix C – Analysis Clinical Ward 4b (U403) IV
Appendix D – Analysis Clinical Ward 5a (U502) IV
Appendix E – Analysis Clinical Ward 5b (U503) IV
Appendix F – input for the INT case study V
Appendix G – Case type matrices per specialty VII

Table of concepts

- *Bed distribution*: the division of all beds over the wards and the assignment of beds on a ward to a specialty
- *Boarding*: assigning a patient to a bed on a different ward than the intended ward for this patient group
- *Closed bed*: a bed that is physically there but there is no personnel scheduled to support it. Due to quality of care issues a patient can never be assigned to a closed bed
- *Designated-ward*: the intended ward for a patient
- *Elective patient*: scheduled patient requiring non-urgent care
- *Emergency patient*: unscheduled patient requiring urgent care
- *Home-patients*: the patients intended for a specific ward
- *Inflow of patients*: the number and type of patients entering the hospital or parts of the hospital
- *Inpatient*: a patient admitted to one of the wards in the hospital
- *Intake planners*: staff assigning patients in a FIFO order to a specific block in the MSS
- *Intake*: the moment a patient arrives at the hospital on the day of the treatment/operation
- *Length of stay (LOS)*: the amount of time (days/hours) a patient occupies a bed
- *Master Surgery Schedule (MSS)*: the schedule assigning blocks of 4 hours in a specific OR to a specific specialty
- *Medicine specialty*: non-operative medicine
- *Occupied bed*: a bed with a patient assigned to it
- *Opened bed*: a bed for which supporting personnel is scheduled on the wards
- *Operating room (OR)*: the room equipped for performing surgeries. The medical equipment available differs per OR
- *Operating room schedule*: the schedule assigning patients, specialists, staff and equipment to an operating room
- *Outflow of patients*: the number and type of patients leaving the hospital or parts of the hospital
- *Outpatient*: a patient that is not admitted to one of the wards in the hospital
- *Overflow*: the number and type of patients for whom no beds are available on their designated ward at a point in time
- *Specialty*: a branch of medicine with expertise in a specific field
- *Surgery specialty*: operative medicine
- *Turning down a patient*: denying a patient entrance to the hospital system due to lack of resources
- *Utilisation of resources*: the amount of time a resource is used in relation to the amount of time available on that resource
- *Ward*: a part of the hospital designed to take care of patients from certain patient groups who need a bed

1 Introduction

This report describes the research conducted to reduce peak fluctuations in bed demand in the St. Antonius hospital. The two main goals of this research are *reduction of artificial variation* in bed demand and ways to *better react to natural variation* in bed demand. Reducing artificial variation is achieved by improving the admission planning of elective surgical patients using mathematical modeling. The contribution of this model is that, given a master surgery schedule (MSS), it provides an optimal case mix per OR session. The model takes into account deterministic surgery durations and stochastic LOS distributions per case type. To our knowledge there are no models available assigning variable volumes of -length of stay based- case types to ORs within the bounds of an existing MSS, with the goal of reducing variation in bed utilisation.

The planning model proposed can be applied to all hospitals using a master surgery schedule (MSS) but the interpretation of the model's results and the consequent planning guidelines are specific for the St. Antonius hospital location Utrecht. The interventions proposed to react to fluctuations in bed utilisation are applicable in a wide variety of health care environments.

Chapter 1 provides the reader with an introduction to this research. Section 1.1 gives an overview and some key figures about the hospital where this research is conducted. Section 1.2 offers a concise problem description and introduces the core problem. Section 1.3 explains the research goal followed by the scope of the research in Section 1.4 and the methodology in Section 1.5. Finally Section 1.6 elaborates on the problem description and research goal by stating the research questions.

1.1 Background

The St. Antonius hospital is a large regional hospital in the Utrecht region in the centre of The Netherlands. The hospital has 5 locations of which two main clinical hubs and 3 outpatient clinics. The two main hubs are located in Nieuwegein and in Utrecht. The Utrecht location recently opened (16th of September 2013) and is intended mainly as a centre for low complexity care (ASA1), whereas patients with mid to high complexity care (ASA 2 & 3) are intended for the Nieuwegein location.

The hospital in its totality employs 4.860 employees, 272 medical specialists and 150 resident physicians. Around 850 beds and 22 operating rooms (ORs) are available. Nationwide the Antonius hospital is known for its expertise in the fields of cardiovascular disease, lung disease and cancer. It is also the largest non-academic teaching hospital in the Netherlands [1].

1.2 Problem Description

The St. Antonius hospital currently faces large peaks in bed demand. These peak demands lead to overflowing of the wards, thereby having to resort to boarding patients. Boarding is described as admitting patients on another ward than the patient's designated ward. The core problem is defined as:

The percentage of boarded patients is too high

The process of boarding due to overcrowded wards is believed to have a negative influence on both the quality of care and the efficiency of the hospital. Boarding decreases the quality of care by placing the patient in a suboptimal care environment, extending waiting times and unnecessary transportation of the patient. These factors decrease the efficiency of the care process, as well as the additional planning effort required to provide all patients with a bed. These factors also affect the financial performance of the hospital. Peak demands are believed to cause occasional cancellations of surgical procedures and admission stops.

1.3 Research goal

Stakeholders from the hospital have set the following goals for this research:

1. *To minimise artificial variation in bed demand by improving the OR planning.*

2. *Create strategies to cope with natural variation in bed demand*

Minimising the artificial variation in bed demand is achieved by regulating the number of patients flowing into the wards from the OR by taking into account the length of stay of patients when scheduling elective surgical admissions. Strategies to cope with peaks in bed demand are developed after data analysis and meetings with the heads of the wards.

1.4 Scope

This research concerns patient flows through the admissions department, Operating Rooms (ORs) and the wards of the Utrecht location of the hospital. We define the scope of this research as the elective surgical admission planning within OR sessions in the Utrecht location of the St. Antonius hospital. The flows of emergency and non-surgical patients are outside the scope of this research, as are the outpatient clinic and the post-ward activities. This research provides the hospital with multiple interventions to tackle the peak bed demand problem. We position this research in the healthcare planning and control framework [2] at the tactical and offline-operational level of resource capacity planning, see Figure 1-1.

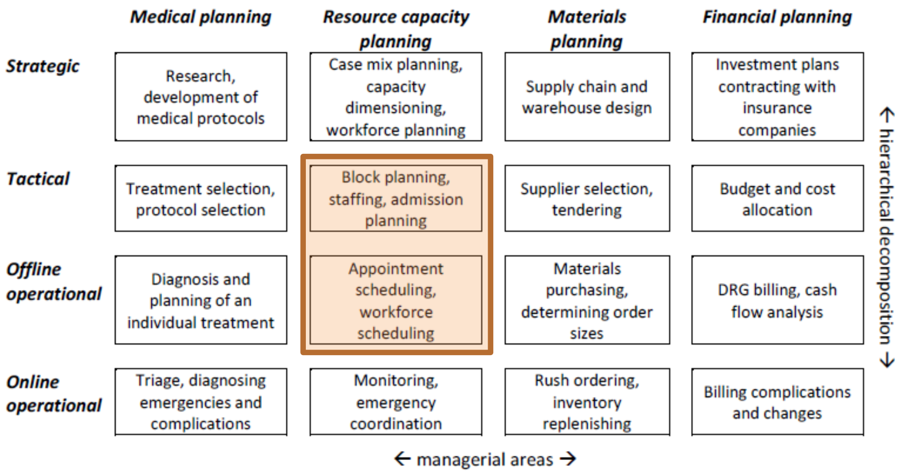


Figure 1-1 Healthcare planning & control framework, Hans et al. (2010)

1.5 Methodology

This research follows the five steps proposed in the Define-Measure-Analyse-Improve-Control improvement cycle.

Define – in the define phase we describe the process and identify performance indicators

Measure – in the measure phase we map the perceived problem situation and collect data from stakeholders and the hospitals information systems.

Analyse – In the analyse-phase we conduct a quantitative and qualitative retrospective analysis of the performance of the system based on the identified performance indicators. Consequently, a problem analysis is conducted.

Improve – In the improve phase we identify and select improvement areas and interventions. We do this by executing the following steps:

1. Literature research in the areas of variability and planning & scheduling models in healthcare
2. Selection of improvement interventions
3. Devising a mathematical model to optimise the admission scheduling problem
4. Provide practical planning guidelines to assist the hospital planners in the short term
5. Analyse the potential benefit of interventions to better react to peak bed demand

Control – In the control phase we provide the means to keep improving the planning process using the devised model and recommend future steps.

1.6 Research questions

1. **What does the current situation look like, how is it controlled and what is its current performance? [Chapter 2]**
    - Process description.
    - What are suitable evaluation criteria/performance indicators?
    - What is the core problem, what are the consequences of the core problem and what factors influence the core problem?

2. **What planning and control concepts regarding the core problem are available in the literature? [Chapter 3]**

3. **What are suitable improvement interventions? [Chapter 4]**

4. **How can we model and improve the patient admission process? [Chapter 5]**
    - Creating an optimisation model

5. **What is the improvement potential for the patient admission process? [Chapter 6]**
    - Case study test instance results
    - Case study practice results
    - Full system results

6. **How can we improve the ability of the system to react to peak bed demands? [Chapter 7]**

7. **What steps need to be taken to improve the OR-Ward system using the identified leverage points and the results of the model? [Chapter 8]**

2 Situational analysis

In this chapter we analyse the processes connected to the issues the St. Antonius hospital is experiencing. This information helps to accurately define the problem and the causal relation between variables but also provides essential insights needed to adequately model the system. The analysis starts by describing the process' resources, patient flows and control structure in Section 2.1. In Section 2.2 the planning & control framework for elective patients is introduced, where Section 2.3 introduces the stakeholders and positions them in a framework according to their properties. In Section 2.4 a list of performance indicators is composed to evaluate the performance of the system and give feedback. These performance indicators are consequently used to evaluate the current performance of the system and to zoom in on the core problem in Section 2.5.

2.1 Process description

To understand the processes surrounding the problem, we map the patient population and their flow through the hospital. The resources involved are summed up and explained and an overview of the control structure is given.

2.1.1 Patient population

Two main defining characteristics a patient has from both a medical and a logistical perspective are his specialty type and the urgency level, see Figure 2-1. On the specialty axis a patient can require surgical care or medicine care. On the urgency axis a patient can be admitted as an emergency patient or as a planned (elective) patient. This division is important because it largely determines the general route a patient is going to follow leading up to the wards. In practice, elective patients are mostly surgical patients and emergency patients are mostly from the medicine specialty. Clinical patients are admitted to a clinical

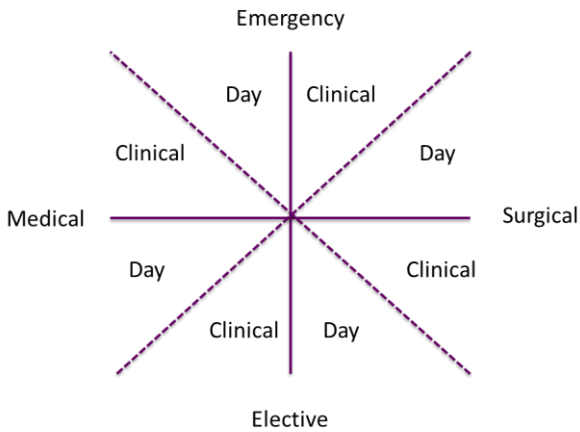


Figure 2-1 Patient types in the patient population

ward and usually stay one night or more. Day patients go to the day treatment ward and do not stay overnight.

2.1.2 Clinical course of patients

There are numerous clinical courses a patient can take through a hospital; entities a patient has to attend and the procedures performed all depend heavily on the unique characteristics of that patient. We identify the patient flows coming through the wards in the context of this problem. Elective patients usually enter the system through an outpatient clinic and emergency patients usually enter the system at an emergency department. All elective surgical patients visit the pre-operative screening and admission planners before surgery. Almost all patients are placed in a bed before diagnostics or the OR. After the OR, patients always visit a recovery before arriving back at the ward. A graphical representation of the patient flows can be seen in Figure 2-2.

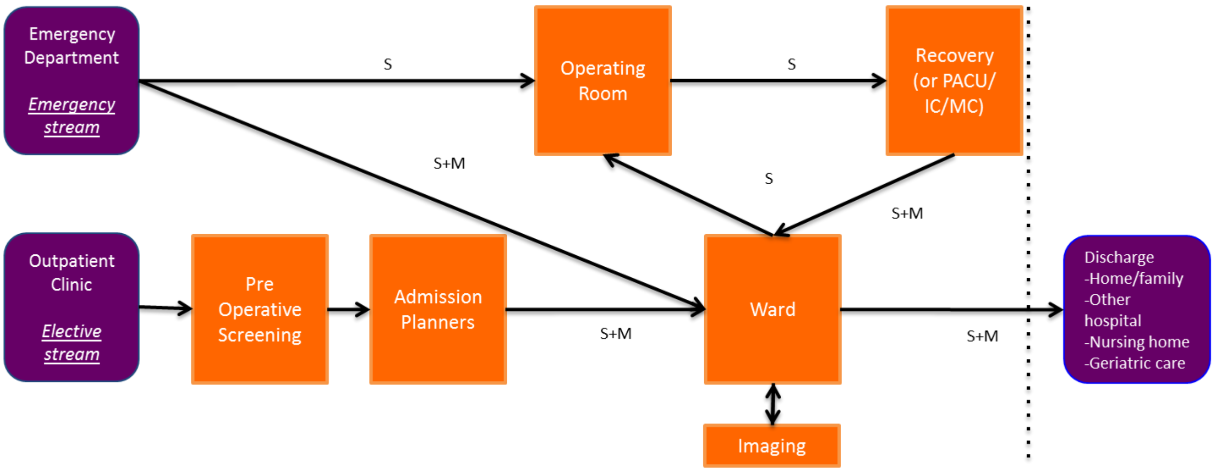


Figure 2-2 Patient flows through the system in the St. Antonius Hospital (S represents Surgical specialty, M represents Medicine specialty).

2.1.3 Entities in the system

Outpatient clinic - The outpatient clinic is aimed at medical consultation and performing small procedures for outpatients. If more complicated procedures are necessary, the patient needs clinical care. In case of a surgical patient, the patient is placed on a waiting list and is referred to the preoperative process to get a date and prepare for an operation. In case of a medicine patient, the patient is planned to be admitted on a bed and scheduled for a procedure or scan. The outpatient clinic functions as a gateway to the hospital for elective patients.

Emergency Department - The emergency department (ED) is designed specifically for acute care. Patients arrive unscheduled with a wide range of medical issues and varying urgency. Even though the hospital has no control over the inflow and characteristics of emergency patients, it is still possible to forecast demand. The ED functions as a gateway to the hospital for emergency patients.

Pre-Operative Screening - In the preoperative process, the patients consults with a pharmacist, an anaesthesiologist and nursing staff to exchange all relevant data and to get informed. The patient can choose when he wants to attend the preoperative process, as long as it is no more than 6 months prior to the surgery. Emergency patients undergo an adapted version of the preoperative process. After attending the POS, a patient can be scheduled for surgery.

Admission planning - Elective surgical patients receive an admission date for the surgery roughly two weeks prior to the surgery from the admission planners in the preoperative process. The OR date is determined by available sessions in the MSS per specialty. The admission planners add patients from the waiting list to a session until the session is full. For this they use the available time in a 4-hour half-day session and a periodically updated expected surgery duration for the specific patient type. Two half-day sessions in a row are frequently assigned to a single specialty so they have the OR for the entire day. There is a dedicated admission planner for every specialty who is familiar with specific session details like specialist preferences and special patient groups like children. The planner tries to incorporate these planning preferences in the admission planning. A patient can also express a preference for an OR date and sometimes a patient can only be scheduled to a specific specialist.

OR - The operating room is a facility where surgical operations take place. OR time is distributed over the surgical specialties by the Master Surgery Schedule (MSS). The MSS gives for each available half-day session in an OR the specialty that may use that session. The idea behind a master surgery schedule is to create predictive cyclical schedules for the medical specialists and other resources to base their own planning on. The MSS is typically revised every three months on a strategic level, on a tactical level sessions can be added or cancelled depending on demand.

Two days before the scheduled surgery, the OR planner sequences the patients planned by the admission planner for that session. Surgeon preferences and rules of thumb like children first dictate the sequencing process. After sequencing, the admission time is communicated back to the patient.

Recovery & IC/MC - The recovery area functions as a resting area right after surgery with heightened monitoring of vitals. Patients are transferred from the recovery to the ward when the condition of the patient allows for it. Instead of taking the patient to the normal recovery area after surgery, patients are occasionally transferred to the intensive care (IC) or the medium care (MC) unit depending on medical urgency.

Wards - A ward is a facility inside a hospital dedicated to the care of inpatients of a specific medical specialty. There are typically two types of wards: day treatment and clinical (long term) care. Day treatment wards can have beds and lounge chairs, clinical wards usually only have beds. A clear distinction needs to be made between "closed" beds and "opened" beds. A bed is opened when it is staffed, that is, personnel are scheduled to attend to that bed. Closed beds are physically present but are not staffed. In this research "beds" refer to opened beds. Figure 2-3 shows the layout of the clinic and the day treatment centre. The wards have the following capacities throughout the week:

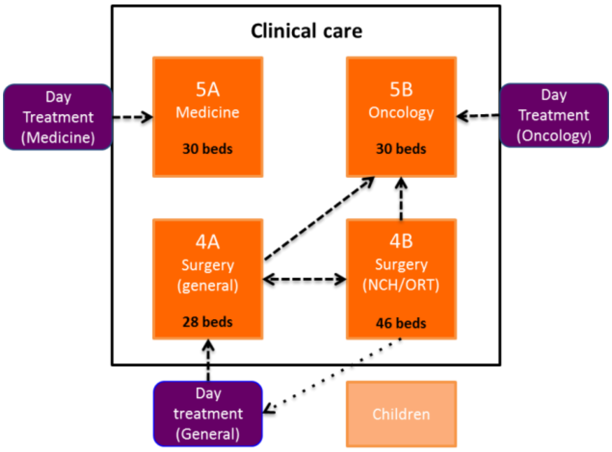


Figure 2-3 Layout of the clinical and day treatment wards in the St. Antonius hospital Utrecht

•	Day Treatment:	Monday to Friday 08:00-22:00 28 beds opened
•	4a:	Monday 08:00 to Saturday 12:00 28 beds opened
•	4b:	Monday 08:00 to Saturday 12:00 46 beds opened
		Saturday 12:00 to Monday 08:00 38 beds opened
•	5a:	All week 30 beds opened
•	5b:	All week 30 beds opened

Inflow on the wards - Patients leaving the operating room (OR) almost always need a bed on a specific ward, the patients "designated ward". Patients can be assigned to a bed on the day of the surgery or earlier. From the moment a patient is assigned to a bed during the intake procedure the bed is no longer available to other patients. The hospital has control over the inflow of elective patients through the MSS, admission planning, surgeon scheduling and bed planning. The available capacity depends on the total number of available beds and their distribution over the various wards.

Outflow of the wards - Patients leave the bed and the ward in the discharge process. The time between intake and discharge is known as the length of stay of these patients. The time of the discharge depends largely on protocol and medical indicators. The length of stay increases when a patient cannot be discharged. This occurs when there is no specialist available to discharge the patient or when the patient cannot proceed intramural (no access to the OR or imaging) or extramural (family, nursing home, geriatric facility, other hospital). Length of stay also increases if the discharge procedure takes longer than usual due to, for instance, medical circumstances or specialists in training who require more time.

Boarding - If there is no bed available on a patient's designated ward the patient is temporarily placed on a different ward until a bed on the right ward becomes available, a process called boarding. Because wards are designed and staffed to take care of patients of a specific specialty, some wards are more suitable than others for certain types of patients. Medical specialists also prefer their boarded patients to be close to their designated ward. If no beds are available at any of the wards, the patient is either not admitted to the hospital pre-OR or is transferred to another hospital post-OR.

2.2 Control structure

The planning and control structure of the St Antonius hospital is aimed at planning the elective patient stream, reacting to the emergency stream and controlling the capacity usage resulting from these streams. Section 2.2.1 covers the planning and control structure for the elective patient stream. Section 2.2.2 covers the monitoring and control structure for the emergency patient stream.

2.2.1 Planning & control: elective patient stream

Planning and control is conducted on the strategic, tactical and offline operational level. Figure 2-4 illustrates the hospital's control structure on all three different levels. On the strategic level, the organisation needs to determine which type of patients it wants to serve and at what volumes, i.e. the patient mix planning. The aggregated resource requirement for operating rooms (ORs) and beds is also determined to create an aggregated resource planning. On the tactical level, both aggregated OR and aggregated ward capacity is divided amongst specialties based on norms set by the hospital and the state of the system (demand, staff availability etc.). In practice, the allocation of beds over the specialties is not updated frequently. The division of OR sessions over the specialties, in the form of the master surgery schedule, is updated every three months to match the capacity allocated to a specialty to changes in this specialty's demand. On the offline operational level, patients are assigned to resources based on the specialty they belong to.

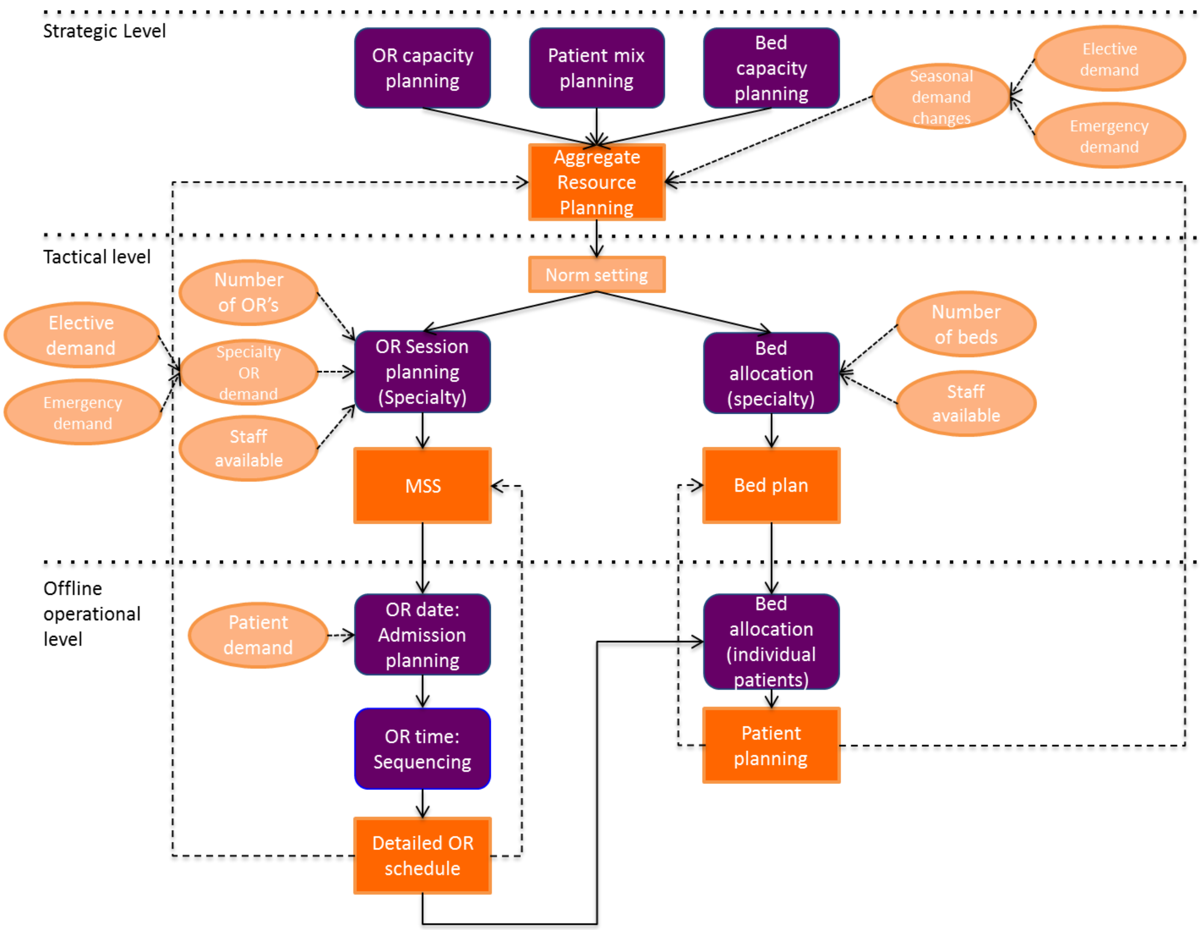


Figure 2-4 Control structure of the OR and wards of the St. Antonius hospital on a strategic, tactical and (offline) operational level for <u>elective patients.</u>

Planning and control information is shared between different resources. Ideally, every resource has access to all the planning and demand information upstream in the system. In practice, however, this is usually not the case. Figure 2-5 shows a diagram with which stations share what planning and demand information with each other.

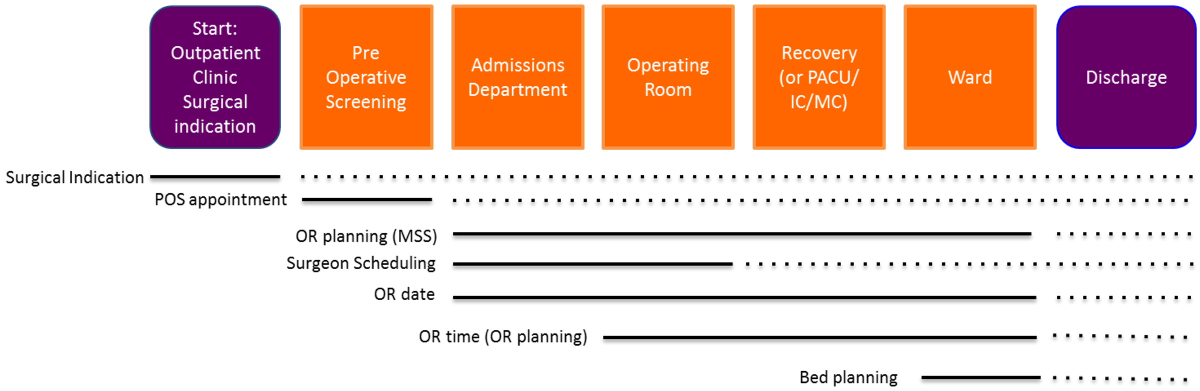


Figure 2-5 Overview of shared planning information between entities in the surgical stream of the St. Antonius Hospital

2.2.2 Monitoring & control: emergency patient stream

Capacity is allocated to the emergency stream on both the strategic and the tactical level, but this capacity cannot be scheduled due to the unplanned arrival of emergency patients. Special sessions in the MSS are allocated to the emergency stream. If there is an emergency patient when there is no dedicated emergency OR available this patient gets preference in an elective OR. On the online operational level, the ED coordinates the emergency stream towards the OR. The emergency coordinator ensures the patient has a bed after the OR. The emergency coordinator also handles and keeps track of boarded patients, both the boarding itself and the eventual relocation to their designated ward. The emergency coordinator has access to the following information:

1. A morning status of the wards
    a. Number of beds occupied
    b. Number of planned admissions
    c. Number of planned discharges
    d. Number and details of boarded patients
2. Regular updates from the ED, OR and wards with changes and recent developments

Based on this information the emergency coordinator tries to get as many patients to their designated ward as possible. In case of a shortage of beds, priorities need to be set. Choices need to be made between where and whether to admit new patients and possibly moving boarded patients to their designated ward. The ranking of the alternatives and their dependencies are shown in Figure 2-6.

