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Reduction of variation in bed occupation by optimizing the Master Surgery Schedule: An Adaptive Large Neighborhood Search approach

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May 23, 2018

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Management Samenvatting

Doel van het onderzoek
Medisch Spectrum Twente (MST) is het top-klinische ziekenhuis van Enschede en heeft sinds July 2016 een nieuw gebouw in gebruik genomen. Het MST heeft hierbij te maken gekregen met hoge bijkomende kosten. Om hoge bijkomende kosten te reduceren, heeft het MST het Rendementsprogramma opgezet. Een van de doelstellingen van het Rendementsprogramma is het reduceren van variabiliteit in processen, waarbij het reduceren van variabiliteit in bedbezetting een van de kernpunten is. Vanuit verschillende invalshoeken worden hier projecten in uitgevoerd. Een van deze invalshoeken is het nivelleren van de electieve patiëntenstroom vanaf de OK naar de verpleegafdelingen. Om deze patiënten instroom meer gelijkmatig te krijgen, onderzoeken wij het het effect van het OK-rooster op de bedbezetting in de verpleegafdelingen. Het onderzoeksdoel dat wij hierbij hanteren is:

"Het reduceren van de variabiliteit in bedbezetting door middel van optimalisatie van het OK-rooster."

Methode
In de context analyse worden de patiëntenstromen onderzocht en vervolgens in kaart gebracht. Om een beeld te krijgen van de verschillende prestatie-indicatoren van de OK afdeling en de verpleegafdelingen is er een prestatie analyse uitgevoerd. Na deze data analyse voeren wij een literatuur onderzoek uit om te bepalen hoe het OK-rooster gelinkt kan worden aan de uitstroom naar de verpleegafdelingen. Aan de hand van dit literatuur onderzoek wordt er een methode gekozen die de chirurgische patiënt linkt aan de uitstroom naar de kliniek. Dit model wordt gekoppeld aan een optimalisatie heuristiek, waarmee een gegeven OK-rooster kan worden geoptimaliseerd op minder pieken in bedbezetting en minder variatie in bedbezetting.

Interventie
Vanberkel et al. (2011b) hebben een model ontwikkeld dat door middel van binomiale kansverdelingen en discrete convoluties een verdeling bepaalt voor de bedbezetting op verpleegafdelingen. Wij gebruiken dit model om de verdere gevolgen van een Master Surgery Schedule (MSS), in werklast voor de verpleegafdeling, in kaart te brengen. Met de verdeling kan tegen een gegeven percentiel bepaald worden, hoeveel patiënten er op alle dagen na de ondergane operaties op de verpleegafdeling liggen. Naast de bedbezetting hebben wij werklast op de verpleegafdelingen gedefinieerd als opnames en ontslagen. Het model gebruiken wij vervolgens in combinatie met de optimalisatie heuristiek Adaptive Large Neighborhood Search (ALNS). Wij maken hierbij gebruik van twee verschillende doelfuncties. Een op basis van piek minimalisatie en een doelfunctie die het bereik

minimaliseert van de bedbezetting.

Resultaten en Conclusie
Na ALNS optimilisatie van de gegeven MSSen zien we dat de variabilitiet van bedbezetting afneemt bij beide doelfuncties. Op basis van onze startoplossing zien we dat de optimalisatie zonder niet-chirurgische patient verdeling, de piek bedbezetting reduceert met 10 bedden (6.80% piek reductie). Met inclusie van de niet-chirurgische patient verdeling vonden we een piek reductie van 4.52%. De experimenten laten zien dat bereik minimalisatie de beste resultaten geeft op het gebied van variatie reductie in bed bezetting. Optimalisatie van OK-roosters van 2018, resulteert in piek reducties tussen 0.42% - 2.12%, wat wij beschouwen als minimaal effect. Desalniettemin, optimalisatie resulteet in lagere varianties per gegeven OK-rooster. De variantie reducties per OK-rooster bedragen 11.11% - 23.52%. Optimalisatie van de gegeven OK-rooster resulteert in minimale verschillen op het aantal opnames en ontslagen. Op basis van deze resultaten, concluderen wij dat het gebruik van ons optimalisatie programma helpt bij het reduceren van de variabiliteit in bedbezetting die ontstaat uit de doorstroom van patiënten van de OK naar de verpleegafdelingen. In de geoptimaliseerde OK-roosters zien we dat als chirurgische specialismes met lage resulterende klinische uitstroom aan het eind van de week worden geplaatst, dat dit helpt in het reduceren van de variation in bedbezetting. Daarnaast, zien we dat variatie in het aantal CH OKs per day de variatie in bedbezetting reduceert. In de initiële OK-roosters was dit 4 tot 5 CH OKs per day en in de geoptimaliseerde OK roosters was dit 3 tot 6 CH OKs per dag.

Implementatie
Voor het opstellen van een MSS hebben wij een programma gebouwd. Dit programma kan binnen de tactische beslissing ondersteuning bieden bij het opstellen van een blokplan, het evalueren van het blokplan en het optimaliseren van het blokplan op basis van pieken in bed bezetting en de spreiding van de bed bezetting.

Overige aanbevelingen
Aan de hand van het onderzoek zijn de volgende aanbevelingen naar voren gekomen:

- In gebruik name van het MSS model. Niet alleen voor het opstellen en optimaliseren van het blokplan, maar ook voor het inplannen van lege OK dagen. Wanneer lege OK dagen aan het einde van de week worden ingepland, worden pieken in bedbezetting afgekapt.

- Het verbeteren van de data kwaliteit. De data vormt de basis voor projecten die gericht zijn op variatiereductie, waarvoor data kwaliteit dus essentieel is.

- Herziening van de definities voor bedbenutting en bedbezetting. Deze definities zijn gedateerd en aangezien MST variabiliteit in deze factoren wil verminderen is dit noodzakelijk. In dt onderzoek stellen wij nieuwe definities van bedbezetting en bedbenutting voor

Management Summary

Research Objective
Medisch Spectrum Twente (MST), the top-clinical hospital of Enschede has a new building in use since July 2016. Along with the deployment of this new building, MST faces economic difficulties. MST started an efficiency program to reduce their costs. One of the main goals of the efficiency program is to save costs by reducing variability of processes. One of the key points here is the reduction of variability in bed utilization. Several projects are done to reduce this variability. One perspective is to balance the elective patient stream from the operating room to the nursing wards. To achieve this, we research the effect of the Master Surgery Schedule (MSS) on the bed occupation in the nursing wards. The research objective we use is:

"To reduce variability in bed utilization by optimization of the Master Surgery Schedule."

Methodology
In the context analysis, we research and map the patient streams. To get a view of the different key performance indicators (KPIs) of the OR department and the nursing wards, we conduct a performance analysis. After we analyse the performance of both departments we conduct a literature search in order to find a method to link the OR to the nursing wards. With such a method, a prediction can be made of the bed occupation given an MSS. We adopt this approach in combination with an optimization heuristic, to find the best MSS proposal given our goal functions.

Intervention
Vanberkel et al. (2011b) developed a model that determines a distribution for the bed occupation at nursing wards, using binomial probability distributions and discrete convolutions. We use this model to evaluate the resulting workload of an MSS. In addition to bed occupation, we define workload as the number of admissions and the number of discharges. With the distribution and a given quantile, we can determine how many patients occupy the nursing wards. We use the approach of Vanberkel et al. (2011b) in conjunction with the optimization heuristic Adaptive Large Neighborhood Search (ALNS). In the optimization, we use two different goal functions. The first minimizes the peak occupation and the second minimizes the range of the bed occupation.

Results and Conclusion
After ALNS optimization of the given MSSs, we see that the variability of bed occupation decreases with both goal functions. On the base of our feasible start solution, we find that the procedure minimizes the peak occupation with 10 beds (6.8% peak reduction) without non-surgical patient distribution and 11 beds (4.52% peak reduction) with non-surgical patient distribution. The ex-

periments show that range minimization gives the best results in reducing the variability of bed occupation. Optimizing the 2018 MSSs, resulted in peak reductions between 0.42% - 2.12%, which we consider to be a minimal effect. However, the optimization approaches resulted in lower variances per MSS. The variance reductions per MSS were 11.11% - 23.52%. Optimization of the MSS showed small effects on the admission- and discharge- rates. Based on these results, we conclude that our model helps to evaluate workload of a specific MSS. Next to that, we conclude that relocation of specialties within the MSS helps to reduce bed occupation at the nursing wards. In the optimized MSSs we explicitly saw that if surgical specialties with a small clinical outflow (SDC and OPT) are relocated to the end of the week, this helps to reduce the variation in bed occupation. Furthermore, we saw that variation in the number of CH ORs per day helps to reduce the variation in bed occupation. In the initial MSSs this was 4 or 5 CH ORs per day and in the optimized MSSs this is 3 to 6 CH ORs per day.

Implementation

For the construction, evaluation and optimization of the MSS, we build an application. This model can be used in the tactical decision phase of building an MSS. Next to that, it can be used for the evaluation of the MSS and the optimization of the MSS on peaks in occupation and on the base of range of bed occupation.

Further recommendations

On the base of our research, we have the following recommendations:

- Use our MSS model. Not only for the construction and optimization of the MSS, but also to plan closed OR days. If empty/closed OR days are planned at the end of the weeks, weekly occupation peaks are cut off.

- Improve the data quality. The data is the base for projects that aim at variability reduction, and therefore data quality is essential.

- Revise the definitions for bed occupation and bed utilization. These definitions are dated and since MST wants to reduce bed utilization, a clear definition is necessary.

Contents

Preface

At the end of September 2017, I started with my master thesis assignment and now, about eight months later, this report means the end of my study. While graduating for my Bachelor Health Science in 2014, I realised I wanted a more quantitative master study. After attending some lectures by Erwin Hans about the Healthcare Technology and Management track of Industrial Engineering and Management, I was convinced that this track fitted my interests. I definitely do not regret this decision and enjoyed the master program, in which I also had the chance to follow a part of master's program in Porto at the University Of Porto.
In the last eight months I learned a lot about the daily running of a hospital, conducting academic research and writing a thesis, and of course my own capabilities. I could not have done this with out some persons and therefore I want to thank them. First of all and most of all, I want to thank my parents Ad and Jeanette for their love and endless support during my complete study period, but especially in the last eights months. The days that I spend at their place, occupying every desktop or laptop I could find to run my optimization program, while I was verbally expressing my frustrations of debugging, were probably not the best ones.
Furthermore, I want to thank Joanne Quist for her support in the last months. Even though she has a busy schedule and her period at MST was already over, she found time to support me with my research. I also want to thank everyone at Rendementsprogramma for their support and help during my research. I can not mention here everybody personally, but I do want to thank Martijn Nijhuis for his daily help and the good times we had as 'roommates'.
Furthermore, I want to thank my supervisors from the University of Twente, Gréanne Leeftink and Erwin Hans. Gréanne's critical feedback and methodical thinking helped me structure my thesis. Besides that, she remained calm and very supportive when I had some difficult moments. I want to thank Erwin for his feedback late in the process and his pep-talks and help after my first assignment did not cover the master's guidelines about a year ago.
There are some persons that I did not name here personally, but they are not forgotten. Hereby, I want to thank them for all their support and help.

Davey Wopereis
Enschede, May 23, 2018

Chapter 1

Introduction

Medisch Spectrum Twente (MST), a top-clinical hospital in Enschede, opened its new building in July 2016. Currently MST is still in the transition phase from moving everything from the old buildings to the new facilities. With the deployment of these new facilities the hospital also faces economic difficulties, which was main reason to start with an efficiency program (in Dutch: *Rendementsprogramma*). MST already decreased their number of operating rooms (ORs) and hospital beds in the last couple of years. At the moment, MST faces high variability in bed utilization at the nursing wards. MST believes that efficiency gains can be made by reducing these fluctuations by focusing on the patient outflow from the ORs towards the nursing wards. The question remains how this reduction in variability in bed utilization can be achieved, which is the topic of this research. Section 1.1 describes the context and developments in healthcare, after which Section 1.2 gives a more in-depth description of MST. In Section 1.3 the problem description is given. After that, Section 1.4 states the research objective of this project. Section 1.5 describes the research questions derived from the research objective.

1.1 Context Description

Healthcare expenditures have been rising for the last years. In the Netherlands this rise in healthcare expenditures has been 1,8% in 2016, which is lower than the rise of the gross domestic product (GDP) of 3,1%. The percentage of GDP spent on healthcare in 2016 reached to 13,8%, which is a lower percentage than the previous years where it came above 14%. Nevertheless, it is significantly higher than the European guideline of 10,5% of GDP spent on healthcare (CBS, 2016). This means that the Dutch healthcare is still focusing on decreasing its costs. The Ministry of Health, Welfare and Sports (VWS) states in their policies that the government will be saving €280 million extra over 2018 (VWS, 2017). What counts for healthcare on national level, counts for MST on hospital level. Because of their financial situation, they have to make large savings. One of the actions MST did to make these savings possible, is that they started an efficiency program (Dutch: Rendementsprogramma). This program runs until the end of 2018 and aims to save 30 million in total costs. In 2016 MST scaled off 83 FTEs (full-time equivalent) in mainly the supporting departments (Medisch Spectrum Twente, 2016). In 2017 an additional number of 155 FTE is required to scale off. A lot of this reduction of FTE will be done by attrition and by cutting in supporting departments. Next to resources in workforce, the number of hospital beds is and will be scaled off. Therefore, the same level of care needs to be delivered with less resources.

1.2 Medisch Spectrum Twente

Medisch Spectrum Twente is located in the city centre of Enschede. It was founded in 1990 through the merger of multiple hospitals and organizations in Enschede, Oldenzaal, Haaksbergen and Losser. MST still has a branch in Oldenzaal. The locations in Oldenzaal and Haaksbergen are still in use as outpatient clinics. In Enschede, two hospitals were connected by a footbridge. Both locations in Enschede were outdated and logistically inefficient and besides that, two locations meant more assets than necessary. The construction of a new facility was inevitable. This new building located in the city centre opened on 11th of June of 2016 . It is one of the larger top-clinical, non-academic hospitals in the Netherlands. MST has a large working area. Besides the region of Twente, it also reaches into Germany. Next to that, MST is the fourth biggest trauma centre with 7.500 trauma patients every year. Table 1.1 details a couple of key figures of MST (MST, 2016). MST has 494 hospital beds in use within its hospital. In this number the beds of the ICUs (Intensive Care Units) and the acute admission department, the department that keeps emergency patients for quick diagnosis, are included. MST has 15 operating rooms (OR) whereof 14 are currently in use. One OR (OR 3) is not fully constructed, but can be operationalised in the future.

Service Area	263.357 inhabitants
Outpatient Visits	374.000
Bed Capacity	494 (hospital in Enschede)
Staff	2.851 employees
Medical Specialists	232
Operating Rooms	14

Table 1.1: Medisch Spectrum Twente - Key Figures.

1.3 Problem Description

In this research, the core problem that MST faces is: high variability in workload at the nursing wards. It is believed that this high variation in bed utilization (and therefore workload) is partly caused by insufficient alignment from the planning department with the nursing wards. Although external parties have calculated that the current level of hospital beds is sufficient to handle the patient streams, nursing wards face problems during the peaks in workload. However, this number of hospital beds will even be decreased in the nearby future. This means that workload needs to be more levelled, so that MST can cope with this decrease in capacity.

The causes for this variability in workload can be found at nursing wards itself or further upstream. An example of a cause of variability, is a lack of standardization in healthcare protocols, so that patients are not discharged on time and therefore stay longer in their beds. Several projects are currently executed to reduce the part of variability in workload and bed utilization that find their cause at the nursing wards itself. A cause of variability in workload at the nursing wards that finds its roots further upstream, is for example the arrival of emergency patients. This arrival is unpredictable and therefore it is hard to reduce the variability it causes at the nursing wards. Another example is the lack of alignment of surgery planning with the outflow and length of stay of patients towards and at the nursing wards. Figure 1.1 shows this all together.

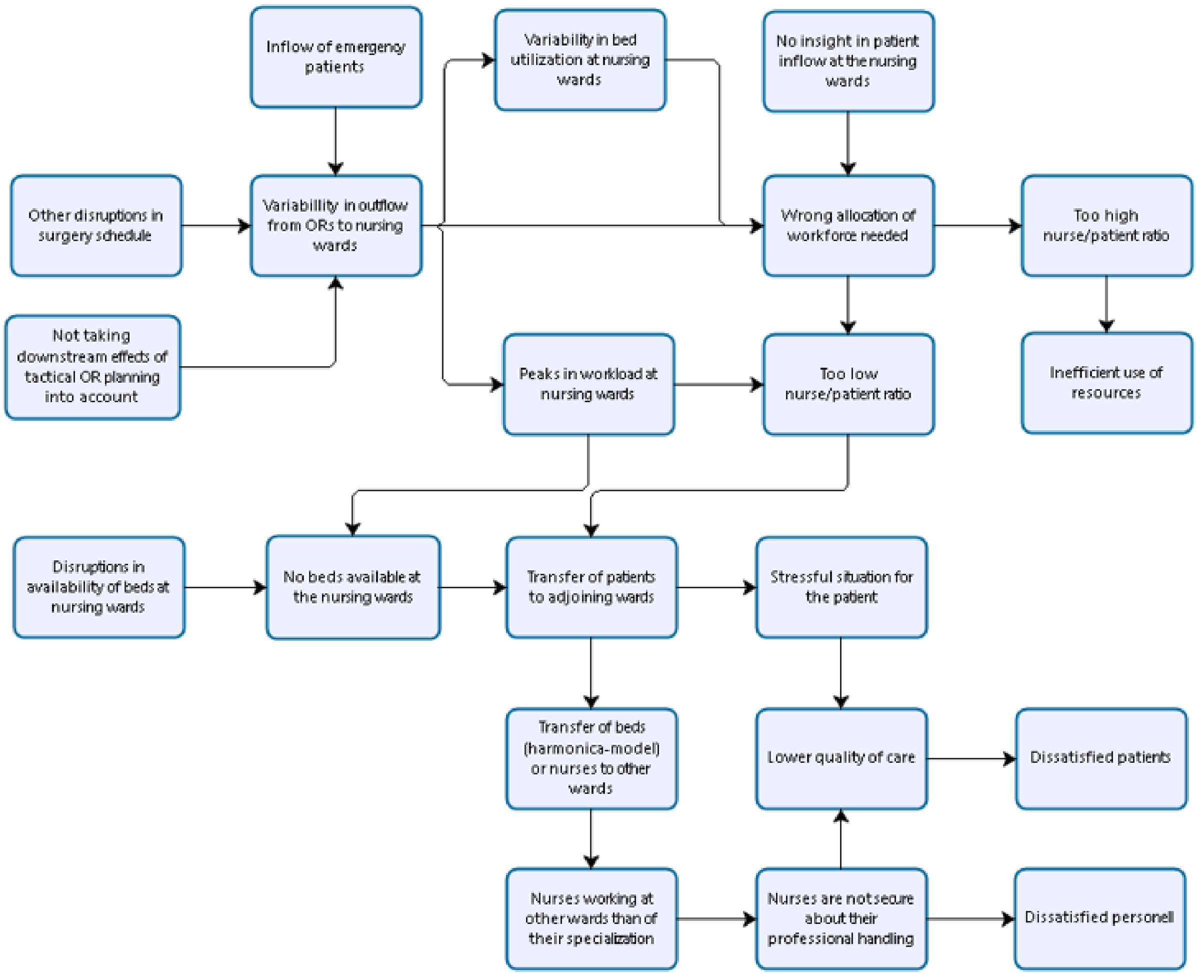


Figure 1.1: Problem Cluster of Variability in Bed Utilization

It shows what variability in outflow from the ORs to the nursing wards causes further downstream. Furthermore, it shows that the OR is the department that influences that workload at other departments the most. And therefore, giving consideration to the downstream effects of the OR department is essential for balancing the workload in a hospital (Peter T. Vanberkel et al., 2011).

The cluster of Figure 1.1 starts with variability in outflow from ORs to nursing wards. Along with the unpredictable arrival of emergency patients and lack of alignment in the planning, this causes variability in outflow at the nursing wards and therefore causes variability in bed utilization. Along with a lack of insight in patient inflow at the wards this variability cause a wrong allocation of resources, which leads to a too high nurse/patient ratio. This is an efficiency problem. The aforementioned factors lead to unavailability of hospital beds and a too low nurse/patient ratio. This nurse/patient ratio is the number of patients that are under the care of one nurse. If the number of patients assigned to one nurse gets too high, the ratio gets too low and falls below the agreed standards of a ward. This leads to the transfer of a patient to adjoining wards. This is a stressful situation for a patient and therefore it might reduce the quality of care and cause dissatisfaction among patients. When nurses are assigned to wards with other patients than their own specialization, they become less secure about their professional handling. This leads to dissatisfied personnel and it can lead to a lower quality of care.

1.4 Research Objective

The objective of this research is: *To reduce variability in bed utilization at the nursing wards by optimizing the OR planning.* It is part of a bigger project solely based on variability reduction within the hospital.

1.5 Research Questions

From the problem description and the research objective we formulate our main research question as: *How can MST reduce its variability in bed utilization at the nursing wards with OR planning optimization?*

On the base of this main research question, we formulate the following sub-questions:

1. What is the path in which the patients flow through the hospital?
2. How is the system organized at the planning department, OR department and the nursing wards?
3. What are relevant key performance indicators (KPIs) of the nursing wards, OR department and the planning department?
4. What is the performance of the planning department, OR department and the nursing wards?
5. What kind of approaches can be used to optimize the surgery scheduling?
6. What approach or model is best applicable?
7. What are the main findings and what are the effects of the model on the KPIs?
8. How can the main findings in the research be implemented in the organization?

Chapter 2

Context Analysis

In this chapter, an analysis is given of processes within MST that are related to the problems formulated in Chapter 1. The main patient flow process is described in Section 2.1. All the hospital departments involved in the process are, along with the OR department and the nursing wards, described in Section 2.2. The OR department and the nursing wards are the departments on which our research is focused. Therefore, the OR department has more in-depth process description in Section 2.3. The processes in the nursing wards are described in Section 2.4. These paragraphs answer research question 1: *What is the path in which the patients flow through the hospital?* Section 2.5 gives an insight in the current surgery planning process from strategic level to the operational level. These sections answer research question 2: *How is the system organized at the planning department, OR department and the nursing wards?*

2.1 Patient Flow Process

In this research we distinguish two main patient streams, namely elective patients and emergency patients. Elective patients are divided into patients that need to undergo surgery and the non-surgical patients. The surgical patients have a division into clinical patients and day treatment patients. The elective patient stream is also divided into other three other sub-categories on the base of urgency. Patients that belong to the high urgent elective category must receive surgery within one week after diagnosis at the outpatient clinic. The second category of patients, medium urgency, needs to undergo surgery within 30 days. The category of patients that can receive surgery after 30 days, is the low urgency patient category. In emergency patients, MST distinguishes three patient groups on the base of urgency. The most urgent category needs to undergo surgery within 30 minutes. Patients in the second category of emergency patients need to undergo surgery within 5 hours. Patients in the last category of emergency patients need to undergo surgery within 24 hours.

Figure 2.1 shows the general process flow of the patient. Elective patients enter the hospital at the outpatient clinic. At the outpatient clinic, patients get diagnosed. In a consult with a physician it is decided whether the patient needs surgery or not. In case patients need surgery, they are put on a waiting list and must undergo pre-operative screening (POS). The patients that are non-surgical are divided into two types. The first type are outpatients. They undergo small procedures at the outpatient clinic. The second type of patient groups are also non-surgical, but still require special medical care and therefore need to be admitted to a nursing ward. In this report we refer to this group as the non-surgical patients. Figure 2.1 also shows the flow of emergency patients throughout the hospital. Emergency patients can go directly from the emergency department to the OR department, and their POS gets done at the OR department. However, most emergency patients first visit the acute admission department. After elective patients underwent surgery, they are brought to the PACU, the recovery, or ICUs to recover from surgery and anaesthesia. When their medical condition is sufficient, they are transferred to their ward. From the wards, patients can get discharged. Other possibilities during the care process are the transfer of a patient to a nursing home or mortality. The possibilities are all denoted with discharge in Figure 2.1.

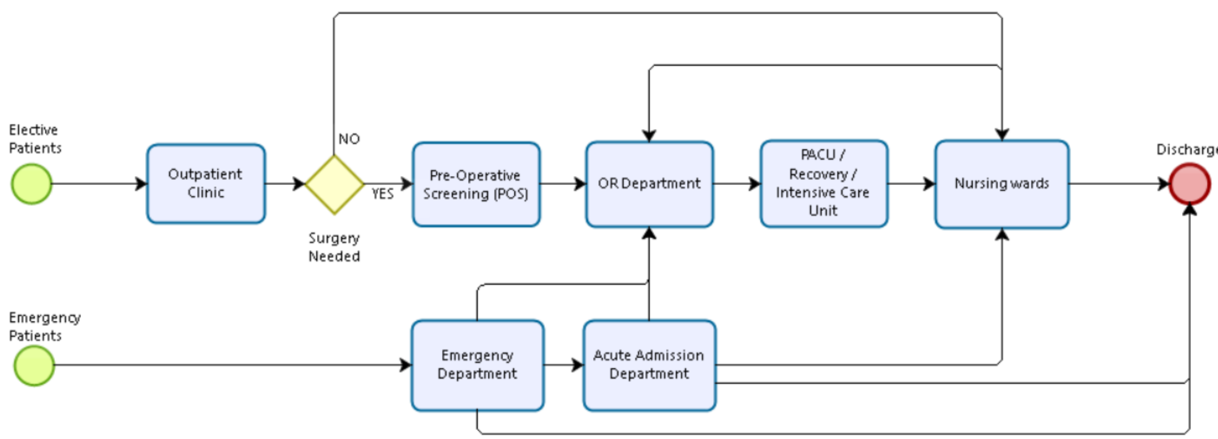


Figure 2.1: Patient Flow Process in MST

2.2 Hospital Departments

This section presents a brief description of the departments around the OR department and the nursing wards and what role each department has in the process. It describes the departments that are presented in Figure 2.1

Outpatient clinic: At the outpatient clinic, patients get diagnosed by a specialist. Most patients enter the hospital through the outpatient clinic. Before patients undergo surgery, they are placed on a waiting list and afterwards referred to the preoperative process. Small procedures are performed at the outpatient clinic, but these patients do not stay overnight at the hospital.

Pre-Operative Screening (POS): Before patients undergo surgery, they have their pre-operative screening. In the screening the patient is checked on factors such as MRSA risk/infection, medication and allergies, blood pressure and several other factors. In case of elective patients, this must be done at maximum six months before the surgery. POS usually consists of several meetings with an anaesthetist(-assistant), physician-assistant and/or dietitian in which all factors are checked to make sure a patient can undergo surgery. It is also used to inform the patient about the surgery, for example regarding medicine use and whether they must be sober or not. After the POS is done patients are planned for surgery. Patients are admitted on the day of surgery or the day before surgery. This can be done in two ways. Some patients first get a bed at a nursing ward and go from a ward to the holding department. Other patients are so called *'NOU-patients'* (Dutch: Nuchtere Opname Unit). These patients only get a bed when they are in the holding department, which means that they walk to the holding. MST has taken this method in use to prevent unnecessary hospitalization. Emergency patients that require surgery immediately get their POS directly at the OR (or in case of a less urgent case it can be done at the nursing wards).

Emergency department and Acute Admission Department: The acute admission department is the department that admits patients from the emergency department. For a maximum of 48 hours these patients can stay at this department. Its goal is to provide quick diagnosis and to separate elective patients from the emergency patients. This leads to less disruptions for the planned elective patient stream. Of the patients at the acute admission department, about 40% is directly discharged. All the emergency patients flow from the emergency department to the acute admission department, except patients for cardiology, obstetrics, paediatrics, psychiatric patients that go to the PAAZ department (Dutch: Psychiatrische Afdeling Algemeen Ziekenhuis) or patients that have specific exclusion criteria. These patients flow directly to the OR department or get discharged. Patients that flow from the emergency department or acute admission department to the OR, follow the same route as elective patients from there on.

Recovery and Post-Anaesthetic Care (PACU): After patients had surgery, they usually stay at the Post-Anaesthetic Care Unit (PACU) or the recovery. In these departments they are monitored while they recover from surgery. When a patient is well recovered from anaesthesia, he/she is transferred back to the nursing ward. Every medical specialist that assigns a patient for surgery indicates whether a PACU bed is necessary after surgery. Hospital beds for PACU patients are allocated to them before these patients are at the OR department.

Intensive Care Unit (ICU): In case of intensive care and monitoring needed, patients stay at the Intensive Care Unit (ICU). When their situation is stable, patients are send to the nursing wards. Every medical specialist that assigns a patient for surgery has to indicate whether a ICU bed is necessary after surgery. Hospital beds for ICU patients are allocated to the patients before these patients are at the OR department.