Preference of actions

1. Admit an emergency patient
2. Move a patient to free up a bed in the IC
3. Move a complicated boarded patient to its home ward
4. Move a boarded patient blocking access for emergency patients
5. Admit a planned patient
6. Move uncomplicated boarded patient to its home ward

Factors determining action:

- Medical grounds/advice
- Amount of available beds on IC
- State of the wards
- The complexity of the procedure of planned elective patients eligible to be cancelled

Factors determining ward selection:

- Amount of available beds on boarding ward
- Preferably place surgical patients on a surgical ward
- Preferably place medical patients on a medical ward
- The know-how of staff on the boarding ward
- The time window free beds are available
- If the patient stays over the weekend or not
- Preferably board a patient on a ward with boarded patients of the same specialty
- Exclusiveness of the boarding ward (e.g. preferably don't board 'general' patients on a ward that is the only ward that can support cancer patients)

Figure 2-6 Preference of actions undertaken by the emergency coordinator and the factors influencing the chosen action and ward in the St. Antonius hospital

2.3 Stakeholders

Stakeholder mapping is a way to identify and rank parties within the organization that have a stake or interest in the problem or organizational change under review [3]. Categorizing the stakeholders is done by identifying the level of influence they have (power) and the interest they hold in the change. The matrix in Figure 2-7 shows the two axes with three intensity levels per axis: low, average and high. Stakeholders in the upper right corner are usually regarded as key stakeholders that need to be intensively involved in the decision making process. The top left stakeholders need to be kept satisfied, where the bottom right stakeholders need to be kept well informed. The bottom left stakeholders only need monitoring. An addition to the power/interest framework is the attitude of the stakeholders towards the project.

Stakeholders are identified by means of brainstorming with a variety of staff members involved in the project. Staff members that have a high degree of knowledge regarding the project and the stakeholders carry out the categorisation and establishment of attitudes.

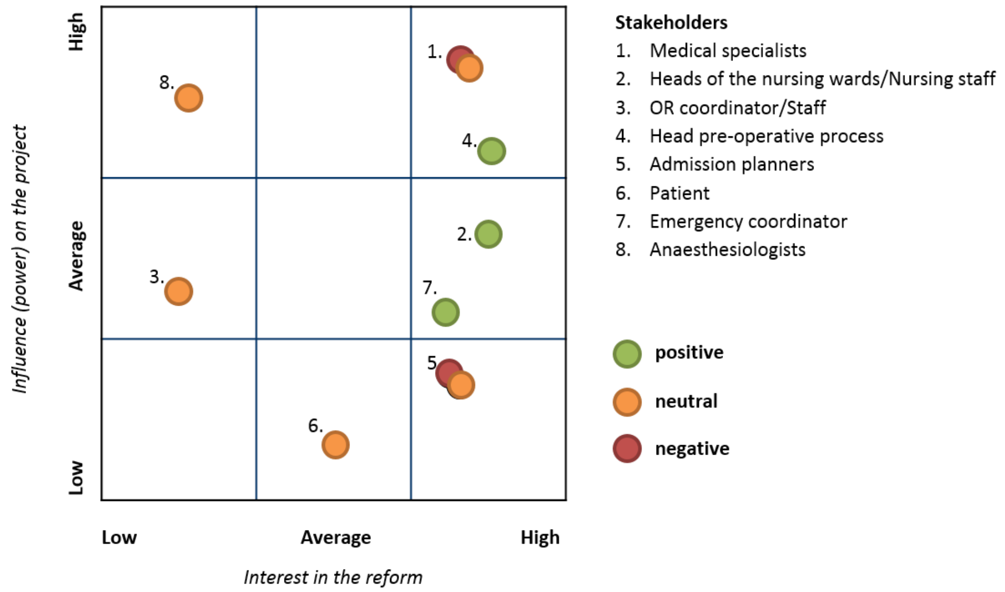


Figure 2-7 Stakeholder map

The stakeholder analysis shows that Medical specialists, the head of the pre-operative (and most importantly the admission planning) process and the heads of the wards are key stakeholders. The head of the pre-operative process and the heads of the wards have a positive attitude towards the project. Medical specialists have a neutral-negative attitude towards the project, mostly because it enters their realm of influence in their working roster, the usage of OR sessions and the placement of their patients on the wards. They, however, also experience the downsides of the current situation where their patients are sometimes scattered over the different wards and where they cannot admit all the patients they want due to overcrowding. This leads them to see room for improvement and the possible advantages of the project.

The OR coordinator and anaesthesiologists are classified as stakeholders that need to be kept satisfied. Both these stakeholders have a neutral attitude towards the project, but have a vested interest in the workings of the OR and will not just accept a decrease in OR performance without convincing arguments why the patient and the hospital as a whole would benefit from it. This project offers the chance to reduce alterations in the operational planning. To achieve this, however, it might require changes in roster and flexibility regarding working hours.

Stakeholders that need to be informed are the emergency coordinator and the admission planners. The emergency coordinator is the central hub for all communication regarding emergency patients and patients that cannot get a bed on the right ward straightaway. This project offers the potential to greatly reduce the workload of the emergency coordinator, leading to a positive attitude towards the project. The admission planners might have to change their working routines as a result of this research. They however also get less complaints about the resulting planning leading them to have a neutral-negative towards the project. Finally, patients need to be monitored as stakeholders. The patient has little direct influence over the project but can clearly benefit from a lower chance of being turned down, boarded or transported multiple times.

To satisfy the needs of the stakeholders, we have weekly meetings with all the heads of the wards, the emergency coordinator and the head of the pre-operative process. This ensures the practical feasibility of the project and provides valuable insights and support for the project.

2.4 Performance indicators

Performance indicators are used to evaluate the performance of a system both retrospectively and continuously for process control purposes. There are two different types of identified performance indicators: control variables and monitoring variables. Control variables directly relate to the objectives set for a process. Monitoring variables can provide useful detailed information in case one or more of the control variables indicate an issue.

2.4.1 Control variables

Table 1 shows the four indicators that serve as control variables. These four variables give an aggregate idea of the performance of the system and should be (semi) continuously monitored.

Table 1 Control variables for the OR-ward chain

Control variables	
•	**The bed requirement needed to fulfil 95% of bed demand**
•	Number (hours) of boarded patients
•	Number of turned down patients
•	Variation In utilisation of sessions

In literature it is common to use resource utilisation as a key performance indicator for process improvement in health care processes. Vissers et al. (2001) argue that maximising resource utilisation, whilst maintaining acceptable standards of service quality, is the most logical objective for their health care production control framework. We propose to use an alternative main objective for health care production control: levelled resource utilisation by minimising process variation. The control variable for the levelling of bed utilisation is defined as: **"The bed requirement needed to fulfil 95% of bed demand"**. There are multiple benefits to using this metric instead of maximising resource utilisation. Minimising process variation improves patient flow through the system (see Chapter 0). Additionally, maximising resource utilisation potentially creates an unwanted incentive to, for instance, extend the length of stay or surgery durations of patients. Consider the hypothetical situation where physician A can do three identical knee operations in a day with almost equal surgery durations, and physician B can do three identical knee operations but with highly varying surgery durations. If the average OR utilisation of the slower physician B is 80% and is 70% for the faster physician A, physician B appears to be more efficient according to the metric proposed by Vissers et al. (2001). Physician B however sometimes has to cancel his last patient because the first two operations happened to be very lengthy, whereas Physician A has the possibility to add a fourth knee operation to his schedule with little chance of having to work overtime or to cancel his patient. We believe that resource utilisation should be monitored but not used as an objective in its own right within the scope of this research.

2.4.2 Monitoring variables

Table 2 shows multiple monitoring variables that provide detailed insight into the state of the system and can indicate which areas need attention. Continuously monitoring all monitoring variables would require a high degree of data analysis, these indicators can once again be determined after control variables indicate a problem might have occurred.

Table 2 Monitoring variables for the OR-ward chain

OR	
•	Number of surgeries
•	Number of sessions
•	% Utilisation of allocated weekly sessions
•	% Utilisation of sessions
•	Variation in utilisation
•	Number of turned down patients <24h before surgery
•	Number of deviations from MSS (cancelled sessions, extra sessions and so forth)
Ward	
•	Number of boarded patients
•	Chance of turning down patients
•	% Utilisation
•	Variation in utilisation
•	Length of stay
•	Variation in length of stay
•	Number of admitted patients (elective and emergency) (target: peak moments only incidentally, not weekly)
•	Variation admitted patients (elective and emergency)
Admissions department	
•	Number of patients on the waiting list
•	Hours of planned and unplanned OR work available

2.5 Current performance of the system

This section gives an overview of the current performance of the system. This overview is compiled by combining the experiences of the stakeholders with data analysis. We start with input from stakeholders followed by proposed hypotheses based on that input. This information is consequently compared to and tested by an extensive data analysis. Together, this gained knowledge serves as the basis for the problem analysis at the end of this section.

2.5.1 Current situation as described by stakeholders

During regular meetings with heads of the wards, certain focal points were mentioned while describing the current situation and the problems experienced. The following perceived situation is a summary of the points mentioned by the heads of the wards before data analysis.

"We experience high and low bed demand, but in general we have trouble placing patients on the right ward, especially emergency patients. For these patients we have to find a bed on another ward, which interrupts and disturbs our regular work and at times reduces the quality of care we can deliver. We have little information in advance on how many patients are coming our way and have hardly any influence over the inflow of patients, meaning we can only react to the sometimes sizeable fluctuations in demand over the day and week. Fluctuations over the day occur mostly in the morning before the discharge and demand over the week usually leads to a peak towards the end of the week. We have the feeling that physician rostering and patient scheduling on the OR might have something to do with the fluctuations."

From this description we conclude that the wards perceive capacity and patient flow issues as the leading cause of boarding patients. These capacity issues are believed to originate in the operating room schedule and patient flow issues possibly originate from the admission and discharge process on the wards. The capacity and flow issues are believed to lead to a large proportion of boarded patients. These suspicions are tested through the means of hypotheses in Section 2.5.3.

2.5.2 Hypotheses

The following hypotheses are proposed based on the situational description given by the heads of the wards and on a preliminary exploratory data analysis. These hypotheses are used to structurally and thoroughly analyse the data in Section 2.5.3:

H1: The bed utilisation exceeds the hospitals threshold of a minimum of 85% for all wards

H2: Demand for beds surpasses the total number of available beds in the clinic at least once in the analysed period

H3: Demand for home-beds surpasses number of available beds on the individual wards at least once per ward in the analysed period

H4: The elective stream causes more variation in bed demand than the emergency stream

H5: The elective surgical stream has the highest variation in inflow of patients of all incoming patient streams

H6: Admission and discharge times on the wards are not synchronised

H7: The average turn-down probability does not exceed the threshold of maximum 5% for all wards

H8: Day Treatment (DT) patients are admitted to ward 4a in case of bed shortage in the DT

H9: Ward 5b is the largest receiver of boarded patients in the clinic whilst having overcapacity

H10: Boarding patients is unnecessary, if we would forbid boarding, all patients would end up with a bed on their designated ward

2.5.3 Data analysis

This section is marked confidential and is removed from the public version of this report

Summary of the tested hypotheses:

Table 3 Summary of the hypotheses in the data analysis

Summary of the data analysis:		
O	Conclusion hypothesis 1:	The bed utilisation is only above 85% for ward 5a. The other wards and the total clinic average do not meet the threshold.
O	Conclusion hypothesis 2:	The total demand for clinical beds never surpasses the number of clinical beds available.
O	Conclusion hypothesis 3:	Not all clinical wards have an expected bed shortage in case of home-patient demand, but some do.
O	Conclusion hypothesis 4:	The elective stream introduces the highest variation in total bed demand. On the ward level the elective stream introduces the highest variation in bed demand on wards 4a, 4b and the day treatment.
O	Conclusion hypothesis 5:	The impact of the variation of the surgical elective stream is the highest on the day treatment ward and wards 4a and 4b. On wards 5a and 5b the variation in the emergency medicine stream has the highest impact.
O	Conclusion hypothesis 6:	On three out of four clinical wards there is a multiple hour mismatch between the peak moment of admission and the peak moment of discharge. There is also a tendency for clinical wards to get more crowded towards the end of the week.
O	Conclusion hypothesis 7:	Ward 5a exceeds the maximum of 5% average turn-down probability.
O	Conclusion hypothesis 8:	Patients with the day treatment as their designated ward almost exclusively flow towards ward 4a in case of an overflowing day treatment.
O	Conclusion hypothesis 9:	Ward 5b has the highest percentage of boarded patients of all wards and is the only ward to receive substantial incoming streams of boarded patients from all other clinical wards.
O	Conclusion hypothesis 10:	Only ward 5b has enough capacity to fulfil all home-patient demand, the other wards don't. If boarding was forbidden not all patient demand for beds on their designated ward could be fulfilled.

2.5.4 Problem analysis

The data analysis and stakeholder meetings reveal the process characteristics that make up the core problem. Figure 2-8 shows a graphical depiction of the (core) problem and its causes. The core problem is stated as:

The percentage of boarded patients is too high

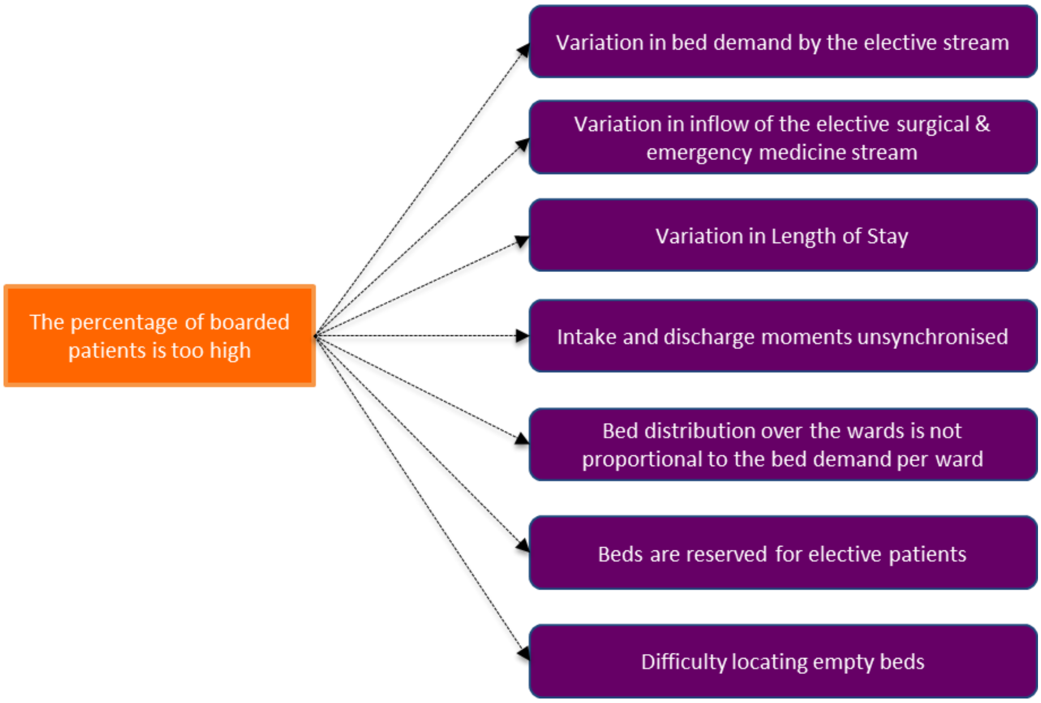


Figure 2-8 Problem bundle: the core problem and its causes

We have found that variability plays a key role. Data analysis has shown that wards are sometimes full but also have periods where bed utilization is relatively low. Average bed utilisation shows that wards should have sufficient space if the variation in inflow and outflow would not be as high as it currently is. Reasons for this can be natural variation but also variation induced by the hospitals own processes: artificial variation. The variation in bed demand is a determining factor for wards. Analysis identified the elective stream to cause the highest level of variation in bed demand. Variation throughout the day results from the lack of synchronisation between the intake and discharge processes. Analysis shows that some wards have less capacity issues than others, indicating that total capacity is not divided over the wards proportional to the bed demand. The analysis shows there are no capacity issues on a macro level: there were never more clinical patients than there were beds in the clinic. Stakeholders indicate that beds are frequently reserved for elective patients scheduled for an OR in the near future. This does not only structurally reduce bed utilisation it also forces emergency patients to be boarded. Patients are also occasionally boarded because there is no complete overview of available beds and when beds become available.

Consequence of the core problem

The lack of synchronisation between inflow, outflow and capacity causes there a surplus of beds on one moment and a shortage on the next. This has a number of consequences:

Not occupying an opened bed leads to a low average utilization of expensive and valuable resources, like medical personnel. On the other hand, a shortage of opened beds is also sub-optimal, both on ward level and on a hospital wide level.

When there is no bed available on a patient's designated ward, nursing staff needs to perform a lot of ad hoc activities to search for alternatives and colleagues are rushed in their activities to free up beds as soon as possible. If no beds can be freed up, the dominant alternative is boarding the patient. Although boarding is preferred over denying patients' entry to the hospital system, it is highly undesirable. Boarding patients leads to large amount of disruptions of regular processes and a reduction in quality of care by placing patients in possible sub-optimal environments of care compared to their designated ward. As mentioned, the alternative to boarding is turning down patients. Turning down patients can lead to a lower OR utilization, resulting in scheduled valuable and expensive resources like the OR and medical personnel to be used sub-optimally. Turning down patients also has a negative effect on patient satisfaction.

2.6 Conclusion

We conclude that the percentage of boarded patients is too high. However, there are no capacity issues on a macro level: there were never more clinical patients than there were beds in the clinic. We identify variability as the root cause of boarding patients. Average bed utilization shows that wards should have sufficient space if the variation in inflow and outflow would not be as high as it is. Reasons for this can be natural variation but also variation induced by the hospitals own processes: artificial variation. We identify the scheduling of elective patients as the largest source of artificial variation in bed demand.

3 Literature research

For years, hospitals responded to delays by adding resources like beds and staff. Increased financial pressure means these options are no longer available. Moreover, work by the Institute for Healthcare Improvement suggests that delays are not a resource problem; they are a flow problem [4]. This literature research reflects on the current views on hospital capacity management and optimal care delivery under minimal cost and is used to find solutions for the problems identified in Section 2.5.4. We conduct our research using the google scholar [5] and ORchestra [6] search engines. The literature review by Vanberkel et al. [7] serves as a starting point for the literature research, as well as the article by Litvak & Long [8]. We identify four topics for our literature research: variability, patient flow, OR scheduling and statistical process control. During the literature research we summarise and categorise literature relating to our research. For each topic we start our search by selecting a recent paper on the topic and consequently going back in time through the references: a snowball technique. Keywords found in relevant articles also help us to both deepen and broaden our literature research. The keywords used in the literature research are stated at the beginning of each section in Chapter 3.

We agree with the views of Eugene Litvak in the acknowledgement of variability as the key determining factor in health care processes [9]. Therefore this chapter starts with literature on variability in healthcare processes and patient flow in Section 3.1. Section 3.2 addresses ways to manage different forms of variability. Different types of planning and scheduling models from Operations Management are addressed in Section 3.3 followed by ways to monitor processes in Section 3.4.

3.1 Variability in health care processes and patient flow

Keywords – Health care, variability, process variability, natural variation, artificial variation, optimisation, patient flow, flow variability, hospital flow, process flow

Healthcare systems are expected to deliver quality care for patients with many different types of disease. Litvak & Long [8] identify four different kinds of variability: clinical, flow, professional and artificial. Clinical variability presents itself as the variation in disease types of patients entering the hospital, the severity of the disease presentation and the different treatment alternatives these patients get. Flow variability can be seen in the random manner in which patients and cases arrive with a need for care. Professional variability can be seen as the difference in working routines, preferences and results of medical professionals in the care delivery process. Litvak & Long [8] describe the constant challenge to the healthcare system as:

> *"To efficiently convert a naturally variable incoming group of sick patients into a homogeneous outgoing stream of well patients. The presence of these "natural" clinical, flow, and professional variability's increases complexity and adds cost to the healthcare system. The goal then is to optimally manage natural variability's. However, dysfunctional management often leads to the creation of a fourth type of variability—"artificial"—that unnecessarily increases the very cost and inefficiency we are trying to control. Compared with natural variability, artificial variability is non-random. Yet it also is unpredictable, driven by numerous competing demands on the surgeons' time that are usually unknown and therefore unaccounted for by the healthcare system"* [8].

This artificial variation, introduced by the way we have set up the care delivery process, far outweighs the variation caused by the randomness of disease presentation [4]. Thus the number of admissions for elective scheduled surgery may be less predictable than the purely random admissions for emergency care in the emergency department [8]. In fact, research has shown that the majority of variability in patient flow is attributable to scheduled admissions, especially when adjusted for patient volume [10]. Patient flow is directly related to the concept of variability. Randomness in disease presentation and care processes are, however, not the only factors influencing flow. When improving flow in hospitals, processes need to be looked at as an interdependent system rather than individual departments, to use an integral systems approach. Any individual that improves flow in its area alone often in fact exacerbates the problem for other dependant departments [4].

3.2 Managing variability

Keywords – process variability, natural variation, artificial variation, managing variation

Managing artificial variability

Artificial variability, described by Litvak [9] as non-random, non-predictable, and driven by individual priorities, unlike natural variability, should not be managed. Rather, it must be identified and eliminated [9]. There is usually far more variation in the pattern of patient discharge than in the pattern of admission. The main cause of this is the way we manage our processes, e.g., ward rounds, which leads to a highly unpredictable length of stay [11]. Operations management techniques offer multiple ways to eliminate artificial variation by, for instance, reorganising schedules. It is important to increase flexibility in the system to be able to cope with natural variation, adding flexibility in the system to cope with artificial variation should be discouraged. Capacity should only be increased when all artificial variation is reduced.

Managing natural variability

Clinical, flow and professional variability, described by Litvak & Fineberg [10], are natural variability. Patients do not present with the same type and severity of diseases, they come to the ED unexpectedly and professionals are not uniform in their care delivery. These three types of variation are random and, in the case of the first two, patient driven. Natural variability cannot be eliminated or even reduced. Instead, it must be optimally managed [9]. Managing natural variability often involves finding a balance between multiple goals. For detailed descriptions on how to manage natural variability by for instance segmenting patient groups we refer the reader to [9].

Buffers play a decisive role in managing natural variation and creating a steady inflow of patients. However, it is not always possible to create buffers between every step in the process. Capacity management and intelligent use of buffers provide the means to create flow. In the chain "Outpatient clinic-OR-Wards", there are multiple interdependent capacity management decisions that influence the chain. These decision and their results can be seen in Figure 3-1.

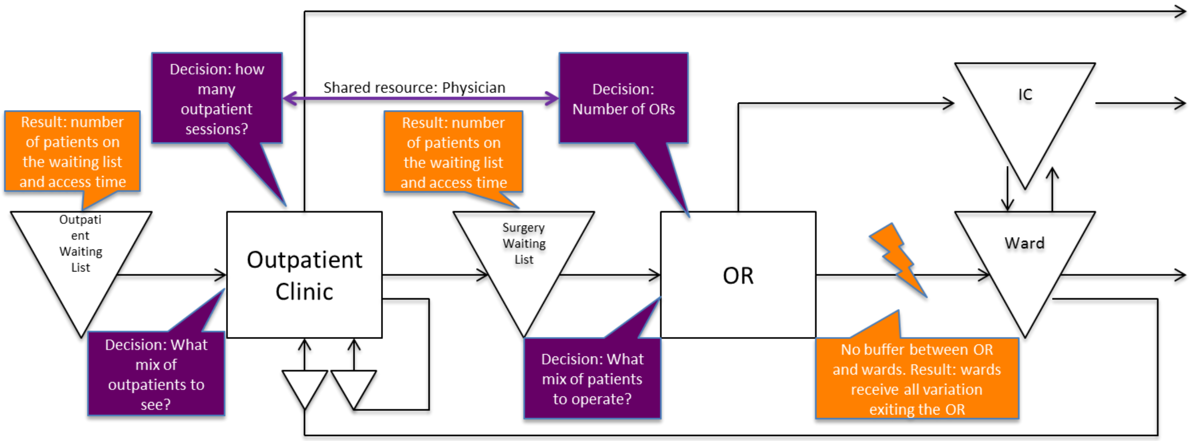


Figure 3-1 Capacity management decisions and their results in the Outpatient Clinic-OR-Ward chain

3.3 OM literature about OR scheduling

This section covers the planning models regarding the OR-ward chain available in literature. The operating room is often referred to as the engine that drives the hospital. The activities inside the operating room have a drastic impact on many other activities within hospitals. For instance, patients undergoing an operation are expected to recover over a number of days. Consequently, bed capacity and nursing staff requirements are dependent on the operating room schedule. By well-thought-out scheduling of the operating room, the expected variability in resource demand can be minimized [12]. The planning and scheduling of an OR can be complicated due to the number of stakeholders and different objectives involved in the process. Adding to the pressure is the importance of the OR to the hospital: the OR is one of the most expensive resources in the hospital, making its optimal utilisation an important goal for the organisation [13]. There are planning and optimisation models available for all three levels of planning (strategic, tactical and operational) for a wide range of OR scheduling problems. The degree of detail incorporated in the models and whether or not they take into account other parts of the system varies. The scheduling of an OR can be seen as a three stage process [12]. First the available OR time needs to be allocated over the different surgical groups, referred to as case mix planning. Second a Master Surgery Schedule (MSS) is determined, which functions as a cyclical timetable assigning the OR time for a surgical group to specific ORs on specific days. Whenever the total OR time or the resource allocation changes a new MSS needs to be created [14]. The third stage involves the day-to-day admission planning of individual patients. A fourth stage not mentioned by

Belien & Demeulemeester [12] regards the sequencing of patients within a session. The remainder of this section covers literature available for stage 2-4, the focus of stage one, OR capacity allocation, lies outside of the scope of this research. Section 3.3.1 covers literature regarding master surgery schedules, Section 3.3.2 covers admission planning and Section 3.3.3 covers case sequencing.