2.3 OR department

The OR department is the department where surgeries take place. The OR department of MST consists of 15 ORs of which 14 are currently in use. Only OR 3 is not fully constructed, but can be operationalized in the future. At the holding, the first patients of the day arrive at 7:45 AM. At 8 AM the first patient is in the operating room along with an OR-team that prepared the OR for surgery. Due to the *twee-tafel-systeem* (which means that every anesthaesiologist works at two ORs at the same time), the anaesthesia procedure starts at 8 AM in the first OR and at 8:15 AM in the next OR. The total program of an OR ends at 4 PM or 4:30 PM, depending on the start of the program. This means that the last patient of the day leaves the OR by that time. Figure 2.2 shows the operational process of a single elective patient. This process is visualized as a critical path, which means that every preceding activity must be finished before the next activity in the flow can be started.

Before patients undergo surgery, they go the holding area where they get admitted to a hospital bed. During the time in the OR, the patient and personnel go through several steps. First, the patient's transfer from the holding towards the OR takes place. After the patient enters the OR, the time-out period takes place which is the final patient check by the surgeon. After the time-out period, the anaesthesiologist starts with the anaesthesia procedure. When the anaesthesiologist is ready, the intervention starts. Once the surgeon is finished, the end of the intervention is registered and the surgeon leaves the OR. Before the patient leaves the OR, the patient is brought out of anaesthesia. The moment the patient leaves the OR is registered and minus the time the patient enters the OR, the planned OR time. The time between the start and finish of the intervention, is the surgery time.

Table 2.1 shows the surgical specialties that have surgery time within the OR department. Furthermore, Table 2.1 shows a brief description of the focus areas of these specialties. The abbreviations given in the table are used throughout this research to indicate the corresponding surgical specialties.

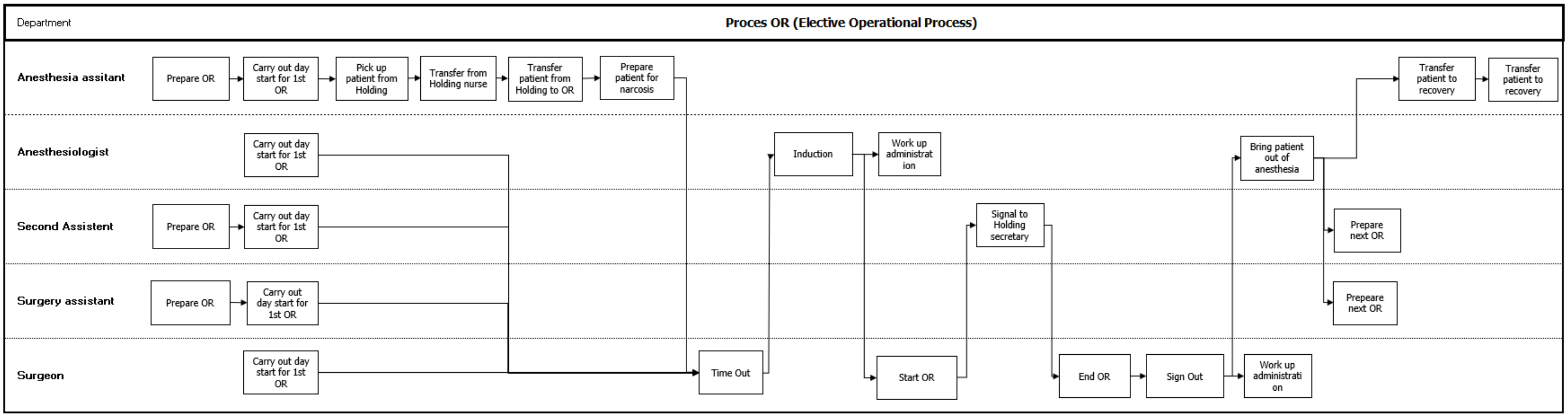


Figure 2.2: Process OR Department

Abbrevation	Specialty	Description
SPC	Special Dental Care	Special surgical care for patients that cannot be treated by a dentist anymore.
CAR	Cardiology	Treatment of cardiovascular diseases
CH	General Surgery	
	- Traumatology	Takes care of patients after traumatic incidents
	- Vascular Surgery	Treatment of vascular abnormalities
	- Oncology	Large and complex digestive surgery related to cancer
CTC	Cardio-Thoracic Surgery	Treatment of diseases in the thorax centre. Disorders in heart, lungs and large blood vessels are treated.
GYN	Gynaecology	Treatment of abnormalities or disorders at the female genitals
MA	Oral and Maxillo-facial surgery	Facial surgery for treatment of diseases in the jaw, mouth, teeth or face.
ENT	Ear, nose and throat surgery	Surgery and treatment of diseases or disorders in ear, nose or throat.
MDL	Gastroenterology	Treatment of digestive disorders.
NEURO	Neurosurgery	Treatment of disorders in the neurological system
OPT	Ophthalmology	Treatment of disorders in the eyes
ORT	Orthopaedics	Treatment of disorders or abnormalities in the musculoskeletal system.
PS	Plastic Surgery	Reconstructive surgery involving hand and wrist surgery.
PPA	Anaesthesia	Treatment of pain, takes care of pain relief (during surgery)
URO	Urology	Treatment of disorders on the urinary-tract system and male genitals

Table 2.1: Surgical Specialties in MST 2017

2.4 Nursing Wards

A ward is a facility within the hospital that provides specific care to the patients. When patients are recovered from surgery at the recovery, the PACU or the ICU, they are transferred to a nursing ward. At the wards, personnel know what the expected arrival of patients is and therefore the admissions it has, which directly translates in the beds it needs. However, the beds are not reserved for a specific patient after surgery. This can lead to more patients than a ward can handle and therefore patients can become boarded. A patient is *boarded* on another ward, when a bed shortage occurs on its designated ward.
Figure 2.3 shows the postoperative process at the nursing wards. When a patient enters the ward the nurse first reads the report about the surgery and the medication. After that, the patient is checked and post-surgical agreements are executed. Afterwards, activities of daily living are done with the patient. Next to that, the patient receives its medication. After these steps, the nurse prepares the physician visitation. With the visitation, the physician determines whether the patient requires a longer stay or that he or she can be discharged. From there on, the discharge process

takes place.

In MST nursing wards are grouped. Table 2.2 shows the groups that are located in Enschede. The groups mentioned here are groups of nursing wards. For example, the thorax centre is the group of nursing wards where cardio-pulmonary- (CTC) and cardiology (CAR) patients go. The table also shows the number of beds that belongs to each group. The 4th floor is fully dedicated to take care of surgical clinical patients. The fifth floor is a mixed floor that takes in surgical clinical patients and non-surgical clinical patients. The sixth floor is dedicated to take care of non-surgical clinical patients. In 2017 MST reduced the number of hospital beds. After the bed reduction and relocation of nursing wards that took place in November 2017, the number of beds per ward became as they are mentioned in Table 2.2. These numbers include beds for day treatment and beds for the Woman Child Centre, which is the centre for medical care for women and children such as gynaecology, obstetrics and paediatrics.

Location	Nursing Ward Group	Number Of Beds
6th floor	Internal Medicine	48
	Lung Department	34
	Gastroenterology	19
	Acute Admission Department	16
5th floor	Neurosurgery / Neurology / Stroke	38
	Thorax Centre	56
	H4 (Urology)	19
4th floor	Oncology	40
	Vascular- / Ortho- / Trauma	47
	Psychiatry Department	23
Ground floor	Acute Admission Department	34
Other	Woman Child Centre	56
	Intensive Care Units	32
	PACU	2
	First Heart Help	6
	Coronary Care Unit	10
	Total	480

Table 2.2: Division of Hospital Beds MST

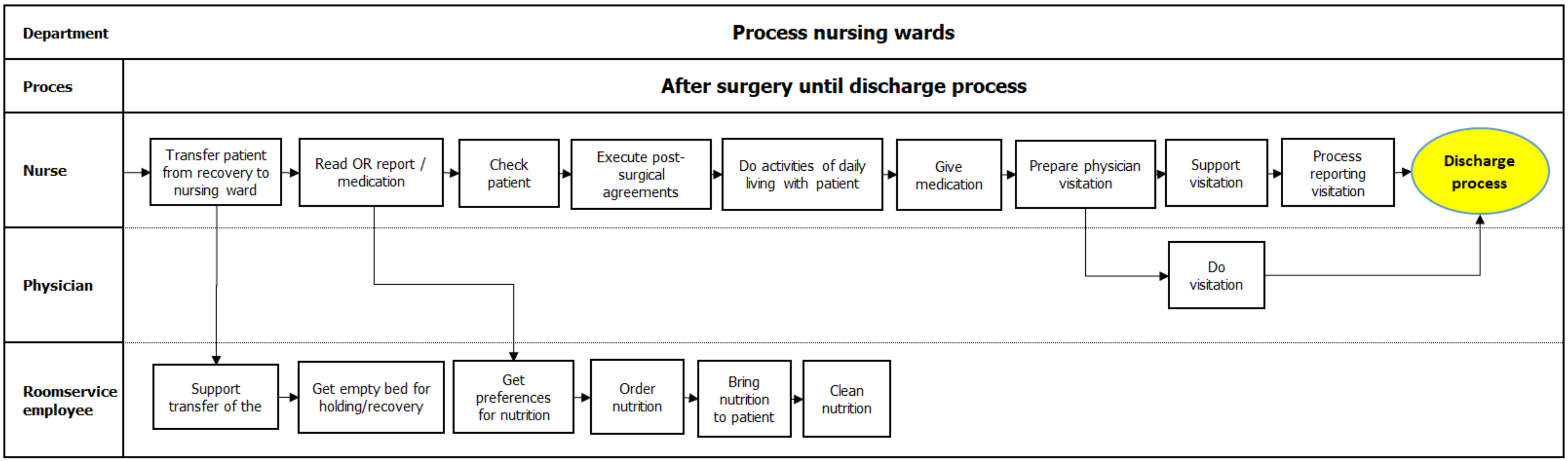


Figure 2.3: Process Nursing Wards

2.5 Planning Process

The scheduling of the OR department has often been mentioned to as a multiple stage process (Fügener et al., 2014; Santibáñez et al., 2007; Vanberkel et al., 2011a). It is a process that consists out of decisions that are made on different hierarchical levels. Figure 2.5 shows the framework for healthcare planning and control by Hans et al. (2012). It shows the various levels in which decisions are made upon scheduling the OR department. Hans et al. distinguish four managerial areas and four hierarchical levels. The planning of the OR department belongs to the resource capacity planning area.

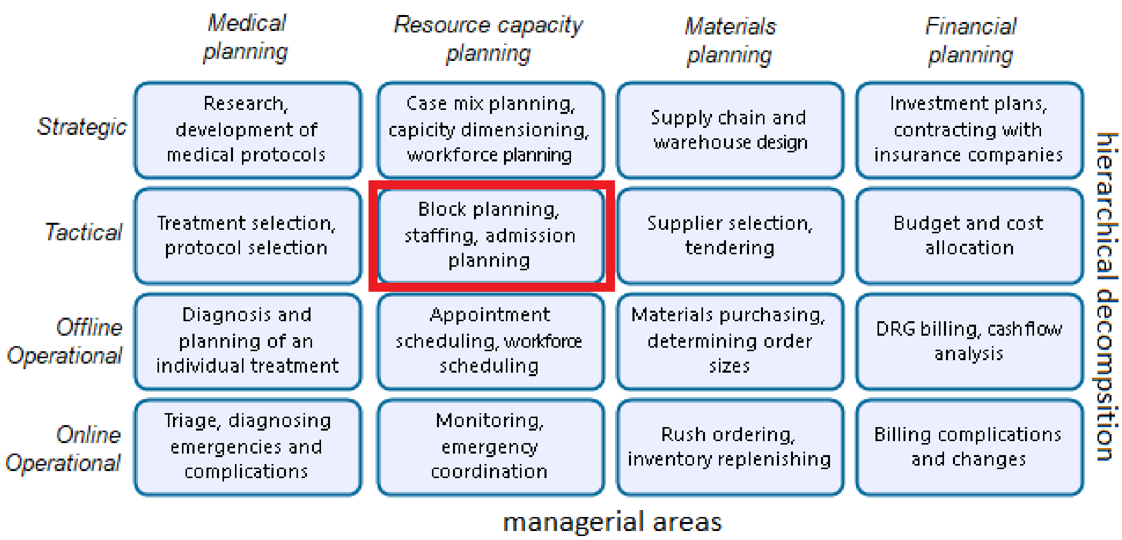


Figure 2.4: Framework for Healthcare Planning & Control. Source: Hans et al. (2012)

The three-stage process of scheduling the OR department starts with Stage 1, the allocation of OR time to the different specialties. This is a step made on the strategic level where the allocation is determined on the base of patient patterns, agreements with health insurance companies and the priorities of the hospital management Vanberkel et al. (2011a). This decision corresponds with the strategical decision in resource capacity planning as mentioned in Figure 2.5. The decision of allocating OR time to the specialties is made by the supporting departments in consult with specialty management. In 2018, this managerial decision is expected to be done by the new department Ketencapaciteitsorgaan. This department is the department that will work on improving efficiency among the healthcare chain in the hospital. The calculation of the necessary capacity per specialty is currently done by supporting departments and the surgical specialties. The necessary capacity depends on four factors, which are sold OR-care products, percentage surgeries done at the OR department, percentage surgeries done within session time and total case time. The sold OR care products depend on the operations done at the OR. These operations get reimbursed by the healthcare insurance companies through diagnosis treatment combinations (in Dutch: DBC).

A diagnosis treatment combination is a standardized price for a care path of a patient. The next part, is the percentage of surgeries that is done at the OR and the percentage of surgeries that is done within session time. Some surgeries are done at the outpatient clinic or at the location in Oldenzaal. Therefore, it is important to know which part of surgeries is done in the OR department at the location in Enschede. The percentage of surgeries done within session time is important for capacity calculations, because some surgery regular hours. For the capacity calculations, MST uses the percentage of surgeries that is done within session time including emergency surgeries. The last factor that is incorporated in the capacity calculation, is *case time*. Case time is the time between the arrival and the departure of the patient at the OR.
The second stage of the OR planning is the decision made on the tactical level. As shown in Figure 2.5 our research is focused on this level. In this stage, a cyclical block schedule is made on the base of the capacity calculations in consultation with specialty managements and supporting departments. In this fixed block schedule of four weeks, surgical specialties are assigned to ORs on specific days (OR-days). During weekend days, no elective surgery takes place. Therefore, the schedule is a cyclic schedule for 20 working days. Out of the block schedule, surgical specialties assign surgeons to OR-days. In this tactical phase, effects of the OR schedule on downstream effects are not considered.

Table 2.3 shows the surgical specialties and in which ORs their surgery can be performed. Some of the surgical specialties can only be done in specific OR and besides that, most surgical specialties have preferences for in which OR they want to perform their surgeries. For example, the surgical specialty urology can only be performed in OR 6 and OR 11 because of characteristics of these two ORs. Another example of OR dedication is OR 14 and OR 15, which are always and fully dedicated to cardio-thoracic surgery.

Specialty	ORs in use
Special Dental Care	8
Cardiology	12
General Surgery	1-13
- Traumatology	7 (preferably)
- Vascular Surgery	12 (preferably)
- Oncology	7,5 (preferably)
Cardio-Thoracic Surgery	13-15
Gynaecology	10
Oral and Maxillofacial surgery	4
Ear, Nose and Throat surgery	1,8
Gastroenterology	8
Neurosurgery	2,4,7
Ophthalmology	7
Orthopaedics	7,8,9,11
Plastic Surgery	7,8,11,13
Anaesthesia	2
Urology	6,11

Table 2.3: ORs in use by Surgical Specialties

Figure 2.5 gives an example of the current block schedule of MST. It shows the number of ORs and it shows that OR 3 is not in use. Figure 2.3 further shows that OR 13, 14 and 15 are mainly used for cardio-thoracic surgery. These ORs are the thorax ORs and almost fully dedicated to cardio-thoracic surgery. Only OR 13 is sometimes dedicated to plastic surgery and general surgery. Figure 2.5 shows that OR 9 is fully dedicated to orthopaedics and that OR 5 is daily dedicated to general surgery.

MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	ENT	NEURO	NEU	CH	URO	ORT	CH	ORT	CH	PS	CH	CH	CTC	CTC
2	CH	PPA	CH	CH	URO	PS	SDC	ORT	GYN	CH	CH	CTC	CTC	CTC
3	ENT	NEURO	NEU	CH	URO	GS	SDC	ORT	GYN	ORT	CH	CH	CTC	CTC
4	ENT	NEURO	CH	CH	CH	OPT	CH	ORT	GYN	ORT	CAR	PS	CTC	CTC
5	CH	CH	MA	CH	URO	NEURO	ORT	ORT	GYN	CH	CH	PS	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	ENT	NEURO	CH	CH	URO	GS	SDC	ORT	GYN	ORT	CH	CTC	CTC	CTC
9	ENT	CH	CH	CH	URO	ORT	ENT	ORT	CH	PS	CH	CTC	CTC	CTC
10	CH	NEURO	CH	CH	CH	ORT	SDC	ORT	GYN	URO	CH	PS	CTC	CTC
11	ENT	NEURO	CH	CH	CH	ORT	CH	ORT	GYN	CH	CAR	PS	CTC	CTC
12	CH	NEURO	MA	CH	URO	NEURO	ORT	ORT	GYN	CH	CH	PS	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	CH	NEURO	NEURO	CH	URO	PS	SDC	ORT	GYN	CH	CAR	CH	CTC	CTC
16	ENT	CH	CH	CH	URO	ORT	GS	ORT	GYN	PS	CH	CTC	CTC	CTC
17	ENT	NEURO	NEURO	CH	CH	CH	SDC	ORT	CH	ORT	CH	CH	CTC	CTC
18	CH	NEURO	CH	CH	CH	OPT	CH	ORT	GYN	ORT	CAR	PS	CTC	CTC
19	ENT	CH	MA	CH	URO	NEURO	ORT	ORT	GYN	CH	CH	PS	CTC	CTC
20	X	X	X	X	X	X	X	X	X	X	X	X	X	X
21	X	X	X	X	X	X	X	X	X	X	X	X	X	X
22	ENT	NEURO	CH	CH	URO	OPT	SDC	ORT	GYN	CH	CH	CTC	CTC	CTC
23	CH	CH	CH	CH	URO	PS	ORT	ORT	GYN	PS	CH	CTC	CTC	CTC
24	CH	NEURO	CH	CH	URO	CH	SDC	ORT	GYN	ORT	CH	PS	CTC	CTC
25	ENT	NEURO	CH	CH	CH	OPT	PS	ORT	CH	URO	CAR	CH	CTC	CTC
26	CH	NEURO	MA	CH	URO	NEURO	ENT	ORT	GYN	CH	CH	PS	CTC	CTC
27	X	X	X	X	X	X	X	X	X	X	X	X	X	X
28	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Figure 2.5: Master Surgery Schedule MST. Source: MSS (6-11-2017 / 01-12-2017)

After the second stage in the OR planning process, Stage 3 is the final assignment of patients to the OR blocks which is done in MST by the planning department. This stage is located in the offline operational level of the framework in Figure 2.5. Prior research has been done within MST on reduction in variation of bed utilization by adjusting the process in this stage. Two studies have been recently conducted with using the Quadrative Assignment Problem (QAP) to come up with an optimal case mix of patients for the OR planning (Sieverink, 2017; Smit, 2015). The QAP method is based on a study by Glerum et al. (2014). Smit (2015) came up with planning rules for the planning department. December 2017, a pilot was started with these planning rules.

Figure 2.5 shows the planning process that belongs to the third stage of the OR planning process. The planning department (in Dutch: Bureau Opname) schedules patients into the OR schedule. Patients that went to the outpatient clinic and have to undergo surgery, and had their POS afterwards, are set into the system and placed on the waiting lists. This is done by setting the POS forms into the program XCare. In the block schedule specialties are assigned to OR days (certain days in the ORs). As previously mentioned, the specialty managements assign surgeons to these OR days. This means that at the planning department, the surgical specialty and the operating surgeon is already given per day. This means that at the planning department the main decision is planning the patient into the OR schedule. The planning department therefore focuses on planning the surgeries within the ORs, while considering the given restrictions. The surgeon that is assigned to a specific OR is planned by specialty management.

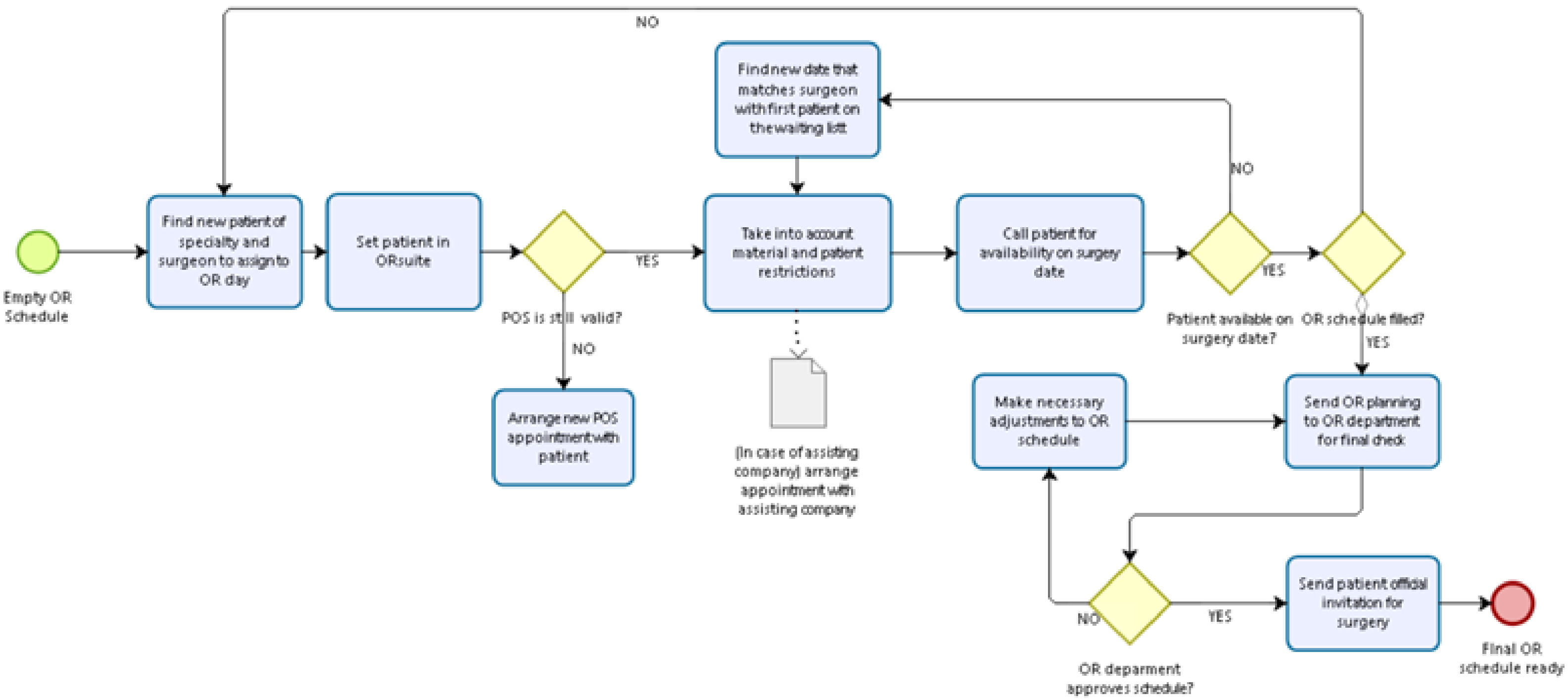


Figure 2.6: Planning Of Operations Process in MST

The specialties for which the planning of surgeries is centralized in the planning department are all specialties except for gastroenterology, oral and maxillofacial surgery, special dental care and thoracic surgery. These four other specialties have their own decentralized planning centre. The planning principle that is being used in the centralized planning is first in, first out (FIFO). The FIFO planning principle keeps access times low. With the FIFO principle, patients that come first on the waiting lists are planned first in the OR schedule. However, patients that are marked in the system as patients of high urgency (surgery within 7 days) have priority. Next to that, the planning department considers patients that want to undergo surgery from the same surgeon that did the diagnosis in the consult at the outpatient clinic. On the waiting list for surgeons, these patients have priority. The planning department fills the schedule and after that on every Tuesday the planning committee discusses the OR schedule (for the next week) on its feasibility. While planning, the planning department faces several restrictions which makes it that a feasible planning is their main priority.

Material availability: The number of instruments that is available influences the number of surgeries of the same type that can be planned on the same day. This includes not only surgical instruments, but also imaging techniques that are used during surgery. A limited amount of surgeries that use imaging techniques during surgery can be performed at the same time.

Surgeon availability and capability: The specialty management of every specialty assigns surgeons to an OR-day. On the base of the surgeon that is scheduled on an OR-day, surgeries are scheduled. Surgical specialties assign their surgeons six weeks in advance to an OR. In general, surgeons cannot perform every surgery within their surgery. Surgeons mostly perform a subset of surgeries. This means that only a limited number of surgeries of a specialty can be planned on a day, because of the limited number of surgeons that are available each day. Next to that, they do not always work on the same day every week.

Patient characteristics: Planners consider some characteristics of the patient. For example, diabetics or children must be placed as early as possible on the schedule. This is because they are weaker during surgery if they must stay sober for a long time.

Holding and recovery / ICU and PACU restrictions: If too many surgeries of a short surgery duration are placed in an OR-day, holding and recovery beds can become overloaded. Another reason for overload at the holding or recovery is that too many surgeries end at the same time. For the ICU and PACU are also limited beds available. The ICU has a large amount of beds, but the PACU only consists out of two beds. After the schedule is filled, the planning committee can ask for modifications in case the planning is overfilled or under filled. In case of too many surgeries (<85% OR utilization) the OR planner can ask for more surgeries in consult with the planning department. The end responsibility for planning surgeries while considering the ICU/PACU beds belongs to the planning department. In case of a too large number of surgeries the program will be discussed with the surgeon for that OR day. Some specialties plan in so-called 'white spots' to incorporate urgent patients in their OR-time, which can lead to an OR day being initially underfilled. The planning committee also looks at PACU/ICU places. Every specialist informs whether a PACU/ICU bed is needed postoperative. Every Wednesday the schedule gets finalized by the committee. After that, changes to the OR schedule can only be made in consult with the OR program coordinator. In case of final approval patients will receive an official invitation for surgery.

In the previously mentioned multiple stage process of OR planning, a fourth stage is sometimes also mentioned as the stage that addresses the monitoring and control of OR activities (van Oostrum et al., 2008; Vanberkel et al., 2011a). At the OR department this operational monitoring is done by the day coordinator OR. This person decides where to operate emergency patients and in which order they undergo surgery. One of the staff members of the planning department also functions as the ward coordinator. This involves the operational communication between departments in case transfers of patients between nursing wards. Every morning the bed coordinator meets with members of all the nursing wards in other to negotiate necessary transfers. Therefore, the planning department also strives towards an inflow of patients that fit the nursing wards. At the moment, this inflow (and outflow) is only visible for the current day and the day of tomorrow.

2.6 Conclusions

In this chapter, we analysed the patient flow throughout the hospital and the main processes at the relevant departments. The following questions conclude this chapter:

Question 1: *What is the path in which the patients flow through the hospital?*

In this chapter we presented the patient flow through the hospital. We showed that the patient streams are divided in the elective and emergency patient streams. Emergency patients enter the hospital at the emergency department and flow into the acute admission department or flow directly to the OR department. From the acute admission department, they flow to the OR department, or they flow to the nursing wards or they get directly discharged. From the OR department patients flow to the nursing wards. The elective surgery patients start their path through the hospital at the outpatient clinic. After consult with a physician and pre-operative screening, they flow to the OR department. After surgery, when patients need intensive care or extra monitoring, they enter the PACU, ICU or recovery. From there on, they flow to the nursing wards. Furthermore, we described all the departments that are relevant in the patient flow process and we presented the process at the nursing wards and the OR that take place for one elective patient.

Question 2: *How is the system organized at the planning department, OR department and the nursing wards?*

In this chapter we presented the main processes at the planning department, the OR department and the nursing wards. We showed process flow charts from processes for a single patient at the OR department and the nursing wards. Furthermore, we presented the process of OR planning and constructing the OR schedule and thereby showed which actor in the process make the managerial decision in the four-staged OR planning process. The tactical and the strategical phase of OR planning are currently made by supporting departments and the board in consult with the specialty managements. From Section 2.5 we conclude that at the tactical level of OR planning, no downstream effects are considered. Only for patients that flow to PACU and ICU units, bed availability is taken into account. The operational phase of the OR planning process is made by the planning department. Furthermore, we showed that the planning department is partly centralized and decentralized. We conclude that in the organization, the downstream effects are partly taken into account, but that they are only visible for a short time horizon.