3.3.1 OR MSS scheduling

Keywords – Cyclic master surgery scheduling, MSS, block scheduling, open scheduling, operating theatre planning, operating room scheduling.

In repetitive production environments cyclical planning approaches are common to reduce demand fluctuations in the supply chain [13]. In the area of OR scheduling these types of schedules, called tactical master surgery schedules, can be divided into two categories: open scheduling and block scheduling [15]. In block scheduling a surgical group gets assigned to an OR on a specific day in which they can schedule patients from their specialty. In this literature research we only cover block scheduling since this is the current practice at the St. Antonius hospital. Within the block scheduling literature there are multiple definitions of an MSS. We identify MSSs on specialty level and MSSs on procedure type level in literature. An MSS on specialty level, as defined by Belien en Demeulemeester [12], cyclically assigns blocks (ORs) to specialties. An MSS on procedure type level, as defined by Van Oostrum et al. [13] cyclically assigning groups of procedures to ORs.

A surgery schedule can be optimised against several different objectives, depending on the hospital's preferences. Maximising OR utilisation is a common objective, especially since it is closely related to OR staffing costs. An alternative objective is to minimise the chance of running into overtime by improving the predictability of the schedule [12]. In recent years there has been increased attention to surgery scheduling incorporating resulting bed demand [12] [16] [17] [18] [15] [19] [20] [21] [13]. Creating optimal master surgery schedules is mostly done by using mathematical programming or heuristics. Some authors [22], [16] use deterministic input parameters like surgery durations and length of stay whereas others [12], [17], [18], [15] use stochastic inputs. Using stochastic parameters increases complexity but significantly improves results [17]. Despite the large volume of literature available about health care scheduling problems relatively few papers have checked their models against real-life data [18].

3.3.2 Admission planning

Keywords – Scheduling elective surgeries, admission planning, operating theatre planning, surgical case scheduling, OR scheduling, procedure scheduling, patient mix optimisation.

Admission planning refers to the scheduling of procedures to specific ORs. Generally, OR actors plan their procedures independently from one another [13]. Optimising the admission planning process therefore might restrict the authority of some actors [23]. Admission planning can serve several goals, such as minimising OR overtime, maximising OR usage, capacity utilisation of downstream capacities and revenue. A variety of papers in literature suggest approaches to optimise admission planning, considering either elective cases or both elective and emergency cases [24]. Few papers take into account downstream resources like beds and most papers simplify reality to a deterministic level.

3.3.3 Case sequencing

Keywords – Case sequencing problem, case sequencing, admission scheduling, OR scheduling.

Case sequencing is the order in which scheduled cases are performed in an OR. Case sequencing can benefit patient waiting time, the available intrusion moments on the OR and the risk of overtime on an OR [25]. For example, sequencing the shortest or least variable cases first within a day generally leads to more cases being completed by any given time during the day. This means an emergency intrusion that disrupts the surgical schedule will disrupt fewer cases. This leads to fewer cancellations and an increase in the average number of cases per day performed [26]. Also, variability in case durations tends to propagate throughout the day. So, putting less variable cases earlier can decrease the overall volatility of the schedule and the probability of case cancellations [26]. For further reading on case scheduling we refer the reader to articles by [23], [25] & [27].

3.4 Statistical process control & control charts

Keywords – Statistical process control, control charts, healthcare, health care processes, improvement, process control, process indicators.

Continuous improvement of healthcare systems requires the measuring and understanding of process variation [28]. Statistically derived decision rules help users to determine whether the performance of a process is stable and predictable or whether there is variation in the performance that makes the process unstable and unpredictable [29].

Statistical Process Control (SPC) distinguishes two types of variation: common (random) cause and special (assignable) cause variation. Common cause variation is comparable to natural variation described by Litvak & Long [8]. Processes that only show common cause variation are considered completely stable and predictable [30]. Please note that this does not mean the process produces desirable results; a process that is in control can still produce unwanted results, e.g., a lab test that is consistently completed in twice the desired time. Special cause variation is comparable to artificial variation as described by Litvak & Long [8]. Special cause variation is created by factors that were not part of the process' design and highlights something unusual going on in the process. These factors are assignable and can usually be eliminated [30]. SPC control charts can aid in identifying these factors. SPC charts are chronological time series analyses of important variables, such as averages, rates or proportions. This graphical presentation of data provides quick insight into the data in a way more understandable to lay decision makers [31]. Lower and upper thresholds are determined statistically using process data and indicate the area of natural variation in which a measure should almost always fall. If a point falls outside the limits, it is an indication that the result was not produced by the same process, either because of a lack of standardization or because a change in the process may have occurred. Such changes could represent either quality improvement or quality deterioration, depending on which control limit is crossed. Control charts are thus quite useful both for monitoring if processes get worse and for testing and verifying improvement ideas [28].

4 Selection of improvement interventions

Using the problem analysis of Section 2.5.4 and the literature research, we identify a number of improvement interventions to reduce variation in bed demand and to better react to incoming bed demand. The interventions are ranked using a cost & benefit framework and consequently a number of suitable interventions are selected for further investigation and implementation.

Areas of improvement

Analysis and available literature both regard elective patient scheduling as a large source of variation in bed demand. Therefore, the first identified improvement intervention is the levelling of the inflow of patients by improving elective patient scheduling. Because it is not reasonable to assume we can completely level the inflow of the elective stream, we determine what interventions are suitable to increase the capability of a ward to handle the remaining variation in inflow of elective surgical patients. First, we identify interventions to create more capacity on the wards during peaks in bed demand. Second, we identify interventions to increase the free bed capacity per ward at all times. Third we identify the preconditions that need to be satisfied for the interventions to be successful.

Admitting patients after surgery and creating temporary buffer capacity are interventions suitable to better match available capacity with remaining fluctuations in bed demand. Reducing the length of stay (LOS) of patients and redistributing bed capacity per specialty increases the number of free beds a ward has available to admit patients. A redistribution of beds across the wards is beneficial to the number of boarded patients considering there is no bed shortage on an aggregated level. However, flexible assignment of beds might be a better option than fixed redistribution. Improvements in the availability of information are necessary to allow wards to better react to incoming bed demand. A central information platform helps to locate available beds and quickly provide an overview of the current situation.

Cost & benefits

To rank the interventions we categorise them using a cost benefit framework, see Figure 4-1. The cost refers to the ease of implementation, not limited to the financial resources needed. The interventions and their ranking can be seen in Table 4.

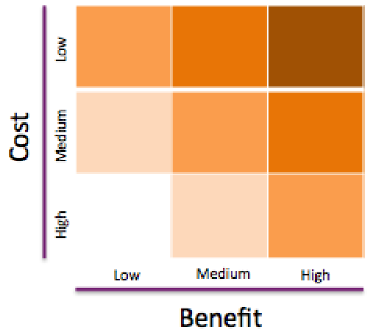


Figure 4-1 Cost & benefit framework

Table 4 Categorised improvement interventions

Levelling incoming bed demand:			Benefit	Cost
	1	Model: reduce artificial variation in bed demand from the elective surgical stream by redesigning elective admission planning	High	Med
Reacting to incoming bed demand:				
	2	Admit patients after surgery	High	Med
	3	Use temporary buffer capacity for peak hours per day	High	High
	4	LOS improvement	Med	Med
	5	Redistribution of beds per specialty	Med	High
	6	Real-time insight in the ‘state of the system’	Med	Med

We discuss Intervention 1 in Chapter 5 and 6. Interventions 2-6 are discussed in Chapter 7. Intervention 1 is the main focus of this research because elective patient scheduling has been selected as an area with a high potential for improvement. Research has shown that the majority of variability in patient flow is attributable to scheduled admissions, especially when adjusted for patient volume, and redesigning the elective scheduling system is reported to show significant improvement results in the number of boarded patients, cancelled operations and session utilisation [10] [11]. We select admission scheduling as the focus for our model predominantly for practical reasons. The St. Antonius hospital uses a block type master surgery schedule which has proven to be difficult to change structurally. Letting go of the block scheduling or continue operations during the weekend are also possible interventions to reduce artificial variation in bed demand but are thought to be infeasible in the short term. Case sequencing is thought to have too little effect on bed requirement. Admission planning therefore has the right balance between practical feasibility and improvement potential. An added motivation to choose admission planning originates from meetings with admission planners and heads of the wards. When scheduling patients, admission planners take into account restrictions, such as available OR-time and physician preference but have no feedback on what the consequences of their planning efforts are on the wards. We identify the planning of elective surgical patients as an area where an integral systems perspective can have a significant improvement over local optimisation.

5 Intervention 1: Approach for levelling incoming bed demand

As introduced in Chapter 4, we aim to reduce peaks and variation in bed demand by improving the admission planning of the elective OR stream. This chapter starts with a conceptual model in Section 5.1, followed by the formal model description and multiple variations on the mathematical model in Section 5.2. Section 5.3 describes the output of the model and the validation of the model is the subject of Section 5.4. Finally Section 5.4 indicates the limitations of our approach.

5.1 Conceptual model

Currently, admission planners schedule individual patients onto sessions without being able to see the result of their planning efforts on the bed requirement. We propose to construct an optimisation model that provides admission planners with advice as to the mix and volume they should preferably schedule on each session to minimise peaks in variation in resulting bed utilisation. Intervention one consists of two phases:

Phase one: determine the theoretically optimal case mix per session with a mathematical model
Phase two: schedule patients based on the case mix prescribed by the model

Figure 5-1 shows a simplified representation of the current scheduling method on the left and the proposed improved scheduling method on the right.

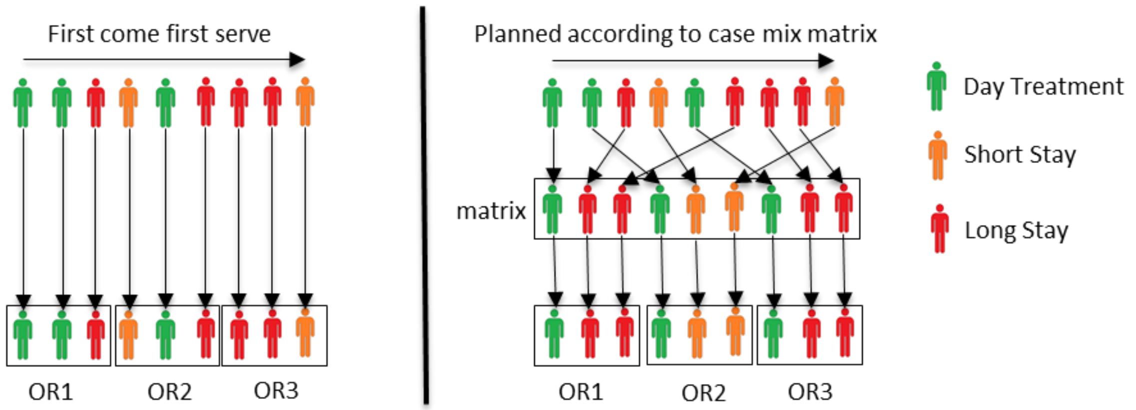


Figure 5-1 Current versus proposed situation for planning elective surgical patients

In the old situation, sessions are filled first come first serve until there is no time left on the schedule. In the new situation planners aim to fill sessions with a predetermined desirable mix, the case mix matrix. In the end the same 9 patients are scheduled, just in a sequence that results in less variation in bed demand.

5.2 Formal model description

Phase one consists of using the mathematical optimisation model to create optimal case mixes. The mathematical optimisation model is based on multiple forms of mathematical programming and is programmed in IBM ILOG CPLEX optimisation studio 12.5 [32]. We use mathematical programming because it provides us with solutions for our combinatorial optimisation problem where we optimally use our resources. Mathematical programming also provides flexibility in adding and modifying constraints.

The phase one objective is to reduce fluctuations in the demand for beds by assigning volume and mix of case types to OR sessions for each day in the planning cycle. The mathematical model gives an answer to the following question:

Given a certain Master Surgery Schedule and expected demand, when should we schedule which case types and in what volumes?

The mathematical model is based on the technique used by [13] to relate the surgical schedule to resulting bed demand. However, there are differences between the approach and goal of our research compared to [13]. Van Oostrum et al. [13] aim to minimise the number of opened ORs and the resulting bed requirement, by creating an optimal cyclic surgery schedule from a set of surgical procedures. We aim to minimise the bed requirement, by creating an optimal case mix per OR session within an existing cyclical block schedule. We therefore provide a refinement on the existing MSS on a specialty level, whereas [13] create a new MSS on procedure type level. For a description of these different types of MSSs see Section 3.3.1. We choose this approach because the St. Antonius hospital currently uses an MSS on specialty level and a new MSS on procedure type level is considered to have a low probability of being implemented. Van Oostrum et al. [13] create their cyclical schedule based on the most frequently occurring medically homogenous case types whereas we use case types based on LOS duration. We can therefore capture all elective demand in our model, where [13] disregard infrequently occurring procedures. Contrary to [13] we do not use a probabilistic representation of the surgery duration, because we only use surgery duration to ensure the case mixes resulting from the model are practically feasible within the existing OR time.

The mathematical model is constructed to fit the characteristics of the St. Antonius' Utrecht location but is designed in a broad and general way. This means the model can also be used to optimize the other location of the hospital and potentially other hospitals that face similar planning and scheduling problems. Hospitals that could also benefit from this approach use an MSS on specialty level, on which patients are scheduled onto the first available suitable session without observing the resulting bed requirement.

5.2.1 Input parameters, entities and variables:

Table 5 through Table 7 show the input parameters and indices and the decision variables used in the mathematical model.

Table 5 Input entities

Entities	Set	Index
Cycle horizon	T	t
Operating rooms	J	j
Bed types	B	b
Case types	I	i
Set of ORs j and days t in which specialty i can perform surgery	S^i	j,t

Table 6 Input parameters

Parameters	Notation
Expected surgery duration in minutes needed by case type I	$e_i \in \mathbb{Z}^+$
Capacity of OR j on day t in minutes	$o_{j,t} \in \mathbb{Z}^+$
Demand for case type i	$d_i \in \mathbb{Z}^+$
Probability of case type i being in bed type b after t days	$p_{b,I,t} \in \mathbb{R}, 0 \leq p_{b,i,t} \leq 1$
Maximum number of nights required in bed type b by case type i	$l_{b,I} \in \mathbb{Z}^+$
Priority factor for bed type b, $\sum c_b = 1$	$c_b \in \mathbb{R}, 0 \leq c_b \leq 1$
Setup time in minutes between operations	$St \in \mathbb{Z}^+$
Weight for objective 1	θ_1
Weight for objective 2	θ_2

Table 7 Decision variables

Decision variables	Notation
Number of case types i scheduled in OR j on day t	$V_{i,j,t}$
Maximum demand for bed type b (performance indicator goal 2)	Z_b
Maximum utilisation of all ORs (performance indicator goal 1)	U
Utilisation of bed type b on day t	$ZZ_{b,t}$
Utilisation of OR j on day t	$UU_{j,t}$
Number of setups needed in OR j on day t	$ST_{j,t}$

5.2.2 Mixed Integer Linear Programming model

The objective function minimises two weighted goals: minimizing the peaks in OR utilisation and minimising the peaks in bed demand. Both measures are normalised by expressing them as percentages utilisation. The peaks in bed demand per bed type are determined by dividing the observed peak in bed demand by the theoretical optimal, completely levelled, bed demand. This is comparable to the technique used by [13]. Minimising peaks in OR utilisation might seem counterintuitive since maximising OR utilisation might free up an entire OR that can be closed. In this case however, considering the inherent variation in surgical durations per case type, we want to maximise the unscheduled time per session to maximise the chances an admission planner is able to fill a session according to the desired mix without overtime. Constraint (1) ensures that all demand is scheduled whilst only allowing case types to be scheduled on a day S^i their specialty has OR time. Constraint (2) sets decision variable $ZZ_{b,t}$ to reflect the daily peak in bed demand for each bed type and day. The term t-f in decision variable $V_{i,j,t-f}$ should be read as modulo T to incorporate patients still in a bed at the end of the cycle horizon. Constraint (3) sets decision variable and performance indicator Z_b at the peak of bed demand for bed b over the entire planning horizon, this is comparable to the technique used by [13] to model a minmax objective. Constraint (4) determines the OR capacity needed by all case types scheduled on that day and OR. Constraint (5) ensures that this workload does not exceed the available capacity of the OR on that day. Constraint (6) sets decision variable and performance indicator U such that it reflects the peak in OR utilisation for all ORs in the planning horizon as a percentage compared to full utilisation. Constraints (7) and (8) determine how many setups are needed in an OR per day, which is equal to the number of surgeries minus one if there is more than one surgery scheduled, zero otherwise.

Objective function:

$$Min\ \theta 1 * U + \theta 2 * \sum_{b \in B} \left[\frac{Z_b}{\left[\sum_{i \in I} \sum_{f=1}^{l_{b,i}} p_{b,i,f} * d_i \right] / T} * c_b \right]$$

s.t.

$$\sum_{(j,t)\in S^i} V_{i,j,t} = d_i \qquad \forall i \in I \qquad (1)$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{f=1}^{l_{b,i}} p_{b,i,f} * V_{i,j,(t-f)^*} = ZZ_{b,t} \qquad \forall b \in B, t \in T \qquad (2)$$

$$ZZ_{b,t} \leq Z_b \qquad \forall b \in B, t \in T \qquad (3)$$

$$\sum_{i\in I} e_i * V_{i,j,t} + ST_{jt} * st = UU_{j,t} \qquad \forall j \in J, t \in T \qquad (4)$$

$$UU_{j,t} \leq o_{j,t} \qquad \forall j \in J, t \in T \qquad (5)$$

$$\frac{UU_{j,t}}{o_{j,t}} \leq U \qquad \forall j \in J, t \in T \qquad (6)$$

$$(\sum_{i\in I} V_{i,j,t}) - 1 \leq ST_{j,t} \qquad \forall j \in J, t \in T \qquad (7)$$

$$\sum_{i\in I} V_{i,j,t} \geq ST_{j,t} \qquad \forall j \in J, t \in T \qquad (8)$$

5.2.3 Quadratic Assignment Problem model

As mentioned in Section 2.4 the goal is to minimise variation in the demand for resources. Even though reducing peaks in demand almost certainly also reduces variation in demand, it is not necessarily the case that minimizing the peak in demand also minimises demand variation. To this end we also model the case type scheduling problem as a Quadratic Assignment Problem (QAP), with the objective of minimising the squared deviation from the mean. To do this we make a few changes to the MILP formulation from Section 5.2.2:

Additional decision variable AV_b: the average bed utilisation for bed type b over the cycle horizon

Additional constraint:

$$\frac{1}{T}\sum_{t\in T} ZZ_{b,t} = AV_b \qquad \forall b \in B \qquad (9)$$

Consequently we also adapt the objective function to reflect the new goal:

$$minimise\ \frac{1}{T * B}\sum_{b\in B}\sum_{t\in T}\left(ZZ_{b,t} - AV_b\right)^2$$

5.2.4 Total Daily Capacity (TDC) model

The MILP and QAP model described in Section 5.2.2 and 5.2.3 assign patient volumes to specific ORs on specific days. This could mean that 3 patients with a surgery duration of 150 minutes cannot be assigned to an OR day where a specialty has two, 4-hour, back to back sessions, where in practice these 450 minutes of OR time fit neatly in the 495 minutes of total OR time available. Considering the total OR time a specialty has on a day instead of at the individual ORs gives the model more freedom to assign patient types, which potentially improves the models performance. The likelihood of this to have substantial negative practical implications in phase two is thought to be minimal, especially considering individual OR times can differ from the expected OR duration for that patient's case type. We create a TDC version of both the MILP and the QAP model by substituting constraint (5) with constraint (5'):

$$\sum_{j \in J'} UU_{j,t} \leq \sum_{j \in J'} o_{j,t} \qquad \forall j \in J, t \in T \qquad (5')$$

Where $J' \subset J$ represents a subset of all ORs J that are assigned to a specialty on day t.

5.3 Model output

The output of the model is a matrix with, for each OR j on each day j, the amount of patients per case type to schedule: the case mix matrix. This is the phase one result. Case mix matrices provide the optimal mix and volume of patients to be planned by admission planners in phase two. Figure 5-2 shows an example of a case mix matrix in for a specialty with three case types and a cycle of 14 days.

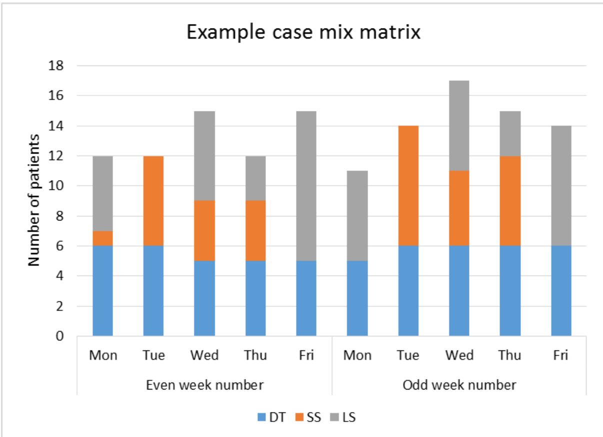


Figure 5-2 Example of a case mix matrix for T=14 days and I=3 (DT=Day Treatment, SS=Short Stay clinical, LS=Long Stay clinical)

5.4 Validating the technical model

It is important that the analysis and the optimization model both produce usable results comparable to practice. In constructing the model regular feedback is obtained from stakeholders inside the hospital to validate the choices and constraints. Involving stakeholders from practice also aids in the creation of awareness and the willingness to accept results produced by the model. The optimisation model is validated by introducing multiple small instances that can also be calculated manually and comparing the results. These checks are executed for different parts of the mathematical model. Results from the model are also manually checked for practical feasibility. The outcome of the model is placed besides the realisation of scheduled patients and cross-checked to see if the patient population, total length of stay and surgery duration match. In all checks the model functions as intended. We recommend the St. Antonius hospital to build a small simulation model to provide an additional validation of the results. Also, more practice validation is needed. Testing the approach in a real life situation can help identify shortcomings in the model or previously unknown restrictions. When implementing this approach we recommend to hold weekly feedback sessions help to validate the model and increase its accuracy.

5.5 Limitations of the approach

There are a number of limitations to the chosen approach. In our approach we can only optimise the scheduling of case types, not the scheduling of actual patients. The properties of individual patients, used in phase two, differ from the expected properties of case types, used in phase one. This variation means the phase two scheduling potentially reduces the improvement potential of the optimisation in phase one.

There are also a number of limitations to the mathematical model. The model simplifies the time of entry and exit, and therefore LOS, in a bed to days instead of hours or minutes. This is believed to be a sufficient level of detail, considering the goal is to schedule case types over weekdays. For sequencing patients within a day we refer the reader to models by [25] [23] [27]. When it comes to the use of OR sessions, the model represents the expected OR-time and expected setup-time needed as a deterministic parameter. The restriction that the expected total case type mix duration in a day may not exceed the available time, forces the model to create mixes that have a high potential to be realised when used by admission planners in planning actual patients. Given the inherent variation in OR-time per individual patient in phase two, it is not necessary to incorporate a higher level of detail in the phase one model. We do need a higher level of granulation when determining the expected LOS per case type to accurately model daily bed requirements. We represent the stochastic LOS variable as deterministic chances of a case type still occupying a bed after t days. Once again, considering the expected LOS distribution per case type most likely differs from the realised LOS of individual patients, this level of granulation is assumed to be sufficient.

At the end of the planning cycle there could be patients still in a bed, while the model assumes all beds are empty at the beginning of the cycle. To capture these remaining patients the model assumes patients who are still in a bed at the last day of the cycle 'continue' in their LOS on the first day of the cycle, by means of a modulo function. This simplification allows us to model the full LOS of all planned patients. The model however cannot take into account the emergency stream of patients, who are by nature not suitable for scheduling in advance. These patients can reduce the improvement potential of the model. Finally, weights for the different bed types and for the two different goals (in case of the MILP model) need to be determined by stakeholders.

6 Intervention 1: Experimental settings & results

Section 6.1 introduces the experimental design to test our approach. The theoretical performance of the mathematical models is tested in Section 6.2. Section 6.3 shows the practical improvements for a single specialty case study by scheduling patients according to the phase one matrices. Section 6.4 introduces the results when incorporating all nine surgical specialties in the Utrecht location.

6.1 Experimental design

In this section we introduce the method to test our approach. Like our approach, the testing is divided into the two phases of the model: creating the case mix matrices in phase one and scheduling patients according to the case mix matrix in phase two. We first do a case study based on a single specialty. We choose to test on one specialty first because it can quickly give an indication of the improvement potential without the need for extensive data analysis. For this case study we choose the orthopaedics (ORT) specialty. We choose ORT for the initial case study because it represents a relatively large proportion of the surgical elective stream. After the ORT case study is completed we extend the scope to an integral planning for all nine surgical specialties: the integral planning (INT) case study.

Figure 6-1 illustrates the experimental design for both phase one and two. In phase one we evaluate the performance of the different types of mathematical model from Section 5.2 compared to a theoretical optimum. In phase two we use the case mix matrices from the best performing model type and evaluate the practical improvement potential it offers in phase two. For evaluating the performance in phase two we test multiple scenarios.