Chapter 3

Performance Analysis

This chapter describes the performance of the departments in the process. We introduce indicators that evaluate the performance of the system. In this chapter we answer research question 3: *What are relevant KPIs for the nursing wards, OR department and the planning department?* and research question 4: *What is the performance of the planning department, OR department and the nursing wards?*. Therefore, Section 3.1 presents a data analysis about the MST patient population. In Section 3.2 we discuss the OR-related performance indicators and in Section 3.3 we present the indicators regarding the nursing wards. We present the performance indicators by the example of the neurosurgery ward, where to neurology-, neurosurgery- and anaesthesia patients are send. In the literature review on operating room planning and scheduling, Cardoen et al. (2010) define seven performance criteria: waiting time, patient deferral, throughput, utilization, makespan, financial measures or preferences. Financial measures and preferences are out of the scope of this research and therefore we look at the waiting time, patient deferral, utilization and makespan of the departments. Moreover, we introduce some other performance indicators that are in use by MST.

3.1 Data Analysis

In the period from 01-01-2017 to 31-12-2017, 22,233 unique patients received surgery in MST. In 10,31% of the data no indication is given about the operating specialty, surgery type or operating surgeon. Therefore, only 18,462 cases are considered. Figure 3.1 shows the total patient population over the given period. The largest specialty is general surgery with 32.11% of the total patient population. The second largest patient population is orthopaedics with 11.98% of the population. The large share of general surgery patients is because it consists out of the sub-specialties: oncology, traumatology and vascular surgery.

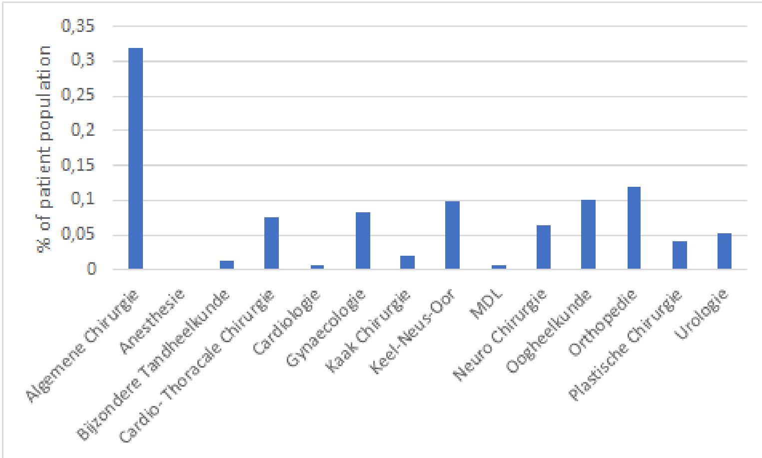
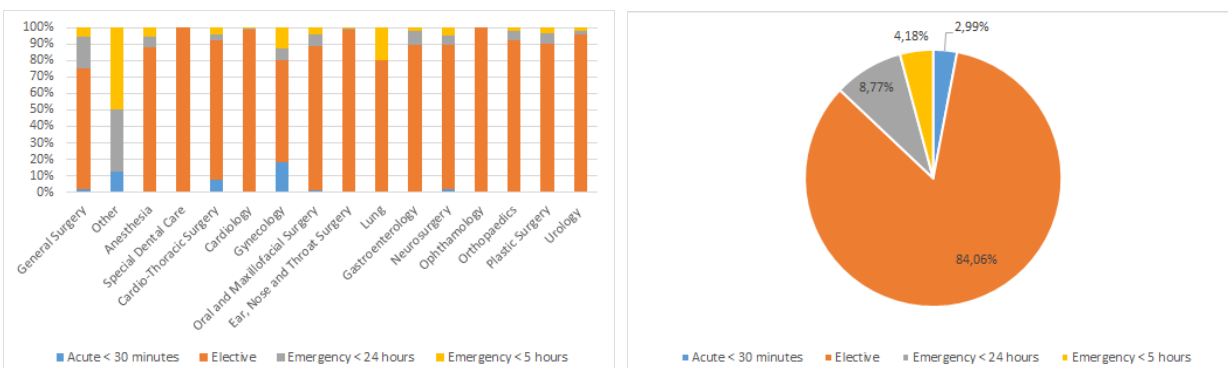


Figure 3.1: Surgical patient population MST. N = 18,462 Source: ORSuite

Figure 3.1 shows which part of the operating of the patient population is elective and which part consists out of emergency patient. Figure 3.1 shows which part of the surgical patient is elective and which part is emergency. In the analysed period, no emergency cases occurred for eye surgery and special dental care. For gynaecology, the percentage of surgeries that is emergency is relatively high, especially the type of emergency patients that require surgery within 30 minutes. This is because of frequent arrival of gynaecology patients that need a C-section. Figure 3.3 shows box-plots of the total surgical emergency patients per day in 2017. An F-test for the comparison of means (α = 0,05) showed that the number of emergency patients is significantly lower in weekend days in comparison to work days. Next to that, on average more emergency patients arrive at the ORs on Friday in comparison with Monday and Tuesday.



(a) Elective and emergency patients per specialty (b) Elective and emergency in total patient population

Figure 3.2: Elective and emergency patients during 01-01-2017 to 31-12-2017. N = 18,414. Source: ORSuite

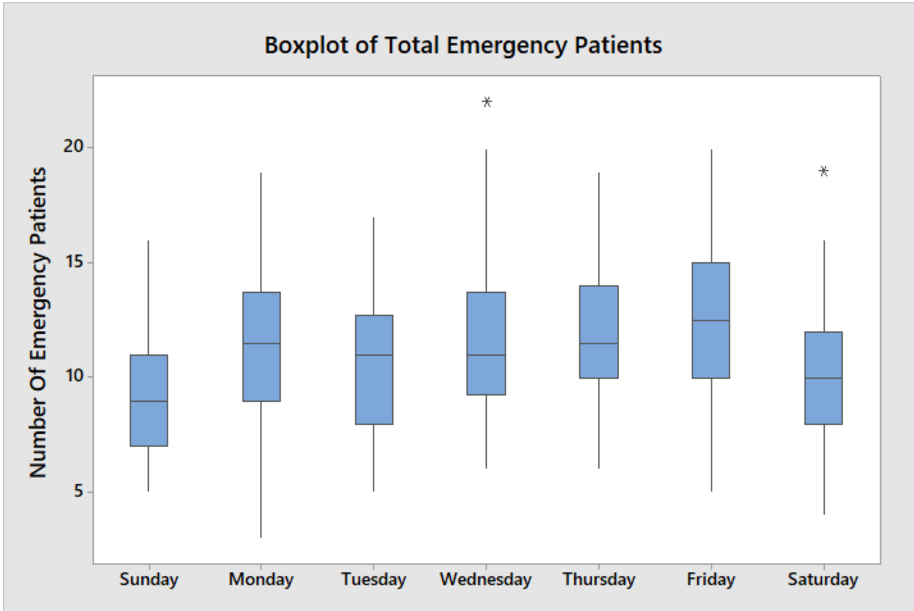


Figure 3.3: Number of emergency patients per day during 01-01-2017 to 31-12-2017 in MST. N = 4,026 Source: ORSuite

3.2 OR Department

In this section we discuss performance indicators of the OR Department. The main performance indicator of the OR department is the OR utilization. The OR utilization, overtime and main reasons of disruptions in the OR schedule, are discussed in Section 3.2.1. Next to this, we look at the throughput of ORs in Section 3.2.2.

3.2.1 OR Utilization

The OR department performs elective surgery from Monday to Friday. In these days, the ORs are opened from 8 AM until 4 PM or from 8:30 AM until 4:30 PM (this difference in starting time depends on the previously mentioned ”twee-tafel-systeem” whereby anaesthesiologists work at two ORs at the same time). This is 8 hours, which means 480 minutes of operating time. Figure 3.4 shows an example of an OR-day for a CTS session, with a CAR surgery. In this example, the OR has a late start, due to the ”twee-tafel-systeem’. Furthermore, the figure shows the terms used for time indications within an OR day. The total time allocated to a specialty to perform their surgeries in is called *session time*. In case a certain specialty has two ORs allocated to it on a specific day, it has 960 minutes of session time. Table 3.1 shows all the surgical specialties with the total amount of session time in hours per weekday in 2017. This table shows that except for CAR, NEURO, OPT and PPA, all the specialties have their ’session peak’ on Tuesday or Wednesday. Under the assumption that sub-specialties are evenly spread among weeks, this peak on Tuesday and Wednesday gives larger admission rates on these days.

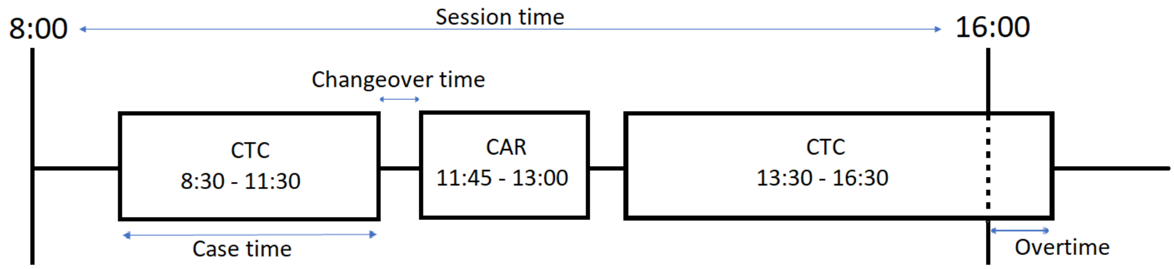


Figure 3.4: OR Day with overtime and changeover time

Specialty	Monday	Tuesday	Wednesday	Thursday	Friday	Total
GS	1710	1841	1820	1631	1642	8645
SPC	128	144	224	16	8	520
CTS	1024	1136	912	848	872	4792
CAR	64	112	0	152	0	328
GYN	336	384	260	344	375	1699
MA	112	0	0	8	384	504
ENT	312	240	376	288	187	1403
GE	24	17	76	0	4	121
NE	528	392	448	416	444	2228
OPT	0	0	4	160	8	172
ORT	632	656	752	720	671	3431
PPA	8	0	4	24	0	36
PS	156	408	232	264	386	1446
URO	280	320	344	288	271	1503

Table 3.1: Total sessions in hours per day per specialty in 2017. Source: SAP Business Objects.

The sum of the total surgeries of specialties done in an OR on a certain day is within MST mentioned to as *case time*. Recall, that the case time is the difference between the moment a patient enters an OR and the moment a patient leaves the OR and gets transferred to a postoperative unit. Case time is the makespan indicator mentioned by Cardoen et al. (2010). Surgery duration is not considered here, because this only is the time in which the surgeon operates. OR utilization is within MST also determined on the base of case time. A side note to the calculation of total used case time per specialty, is that emergency surgeries are always incorporated. This also counts when these surgeries are done within another OR than the OR allocated to that specialty. Case time can be influenced by changeovers. Or in other words, the time that is needed to make an OR ready for the next surgery. This is mentioned to as *changeover time*. The time in which a surgery falls (partly) outside of the session time is called *overtime*. Overtime is what we define as planned surgical operations that are initially planned within session time, but were finished outside session time. This means that an emergency surgery that must be done outside session time, is not calculated as overtime. The opposite of overtime is also possible, namely session time in which no procedure is scheduled. *Undertime* refers to that. Cardoen et al. (2010) define utilization as the time a resource is used against the amount of time a resource is available. The definition of OR utilization that follows out of this is:

$$OR\ Utilization = \frac{Total\ Case\ Time\ per\ day}{Total\ Session\ Time\ per\ day}. \tag{3.1}$$

In Appendix A the OR Utilization is shown for all the specialties in monthly averages. Every figure presents the planned utilization, the realized utilization and the threshold. The target for OR Utilization is the same for every specialty within MST, namely 85%. This target was set in August 2017. In Section 2.5 we mentioned that GE, MA, SDC and the thoracic specialties (CTC and CAR), have a decentralized planning. Of these decentralized planned specialties, we see that GE did not realize the target in any month in 2017, but hereby it needs to be mentioned that in only 5 of the 12 months the average planned utilization was above the 85% target. For the thoracic specialties we see that after the introduction of the 85% target, realized and planned utilization increased for CTC, to above the target by the end of 2017. However, CAR and CTC had their planned utilization under the target for the biggest part of 2017. The MA specialty had their realized OR utilization above the target for only one month in 2017 and thereby they reached a planned versus realized utilization gap of more than 20%. The last of the specialties that is planned decentralized is SDC. With about five specialties per month on average in 2017, this is a small specialty. Except for December, they realized their utilization close around the target throughout the 2017.

For ENT, GYN, NEURO and ORT we see a rise of the average planned utilization and realized utilization after August 2017. For ENT surgery, we see that they never reached the utilization target of 85% in 2017, but that the planned utilization was never above the target. For GS, we see a comparable situation. For this specialty, the utilization target was never reached. However, the planned utilization was never above 90%. For both ENT and GS, we see that the gap between planned and realized utilization is small ($\leq$ 6%). This means that they can work close to the planned utilization level. Nevertheless, since this planned utilization level is sometimes not even the threshold, the specialties cannot even work above the target utilization. Of the other centralized planned specialties we see that SDC always performed above the planned utilization level. We assume this to be administration errors, because this should mean that surgeries always last longer than the time planned. We assume that SDC surgery times do not correspond with the surgery times that the planning department plans in for the ORs. URO realized an utilization of 80% - 85% throughout 2017 and hereby also counts that the planning versus realization gap was never above 10%. PS is the surgery that had the highest average level of planned OR utilization (92% as yearly average). However, the realized OR utilization only reached the target once.

All together, we conclude that specialties increased their performance in OR utilization after August 2017. Research by Hans et al. (2012) showed that an OR utilization target is directly related to overtime risk. In other words, the same OR utilization target leads to difference in overtime per surgical specialty. In their example an OR utilization target of 80%, leads to 12% overtime for ophthalmology and 35% overtime for ENT surgery. They state that in general, a complex patient mix and a low risk of overtime leads generally to a low achieved OR utilization. Furthermore, we see that performance in realized OR utilization depends on the planned utilization and that several specialties do not have a sufficient amount of planned surgeries, so that the OR utilization can get to, or above the target.