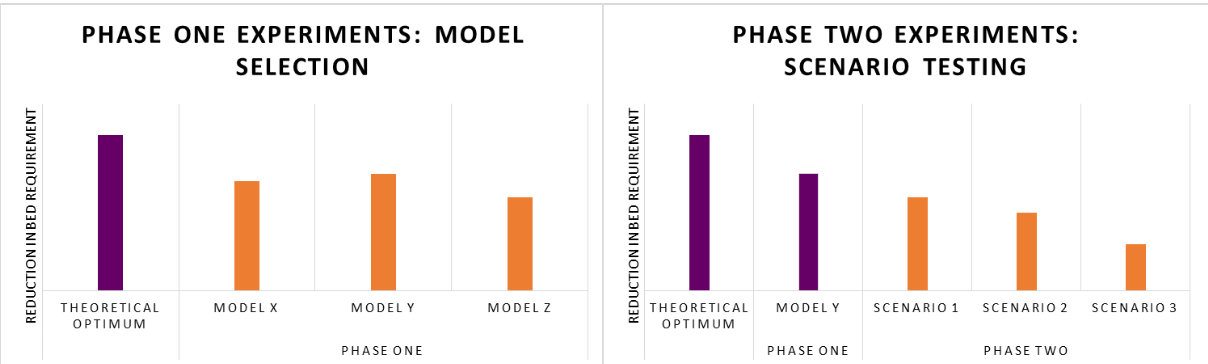


Figure 6-1 Illustration of the 2-phase experimental design

Section 6.1.1 elaborates on the different tests and scenarios, where Section 6.1.2 explains how we determine the input parameters for the mathematical model.

6.1.1 Test instances & scenarios

The detailed description of the test instances scenarios are, once again, split up into the two phases. Phase one and phase two are covered for both the ORT case study and the INT case study.

6.1.1.1 ORT case study: Phase one test instances

In phase one of the ORT case study we evaluate the performance of the different model types using input parameters based on the ORT specialty. We compare the results by scheduling all orthopaedic patients in the observed 12 week period 30-09-2013 to 20-12-2013 according to their realised OR date and the OR dates suggested by all model variants. We also compare the results with the theoretical optimum where demand is spread perfectly over the available capacity. We compare the following instances:

- Realised planning
- Model: MILP variant
- Model: QAP variant
- Model: MILP TDC variant
- Model: QAP TDC variant
- Theoretical optimum

6.1.1.2 ORT case study: Phase two test scenarios

Phase two of the ORT case study consists of assigning individual orthopaedic patients in the 12 week period 30-09-2013 to 20-12-2013 to the OR session according to the mix determined by the best performing phase one model. In the St. Antonius hospital, assigning patients to the OR sessions is a task for the admission planners. There are practical restrictions a planner faces that are not incorporated in the model. For instance not every physician can perform all procedures, combined with a physician roster this means that a patient cannot be assigned to every OR session from that specialty. Certain patients can even only be operated on by one specific physician for medical or personal reasons, called “strict” patients. This planning difficulty has always existed and planners are used to working within this restriction, it might however limit the degree to which the optimal mix from phase one can be adhered to. Therefore, we also need to make sure that the following practice constraints are met:

- We have to assign a patient to an OR within one week of their original OR date, to make sure that no patient is on the waiting list for too long in the new situation
- We cannot overload an OR, once it is filled we have to start on the next session
- We can only assign patients to an OR where there is a physician scheduled that can perform the operation (only in the Strict QAP scenario)

We create three scenarios and test them. These scenarios all use case mix matrices based the case types and the expected length of stay obtained by analysing the Orthopaedics patient population in the period 16-09-2013 to 24-01-2014. The expected demand and available OR time differs per scenario. We test the scenarios with the inputs and models as shown in Table 8. The scenarios are benchmarked against the observed bed demand in the case study period.

Table 8 Scenario inputs and models they are tested with

	Demand	OR schedule	Strict restriction
Standard	Long term expected demand	Basic MSS	No
Custom	Exact demand observed in case study	Realisation of MSS in case study period	No
Strict	Exact demand observed in case study	Realisation of MSS in case study period	Yes

Standard Scenario - In the standard scenario, we use the basic MSS that was in effect in the case study period to determine available OR time, represented in Figure 6-7. We also use the expected 14-day demand obtained by analysing the Orthopaedics patient population in the period 16-09-2013 to 24-01-2014

Custom - Fill the 2 week cycle custom case mix matrix with patients. This is based on the observed demand in the 12 week case study period and accounts for cancelled or added OR sessions. This scenario therefore assumes we can perfectly forecast demand and available OR time.

Strict - Fill the 2 week cycle custom case mix matrix with patients but ONLY with their own physician in case of strict patients. This is again based on the observed demand in the 12 week period and accounts for cancelled or added OR sessions and therefore this scenario also assumes we can perfectly forecast demand and available OR time.

6.1.1.3 INT case study: Phase one test instances

In phase one of the INT case study we evaluate the performance of the two best performing model types in phase one of the ORT case study. We use input parameters based on all nine surgical specialties on the Utrecht location. We compare the results by scheduling all patients in the observed period according to their realised OR date and the OR dates suggested by the model variants. We also compare the results with the theoretical optimum where demand is spread perfectly over the available capacity. We compare the following instances:

- Realised planning
- Model: best performing variant from phase one ORT case study
- Model: second-best performing variant from phase one ORT case study
- Theoretical optimum

6.1.1.4 INT case study: Phase one test scenarios

Unlike phase two of the ORT case study, where we scheduled all orthopaedic patients by hand according to the case mix matrix, we do not schedule patients in the INT case study. Manually scheduling all patients for nine specialties is considered too labour intensive to complete within the timeframe of this research. Alternatively, we compare the factors limiting the improvement potential in the ORT case study with the limiting factors in the INT case study. Comparing these limiting factors enables us to give an indication of the practical improvement potential for the integral planning.

6.1.2 Parameter setting

The phase one needs a number of input parameters. Available *OR time* per day can be found in the hospital information system and in the master surgery schedule. The total population of elective surgical patients is also obtained from the hospital information system, providing information on *demand*, *surgery duration* and *length of stay*. The deterministic expected surgery duration is based upon the assumption that surgery durations follow a lognormal distribution. We make this assumption considering the data has a low predictive value. We fit the data to a lognormal distribution and use the expected value as an estimator for the surgery duration. This logistical information serves as the bases for the creation of case types. The highest aggregation level in the case types will be the specialty to which the patients belong, corresponding with the blocks in the master surgery schedule. The division of patients into subgroups within a specialty is based on the surgery duration and length of stay, with their corresponding stochastic distributions. To illustrate the creation of case types we use the orthopaedic patients as an example.

Creating case types

To distinguish case types in the total orthopaedic-patient population we look at the surgery duration and length of stay of elective orthopaedic patients operated between 16-09-2013 and 24-01-2014. We need to exclude some patients from the population due to special circumstances. First, we have to exclude emergency patients since they cannot be planned in advance. Second, we exclude patients going to ward U001 (children) and U003 (GE) after surgery. These are special isolated wards that do not fall within the scope of this research. This leaves us with 94% of all orthopaedic patients that are suitable for planning using our model. To determine demand for this group we can, due to data issues, only look at patients that have had surgery only once in the reviewed period. We account for the exclusion of multiple-visit patients by marking up the demand to a full 100% using the case type properties based on the single visit patients. It is assumed this leads to an appropriate representation of the patient population that is suitable for planning by our model. The patient population suitable for planning by the model is shown in Figure 6-2.

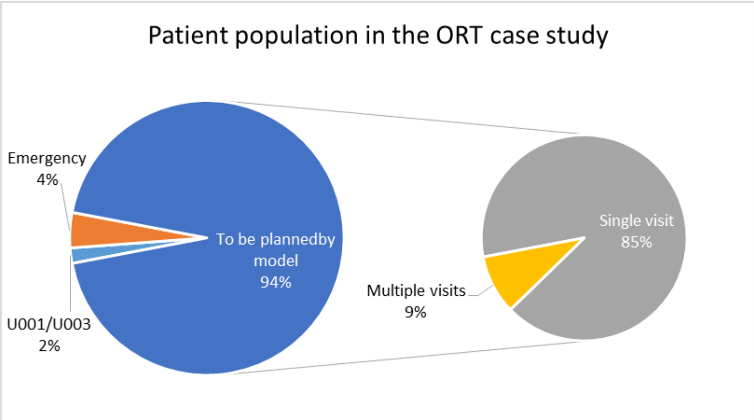


Figure 6-2 Patient population in the ORT case suitable for scheduling by the model - 16-09-2013 to 24-01-2014, n = 1130, source: Hospital IT system

A total of 959 elective orthopaedic patients have been to the OR in this period. Figure 6-3 shows the histogram for both the surgery duration and the length of stay of all patients.

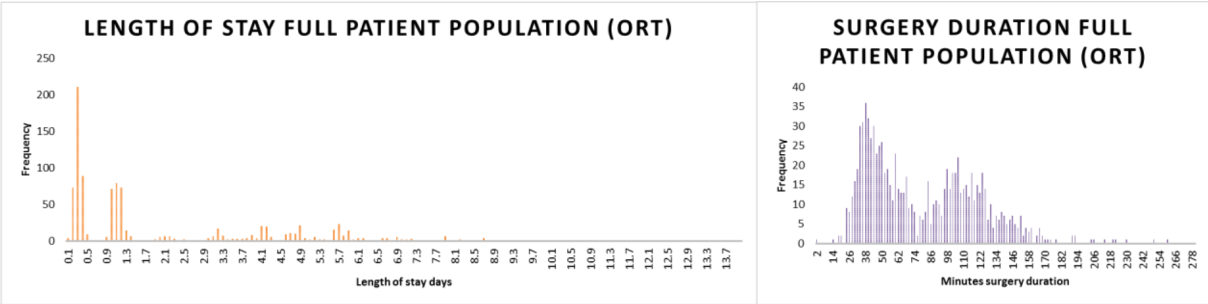


Figure 6-3 Histogram surgery durations and length of stay full orthopaedic patient population - 16-09-2013 to 24-01-2014, n=959 patients

In separating the patient population into case types, we first differentiate to which ward the patients need to go. The day treatment patients go to the day treatment ward and the clinical patients go to ward 4b. There is a clear distinction in the length of stay of clinical patients: patient that stay one night, a length of stay <1,5 days, and clinical patients that stay longer than 1,5 days. This distinction confirmed by the head of ward 4b. When differentiating into these three types, day treatment (DT), short stay clinical (SS) and long stay clinical (LS), we obtain the histograms in Figure 6-4-Figure 6-6. The differentiation into case types is based on an optimum between having enough demand per type and reducing variation in surgery duration and LOS. Also, it is believed that a higher number of case types makes the scheduling task of planners increasingly difficult. When looking at the data in combination with stakeholder preference we end up with the three case types as described.

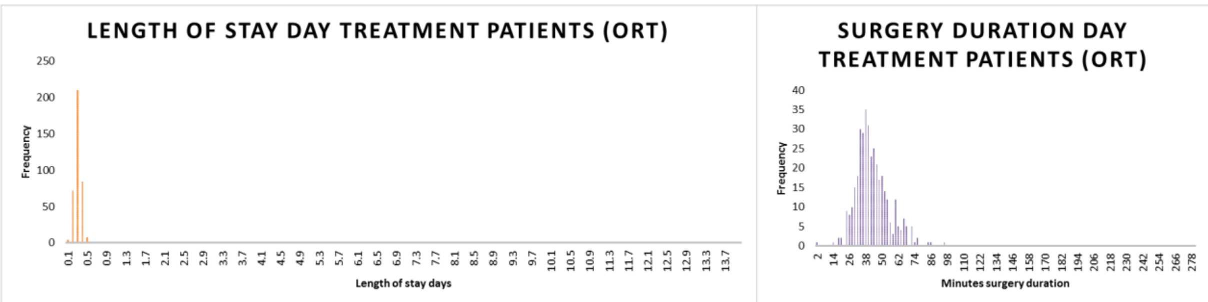


Figure 6-4 Histogram surgery durations and length of stay day treatment orthopaedic patient population - 16-09-2013 to 24-01-2014, n=377 patients

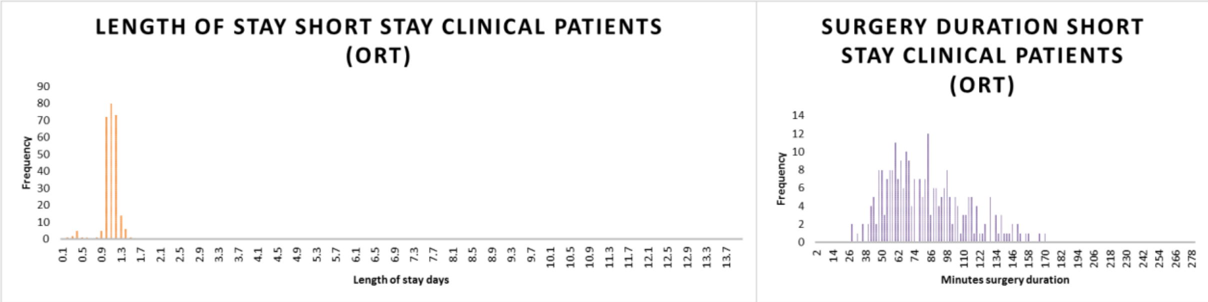


Figure 6-5 Histogram surgery durations and length of stay short stay clinical patients - 16-09-2013 to 24-01-2014, n=260 patients

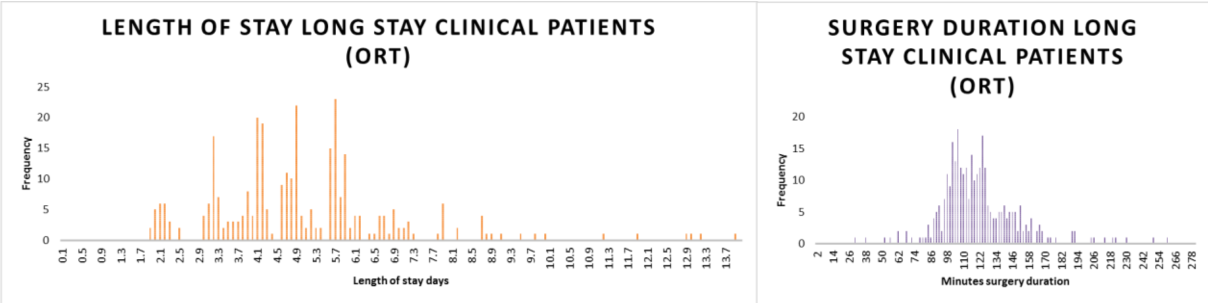


Figure 6-6 Histogram surgery durations and length of stay long stay clinical patients - 16-09-2013 to 24-01-2014, n=322 patients

6.2 ORT case study phase one

In section 6.2.1 we evaluate the performance of the different model types using input parameters based on the ORT specialty. Section 6.2.2 summarises the conclusions from phase one of the ORT case study whereas Section 6.2.3 covers the limitations of phase one of the ORT case study.

6.2.1 Results ORT case study phase one

6.2.1.1 Input parameters

To create a case mix matrix we need to determine the demand, surgery duration and length of stay distribution for each case type. These input parameters, based on the 12 week period 30-09-2013 to 20-12-2013, can be seen in Table 9 and Table 10. Day 1 is defined as the day of surgery. The master surgery schedule (MSS) also needs to be determined. For the orthopaedic specialty there is a two-week cycle MSS. The number of sessions and available time per session can be seen in Figure 6-7.

Table 9 Surgery durations and demand per case type for orthopaedic patients – 30-09-2013 to 20-12-2013, n = 741, source: Hospital IT system

Case types phase one	DT	SS	LS
Demand per 2 week cycle (patients)	46	34	43
Surgery duration (minutes)	41	78	118

Table 10 Percentage of patient still occupying a bed t days after surgery – 30-09-2013 to 20-12-2013, n = 741, source: Hospital IT system

Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14
DT	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
SS	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
LS	100%	100%	93%	81%	59%	38%	15%	8%	5%	3%	2%	2%	1%	0%

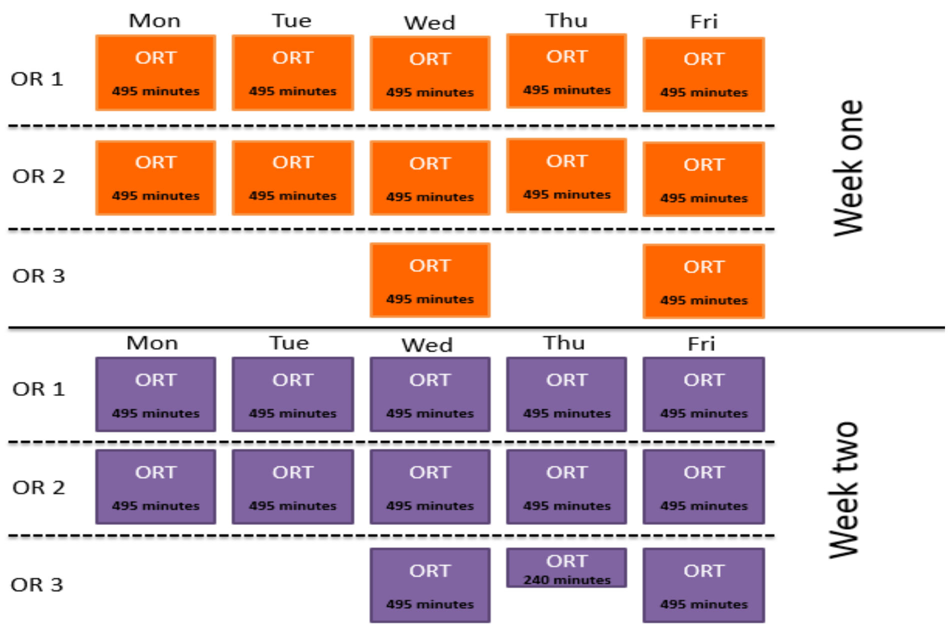


Figure 6-7 Two week session cycle for the orthopaedics specialty

6.2.1.2 Instance testing

Using the input parameter we run the Mixed Integer Linear Problem (MILP), the Quadratic Assignment Problem (QAP) and the TDC version for both models (MILP TDC & QAP TDC). The MILP versions of the model use weight $\theta 1 = 0.1$ for levelling OR utilisation and weight $\theta 1 = 0.9$ for reducing peaks in bed utilisation. The MILP model reaches a 0.2% optimality gap after only 5 seconds, the QAP model reaches an optimality gap of 3.5% after 8 seconds. Both optimality gaps are considered small enough to be acceptable.

The minimal bed requirement is calculated based on the performance indicator as defined in Section 2.4, where we calculate the bed requirement needed to fulfil 95% of all demand. The results can be seen in Table 11. For more accurate comparison of the solutions, we calculate the bed requirement to the nearest decimal.

Table 11 Results for phase one of the ORT case study: instance testing - 30-09-2013 to 20-12-2013, n = 741, source: Hospital IT system & optimisation model

	Realised Planning	MILP	MILP TDC	QAP	QAP TDC	Theoretical Optimum
DT bed requirement	7.6	4.8	4.8	4.8	4.8	4.4
4B bed requirement	20.8	17.9	17.9	17.4	17.4	17.2
DT % reduction		37%	37%	37%	37%	43%
4B % reduction		14%	14%	16%	16%	17%
Total reduction		**20%**	**20%**	**22%**	**22%**	**24%**

It is clear that both QAP and MILP models provide a theoretical benefit to the bed requirement for both the day treatment ward and ward 4b. The QAP model provides an additional 2% reduction in bed requirement. It can be seen that the TDC version of the models do not lead to additional reductions. This can be explained by the fact that we are only able to schedule 85% percent of the total surgical orthopaedics patient population. This means there is some spare time in each OR session which gives the model the same flexibility in scheduling case types as the TDC version does. We therefore do not investigate the TDC variant any further. When looking at the variation, there are also notable differences for both wards. Figure 6-8 shows the results, where it can be seen that both the QAP and the MILP model significantly reduce variation in bed demand and that the QAP model again outperforms the MILP model.

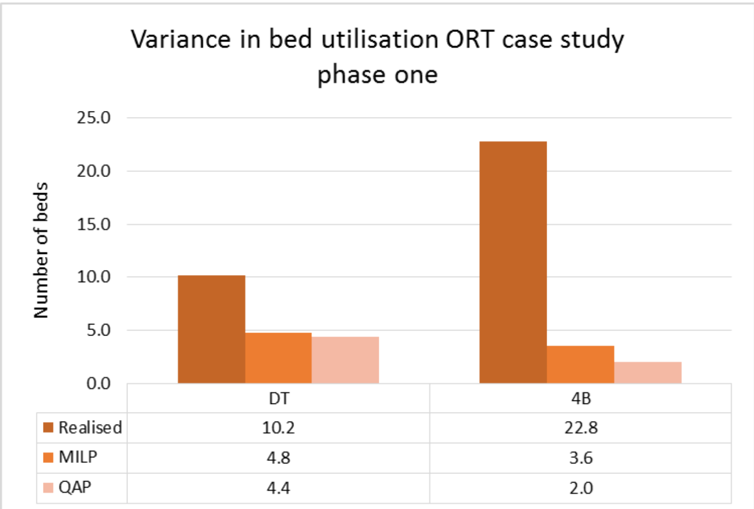


Figure 6-8 Variation in bed utilisation for the different scenarios in phase one of the ORT case study - 30-09-2013 to 20-12-2013, n = 741, source: Hospital IT system & optimisation model

When comparing the QAP and the MILP model in terms of daily bed utilisation on the Day Treatment and ward 4b we obtain Figure 6-9 and Figure 6-10. It can be seen that both model instances provide a more stable and predictive pattern, confirming the model's ability to reduce variation and increase its performance on the key performance indicator.

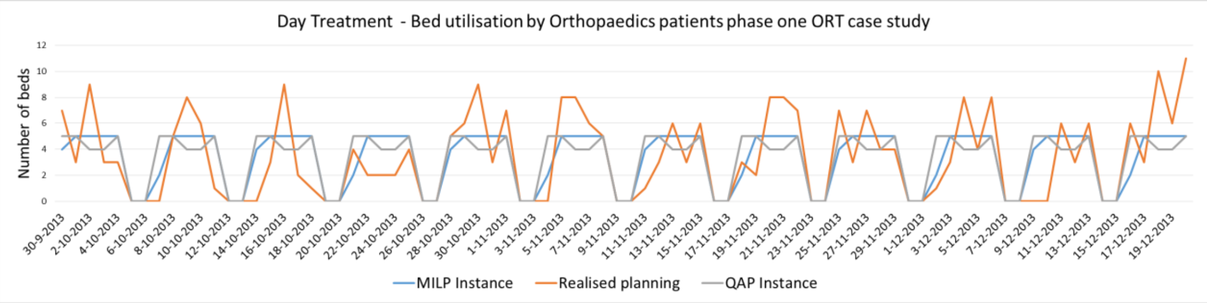


Figure 6-9 DT - Bed utilisation by Orthopaedics patients ORT case study phase one - 30-09-2013 to 20-12-2013, n = 741, source: Hospital IT system & optimisation model

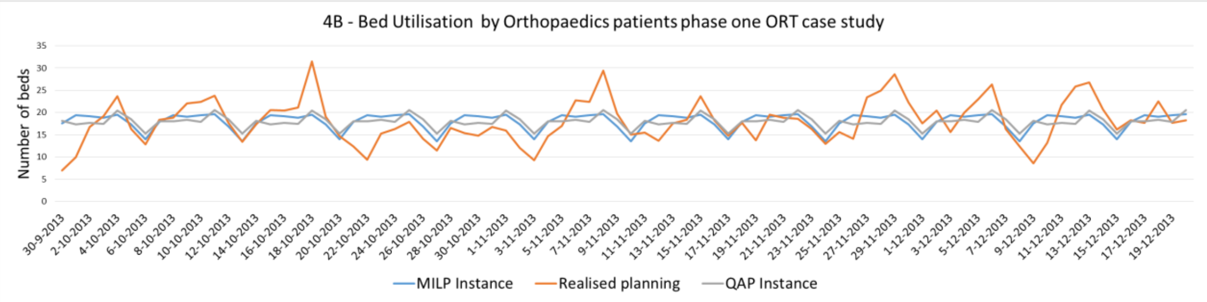


Figure 6-10 4b - Bed utilisation by Orthopaedics patients instance testing - 30-09-2013 to 20-12-2013 n = 741, source: Hospital IT system & optimisation model

The performance of both models is also evaluated with regard to the OR utilisation. Figure 6-11 shows the OR utilisation per day for the ORT case study for both the QAP en the MILP model, where Figure 6-12 shows the coefficient of variation for the OR utilisation. It can be seen that both models create more variation in OR utilisation than the realised situation.

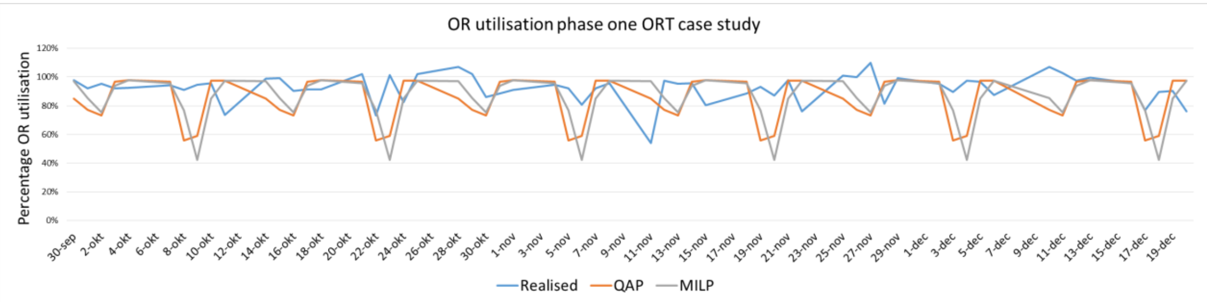


Figure 6-11 OR utilisation per day resulting from phase one of the ORT case study - 30-09-2013 to 20-12-2013 n = 264, source: Hospital IT system & optimisation model

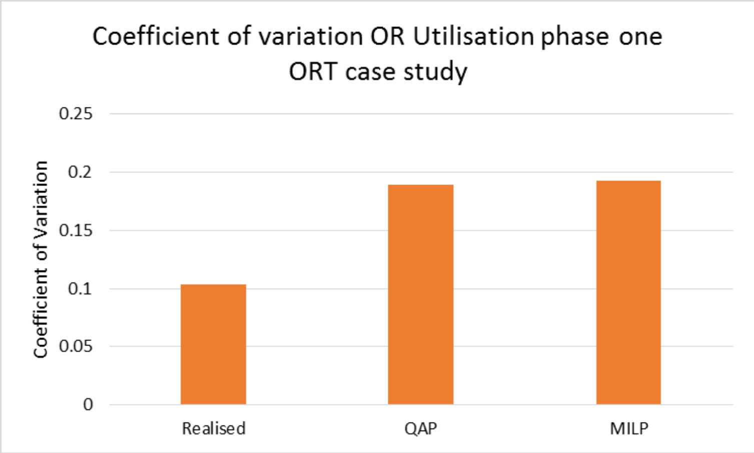


Figure 6-12 Coefficient of variation OR utilisation phase one ORT case study - 30-09-2013 to 20-12-2013 n = 264, source: Hospital IT system & optimisation model

6.2.2 Conclusions ORT case study phase one

The model is able to plan the patients in such a way that the variation in bed demand is reduced. The model also reduces the minimum bed requirement, where the QAP outperforms the MILP and the TDC variant of both models does not offer additional benefits, as can be seen in Figure 6-13. The model is able to plan the case types in such a way that the bed utilisation approaches the theoretical optimum. The OR utilisation resulting from the model shows a higher variation than in the observed situation, indicating that optimising bed utilisation has a negative effect on the variation in OR utilisation.