Disruptions in OR Utilization: As mentioned, the OR utilization is determined by the case time, the available session time, the planned utilization level. However, disruptions frequently happen that influence the OR utilization negatively. Figure 3.5 shows the most frequent disruptions in the surgical schedule over a period of 10 weeks, that caused at least 1% of the total lost time. Within this period, 60 different causes for disruption in the schedule were given. With the first 20% of the causes leading to 80% of the disruptions within the schedule, the pareto-effects counts here. In total 15734 minutes were lost in this 10-week period, which make 32,78 sessions lost due to disruptions in the OR-schedule. The two biggest causes that have at least 15% of the total lost time are running up into the planning and cancelled surgery. With running up into the planning, we mean finishing a surgery earlier than the planned and expected surgery time. For some specialties the planned surgery time did not correspond with the total case time. The main specialty that caused this large amount of total lost time due to running up into the planning is PS. Their planned and expected surgery time did not correspond with their realized surgery time, wherefore a lot of time went lost, since no surgeries were scheduled in this time. This also explains their poor performance in OR utilization, mentioned in Section 3.2.1. A closer look at the number of cancelled surgeries showed that the main specialties that lost OR time due to cancellation are GS (sub-specialties vascular surgery and general surgery), NEURO and ORT. We assume that especially for GS and ORT this comes forth out of the waiting time and the urgency an operation has for a patient. An orthopaedic surgery is less urgent to happen and has a smaller waiting list in comparison with a large cardio-thoracic surgery. For Neurosurgery, this comes forth out of their planning method. This specialty frequently has patients of high urgency that must undergo neurological surgery within one week. This means that small elective surgeries need to be cancelled and set to a later moment.

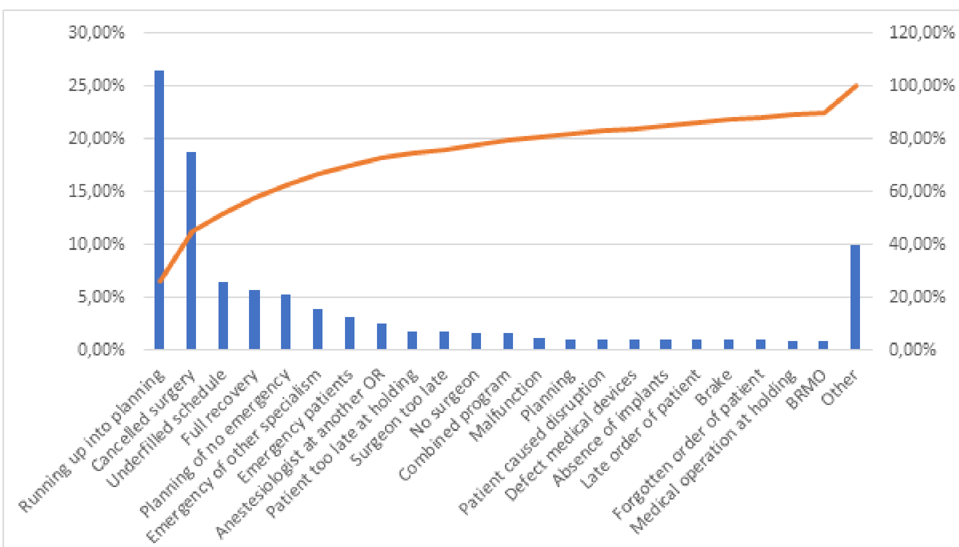


Figure 3.5: Most frequent OR disruptions in 2017. Week 31 - 40. Source: ORSuite.

3.2.2 Case Time and Surgery Duration

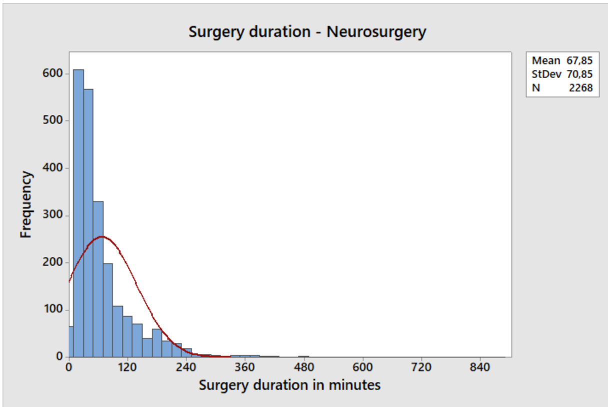
The realized OR utilization is affected by several factors. In Section 3.2.1 we showed the influence of planned utilization and main disruptions. The case time per specialty is the other factor that influences the OR utilization. We assume that specialties with less variation in surgery duration have less difficulties to reach the planned utilization level and that specialties with larger variance in surgery duration have more difficulties with reaching the target. This is because the gap between the planned surgery time and the realized surgery time stays small and therefore less OR time will be lost due to the gap in planning and realization.

In Appendix C we present the probabilities of surgery time and case time. Recall, that case time is total difference between the moment a patient enters the OR and leaves the OR and that surgery time is the net intervention time. So, in comparison with surgery time, case time includes for example anaesthetic procedures. Next to the case time and surgery time, the figures in Appendix C also show the means and standard deviation of these probabilities.

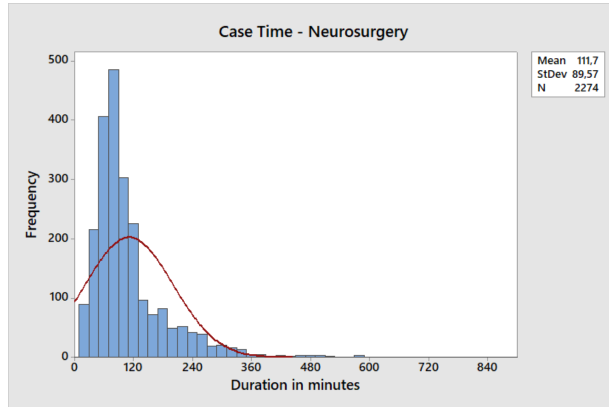
The CTS specialty shows the highest standard deviation in surgery duration. For this specialty we see two peaks in surgery duration and a visible division around 120 minutes. This division comes forth out of small cardio-thoracic procedures to the cardiac valves. The subspecialty that shows its peak at 200 minutes of surgery time are the larger cardio-thoracic surgeries. Different peaks in surgery duration for subspecialties are also visible for ORT and ENT. These specialties ORT and CTS, seem to have a large standard deviation on specialty level, but the separate subspecialties have a lower standard deviation. Therefore, our aforementioned assumption does not work for ORT and CTS. These specialties were also able to reach the planned OR utilization, which we showed in Section 3.2.1.

For all the other surgical specialties we found right-skewed graphs, with the mode of surgery duration and case time left to the mean value. The figures in Figure 3.6 give an example of the NE specialty. These figures show the surgery duration and the case time of Neurosurgery. It is visible that for this specialty the surgery duration and case time have a right-skewed graph. The both have a tail, that reaches respectively to 480 minutes and 600 minutes.

After CTS, we see that PS has the largest standard deviation and therefore variation in surgery duration. This was also the specialty with the highest gap between planned and realised utilization.



(a) Surgery Duration Neurosurgery Patients



(b) Case Time Neurosurgery Patients

Figure 3.6: Case Time and Surgery Duration from 01-01-2016 until 1-10-2017. N = 2,071. Source: XCare

In Section 3.2.1 we mentioned overtime per specialty. Table 3.2 shows the overtime of the surgical specialties in 2017. On the base of the case time in Appendix C we see that the five specialties with the highest percentage of overtime all had surgeries with a case time longer than 480 minutes. For CTS, this meant already a total of 115 hours in overtime due to case time length. The same is noticed for MA, CAR, PAS, GS and NEURO.

Surgical Specialty	Total Overtime in Hours	Average Overtime Per Session
CTS	572.87	12.52%
MA	8.38	2.23%
CAR	5.57	1.99 %
PS	16.93	1.37%
GS	92.9	1.17%
NE	1.88	0.85%
URO	8.73	0.67%
ENT	11.75	0.60%
GYN	6.23	0.36%
ORT	3.52	0.13%

Table 3.2: Overtime per Session for Surgical Specialties in 2017. Source: SAP Business Objects.

OR Throughput: Throughput is one of the performance indicators defined by Cardoen et al. (2010). The throughput of a specialty is what we define as the number of surgeries planned within an OR. In Appendix B the number of surgeries per session per specialty are presented. Figure 3.7 presents the number of surgeries per session for NE. If the surgery duration and case time graphs have a right-skewed graph, the surgeries per session must have a left-skewed graph. In other words, if the surgery duration is small, a lot of surgeries fit in one session. This counts for NEURO, the mode of the case time is 70 - 90 minutes and the mean is 111.7 minutes. The peak in number of surgeries per session is 4 surgeries.

The figures of Appendix B show that the smaller specialties ($\leq$ 5 sessions in MSS) SDC, OPT, MA, GE and ENT show large variation in number of surgeries per session.

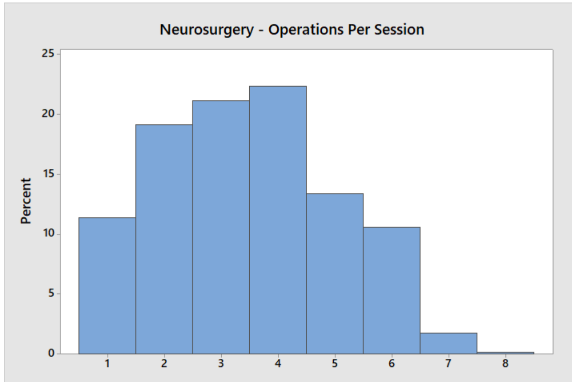


Figure 3.7: Number of Surgeries Per Session Neurosurgery from 01-01-2016 until 1-10-2017. N = 1739. Source: XCare

3.3 Nursing Wards

In this section we discuss performance indicators for measuring the performance of the nursing wards. First, we look at bed utilization and occupation at the nursing wards and the length of stay of the patients. In Section 3.3.1 we discuss the bed occupation and utilization and variability of bed utilization at the nursing wards. Cardoen et al. (2010) define makespan, a performance measure for wards, as the completion time of the last patient's recovery. We define we define makespan here as length of stay (LOS) of patients. We discuss LOS of the different specialties in Section 3.3.2. However, the workload at the nursing wards does not solely depend on these first three indicators. Therefore, number of admissions and discharges are also analysed in Section 3.3.3. In all these sections, we refer to the nursing wards with the names MST uses. Therefore, Table 3.4 shows the nursing ward groups and their names. We focus on the department for neurosurgery and neurology, because with these two surgeries we have a patient mix of short stay and long stay patients and a surgical and non-surgical specialty. The departments ENEUVP and ESTRVP belong to this. In the remainder of this report we refer to these departments as ENEUVP.

Nursing Ward Group	Name	Wings
Internal Medicine	EINTVP	C6/E6
Lung Department	ELONVP	C6/A6
Gastroenterology	EMDLVP	A6
Acute Admission Department	EAOVVP	A6
Neurosurgery / Neurology / Stroke	ENEUVP + ESTRVP	E5/C5
Thorax Centre	ETHOVP	C5/A5
H4 (Urology)	EGUOVP	E5
Oncology	ECONVP	E4
Vascular- / Ortho- / Trauma	ECVTVP	B4/C4/E4
Acute Admission Department (Ground Floor)	EAOBVP	AOA
Gynaecology	EGYNVP	GYN
Day-treatment	ESNYDV	SNY

Table 3.3: Nursing Wards in MST

3.3.1 Bed Occupation and Bed Utilization

The main research objective is to reduce variability of bed utilization in nursing wards. Therefore, we need to define variability. (Litvak et al., 2005) divides variability into two types: artificial variability and natural variability. Natural variability is the uncontrollable variability of the process, the variability that is inherent to the process. An example of natural variability in the process, is the flow of emergency patients. Their arrival at the OR is driven by sickness, while the arrival of elective patients at the OR is driven by scheduling practices. The variable arrival of emergency patients is therefore uncontrollable and natural. On the other hand, artificial variability is the variability that is potentially controllable (Litvak et al., 2005). Artificial variability is for example the flow of elective patients, because their flow is mostly driven by scheduling methods and this variability can be controlled. Therefore, when variability is mentioned in this research, artificial variability is meant. Next to the definition of variability, a measure of variability is needed. Standard deviation is a frequently used measure to calculate the spread of data. However, standard deviation is not related to the mean. For example, if two wards with respectively hundred and ten beds both have a standard deviation of 10 beds, no difference in performance is seen. Therefore, we use the coefficient of variation, which is the dimensionless coefficient that results from dividing the standard deviation (σ) by the mean (μ). It is denoted by c_v and it is calculated by:

$$c_v = \frac{\sigma}{\mu} \tag{3.2}$$

Bed Occupation: Within MST, bed occupation is defined as the percentage that comes of dividing the number of occupied beds by the number of available beds (De Vries-Banken, 2010). However, if the initial number of available beds is not sufficient to handle inflow of patients and initially blocked beds are taken in use, this ratio can rise above 1. In our research, we did not have sufficient data to incorporate bed blocking. Therefore, we use a different definition for bed occupation. We define bed occupation as the number of occupied beds per day. This means that if a bed is used during a day, it is measured as occupied. It does not matter whether a bed is used multiple times per day or just once, after it has been taken into use it counts as an occupied bed. Figure 3.8 shows the occupation per weekday of ENEUVP in the period of 01-01-2017 until

01-01-2018. The box-plots show the minimum number, maximum number of beds used and the average number of occupied beds.

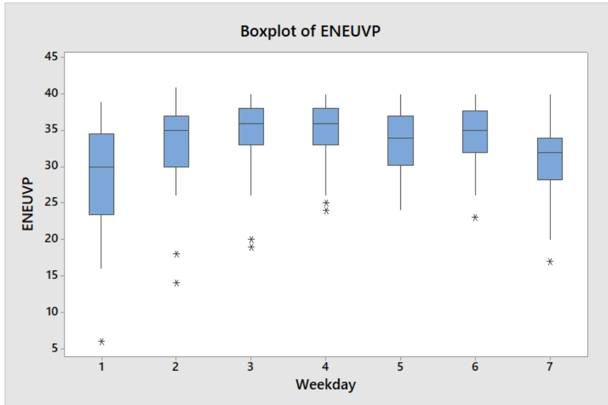


Figure 3.8: Boxplots of bed occupation on weekdays ENEUVP from 01-01-2017 - 01-01-2018. Source: XCare

Table 3.4 shows the outcomes of the F-test between the days throughout 2017 for ENEUVP. The p-values are given in the table. Where p-values are lower than 0.05, a significant difference in yearly occupation is found. Therefore, out of 3.4 we conclude that in weekend days the ENEUVP ward has significantly less beds occupied, which can be explained out of the fact that no elective surgeries are performed in weekend days. or all the nursing wards we have conducted F-tests with ($\alpha = 0.05$) to check whether differences in means between weekdays exist, which are included in Appendix D. We refer to the Appendix D for the complete analysis per ward. However, out of the figures in Appendix D we conclude that bed occupation for all the wards show a significant lower bed occupation on Sundays. Most of the wards show peak occupation in weekdays and lower occupation in the weekend days. Only ECONVP and EMDLVP and the acute admission departments show difference in here. ECONVP shows a stable occupation throughout the week. For EMDLVP, this can be caused by patient admissions. In Appendix F, we present the variance parameters for all the surgical and non-surgical wards. Of the surgical wards, especially EGUOVP and EGYNVP show large values in c_v. EGUOVP is also used as surgical short-stay ward, therefore the variance in occupation may be higher. Next to that, for EGYNVP a large number of non-surgical patients enter this ward. We discuss this in Section 3.3.3. As mentioned before, the acute admissions departments admit emergency patients and keep them for a maximum amount of time. Therefore, it be can be explained that their occupation is constant.