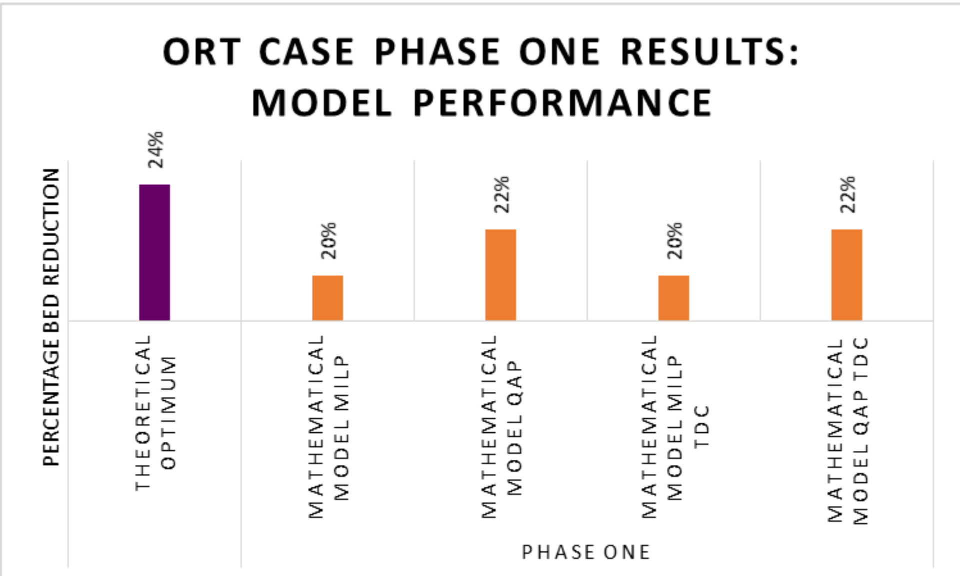


Figure 6-13 ORT case study phase one results: model performance

6.2.3 Limitations ORT case study phase one

There are a number of assumptions and limitations in phase one of the model that need to be addressed when reflecting on the results. First, we assume for the entire case study period that every 14-day cycle has the same MSS. In practice reduction periods and session-changes create slightly different MSSs every week. In phase one we also assume that a patient can be assigned to any session from a specialty in the MSS that patient belongs to. In practice some patients can only be assigned to a session where a specific physician is scheduled, called strict patients. Regarding the case types, there is only limited data available to base the sub-grouping, demand forecasting, expected LOS and expected surgery duration on. In phase one we assume all patients within a case type have the same expected LOS and surgery duration and that we can perfectly forecast demand. Due to the limited data set the chances increase that the demand forecast, expected surgery duration and expected LOS do not coincide with properties of the future patient population. Finally, we base the case types on LOS alone. This decision means that the variation of surgery duration within a case type is higher than when the case types are divided further to include subgroups based on surgery duration.

6.3 ORT case study phase two

In section 6.3.1 we evaluate the practical performance of the phase one case mix matrices. Section 6.3.2 summarises the conclusions from phase two of the ORT case study whereas Section 6.3.3 covers the limitations of phase two of the ORT case study.

6.3.1 Results ORT case study phase two

6.3.1.1 Input parameters

In phase two we schedule all orthopaedic elective demand for the wards within the scope of this research, this represents 94% of the total Orthopaedics patient population as can be seen in Figure 6-2. The expected 14-day demand can be seen in Table 12. These demand figures are used in the “standard” scenario, just as the MSS in Figure 6-7. The other scenarios use week-specific demands and week-specific OR schedules. The surgery durations are the same as in phase one (see Table 9).

Table 12 Expected 14-day case type demand - 16-09-2013 to 24-01-2014 n = 959, source: Hospital IT system

Case type demand phase two	DT	SS	LS
Demand per 2 week cycle (patients)	55	38	47

6.3.1.2 Scenario testing

Scheduling patients to the sessions according to the case mix matrix prescribed by the models within one week of their original OR date did not pose substantial issues, even with the restriction of roughly 60% of the orthopaedic patients being strict. In this most restricted planning scenario we were able to plan 67% of the days exactly according to the case mix matrix and in total only had to deviate 5,5% from the prescribed case mix matrix. This means an admission planner is able to plan most patients according to the preferred mix. Figure 6-14 to Figure 6-16 show the case mix scheduled on the OR for the realised situation, the theoretically optimal case mix and the case mix as planned in phase two for the two week period 4-11-203 to 15-11-2013. It can be seen that the case mix resulting from planning using the matrix is a closer match to the theoretical optimal mix than the realised case mix.

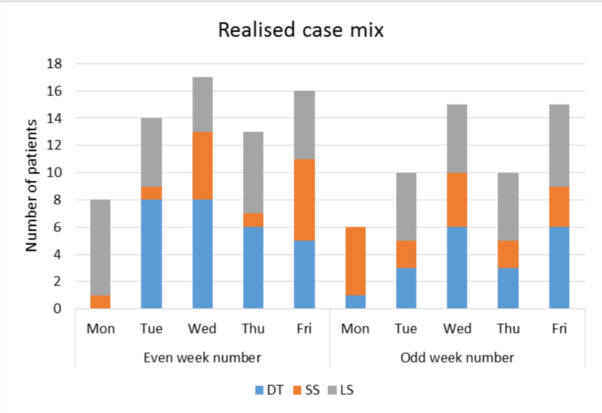


Figure 6-14 Observed (actual) scheduled case mix - 4-11-2013 to 15-11-2013, n = 78, source: Hospital IT system

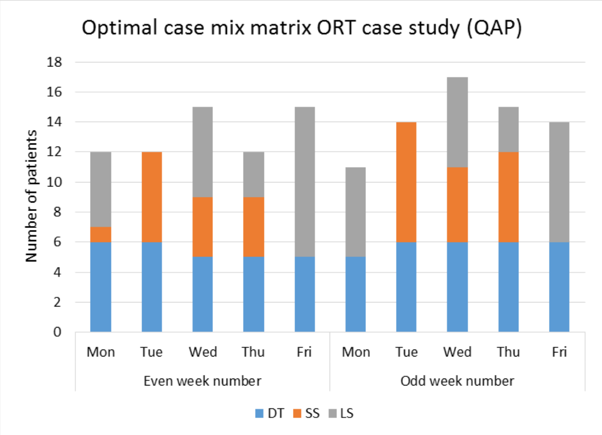


Figure 6-15 Optimal case mix matrix according to the QAP model based on observed case study demand and realised OR sessions

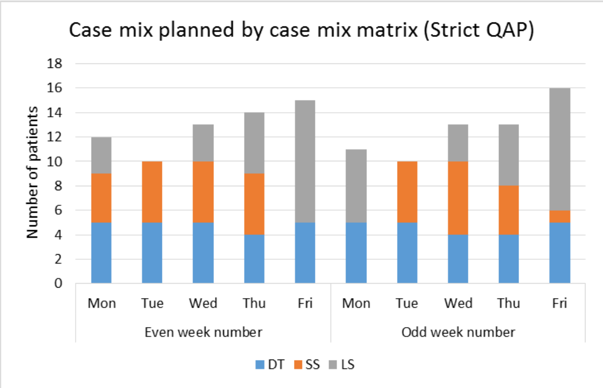


Figure 6-16 Case mix resulting from scheduling patients to OR sessions. Restrictions: OR time, strict patients and no more than one week from original OR date

The results of scheduling the patients according to the different matrices can be seen in Table 13. It is clear that the added restrictions in phase two, and the deviations between expected and observed length of stay reduce the improvement potential.

Table 13 Results for phase two of the ORT case - 30-09-2013 to 20-12-2013, n = 741, source: Hospital IT system & optimisation model

	Realised Demand	Standard MILP	Standard QAP	Custom QAP	Strict QAP	Theoretical Optimum
DT bed requirement	7.6	5	5.3	4.9	5.1	4.4
4B bed requirement	25.2	23.9	23.4	22.9	22.7	20.7
DT % reduction		34%	30%	36%	33%	42%
4B % reduction		5%	7%	9%	10%	18%
Total		12%	13%	15%	15%	23%

Figure 6-17 shows the variation for both wards and all scenarios. Again it is clear that the model reduces variation in bed demand, and that the QAP model outperforms the MILP model.

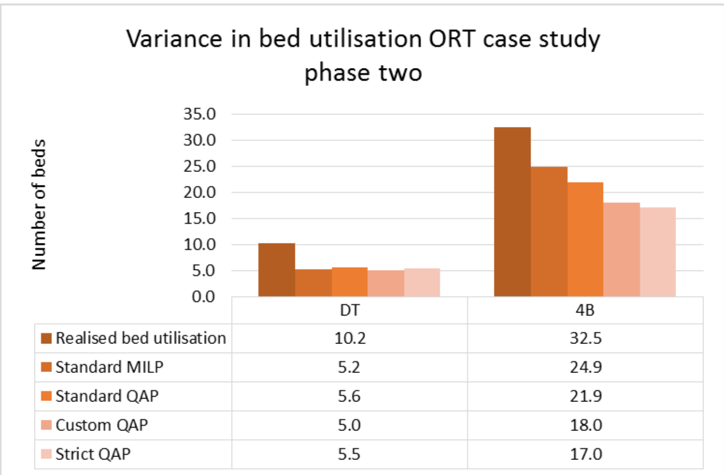


Figure 6-17 Variation for the different scenarios in phase two of the ORT case study - 30-09-2013 to 20-12-2013, n = 741, source: Hospital IT system & optimisation model

When looking at daily bed utilisation on the Day Treatment and ward 4b resulting from planning according to the case mix matrix we obtain Figure 6-18 and Figure 6-19. It can be seen that filling the case mix matrices from phase one with actual patients provides a more stable and predictive pattern than the observed bed utilisation, confirming the models' ability to reduce variation and increase its performance on the key performance indicator.

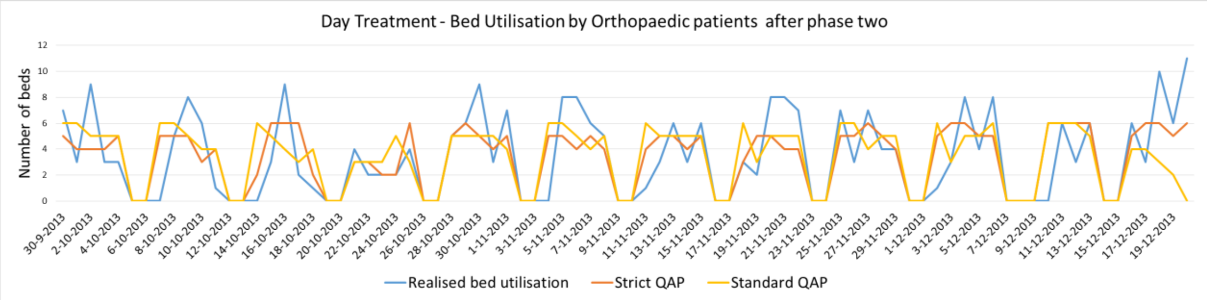


Figure 6-18 DT - Bed utilisation by Orthopaedics patients after phase two ORT case study - 30-09-2013 to 20-12-2013 n = 741, source: Hospital IT system & optimisation model

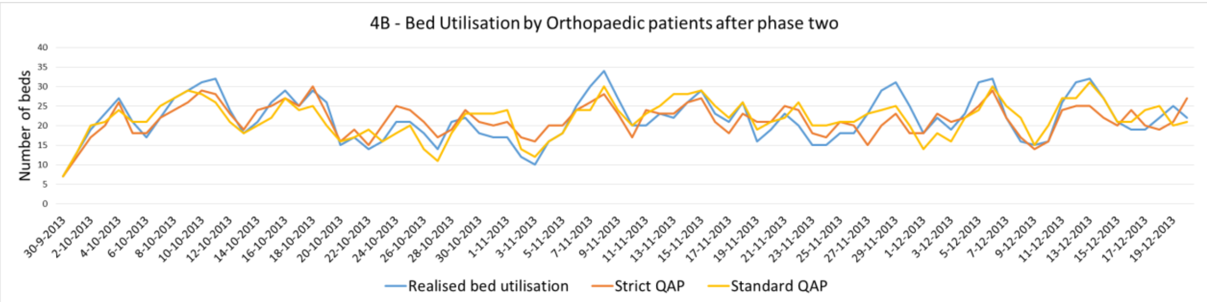


Figure 6-19 4b - Bed utilisation by Orthopaedics patients after phase two ORT case study - 30-09-2013 to 20-12-2013 n = 741, source: Hospital IT system & optimisation model

The performance of both models is also evaluated with regard to the OR utilisation. Figure 6-20 shows the OR utilisation per day for the ORT case study for both the QAP en the MILP model after scheduling patients according to the case mix matrices, where Figure 6-21 shows the coefficient of variation for the OR utilisation. It can be seen that the using case mix matrices creates more variation in OR utilisation than the realised situation, but that a large portion of the variation in OR utilisation is reduced in phase two compared to phase one.

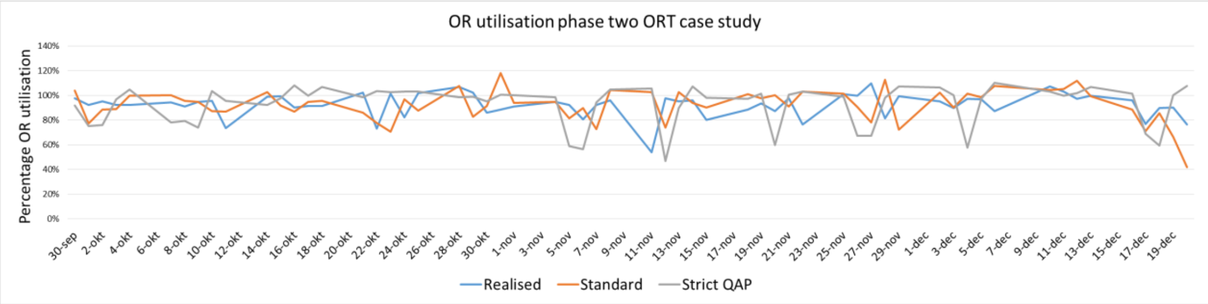


Figure 6-20 OR utilisation per day resulting from phase two of the ORT case study - 30-09-2013 to 20-12-2013 n = 264, source: Hospital IT system & optimisation model

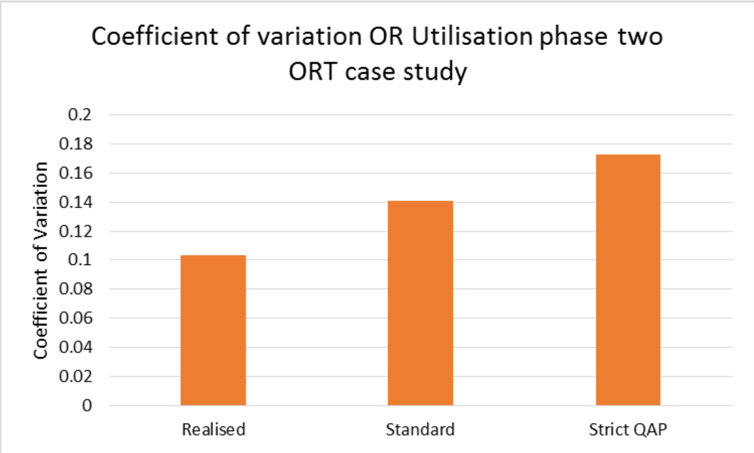


Figure 6-21 Coefficient of variation OR utilisation phase two ORT case study - 30-09-2013 to 20-12-2013 n = 264, source: Hospital IT system & optimisation model

6.3.2 Conclusions ORT case study phase two

It is to a high degree possible to schedule individual patients to OR sessions according to the prescribed matrix, whilst staying within the constraints of the total OR-time, original OR date of the patient and strict patients. The use of case mix matrices results in reduced variation in bed demand for all phase two scenarios, but do not meet the expectations raised by the phase one model results, as can be seen in Figure 6-22. This is due to deviations in the MSS, surgery duration, LOS and demand per case type compared to the expected value. In case of the strict scenario there are also additional scheduling limitations.

The custom matrices based on the observed demand and the realised MSS perform better than the general matrices based on forecasted demand and the base MSS. We therefore conclude that accurate forecasting of input parameters plays a vital role in the effectiveness of the case mix matrix. We also conclude that it is much more difficult to achieve the improvement potential put forth by the model on ward 4b than it is on the Day Treatment. This is partly explained by the higher variability in LOS for long stay clinical patients but also because a longer LOS means reduction periods have a higher impact on ward 4b. The variation in utilisation of OR sessions increases slightly in the new situation, once again indicating that variation reduction in bed demand causes increased variation in OR utilisation.

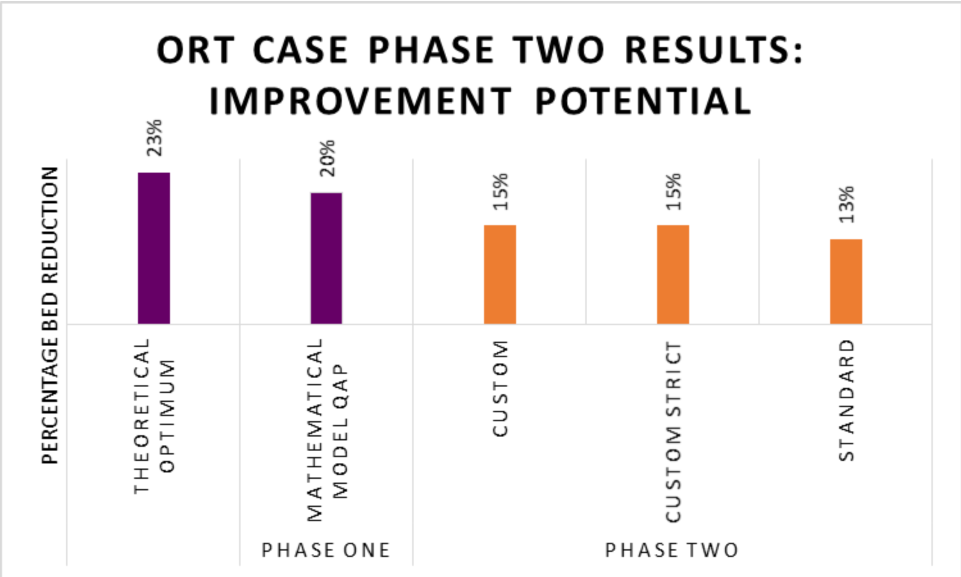


Figure 6-22 ORT case study phase two results: improvement potential

6.3.3 Limitations ORT case study phase two

There are several limitations to phase two of the ORT case study. First, the model used case type properties based on patients who only visited the hospital once in the analysed period and assumes the same properties hold for the multiple-visit patients. Second, we planned the patients a week from their original OR date, not as soon as possible after the date they were ready to be operated on. This data is not available from the hospital information system. This planning method does not necessarily reflect the order in which the admission planners scheduled the patients originally and therefore makes the comparison with the realised situation less accurate. Also, the scheduling of patients is not an exact science. The schedule we made, based on the data, is feasible but does not reflect all daily factors influencing the schedule, such as patient preference for a date and personal preference of physicians. These factors potentially reduce the improvement potential of the case mix matrices. Finally, in the case of the orthopaedics specialty around half of the patients get an OR-date directly instead of being placed on the waiting list. The admission planner therefore has less flexibility in selecting the right patients to be able to get close to the preferred case mix. The practical implications of this restriction need to be determined in the implementation process.

6.4 INT case study

This section covers experiments that include all nine surgical specialties on the Utrecht location. As mentioned in the experimental design we test phase one for the INT case study the same way we did in the orthopaedics case study, and then see if the limiting factors in phase two of the INT case study are comparable to the limiting factors in the ORTs case study. If the limiting factors are comparable we assume we can extrapolate phase two results for the ORT case study to the INT case study.

6.4.1 Results INT case study phase one

6.4.1.1 Input parameters

Appendix F shows the following input parameters for the model describing all nine surgical specialties, containing the general day treatment beds and wards 4a, 4b, 5a & 5b:

- Base Master Surgery Schedule
- Case types per specialty and their designated ward
- Forecasted demand per case type
- Expected length of stay per case type
- Expected surgery duration per case type

Not all specialties have three case types like the ORT case study. Some specialties, for instance, only have day treatment patients. How many case there are per specialty can be seen in Appendix F.

6.4.1.2 Instance testing

Influence of integral approach

Contrary to the ORT case study, we now aim to simultaneously minimise variation in bed demand for all nine surgical specialties operating in the Utrecht location. Considering that all specialties jointly use three wards, this means scheduling activities of one specialty needs to be synchronised with other specialty’s planning activities. The impact of the integral approach compared to the stand-alone approach from the ORT case study is shown in Figure 6-23-Figure 6-25. Integral optimisation noticeably changed the optimal matrix for the orthopaedics specialty compared to the single-specialty optimisation in the ORT case study, indicating the substantial impact the schedules have on each other and advocating the use of an integral systems approach in these types of optimisation projects. When looking at the total case mix for the surgical specialties on the Utrecht location in Figure 6-25, there is once again a clear parallel in case mix patterns with the ORT case study case mix. The case mix matrices for all nine specialties in the integral optimisation can be seen in Appendix G.

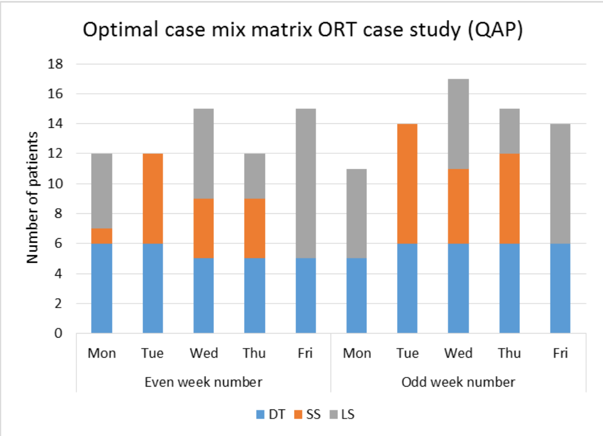


Figure 6-23 Optimal case mix in the ORT case study (QAP model)

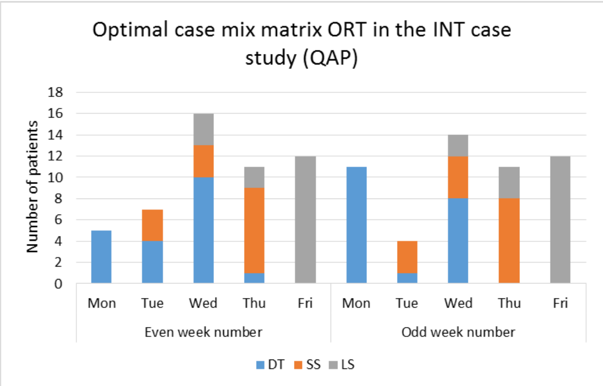


Figure 6-24 Optimal case mix for the orthopaedics specialty using integral optimisation of the Utrecht location (QAP model)

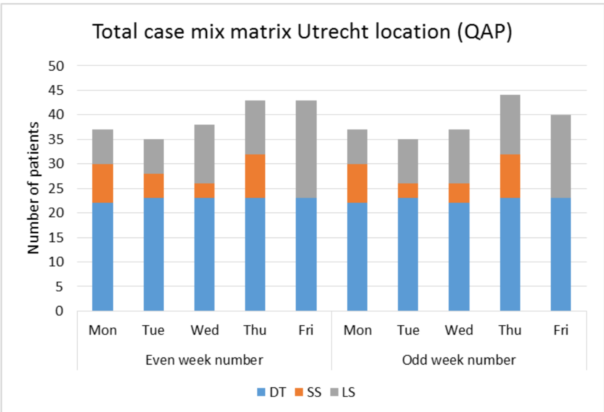


Figure 6-25 Optimal case mix for all 9 specialties combined in the INT case study (QAP model)

Impact on bed utilisation

Running the MILP and QAP model for INT case study provides the results shown in Table 14. The MILP model reaches s 3.0% optimality gap after only 4 seconds, the QAP model reaches a 0.2% optimality gap after 2.4 seconds.

Table 14 Results INT case study MILP and QAP model – 16-09-2013 to 18-03-2014, n = 1656, Source = Hospital IT system & optimisation model

	Realised planning	MOD MILP	MOD QAP	Theo opt
Beds DT	28.1	21.7	21.6	21.6
Beds 4A	13.3	8.9	8.7	6.6
Beds 4B	21.6	17	16.7	16.4
Total beds	**63**	**47.6**	**47**	**44.6**
% impr DT		23%	23%	23%
% impr 4A		33%	35%	51%
% impr 4B		21%	23%	24%
% impr TOT		**24%**	**25%**	**29%**

These results are similar to the phase one results in the ORT case study and show potential for improving the current method of planning by using case mix matrices.

Figure 6-26 shows the variance in bed utilisation resulting from testing the INT case study. The variance once again shows the same pattern as the ORT case study.

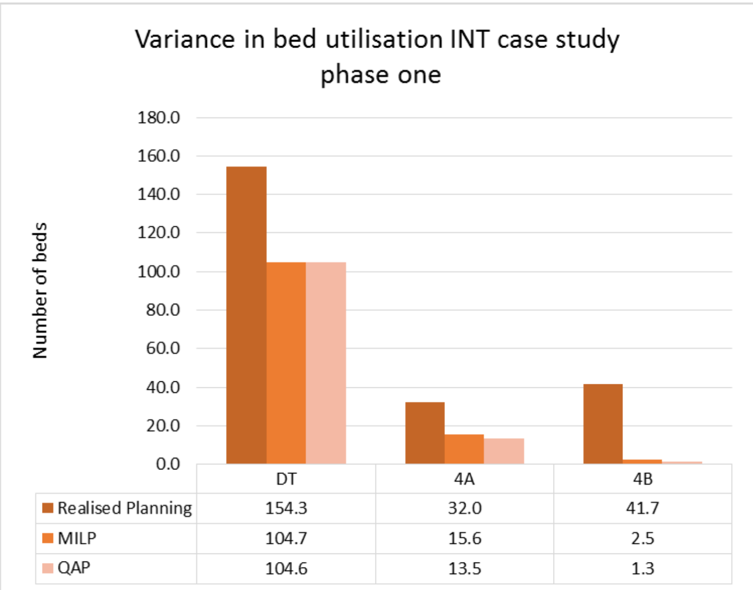


Figure 6-26 Variation for the different scenarios in phase one of INT case study - 16-09-2013 to 18-03-2014, n = 1656, source: Hospital IT system & optimisation model

Figure 6-27 to Figure 6-29 show the bed utilisation by the planned patient population for all three wards. Again the patterns are comparable with those seen in phase one of the ORT case study.

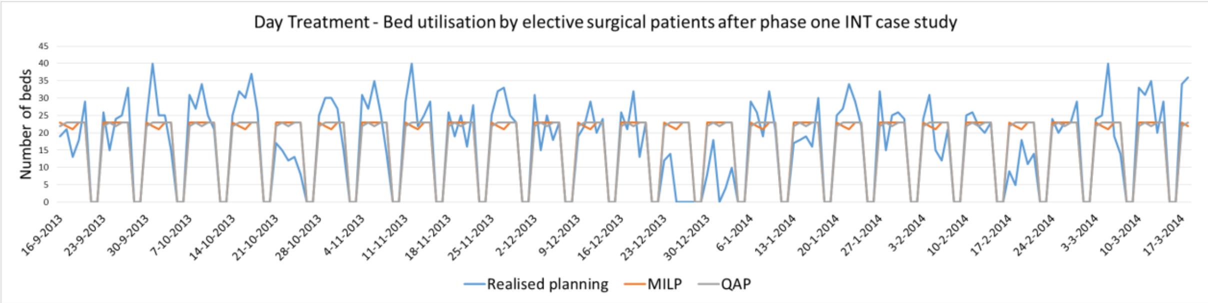


Figure 6-27 DT - Bed utilisation by elective surgical patients after phase one of the INT case study - 16-09-2013 to 18-03-2014, n = 1656, source: Hospital IT system & optimisation model

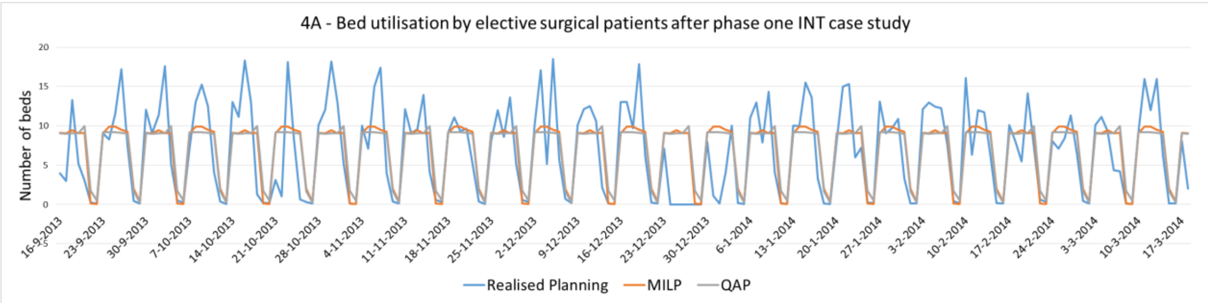


Figure 6-28 4a - Bed utilisation by elective surgical patients after phase one of the INT case study - 16-09-2013 to 18-03-2014, n = 1656, source: Hospital IT system & optimisation model

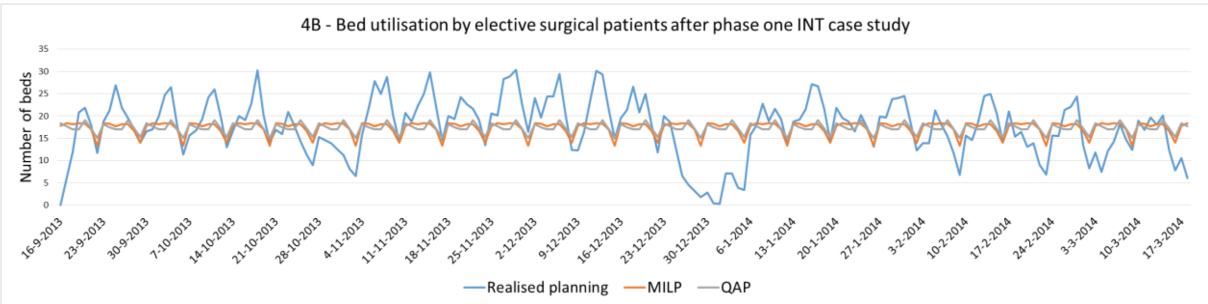


Figure 6-29 4b - Bed utilisation by elective surgical patients after phase one of the INT case study - 16-09-2013 to 18-03-2014, n = 1656, source: Hospital IT system & optimisation model

6.4.2 Results INT case study phase two

The phase one results show similar improvement potential for the ORT case study and the INT case study. In the ORT case study however we saw that phase two reduces the improvement potential due to a number of variables. For the following variables we compare the ORT case study with the INT case study:

- Percentage of patient population suitable for planning by model
- Percentage strict patients
- Percentage of patients scheduled from waiting list
- Variation in surgery duration

We assume the degree of variation in expected demand, LOS and MSS are comparable to the ORT case study.

Percentage of patient population within the scope of this research

In the ORT case study we were able to plan 94% of all patients using the case mix matrix. The more patients suitable for planning by the model the closer a ward can get to the improvement potential indicated by the model. In total 76% of all patients are suitable for planning in the INT case study, considerably less than in the ORT case study. However if we take the large volume of children (U001) out of the calculation, considering they go to the stand alone children's ward, we end up with just under 92% of the patients suitable for planning, comparable to the ORT case study. Please note that the children still require OR-time, they only get excluded from the calculation because they do not go to a ward that falls within the scope of this research. See Table 15 for the detailed percentages.

Table 15 percentage of patients suitable for planning by the model - 16-09-2013 to 18-03-2014, n = 9036, source: Hospital IT system

	Scheduled by model		Not scheduled by model		Total
	Percentage	# patients	U001&U003	Emergency	Population
KCH	74%	110	28	11	149
CHI	79%	1034	77	203	1314
GYN	88%	288	2	36	326
KNO	46%	1161	1315	67	2543
OOG	89%	1879	35	193	2107
ORT	94%	1491	34	59	1584
PCH	88%	257	26	8	291
URO	84%	367	46	24	437
NCH	93%	266	2	17	285
Total	**76%**	**6853**	**1565**	**618**	**9036**

Percentage strict patients

The more patients categorised as strict, the less flexibility an admission planner has in scheduling patients. A large percentage of strict patients therefore reduces the chances of adhering to the case mix matrix which in turn reduces the improvement potential. In the ORT case study, the patient population consists of around 60% strict patients and 40% pool patients who could be operated by any physician of the specialty. Figure 6-30 shows that in total for all specialties around 41% of the population is strict and 59% is pool, meaning more flexibility than in the ORT case study. Three specialties with a high percentage of strict patients, KCH, PCH and NCH, potentially create problems for the admission planner. These specialties together however represent less than 10% of the patients suitable for planning by the model (see Table 15).

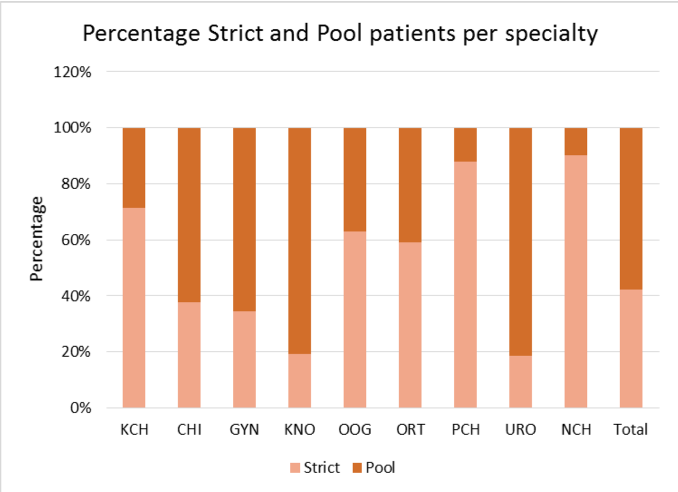


Figure 6-30 Percentage strict and pool patients per specialty - 16-09-2013 to 18-03-2014, n = 9036, source: Hospital IT system

Variation in surgery duration

The higher the variation in surgery duration the smaller the chances of adhering to the case mix matrix, considering the matrix is based on the deterministic expected surgery duration. To be able to compare the variation in surgery duration, we use the coefficient of variation. Figure 6-31 shows that the average coefficient of variation for all specialties in Utrecht is smaller than the coefficient of variation for orthopaedic surgery durations across all three case types. This indicates that variation in surgery duration is less of a restriction in the INT case study than in the ORT case study.

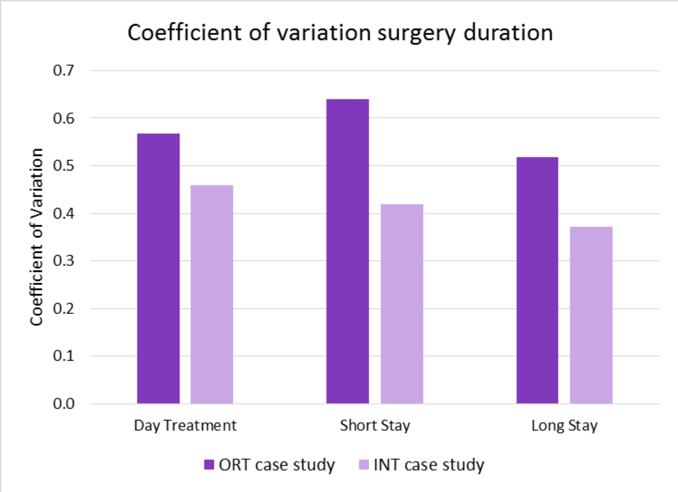


Figure 6-31 Coefficient of variation for the surgery duration - 16-09-2013 to 18-03-2014, n = 9036, source: Hospital IT system

Percentage of patients scheduled from waiting list

The percentage of patients scheduled from the waiting list indicates a planning degree of freedom for admission planners. When all patients are scheduled from the waiting list, an admission planner can carefully select suitable patients to 'fill the gaps' in the OR-schedule whilst adhering to the case mix matrix. If all patients are walk-in and need an OR date immediately this is no longer an option. As mentioned in the case study limitations (see Section 6.3.3) it is not possible to replicate this effect retrospectively. This effect therefore reduces the improvement potential for both the ORT case study and the INT case study. Figure 6-32 shows these percentages for all specialties. Further research is needed to determine whether or not these figures significantly reduce the improvement potential.

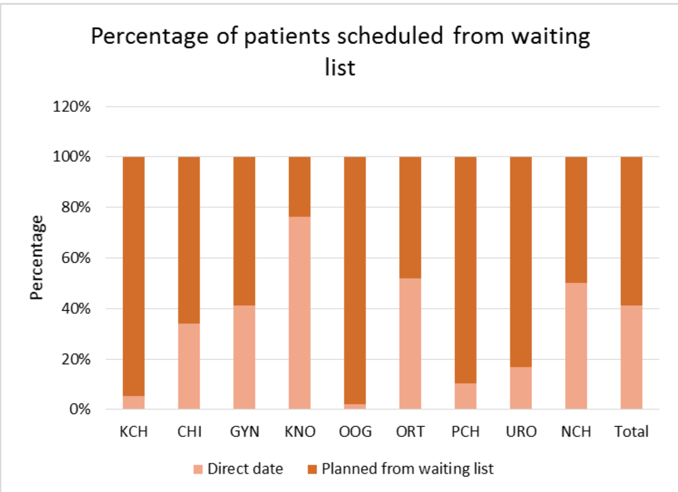


Figure 6-32 Percentage of patients scheduled from waiting list – 27-03-2014 to 26-03-2014, n = 973, source: registration list preoperative screening

6.4.3 Conclusion INT case study

We conclude that the percentage of patients suitable for planning introduces a comparable limitation in both case studies. The number of strict patients provide less of a limitation for the INT case study, as does the variation in surgery duration. The limitation posed by the "percentage of patients scheduled from the waiting list" is unclear but the data reveals this factor to be comparable for both case studies. We therefore conclude that it is reasonable to assume the improvement potential seen in the ORT case study is also obtainable for the INT case study. If we assume a comparable improvement potential for phase two of the INT case study as we have seen in phase two of the ORT case study, we expect the improvement potential from Table 16 for using case mix matrices to plan elective surgical patients in the Utrecht location of the St. Antonius hospital.

Table 16 Expected improvement potential for using case mix matrices to schedule elective surgical patients

Expected practical improvement potential	Realised planning	Long term forecasting	Perfect forecasting	Theoretical optimum
Total bed requirement	**63**	**56**	**54**	**45**
Bed reduction		**7**	**9**	**18**
% impr TOT		**12%**	**15%**	**29%**

6.5 Conclusions

In phase one it is possible to plan patients in such a way that theoretical variation in bed demand is reduced. The models are also able to theoretically plan the case types in such a way that the bed utilisation approaches the theoretical optimum. The results can be seen in Figure 6-33.

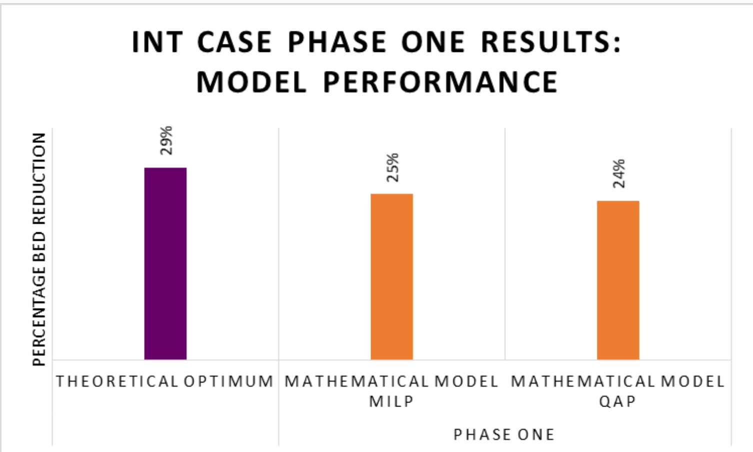


Figure 6-33 Model performance for planning elective surgical patients using case mix matrices

In phase two we find it is possible to schedule individual patients to OR sessions according to the prescribed theoretically optimal case mix, whilst reducing variation in bed demand. During the planning of patients in phase two, we find the improvement to be lower than the theoretical performance of the model due to the following causes:

- There are patients who can only be operated on by a specific physician (strict patients)
- Not all patients are planned from the waiting list, some require an OR-date immediately
- There is variation in surgery duration
- There is variation in demand
- There is variation in Length of stay
- There are variations on the basic MSS

The first two causes reduce the flexibility planners have in scheduling patients. We identify strict patients as the largest restriction to adhere to the case mix matrix. The percentage of strict patients therefore must be as low as possible to reach the highest improvement potential. The last four causes are model inputs that determine the degree to which the models correctly represent reality. The better these inputs forecast reality the more effective the case mix matrix are. Considering the limiting factors are comparable between the ORT case and the INT case, we expect our model to have the improvement potential seen in Figure 6-34 for using case mix matrices to plan elective surgical patients in the Utrecht location of the St. Antonius hospital.

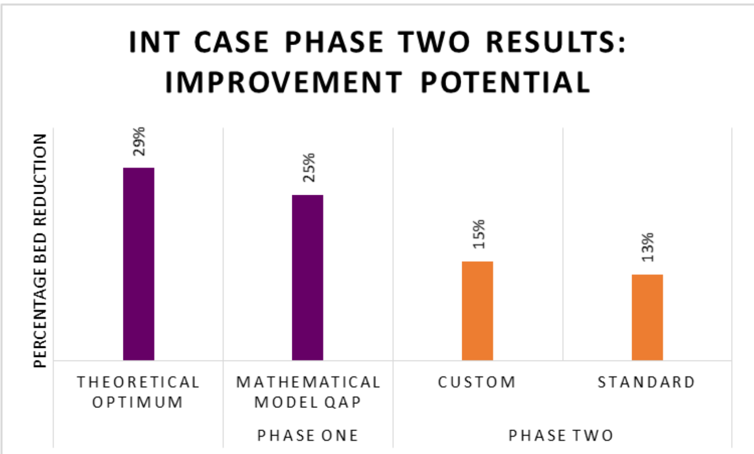


Figure 6-34 Practical improvement potential for planning elective surgical patients using case mix matrices

7 Interventions for reacting to incoming bed demand

This chapter describes interventions 2-6, selected in Chapter 4 (see Table 4) for better reacting to incoming bed demand. Because it is not reasonable to assume we can completely level the inflow of the elective stream, we introduce five interventions that are suitable to increase the capability of a ward to handle the remaining variation in inflow of elective surgical patients. First, we identify two interventions to create more capacity on the wards during peaks in bed demand. Second, we identify two interventions to increase the free bed capacity per ward at all times. Third we identify the preconditions that need to be satisfied for the interventions to be successful. Each section covers one improvement intervention and Section 7.6 summarises the conclusions of this chapter.

7.1 Intervention 2: Admitting patients after surgery

The current practice of admitting patients on a bed before surgery means that patients wait for surgery in a bed instead of in a waiting area, creating peak moments in bed demand. Stakeholders mention a high percentage of the patients do not need a bed for medical reasons before surgery and some patients actually feel uncomfortable being admitted to a bed at such an early stage. Admitting a patient only after surgery, when it is actually medically necessary, frees up that bed for the whole duration of pre-surgery waiting and the time spent in the holding and the OR. Admitting patients after surgery is an intervention for *peak reduction*. Section 7.1.1 illustrates the effect of admitting patients after surgery for the Day Treatment ward, whereas Section 7.1.2 illustrates this effect for ward 4b.

7.1.1 Day treatment

On the day treatment ward, which has a high turnover, the second ‘wave’ of patients arriving on the ward need a bed while the first wave patients are still in a bed. Admitting day treatment patients after surgery can delay the admission time by several hours, creating enough time to have discharged a first-wave patient. This way the same bed can be used for two patients on a day instead of one. An initial analysis shows the promising potential of this method (see Table 17). The analysis also takes into account the possibility for the hospital to move patients from their bed to a lounge chair after two hours in a bed if the situation medically allows for it.

Table 17 Results initial analysis " bed after OR" scenario Day Treatment – 01-10-2013 to 24-11-2013, n = 277, source: Hospital IT system

	Current	Bed after OR	Chair >2u	Combination
Beds required	23	13	18	11
% bed reduction		46%	23%	53%

A case study initiated together with the head of the day treatment ward shows the real impact this measure has. The case study assumes there are 24 beds on the ward and disregards the anaesthesia patients (these patients almost always get placed on the remaining 4 beds of the 28-bed ward). “Double beds” means the number of beds that have been used for two patients on that day.

Table 18 Results case study "bed after OR" scenario Day Treatment - week 47-48 2013, n = 277, source: Hospital IT system

	Non-ANA	Current situation		Bed after OR		
Case wk 47/48	Patients	Double beds	Beds required	Double beds	Beds required	% improvement
11-11-2013	19	2	17	5	14	18%
12-11-2013	24	3	21	7	17	19%
13-11-2013	18	0	18	6	12	33%
14-11-2013	22	0	22	6	16	27%
15-11-2013	24	0	24	7	17	29%
18-11-2013	21	1	20	7	14	30%
19-11-2013	18	2	16	5	13	19%
20-11-2013	23	0	23	8	15	35%
21-11-2013	17	5	12	7	10	17%
22-11-2013	23	0	23	2	21	9%
				Average case study		24%

It can be seen that the average improvement is 24%, a lot lower than the 46% in the initial study. This is because the exclusion of anaesthesia patients leaves less options to use beds multiple times a day. The improvement potential is still significant and frees up between 2 and 8 beds in the case study period. Considering the number of patients flowing into the clinical ward 4a is roughly four per day, this intervention has the potential to almost completely remove the need for boarding day treatment patients on the clinical wards. The intervention where patients get a lounge chair after 2 hours in a bed is planned to be investigated in detail after the successful implementation of the "bed after OR" intervention.

7.1.2 Ward 4b

Clinical wards can also benefit from admitting patients only after surgery. The situation is different compared to the day treatment because patients stay overnight. To show the logic behind this, we once again look at the admission and discharge periods throughout the day for clinical wards. Figure 7-1 shows the pattern for ward 4b. It is clear that the morning admission period is multiple hours earlier than the discharge period. This mismatch creates a multi-hour period each day where there are 'double patients', causing a peak demand for beds. Shifting the admission period further ahead of time to just behind the time of discharge can reduce this peak demand.

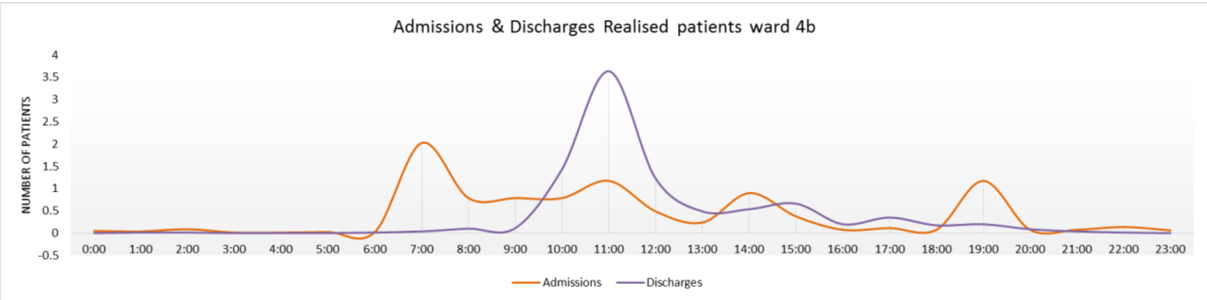


Figure 7-1 Admission and discharge periods ward 4b - 30-09-2013 to 18-12-2013, n = 1920, source: Hospital IT system

Figure 7-2 and Figure 7-3 show the average mutations in patient attendance throughout the week for both the current state and the future state. The future state is defined by shifting the admission time 4 hours into the future for all patients coming in between 07:00 and 11:00. In the current state the peak moments every day can be seen clearly, in the future state these peaks are minimised. The build-up of patients throughout the week cannot be tackled using this intervention.

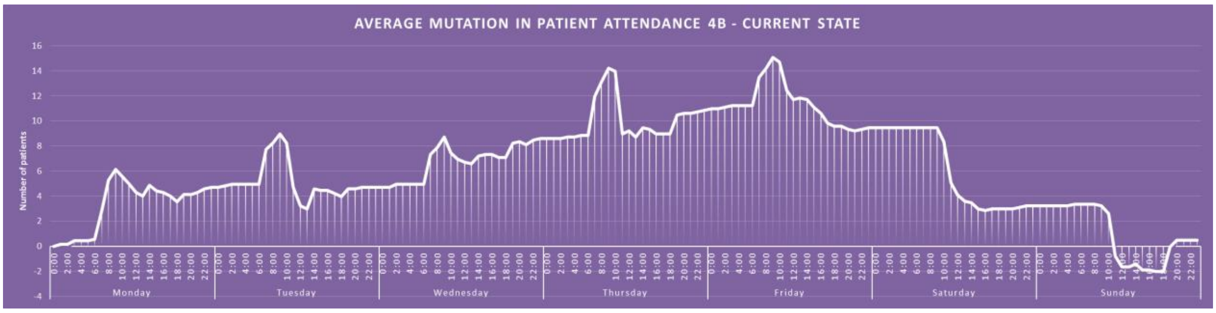


Figure 7-2 Current average mutation in patient attendance ward 4b – 01-10-2013 to 24-11-2013, n = 2640, source: Hospital IT system

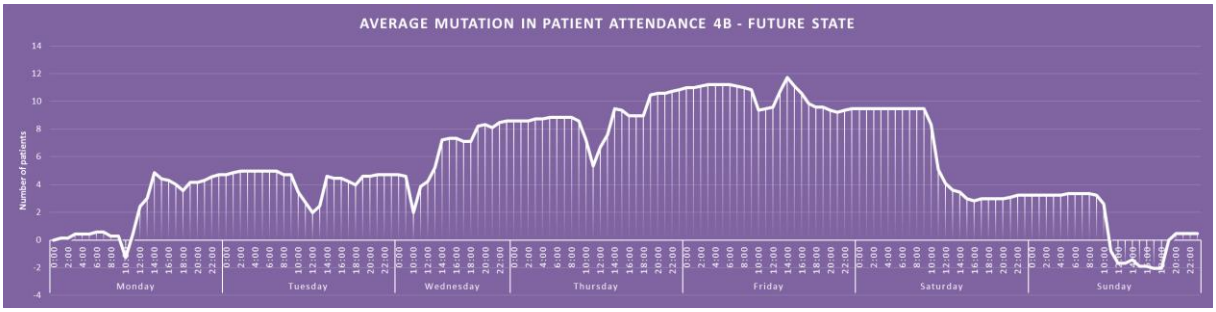


Figure 7-3 Average mutation patient attendance ward 4b Future State - 01-10-2013 to 24-11-2013, n = 2640, source: Hospital IT system

The result for various scenarios of shifting patient groups can be seen in Table 8. It can be seen that in the most positive scenario, also depicted in Figure 7-3, the maximum number of beds needed drops by 3.4 beds.