ENEUVP	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Sunday		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.010**
Monday			0.264	0.224	0.842	0.675	**0.010**
Tuesday				0.921	0.188	0.485	**0.000**
Wednesday					0.157	0.425	**0.000**
Thursday						0.536	**0.018**
Friday							**0.003**
Saturday							

Table 3.4: P-Values of F-Test for differences in means for ENEUVP

Next to the differences per weekday, we want to measure the variation in occupation of the wards. Table 3.4 shows that a significant difference is only found between weekdays and weekend days and therefore we measure variance for both.

ENEUVP	μ	σ	c_v
Monday - Friday	33.54	5.49	0.163
Saturday and Saturday	33.07	4.75	0.144

Table 3.5: Occupation variance parameters for ENEUVP

Bed Utilization: In Section 3.2 we have already shown that utilization is the time in which a resource is used, divided by the time a resource is available. Therefore, bed utilization is time in which the hospital beds are used divided by the time the beds are available. However, MST currently defines bed utilization as *"the number of times a patient occupies a bed divided by the number of available beds."* This leads to percentages higher than 100% in case more than one patient are placed on a single bed per day. Next to that, this definition lacks any time dimension. Therefore, we define bed utilization as:

$$Bed\ Utilization = \frac{Total\ time\ bed\ occupied\ per\ day}{Total\ time\ of\ bed\ availability\ per\ day} \tag{3.3}$$

It requires large calculations to measure this indicator, because every moment that a patient is located in a bed at a ward is measured in this calculation. In other words, re-locations or transfers back to the OR department or a different ward must be exactly available in the data. A patient could also be relocated on another bed, but still stay at the same ward. If patients get allocated to a different bed, the utilization of two beds must be measured. Patients are not planned onto a bed within MST, but onto a room. Therefore, we checked the utilization of the rooms to which the patients are dedicated. In order to do so, we took 24 moments per day and checked whether a room was occupied by a patient over a period of one whole year. This is done for all the nursing wards. Out of that, we were able to calculate the bed utilization per day, per nursing ward. A distinction can be made between gross- and net- utilization. Gross utilization is what we define as the total time a patient occupies a bed divided by the bed availability. We define net bed utilization as the total time a patient occupies a bed divided by bed open bed availability. Here, blocked beds are incorporated. In other words, the denominator in equation (3.3) becomes the number of available beds minus the number of blocked beds. However, not enough data was available to calculate the net bed utilization. For the remainder of this report, we therefore use gross utilization as performance indicator.

To provide a better view on the bed utilization, we calculated the bed utilization for all the wards. We present these calculations in graphs in Appendix E. In Appendix F, we present the variance parameters for all the surgical and non-surgical wards for bed utilization. It shows that the variance in utilization is larger than in occupation. In comparison to bed occupation, we see large variation in the EGUOVP and the EGYNVP wards. Figure 3.9 presents the utilization of ENEUVP. It shows clear peaks around May, June, and it shows a decrease in bed utilization from August to September and finally it shows peaks near the end of December. The low peaks in the beginning of January and the end of December can be explained by the fact that elective surgeries are not performed in the last weeks of December. Therefore, bed utilization lowers in these days. The decreasing line in the summer period can be explained by the fact that surgeons and physicians spend less that at the polyclinics and therefore less patients get admitted to the wards. After this period, an increase took place because surgeons and physicians spend more time at the polyclinics. For, the low peaks in May and June we assume that this comes forth out of a reduction period for elective surgeries. Most of the wards show a comparable pattern. The end and the beginning of a year show a decrease in utilization along with the summer period. Next to that, Table 3.6 shows the corresponding numbers. It shows that in 66,9 % of the time patient occupy beds in the ENEUVP ward. In comparison to the occupation, more variability can be found in utilization. This comes forth out of the fact that the bed occupation for a given day can be 1, while the utilization for the same bed can vary between 1% and 99%.

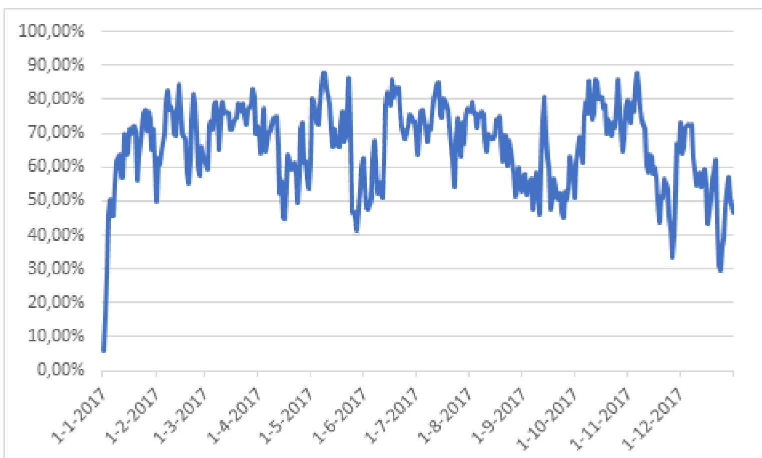


Figure 3.9: Gross Bed Utilization of ENEUVP from 01-01-2017 - 31-12-2017. Source: XCare

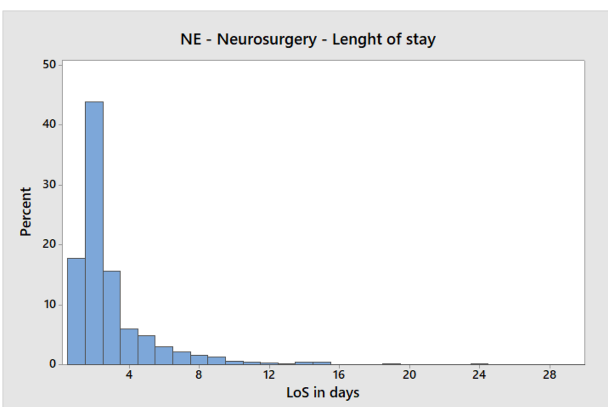
ENEUVP	μ	σ	c_v
Monday - Friday	0,669	0.111	0.167
Saturday and Sunday	0.668	0.119	0.178

Table 3.6: Utilization variance parameters for ENEUVP

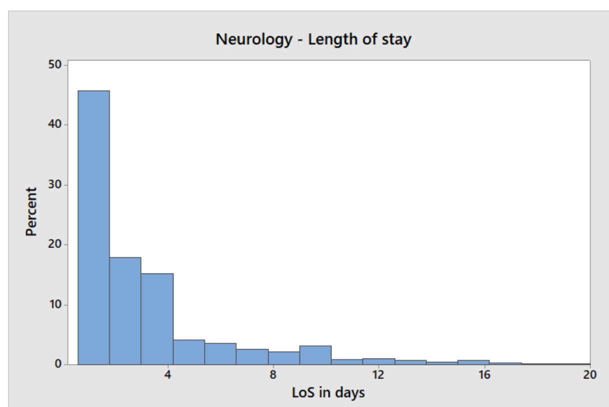
In total, we see that the lowest average bed utilization is reached at EGUOVP. Note, that this ward is the short-stay ward and therefore more admissions and discharges take place. We assume that this means that the beds are idle more frequently. A ward with long stay patients such as ETHOVP reaches a larger bed utilization with $\mu = 0.79$. This means that on average 79% of the total time, a patient occupies a bed. We consider this average to be a high utilization for several reasons. First, we calculated the gross bed utilization and blocked beds are not included. Next to that, relocation of patients, admissions and discharges result in a lower utilization. In the results, we see that wards with long-stay patients have a higher average bed utilization. For example, the ESNYDV (day-treatment) ward has a $\mu = 0.39$ for all the weekdays. Next to that, relocation of wards in 2017 also influenced this utilization. Most of the surgical patient wards reached a bed utilization of 70%, which we consider to be a high bed utilization rate for the aforementioned reasons.

3.3.2 Length Of Stay

Length of stay (LOS) is what we define as the number of full days a patient stays in the nursing ward. It is the amount of time between admission and discharge. In case of discharge on the same day, the length of stay is 0. When a patient stays overnight on the day before surgery and their stay is already longer than 24 hours before they undergo their surgery, their LOS is already 1 day. This is because the bed is already in use and therefore this influences the bed occupation and utilization. This length of stay largely differs per specialty, as for example a patient takes less time to recover from a small ear, nose and throat surgery than from a large thoracic surgery. Appendix G presents the LOS of the surgical specialties and non-surgical specialties. These figures show the LOS of the specialties at the nursing wards. Figure 3.10 shows the length of stay of patients of the ENEUVP ward. Neurology is a non-surgical specialty and neurosurgery is a surgical specialty. For neurosurgery LOS we see that their peak is further to the right, compared to neurology LOS. This can be explained by neurosurgery being surgical and because surgical patients often get admitted to the wards on the day before surgery.



(a) Length of Stay Neurosurgery patients. N = 5102



(b) Length of Stay Neurology patients. N = 2637

Figure 3.10: Length of Stay ENEUVP patients in 2016 and 2017. Source: XCare

3.3.3 Admissions and Discharges

In their research, Vanberkel et al. (2011a) define workload as the number of admissions, the number of discharges and ongoing intervention treatment by recovering patients. The number of ongoing intervention treatment by recovering patients has already been made visible in Section 3.3.2. Discharges and admission occur constantly throughout the day. Figure 3.11 shows the occurrence of discharges and admissions throughout the day in 2017. Most patients are admitted to a ward before surgery, this explains the admission peak at 8:00 AM. Next to that, most discharges take place between 11:00 AM and 2:00 PM. It is a general guideline throughout MST that physicians' consult takes place every morning before 11 AM. In case the physician determines that the patient is recovered from surgery, discharge can take place. Thereby, the discharge peaks between 11:00 AM and 2:00 PM in Figure 3.11 can be explained.

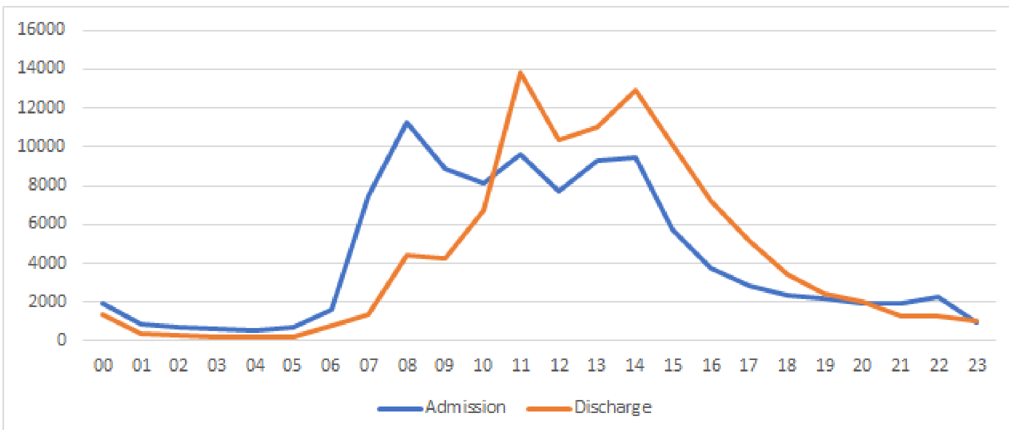


Figure 3.11: Peak moments of admission and discharge per day in 2017. N = 102531. Source: XCare

Admissions: Patient admission is the arrival of patients at the nursing wards. Patients mostly get admitted to nursing wards on weekdays, because OR time session is only planned for workdays and not in the weekend. Figure 3.12 shows the number of admissions for ENEUVP (+ ESTRVP) department. Out of a F-test for analysis of differences in means ($\alpha = 0,05$) we conclude that there are some statistically differences in patient admissions at the ENEUVP ward. Figure 3.12 shows box-plots per weekday for the ENEUVP ward. Next to that, in Table 3.7 we present the p-values that resulted from an F-test. Admissions on Sunday are significantly lower, than the other weekdays except for Thursdays and Saturdays. Furthermore, we see that admissions on Monday are significantly higher than admissions on Thursday and Saturday. In Table 3.1 we presented the number of sessions per specialty throughout 2017. The admission peak on Monday corresponds with the peaks of sessions throughout 2017. However, Figure 3.13 shows that neurology has admission peaks on Monday. In Figure 3.13 we have conducted the F-tests for differences in means, to show the admission rate on specialty level. These figures also show that Fridays show admission peaks for neurosurgery even though 10 more sessions were performed on Mondays in 2017. This difference can only be explained by case-mix. Smaller procedures of neurosurgery were mostly performed on Fridays in 2017. Therefore, the admission peaks are relatively high on Fridays, but the number of sessions is not. The number of sessions performed on the OR, does not directly mean a higher admission rate at the nursing wards.