Table 19 Results of multiple future states "bed after OR" scenario for ward 4b - 01-10-2013 to 24-11-2013 n = 2640, source: Hospital IT system

		Amount of freed up beds on peak							
	Current situation	7>10	7>10 8>11	7>11	7>11 8>11	7>10 8>11 9>12	7>11 8>12	7>11 8>12 9>13	7>11 8>12 9>13 10>14
Mon	6.1	0.6	1.1	1.1	1.1	1.3	1.3	1.3	1.3
Tue	9.0	0.8	1.5	2.8	3.5	2.3	3.5	4.0	4.0
Wed	8.7	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Thu	14.2	0.3	1.4	3.1	3.4	2.8	3.4	3.4	3.4
Fri	15.1	0.4	1.3	2.4	2.6	2.3	3.3	3.3	3.4
Max	15.1	0.4	1.3	2.4	2.6	2.3	3.3	3.3	3.4

7.2 Intervention 3: Use buffer capacity during peak demand

Intervention two aims to reduce peaks in bed demand to better match demand patterns with available capacity. If there is still a mismatch after successful implementation of intervention two we can use (temporary) buffer capacity during peak moments to fully match demand with available capacity. Figure 7-4 shows the average daily mutation in realised patient attendance for ward 4a. If ward 4a has three beds free at the start of the day, then patients four and five need to be boarded on another ward. To prevent this, it could be worthwhile to place, on average, two extra temporary beds on the ward from 07:00 to 10:00. The same effect can be seen in ward 4b where they would need, on average, three temporary beds between 06:00 and 11:00. When looking at the weekly pattern in Figure 7-5, we see that the temporary beds are most useful on Tuesday, Wednesday and Thursday on ward 4a. Ward 4b can benefit the most from deploying temporary beds on Thursday and Friday. On the other days, the peaks are less likely to be higher than the maximum capacity of the ward. This temporary capacity of beds is less useful in the day treatment because of the gradual increase and decrease in number of patients during the day.

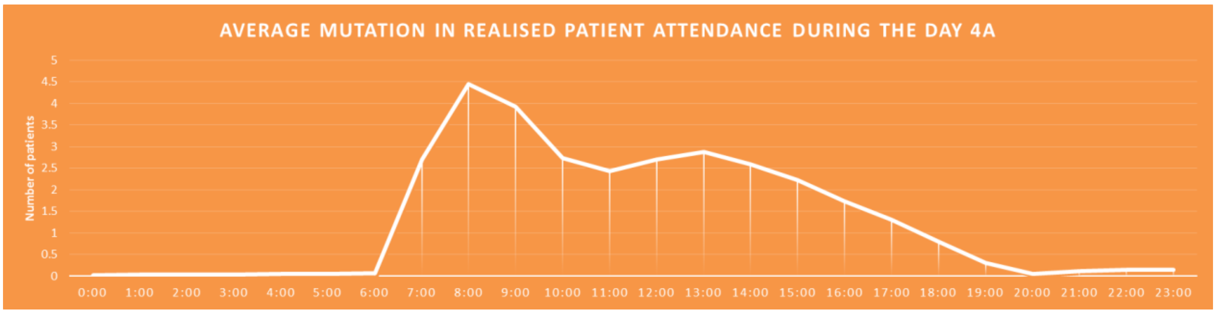


Figure 7-4 Average daily mutation in realised patient attendance ward 4a - 30-09-2013 to 18-12-2013 State - 01-10-2013 to 24-11-2013, n = 1920, source: Hospital IT system

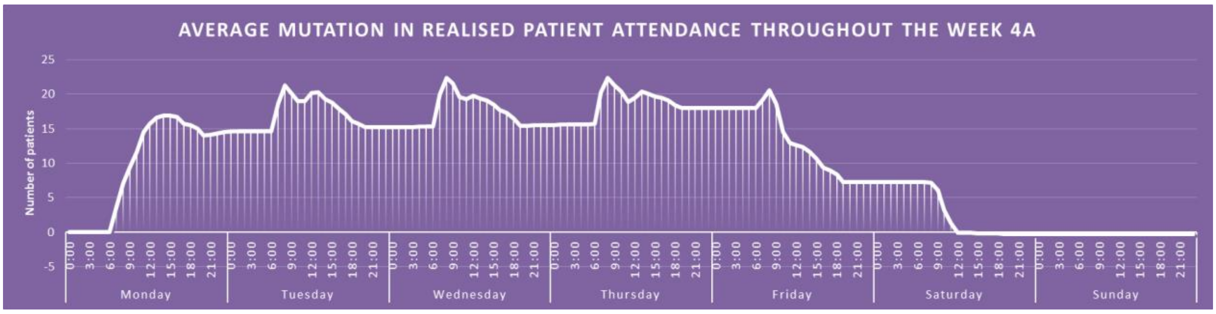


Figure 7-5 Average mutation in weekly realised patient attendance ward 4a - 30-09-2013 to 18-12-2013, n = 1920, source: Hospital IT system

7.3 Intervention 4: Length of stay improvements

Meetings with stakeholders reveal that the observed length of stay (LOS) of patients is frequently not the same as the LOS in an optimal recovery process. This means that patients occasionally stay in a bed longer than medically necessary. It is however not necessarily the case that a patient's LOS is too high, sometimes it is preferable from a medical perspective to increase the length of stay of a patient if it lowers the chance of readmitting this patient later on. Most of the issues, however, relate to patients having an increased LOS due to logistical reasons. Patients frequently have an increased length of stay because they cannot proceed to the next stage of their treatment plan, e.g., nursing home or a physiotherapist. Extending the chain to extramural care units, like a ventilator unit, helps to improve the LOS and the flow out of the hospital. Accurate LOS predictions and LOS reductions free up capacity and also make the planning of beds easier. Orchestrating the check in/out process, for example discharging during the evening shift and during the weekends, can reduce the LOS and the variation in LOS. Currently discharging patients is done one or multiple times a day, meaning that patients have to wait until the next 'round' to be discharged. Continuous discharging ensures that patients get to leave their bed as soon as possible after being ready for discharging, thereby also freeing up the bed earlier. A pilot project on an emergency ward in the Nieuwegein location shows a significant LOS reduction by continuously discharging patients. It is also beneficial to standardise the admission & discharge processes by developing criteria and guidelines.

An extended length of stay is a strain on the care process from a logistical perspective and it is recommended that the St. Antonius critically reviews its performance on length of stay of patients.

7.4 Intervention 5: redistribution of beds

Analysis shows that, in the reviewed period, ward 5b had the lowest turn-down probability. Ward 5b also had no bed shortage for the scenario where every patient gets a bed on their designated ward. In the current situation it is common practice to board patients on ward 5b rather than anywhere else. Permanently moving a specific patient group from ward 4a to ward 5b better matches the ward's capacity with their corresponding demand. The beds on ward 4a that this frees up can then serve as buffer beds for both ward 4a and ward 4b, decreasing the stream of boarded patients from the 4th floor to the 5th. Urology patients are considered to be a suitable patient group to move from ward 4a to ward 5b. The care for urology patients closely resembles the care provided on ward 5b. This intervention only reallocates beds and thus only minimizes the extra work coming from boarding patients, there is no structural decrease in variation and size of bed-demand.

We recommend that the St. Antonius carefully weigh the benefit of a decrease in extra work to a radical restructuring of the ward layout.

7.5 Intervention 6: Insight in the "state of the system"

Staff confronted with the issue of peak bed demand frequently mention the low availability of information. The use of an information system can support real time insight into the state of the system. Ward bed planning, how many boarded patients there are and where they are, current occupation of the wards and upcoming demand are mostly registered locally in Microsoft Excel files, on whiteboards or on paper. An information system showing the real-time state of the wards, patient length of stay, boarded patients and expected upcoming demand provides operational assistance to ward staff and the emergency coordinator, reducing the amount of time spent creating ad-hoc solutions on moments of peak demand. For instance, when an emergency patient arrives the information system can provide advice on which bed the patient should be admitted. Also, if the ward is full and a new patient needs to be admitted, the information system can provide information on beds on that become available in the near future on the patients designated ward or provide the best bed to board this patient on. When wards can observe expected demand and expected bed utilisation it is also possible for them to alert the admission planners to schedule no more than a maximum number of admissions in the peak period.

7.6 Conclusion

This chapter provides interventions aimed at increasing the wards ability to react to incoming bed demand. Analysis shows admitting patients to a bed after surgery instead of before surgery offers a large improvement potential for reducing peaks in bed demand. Buffer capacity offers temporary capacity to react to remaining bed demand. We conclude that length of stay improvements and flexible discharge moments have the potential to permanently free up capacity, which can be used to cope with peak demand. We identify the redistribution of beds as a possibility to decrease the percentage of boarded patients, but with little improvement potential for reacting to peak bed demand. Real time insight into the state of the system is a precondition for better coping with peak bed demand.

8 Implementation

In this chapter we identify what steps need to be taken to improve the levelling of bed requirement using the identified leverage points and the results of the model. The hospital aims to eventually have an admission planning system that integrally optimises admissions over multiple resources and provides real time support to admission planners, to achieve a more levelled resource requirement. We believe our model represents the first step towards that goal. The implementation is divided in seven steps. We start with only one specialty in step one because each specialty has *specialty-specific methods and restrictions* when it comes to scheduling patients. Starting small enables us to keep focus in fine-tuning the process for one specialty. After evaluating and improving the method for one specialty we can expand to other specialties. During implementation we suggest to minimise the risk of failure by assembling a cross-functional focus group with a medical specialist, a head of one of the wards, an anaesthesiologist, an admission planner, and the OR coordinator. Whenever possible we recommend involving stakeholders from the specific specialty where the method is being implemented. The focus group gives regular feedback on progress and provides valuable insights into the issues surrounding the implementation. It also ensures that relevant stakeholders are kept informed and are given a chance to express their opinions. Step 1-4 of the implementation are directly implementable using the results of this research, step 5-7 are recommended future implementation steps.

Step one – General decision rules

Integrating the case mixes into the existing IT system is considered to be unrealistic at this stage. Therefore, the first step in implementing the model requires no IT tools. We suggest to start with only one specialty to extensively evaluate the usability of the approach. Implementation starts with the simplest form of planning guidelines: decision rules. These general decision rules are extrapolated from the case mix matrices per specialty, e.g., no short stay clinical patients on Monday and Friday, and communicate these rules to the admission planners. From experience, the admission planners know which procedures produce long and short stay patients and try to incorporate the general decision rules in the admission planning. The system indicates which ward every patients goes to after surgery. Decision rules are less detailed than case mix matrices and therefore do not have the same improvement potential. They are, however, easy to understand and flexible. Evaluation is key in this early implementation stage. Obtaining as much feedback as possible from admission planners and physicians about the issues identified with the new planning approach provides essential information for improvement. Identified restrictions or problems can, for instance, be difficulty adhering to the case mix matrix or resistance from physicians. We recommend doing a daily feedback session with an admission planner at the end of the day in the first week, then proceed with a weekly meeting with an admission planner and a physician. Considering patients are scheduled onto OR-sessions weeks in advance, bed utilisation analysis cannot indicate improvement in the first weeks after a change in planning routines.

Step two – Flexibility to adapt

In step one issues resulting from scheduling according to case mixes in the admission scheduling process are identified and tackled. For this we use generalised decision rules. In step two the use of case mix matrices in the admission scheduling process are implemented. Planning according to case mix matrices instead of decision rules increases the improvement potential of the approach. However, case mix matrices are created based on expected input parameters, and these parameters can differ in practise. For example, the matrices are determined based on the basic MSS and expected demand. If there are changes in the MSS, both temporary and permanent, the case mix matrix changes. The same holds for changes in demand. To be able to keep using the matrices we must create ways to adapt them to reflect changes in the MSSs and demand. A first response to changed demand or the MSS are “step changes”; if demand for a case type drops by more than 50% then reduce the advised number of patients of that case type by half. If one of three OR sessions is being cancelled, only schedule 2/3 of that days patients, but in the same ratio. In the same way, if a ward indicates that there are only limited beds left due to, for instance, patients staying longer than expected, admission planners can cap the number of patients scheduled but can keep the ratio proposed by the matrix. It is possible to set up a traffic light system where, for example, 'green' indicates that wards have enough space available and planners can fill the matrices as best as they can, 'orange' means wards foresee problems in coping with upcoming demand so only plan 75% of the matrix and red means wards are overflowing, only plan 50%. This introduces a real time feedback link into usage of the matrices which can add flexibility. Diverging from the matrix however potentially reduces the benefit from its use. In implementing this system we propose introducing a self-learning system. Weekly feedback with admission planners allows us to detect bottlenecks and to adjust schedules. This weekly feedback also allows us to find out what practical restrictions we have not modeled into the system. The practical restrictions can consequently be tackled or the model/matrices can be adjusted accordingly.

If outcome indicators show a significant reduction in performance, even after flexible use of the matrices, it is advised to update the model's inputs and create entirely new matrices.

Step three – Expand to more specialties

In step two we propose a method for the admission planners to work with case mix matrices in an uncertain environment. In step three we expand the scope to include multiple departments. Expanding the scope starts with including the four largest specialties (CHI/KNO/OOG/ORT), together performing 80% of all elective surgeries in the Utrecht location. To include these specialties we suggest to follow steps one and two again. After these four specialties are included all nine specialties can be included.

Step four – Expand to other location

After including all specialties in the Utrecht location the approach can be extended to include the Nieuwegein location as well. To apply the model to the new location it is necessary to perform a similar analysis as seen in Chapter 2, to identify if variation in the elective surgical stream is a root cause of capacity problems. Also, another extensive data analysis is needed to:

- Determine number of specialties, wards and ORs
- Determine patient population, patient types and demand
- Determine patient flows
- Determine surgery durations and length of stay

Using this data as input for the model case mix matrices can be created for the Nieuwegein location. In case of implementation in another hospital first the scheduling method of that hospital needs to be identified, to determine if case mixes offer potential for improvement.

Step five – Supporting IT system (recommended)

The hospital's IT system can provide support for the planner in using the case mix matrices. The planning and waiting list databases need to register to what case type a patient belongs. In most cases planners intuitively already know but when registered in the system they can do post-planning checks to see how many patients from each case type they have already scheduled on a session.

Step six – Embed in IT system (recommended)

Embedding the approach in an IT system offers the opportunity to completely automate the matrix generation. This means that custom matrices can be generated based on the most recent MSS, bed utilisation and demand forecast. We suggest integrating the tool in a smart IT system already available in the hospital. This IT system makes input data readily available and can show the effect of scheduled patients on the bed demand. Additionally, stakeholders indicate the high failure rate of introducing separate tools for processes, advocating integration in an existing system.

Step seven (recommended)

In this final step we propose the construction of a full planning decision making tool, which gives advice when to plan patients based on the most recent state of the system. This means planners do not have to schedule patients anymore, they just have to offer and communicate a computer generated OR date to a patient. In this future scenario it is also possible to offer an online platform to patients where they can select an OR date. The case mixes proposed in this research are part of the planning algorithm of this decision making tool.

9 Conclusion & Recommendations

This chapter summarises the conclusions of the research and gives recommendations for future research. Section 9.1 lists the conclusions, Section 9.2 provides recommendations.

9.1 Conclusions

The core problem is identified as the percentage of boarded patients being too high. A patient is 'boarded' on another ward when there is a bed shortage on that patients designated ward. However, there is no bed shortage on a macro level: in the analysed period there were never more clinical patients than there were beds in the clinic. Literature research mentions variability as a key element in capacity and flow problems in hospitals. Based on data analysis we identify variability as the root cause of boarding patients. Average bed utilization shows that wards should have sufficient space if the variation in inflow and outflow would not be as high as it currently is. Variability literature suggests reasons for this can be natural variation but also artificial variation, the variation introduced by the hospitals own processes. Based on data analysis and literature research we identify the scheduling of elective patients as the largest source of artificial variation in bed demand. The hospital would like to have a new planning approach to reduce this variation. Because it is not possible to remove all variation in the scheduling of elective patients we also create strategies to cope with remaining variation. To tackle the core problem we need to <u>reduce artificial variation</u> and <u>react to natural variation</u>.

Reducing variation – We identify the scheduling of elective surgical patients within the existing Master Surgery Schedule (MSS) to be the area with the best balance between practical feasibility and improvement potential. We construct two variants of a mathematical optimisation model that provides admission planners with advice as to the mix and volume of patient types they should preferably schedule on each session to minimise peaks in variation in resulting bed utilisation. This Intervention consists of two phases:

Phase one: determine the theoretically optimal case mix per session with a mathematical model
Phase two: schedule patients based on the case mix prescribed by the model

Case studies showed that, in phase one, it is possible to plan patients in such a way that theoretical variation in bed demand is reduced. The models are also able to plan the case types in such a way that the bed utilisation approaches the theoretical optimum. Figure 9-1 shows that the models theoretically achieve a reduction in bed requirement of 24% and 25%, for all nine surgical specialties in the Utrecht location. This is close to the 29% theoretical optimum.

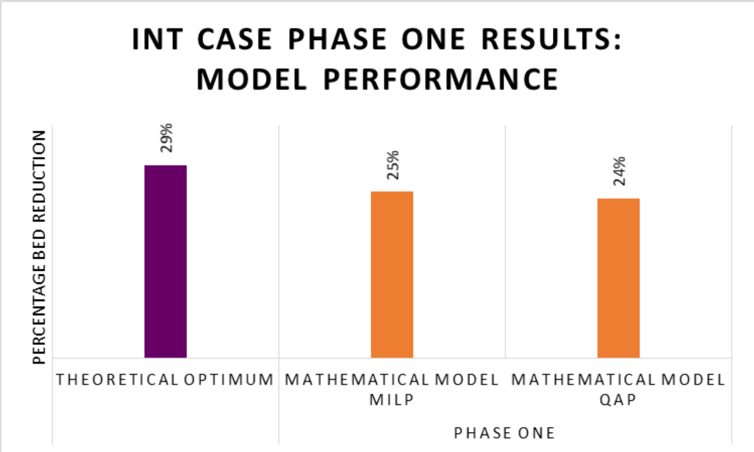


Figure 9-1 Model performance for planning elective surgical patients using case mix matrices

In phase two we find it is possible to schedule individual patients to OR sessions according to the prescribed theoretically optimal case mix, whilst reducing variation in bed demand. During the planning of patients in phase two, we find the improvement to be lower than the theoretical performance of the model due to the following causes:

- There are patients who can only be operated on by a specific physician (strict patients)
- Not all patients are planned from the waiting list, some require an OR-date immediately
- There is variation in surgery duration
- There is variation in demand
- There is variation in Length of stay
- There are variations on the basic MSS

The first two causes reduce the flexibility planners have in scheduling patients. We identify strict patients as the largest restriction to adhere to the case mix matrix. The percentage of strict patients therefore must be as low as possible to reach the highest improvement potential. The last four causes are model inputs that determine the degree to which the models correctly represent reality. The better these inputs forecast reality the more effective the case mix matrix are. Considering the limiting factors are comparable between the ORT case and the INT case, we expect our model to have the improvement potential seen in Figure 9-2 for using case mix matrices to plan elective surgical patients in the Utrecht location of the St. Antonius hospital.

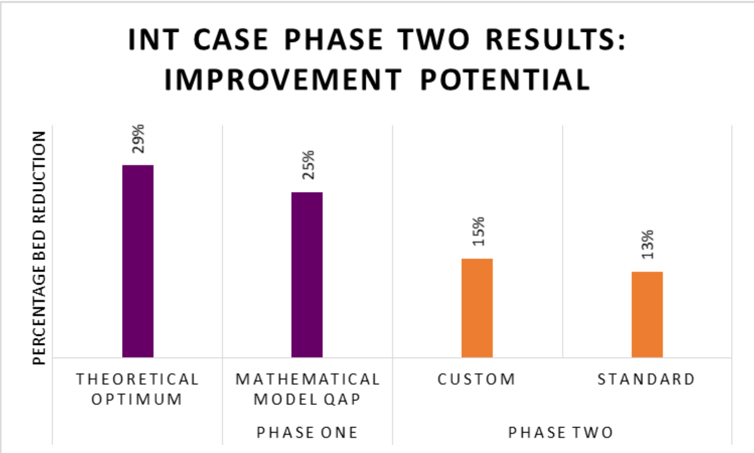


Figure 9-2 Practical improvement potential for planning elective surgical patients using case mix matrices

Reacting to variation – Analysis shows admitting patients to a bed after surgery instead of before surgery offers a large improvement potential for reducing peaks in bed demand. Buffer capacity offers temporary capacity to react to remaining bed demand. We conclude that length of stay improvements and flexible discharge moments have the potential to permanently free up capacity, which can be used to cope with peak demand. We identify the redistribution of beds as a possibility to decrease the percentage of boarded patients, but with little improvement potential for reacting to peak bed demand. Real time insight into the state of the system is a precondition for better coping with peak bed demand.

9.2 Recommendations

Recommendations for improving and working with the model

We recommend using statistical process control (SPC) to monitor and control the performance of the ORs and the wards. If there is no feedback loop, an integral approach to admission planning is most likely going to fail. SPC can also be used to see if the forecasting of input parameters is improving or deteriorating. Furthermore, in the integral approach there is usually an optimum between stakeholder interests. In this case it is worth investigating where the optimum lies between variation in OR utilisation and variation in bed utilisation. The model can better predict OR utilisation if there is less variation in surgery duration per case (patient) type. We recommend investigating the possibility to create sub-groups within the case types, by subdividing a case type into different clusters with homogenous surgery durations. It is also recommended to do research on how much improvement potential is lost due to giving patients a date immediately. Finally, we recommend implementing an IT system that provides planners with insight to the impact of their planning efforts on the bed requirement.

Recommendations for improving OR scheduling in general

It is recommended to do an exploratory analysis of the benefits or downsides of planning ORs during the weekends. This most likely increases personnel costs but has the potential to eliminate a large amount of artificial variation. Analysis needs to determine when this scenario provides beneficial results for both the hospital and the patients, and how much benefit it amounts to. Furthermore, it is possible to reduce surgery time variation by standardisation and implementation of best practices. We recommend that the St. Antonius hospital investigates the potential benefit of these strategies. Besides using our model to create optimal case mixes, we recommend to rethink the sequencing of patients. Case sequencing can improve patient waiting time and OR utilisation, but has to incorporate a substantial amount of practical restrictions. We recommend to investigate the benefit of using case sequencing from a logistical standpoint and to see which practice restriction are preferential and which are medically necessary. Finally, we recommend the St. Antonius hospital to investigate the potential and practical feasibility of eliminating the batching of patients in the OR by letting go of the MSS block schedule. This has the potential to provide a lot more flexibility towards the patient, but there are sizeable practical restrictions. For future research we recommend to extend our research by using stochastic surgery durations, for example by employing the technique used by Van Oostrum et al. [13].

Bibliography

[1] St. Antonius Ziekenhuis, „Kerngegevens St. Antonius Ziekenhuis," 2014. [Online]. Available: http://www.antoniusziekenhuis.nl/overstantonius/feiten_ziekenhuis/kerngegevens/.

[2] E. Hans, M. van Houdenhoven en P. Hulshof, „A framework for health care planning and control," *University of Twente,* 2010.

[3] R. Mitchell, B. Agle en D. Wood, „Toward a Theory of Stakeholder Identification and Salience: Defining the Principle of who and What Really Counts," *Academy of Management Review,* vol. 22, nr. 4, pp. 853-886, 1997.

[4] C. Haraden en R. Resar, „Patient Flow in Hospitals: Understanding and Controlling it Better," *Frontiers of Health Services Management,* pp. 3-15, 2004.

[5] Google, „Google Scholar," Google, 2011. [Online]. Available: http://scholar.google.nl/. [Geopend November 2013].

[6] CHOIR, „ORchestra - Categorized bibliography for Operations Research/Management Science in Health Care," CHOIR, 2014. [Online]. Available: http://www.choir-ut.nl/. [Geopend November 2013].

[7] P. Vanberkel, R. Boucherie, E. Hans, J. Hurink en N. Litvak, „A Survey of Health Care Models that Encompass Multiple Departments," Department of Applied Mathematics University of Twente, Enschede, 2009.

[8] E. Litvak en M. Long, „Cost and Quality under Managed Care: Irreconcilable Differences?," *American Journal of Managed Care,* pp. 305-312, 2000.

[9] E. Litvak, „Chapter 4: Optimizing Patient Flow by Managing its Variability," in *From Front Office to Front Line: Essential Issues for Health Care Leaders*, Institute for Healthcare Improvement, 2005, pp. 91-112.

[10] E. Litvak en H. Fineberg, „Smoothing the Way to High Quality, Safety, and Economy," *The New England Journal of Medicine,* pp. 1581-1583, 2013.

[11] NHS Modernisation Agency, „10 High impact changes for service improvement and delivery: a guide for NHS leaders," 2004.

[12] J. Belien en E. Demeulemeester, „Building cyclic master surgery schedules with leveled resulting bed occupancy," *European Journal of Operational Research,* pp. 1185-1204, 2007.

[13] J. Van Oostrum, M. Van Houdenhoven, J. Hurink, E. Hans, G. Wullink en G. Kazemier, „A master surgical scheduling approach for cyclic scheduling in operating room departments,” *Operations Research Spectrum,* pp. 355-374, 2008.

[14] J. Blake en M. Carter, „A goal programming approach to strategic resource allocation in acute care hospitals,” *European Journal of Operational Research,* pp. 45-68, 2002.

[15] M. Carter en S. Ketabi, „Bed Balancing in Surgical Wards via Block Scheduling,” *Journal of Minimally Invasive Surgical Sciences,* pp. 129-137, 2012.

[16] P. Santibanez, M. Begen en D. Atkins, „Surgical block scheduling in a system of hospitals: an application to resource and wait list management in a British Columbia health authority,” *Health Care Management Science,* pp. 269-282, 2007.

[17] I. Adan, J. Bekkers, N. Dellaert, J. Vissers en X. Yu, „Patient mix optimisation and stochastic resource requirements: A case study in cardiothoracic surgery planning,” *Health Care Management Science,* pp. 129-141, 2009.

[18] J. Belien, E. Demeulemeester en B. cardoen, „A decision support system for cyclic master surgery scheduling with multiple objectives,” *Journal of Scheduling,* pp. 147-161, 2009.

[19] Y. Tan, T. ElMekkawy, Q. Peng en L. Oppenheimer, „Mathematical programming for the scheduling of Elective Patients in the Operating Room Department,” *Proceedings of the Canadian Engineering Education Association,* 2007.

[20] J. Vissers, I. Adan en J. Bekkers, „Patient mix optimization in tactical cardiothoracic surgery planning: a case study,” *IMA Journal of Management Mathematics,* pp. 281-304, 2005.

[21] I. Adan, J. Bekkers, N. Dellaert, J. Jeunet en J. Vissers, „Improving operational effectiveness of tactical master plans for emergency and elective patients under stochastic demand and capitated resources,” *European Journal of Operational Research,* pp. 290-308, 2011.

[22] S. Chaabane, N. Meskens, A. Guinet en M. Laurent, „Comparison of two methods of operating theatre planning: Application in Belgian Hospital,” *Journal of Systems Science and Systems Engineering,* pp. 171-186, 2008.

[23] A. Jebali, A. Alouane en P. Ladet, „Operating rooms scheduling,” *International Journal of Production Economics,* pp. 52-62, 2006.

[24] M. Lamiri, F. Grimaud en X. Xie, „Optimization methods for a stochastic surgery planning problem,” *Internation Journal of Production Economics,* nr. 120, pp. 400-410, 2009.

[25] B. Cardoen en Demeulemeester, „Optimizing a multiple objective surgical case sequencing problem,” *International Journal of Production Economics,* pp. 354-366, 2009.

[26] W. Hopp en W. Lovejoy, Hospital operations: principles of high efficiency health care, New Jersey: FT Press, 2013.

[27] B. Denton, J. Viapiano en A. Vogl, „Optimization of surgery sequencing and scheduling decisions under uncertainty,” *Health Care Management Science,* nr. 10, pp. 13-24, 2007.

[28] W. Woodall, B. Adams en J. Benneyan, „Chapter 13: The Use of Control Charts in Healthcare,” in *Statistical Methods in Healthcare*, 2011.

[29] J. Thor, J. Lundberg, J. Ask, J. Olsson, C. Carli, K. Harenstam en M. Brommels, „Application of statistical process control in healthcare improvement: systematic review,” *Quality and Safety in Health Care,* pp. 387-399, 2007.

[30] NHS national service scotland, „Quality Indicators,” 2010. [Online]. Available: http://www.indicators.scot.nhs.uk/SPC/Statistical_Process_Control_Tutorial_Guide_V5.pdf.

[31] J. Benneyan, R. Lloyd en P. Plsek, „Statistical Process Control as a tool for research and healthcare improvement,” *Quality and Safety in Health Care,* pp. 458-464, 2003.

[32] IBM, „IBM ILOG CPLEX Optimization Studio,” IBM, [Online]. Available: http://www-03.ibm.com/software/products/nl/ibmilogcpleoptistud/. [Geopend 3 April 2014].

[33] C. Brecher en S. Speizio, „Privatization and Public Hospitals,” p. 55, 1995.

[34] G. Reed, F. Lynn en B. Meade, „Use of Coefficient of Variation in Assessing Variability of Quantitative Assays,” *Clinical and Vaccine Immunology,* pp. 1235-1239, 2002.

[35] J. Vissers, J. Bertrand en G. De Vries, „A Framework for production control in health care organizations,” *Production Planning & Control,* pp. 591-604, 2001.

Appendix A – Analysis Day Treatment (U008)

This section is marked confidential and is removed from the public version of this report

Appendix B – Analysis Clinical Ward 4a (U402)

This section is marked confidential and is removed from the public version of this report

Appendix C – Analysis Clinical Ward 4b (U403)

This section is marked confidential and is removed from the public version of this report

Appendix D – Analysis Clinical Ward 5a (U502)

This section is marked confidential and is removed from the public version of this report

Appendix E – Analysis Clinical Ward 5b (U503)

This section is marked confidential and is removed from the public version of this report

Appendix F – input for the INT case study

The master surgery schedule

	endo OK		endo OK			endo OK		endo OK		
Even week	1	2	3	4	5	6	7	8	9	10
Maandag	URO	CHI	PCH	CHI	VRY	NCH	ORT	ORT	OOG	KNO
	URO	SPD	PCH	CHI	VRY	NCH	ORT	ORT	OOG	KNO
Dinsdag	URO	GYN	MAM	CHI	VRY	KCH	ORT	ORT	OOG	KNO
	URO	SPD	MAM	CHI	VRY	KCH	ORT	ORT	OOG	KNO
Woensdag	CHI	CHI	PCH	KNO	VRY	ORT	ORT	ORT	OOG	KNO
	CHI	SPD	PCH	KNO	VRY	ORT	ORT	ORT	OOG	KNO
Donderdag	GE	GYN	PCH	KNO	VRY	NCH	ORT	ORT	OOG	KNO
	GE	SPD	PCH	KNO	VRY	NCH	ORT	ORT	OOG	KNO
Vrijdag	VRY	CHI	VRY	CHI	VRY	ORT	ORT	ORT	OOG	KNO
	VRY	SPD	VRY	CHI	VRY	ORT	ORT	ORT	OOG	KNO

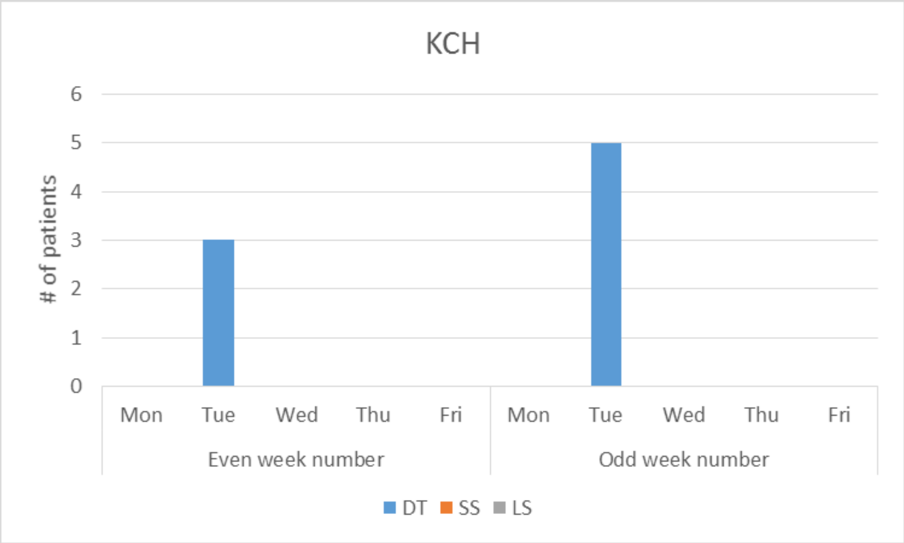
	endo OK		endo OK			endo OK		endo OK		
Oneven week	1	2	3	4	5	6	7	8	9	10
Maandag	URO	CHI	PCH	CHI	VRY	NCH	ORT	ORT	OOG	KNO
	URO	SPD	PCH	CHI	VRY	NCH	ORT	ORT	OOG	KNO
Dinsdag	GYN	CHI	VRY	MAM	VRY	KCH	ORT	ORT	OOG	KNO
	URO	SPD	VRY	MAM	VRY	KCH	ORT	ORT	OOG	KNO
Woensdag	CHI	CHI	PCH	KNO	VRY	ORT	ORT	ORT	OOG	KNO
	CHI	SPD	PCH	KNO	VRY	ORT	ORT	ORT	OOG	KNO
Donderdag	URO	CHI	NCH	KNO	VRY	ORT	ORT	ORT	OOG	KNO
	URO	CHI	NCH	KNO	VRY	SPD	ORT	ORT	OOG	KNO
Vrijdag	GYN	CHI	VRY	VRY	VRY	ORT	ORT	ORT	OOG	KNO
	VRY	SPD	VRY	VRY	VRY	ORT	ORT	ORT	OOG	KNO

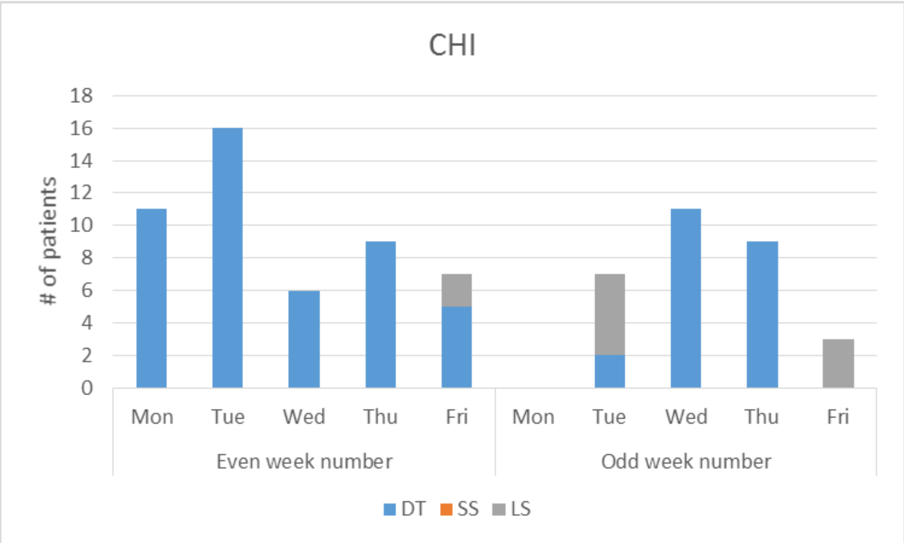
Figure 0-1 Basic MSS week 38 2013 to week 1 2014

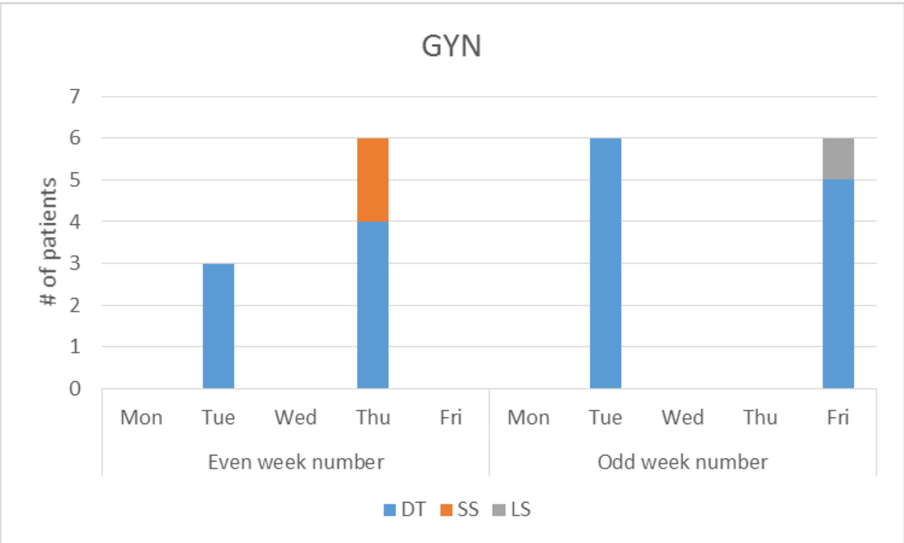
Table with Case type properties

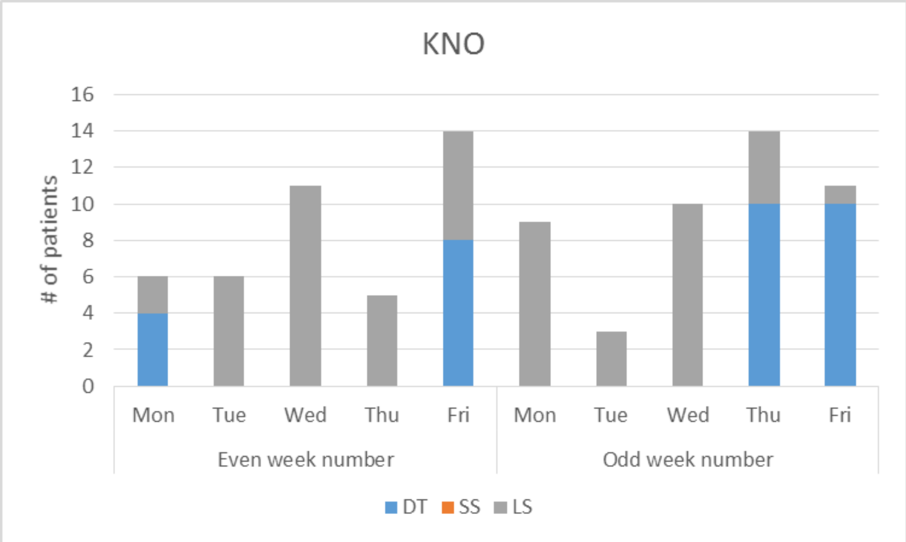
Specialty	Type	Patients	Designated ward	Expected demand(14d)	Expected surgery duration (minutes)	LOS probability distribution per day 1	2	3	4	5	6	7	8	9	10	11	12	13	14
CHI	D	All DT	DT	69	45	1	0	0	0	0	0	0	0	0	0	0	0	0	0
CHI	SS	n.a.	4A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CHI	LS	All Clinical	4A	10	67	1	0,098214	0,026786	0,008929	0,008929	0,008929	0	0	0	0	0	0	0	0
GYN	D	All DT	DT	18	33	1	0	0	0	0	0	0	0	0	0	0	0	0	0
GYN	SS	Clinical <=1	4A	2	40	1	0	0	0	0	0	0	0	0	0	0	0	0	0
GYN	LS	Clinical >1,	4A	1	65	1	0,944444	0,166667	0	0	0	0	0	0	0	0	0	0	0
KCH	D	All DT	DT	8	45	1	0	0	0	0	0	0	0	0	0	0	0	0	0
KCH	SS	n.a.	4A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KCH	LS	All Clinical	4A	0	55	1	0	0	0	0	0	0	0	0	0	0	0	0	0
KNO	D	All DT	DT	32	18	1	0	0	0	0	0	0	0	0	0	0	0	0	0
KNO	SS	n.a.	4A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KNO	LS	All Clinical	4A	57	38	1	0,00463	0,001543	0,001543	0,001543	0	0	0	0	0	0	0	0	0
NCH	SS	Clinical <=2	4B	3	78	1	0,827586	0	0	0	0	0	0	0	0	0	0	0	0
NCH	LS	Clinical >2,	4B	15	73	1	1	0,993506	0,188312	0,064935	0,045455	0,025974	0,019481	0,006494	0,006494	0,006494	0	0	0
OOG	D	All DT	DT	142	20	1	0	0	0	0	0	0	0	0	0	0	0	0	0
OOG	SS	n.a.	4A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OOG	LS	All Clinical	4A	2	43	1	0	0	0	0	0	0	0	0	0	0	0	0	0
ORT	D	All DT	DT	44	41	1	0	0	0	0	0	0	0	0	0	0	0	0	0
ORT	SS	Clinical <=1	4B	32	76	1	0	0	0	0	0	0	0	0	0	0	0	0	0
ORT	LS	Clinical >1,	4B	38	117	1	0,997738	0,932127	0,785068	0,590498	0,361991	0,126697	0,070136	0,045249	0,024887	0,022624	0,015837	0,013575	0,004525
PCH	D	All DT	DT	9	60	1	0	0	0	0	0	0	0	0	0	0	0	0	0
PCH	SS	Clinical <=1	4A	8	100	1	0	0	0	0	0	0	0	0	0	0	0	0	0
PCH	LS	Clinical >1,	4A	2	120	1	0,954545	0,454545	0,227273	0,045455	0,045455	0,045455	0,045455	0	0	0	0	0	0
URO	D	All DT	DT	10	43	1	0	0	0	0	0	0	0	0	0	0	0	0	0
URO	SS	Clinical <=1	4A	12	49	1	0	0	0	0	0	0	0	0	0	0	0	0	0
URO	LS	Clinical >1,	4A	6	65	1	0,982759	0,155172	0,017241	0	0	0	0	0	0	0	0	0	0

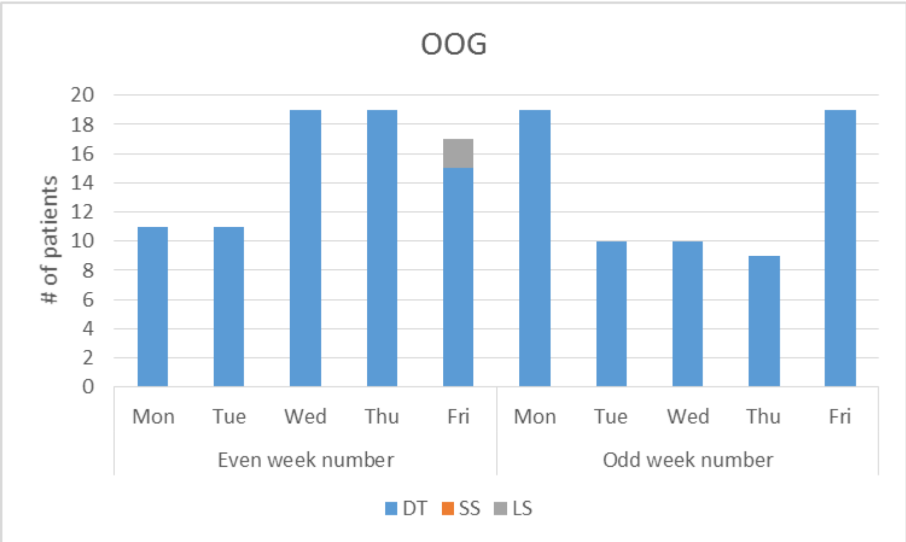
Appendix G – Case type matrices per specialty

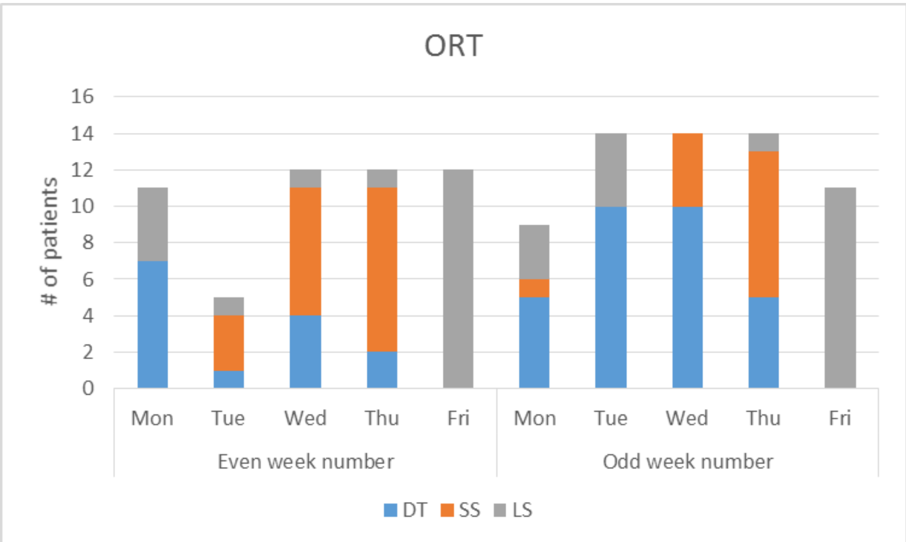


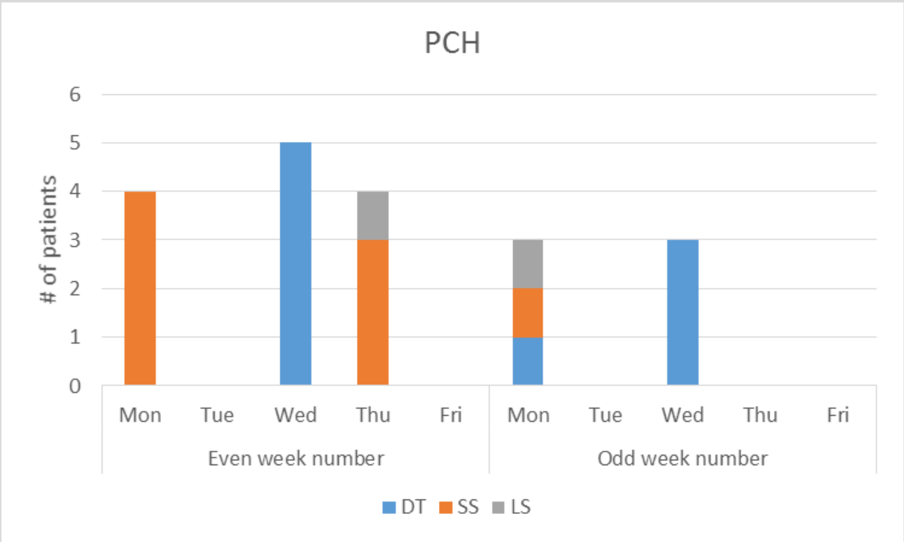


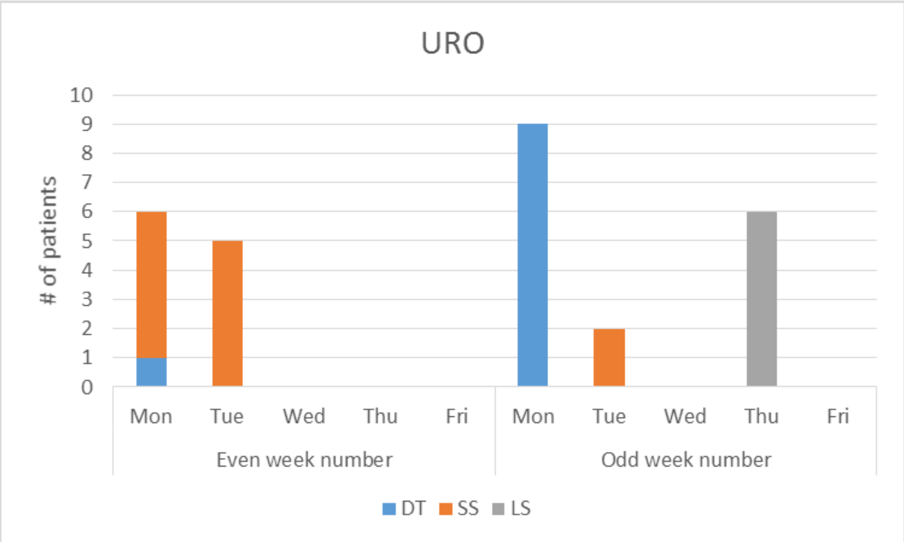


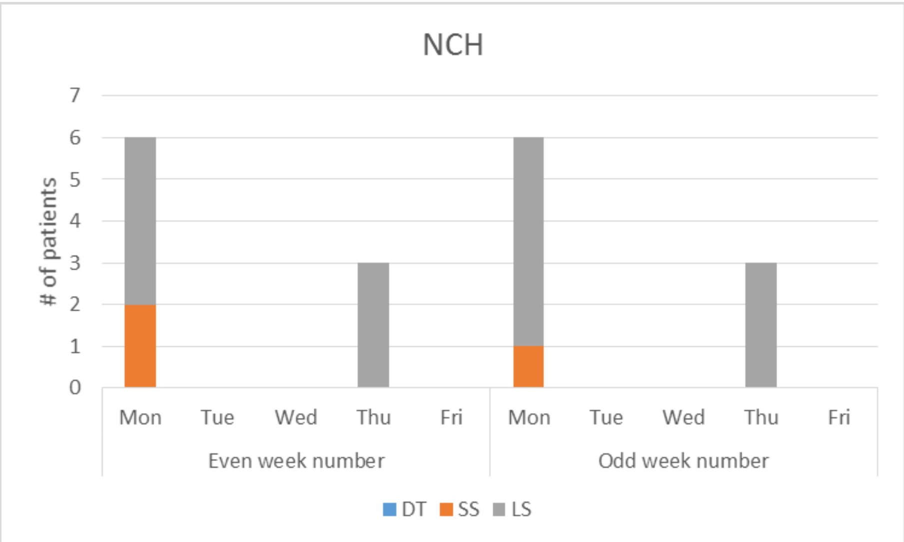

KNO
# of patients
16
14
12
10
8
6
4
2
0
Mon
Tue
Wed
Thu
Fri
Mon
Tue
Wed
Thu
Fri
Even week number
Odd week number
DT
SS
LS

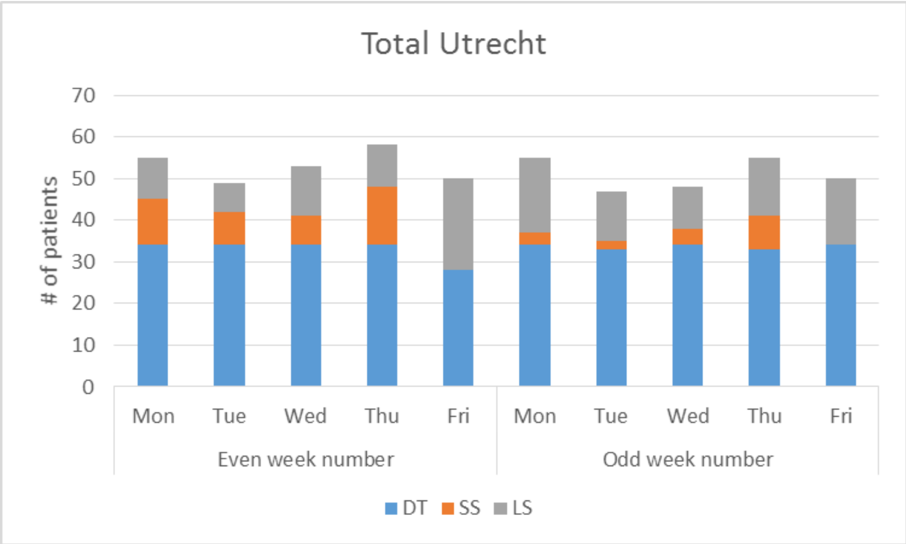

OOG
# of patients
20
18
16
14
12
10
8
6
4
2
0
Mon
Tue
Wed
Thu
Fri
Mon
Tue
Wed
Thu
Fri
Even week number
Odd week number
DT
SS
LS


ORT
# of patients
16
14
12
10
8
6
4
2
0
Mon
Tue
Wed
Thu
Fri
Mon
Tue
Wed
Thu
Fri
Even week number
Odd week number
DT
SS
LS


PCH
# of patients
6
5
4
3
2
1
0
Mon
Tue
Wed
Thu
Fri
Mon
Tue
Wed
Thu
Fri
Even week number
Odd week number
DT
SS
LS


URO
# of patients
10
9
8
7
6
5
4
3
2
1
0
Mon
Tue
Wed
Thu
Fri
Mon
Tue
Wed
Thu
Fri
Even week number
Odd week number
DT
SS
LS


NCH
# of patients
7
6
5
4
3
2
1
0
Mon
Tue
Wed
Thu
Fri
Mon
Tue
Wed
Thu
Fri
Even week number
Odd week number
DT
SS
LS



Total Utrecht
# of patients
70
60
50
40
30
20
10
0
Mon
Tue
Wed
Thu
Fri
Mon
Tue
Wed
Thu
Fri
Even week number
Odd week number
DT
SS
LS

X