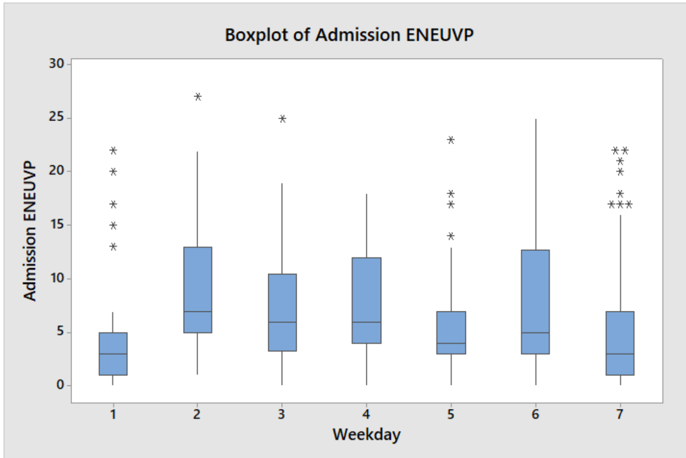


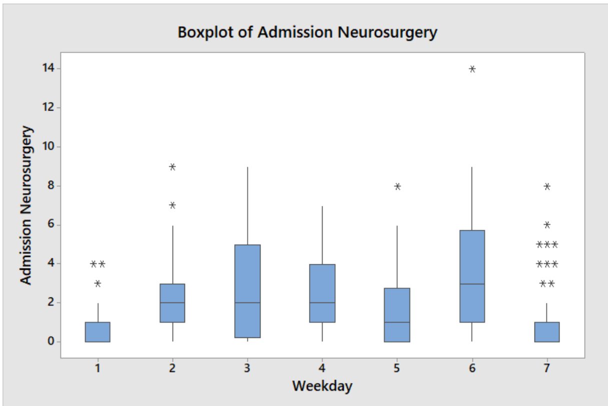
Figure 3.12: Patient Admissions of ENEUVP between 01-01-2017 and 31-12-2017. Source: XCare

ENEUVP	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Sunday		**0.000**	**0.003**	**0.001**	0.114	**0.002**	0.114
Monday			0.157	0.256	**0.006**	0.184	**0.006**
Tuesday				0.779	0.173	0.930	0.173
Wednesday					0.100	0.847	0.100
Thursday						0.147	1.000
Friday							0.147
Saturday							

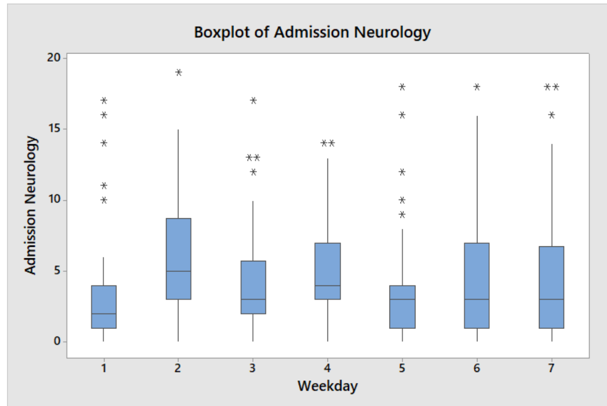
Table 3.7: P-Values of F-Test for differences in means for ENEUVP

We conducted this F-test for all the wards and their patient admissions. Appendix H presents the box-plots of the patient admission per ward and the corresponding statistical tests. Out of the figures in Appendix H we conclude that all the wards, that are dedicated to surgical patients, show a significant difference of admissions on Sunday and the other weekdays. We have already mentioned that patients are frequently admitted a day before surgery. However, our figures show that these admissions before surgery do not occur frequently on Sundays. The wards that are dedicated to non-surgical patients and ENEUVP show that admissions on Sunday are not significantly different than weekday admissions.

Since, we know the number of admissions of all the nursing wards and which specializations have their patients dedicated to those wards, we were also able to map the number of boarded patients per nursing ward. Recall, that a patient is *boarded* on another ward, when a bed shortage occurs on its designated ward. Table 3.8 presents the number of boarded patients per specialty and subsequently the percentage boarded patients per number of admissions. The acute admission departments are left out of consideration here. The table shows that the percentage of boarded patients is relatively high in ELONVP and EMDLVP. These wards frequently admit patients from that are dedicated to the EINTVP ward. This is a ward that is located on the same floor. This also counts for ECONVP. This ward for general surgery also admitted large number of orthopaedic and plastic surgery patients, that are normally admitted to ECVTVP. However, since these wards are located on the same floor and can form a harmonica this is not considered as bad performance.



(a) Admission of Neurosurgery patients. N = 1732



(b) Admissions of Neurology patients. N = 3623

Figure 3.13: Boxplots of specialty specific Patient Admissions at ENEUVP from 01-01-2017 to 31-12-2017. N = 5.355. Source: XCare

Nursing Ward	Number of boarded Admissions	Percentage boarded
EINTVP	55	2.23%
ELONVP	667	15.29%
EMDLVP	152	10.71%
ENEUVP + ESTRVP	88	3.58%
ETHOVP	18	0.46%
EGUOVP	192	6.58%
ECONVP	220	11.89%
ECVTVP	61	2.31%
EGYNVP	70	1.96%

Table 3.8: Number of boarded patients per specialty in 2017. Source: XCare.

Discharges: The patient discharge rate is the number of patients that leave the hospital per day. Normally, patient discharge is higher on workdays than on weekend days. This is because the physician's visitation is in most of the cases necessary to make a patient discharge and most physicians are not scheduled in the weekend days. Figure 3.14 shows box plots of the mean patient discharges in 2017 at the ENEUVP ward. We conducted another F-test for analysis of differences in means ($\alpha = 0,05$). The results of this test are presented in Table 3.9. The values that are lower than the p-value of 0,05 mean a significant difference. Out of this we conclude that there the number of patient discharge is significantly lower on Sunday in comparison with all the other days. Next to that, it shows that the number of discharges on Wednesdays is significantly higher in than on Mondays, Tuesdays and Thursdays. No statistical differences can be found between Wednesdays, Fridays and Saturdays. We also analysed the patient discharge per specialty at ENEUVP. For this, we made box-plots that are presented with Figure 3.14. For neurology we found a significant difference between discharge in weekdays and weekend days. For neurosurgery, we found the lowest patient discharge rate on Sunday and the significant peak in patient discharge on Saturday. We have conducted the same analysis for the other nursing wards. Appendix I shows an overview of the number of discharges per day and the corresponding F-tests. Except for EGYNVP, EGUOVP and the acute admission departments, all the wards have significant lower discharge rates on Sundays. The figures in I also show that the discharge rates are not significantly lower on Saturdays compared to week days for most of the specialties.

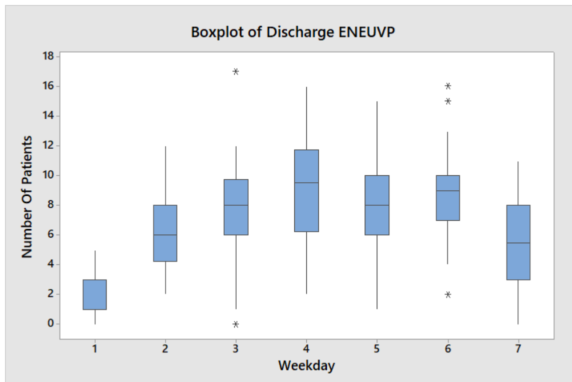
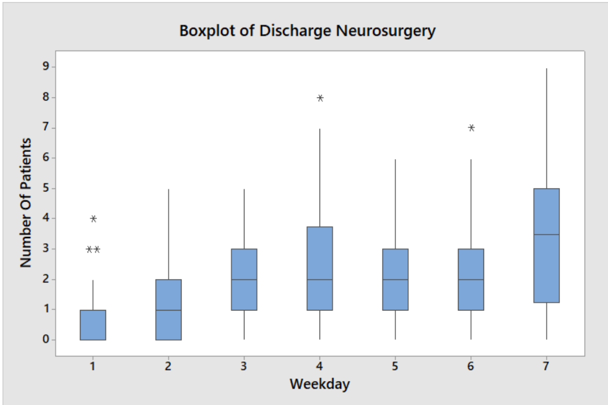


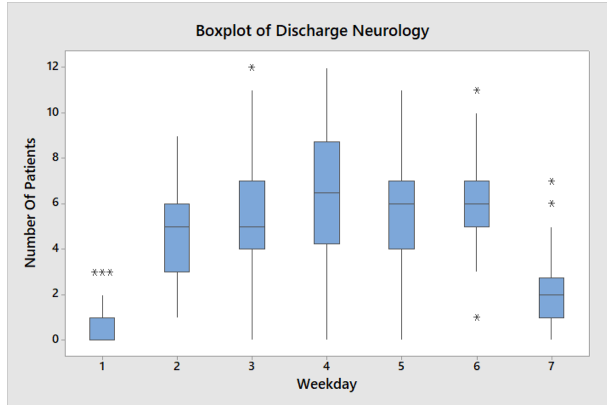
Figure 3.14: Patient Discharges of ENEUVP between 01-01-2017 and 31-12-2017. Source: XCare

ENEUVP	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Sunday		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Monday			0.053	**0.000**	**0.002**	**0.000**	0.139
Tuesday				**0.002**	0.231	**0.019**	**0.001**
Wednesday					0.058	0.459	**0.000**
Thursday						0.245	**0.000**
Friday							**0.000**

Table 3.9: P-Values of F-Test for differences in means for ENEUVP



(a) Discharges of Neurosurgery patients. N = 1732



(b) Discharges of Neurology patients. N = 3623

Figure 3.15: ENEUVP specialty discharges from 01-01-2017 to 31-12-2017. Source: XCare

3.4 Conclusions

In this chapter, we analysed the performance of the OR department and the nursing wards. The following questions and corresponding answers conclude this chapter:

Question 3: *What are relevant KPIs of the nursing wards, OR department and the planning department?*

On the base of the literature review by Cardoen et al. (2010) we formulated multiple performance indicators to measure the performance for both the OR department and the nursing wards. For performance measurement of the OR department and the planning department, we analysed the OR utilization of the specialties. The number of surgeries per session shows the total throughput per operating specialty and thereby the throughput of each surgical specialty.

The main KPI for the nursing ward was initially the bed utilization, because lowering the variance in bed utilization at nursing wards is our research objective. However, in this chapter we have showed that bed utilization is not monitored sufficiently and was not monitored sufficiently in 2017 at MST. Next to that, we have showed that it is an indicator that is difficult to measure. Therefore, we have proposed our definition of bed utilization and measured this KPI at all nursing wards. Bed utilization does not show everything about the performance of a nursing ward and therefore we presented the bed occupation per ward. However, the bed occupation and bed utilization heavily depend on other criteria and therefore we have also presented patient admissions and discharges per ward and the length of stay of patients of all the elective clinical patients. As mentioned, we consider occupation, admission and discharges as the total workload at the nursing wards.

Question 4: *What is the performance of the planning department, OR department and the nursing wards?*

We presented the outcomes of every performance indicator for the OR department and the nursing wards. We showed that some specialties never reached the threshold for OR utilization in 2017. In this chapter we also showed that for most of the specialties the planned OR utilization was already lower than the target OR utilization. Therefore, it is impossible for some of the specialties to even reach the target utilization. Therefore, we conclude that over 2017, the planned OR utilization was too low for most of specialties. Subsequently, we conclude that the realized OR utilization was also too low for most of the specialties. However, a side note must be made that the planned and realized OR utilization showed an increasing line after August for most of the specialties. Furthermore, we see no differences in OR utilization target. As mentioned, this can lead to a larger amount of overtime. We did not find large differences between decentralized and centralized planning. Next to that, we discussed the most common disruptions in their OR schedule, the total overtime and the OR throughput.

For the nursing wards, we conclude that the variability of bed utilization is high throughout the year. We showed that in periods where less OR sessions are performed, the bed utilization decreases. This period is for example in summer months and in the last weeks of December and the beginning of January. We concluded that the surgical patient wards had a average bed utilization rate of 70%, which we consider to be a high utilization rate. Besides utilization, we also analysed the occupation, admission and discharges rates of the specialties and the wards. We showed that all the ward showed lower bed occupation and patient admissions on weekend days. The specialties especially showed significant lower patient occupation and admissions on Sundays, even though many patients get admitted on the day before surgery. For most of the specialties, we found no significant difference in patient admission between week days and weekend days. For patient discharges, this is comparable. Patient discharges are significantly lower on Sundays throughout 2017, for all the specialties. However, we showed that discharge rates are significantly high on Saturdays.

Chapter 4

Literature Research

This chapter includes a literature search for studies that encompass the downstream effects of operating room planning. In this chapter we answer research question 5: *What kind of approaches can be used to optimize the surgery scheduling?* and research question 6: *What approach or model is best applicable?* In our literature research, we specifically looked for papers that focus on the tactical decision level incorporate ward levelling or bed occupancy. With the snowballing method we conducted a literature search that is presented in Section 4.1. We found literature reviews and papers with (mathematical) approaches to construct, build or optimize a master surgery schedule. Section 4.2 informs about the use of MSS within literature and Section 4.3 describes approaches that used to construct and build a MSS. In Section 4.4 we describe studies that focused on the connection between the OR and the nursing wards. In Section 4.5 we discuss the use of optimization heuristics for MSSs. Finally, with Section 4.6 we conclude this chapter.

4.1 Literature Search Method

Within literature, a large amount of operations research papers can be found. We use the snowballing method to quickly asses articles relevant to our research. The snowballing method is a method to conduct a literature review. This method refers to using the reference list and citations of a paper to identify additional papers (Wohlin, 2014). Using the references is called backward snowballing and using the citations of paper is called forward snowballing. For a comprehensive description of the methodology of snowballing we refer to Wohlin (2014).

Start Set: The snowballing method starts with a start set of papers that consist out of a number of characteristics. Wohlin (2014) defines a good start set of papers is a set of papers that cover different publishers, and authors. Next to that, the start set ought to be formulated from keywords in the research question. The start set must not be too small, unless the study area is more specific and therefore requires fewer papers than a broad area. At last, if the search has taken place and too many papers are found, highly relevant and highly cited papers can be used. We consider our study area as a specific research area and therefore we take a small number of research papers as an input set.

Out of our research question, we searched for relevant papers in Google Scholar to define our start set for the snowballing method. We used this by conducting a search with the following strings of words: variability in bed utilization, OR planning optimization, master surgery scheduling. The time frame we chose here was 2000 – 2017, which we considered as a good time frame to find all the relevant articles. Out of this search we found four papers that are relevant to our research objective. We consider our study area to be specific and therefore four papers is a sufficient number for our start set. Table 4.1 presents information about these studies. In this table the first four papers served as our start set. It is noteworthy that this is not a perfect start set, since three papers have one author in common. However, since we used our research question as input for the start set, no further was action was taken.

Authors	**Title**
Bekker and Koeleman (2011)	*Scheduling admissions and reducing variability in bed demand*
Fügener et al. (2014)	*Master Surgery Scheduling with consideration of multiple downstream units.*
van Oostrum et al. (2008)	*A master surgery scheduling approach for cyclic scheduling in operating room departments.*
Vanberkel et al. (2011a)	*An exact approach for related recovering surgical patient workload to the master surgery schedule.*

Table 4.1: Research papers regarding tactical OR planning and downstream effects

Iteration 1: On the base of our start set and our time frame we started with backward- and forward snowballing. Backward snowballing consists out of examining the references on relevance. This is done by first checking the title and author and after that reading the abstract and relevant parts of the paper (Wohlin, 2014). With forward snowballing, those papers are identified that site the initial papers that are being examined. The first screening of the papers is done on information that is found in Google Scholar. If a paper seems relevant, the abstract or relevant parts of the article are checked upon, after which a decision is made whether an article must be included in the set of papers to be examined. As mentioned, we searched for papers that approach operating room planning on the tactical level and thereby focus on ward levelling or bed occupancy. In the first iteration of the snowballing method we found 48 additional papers on the base of title, year and author. After, reading all the abstracts of the papers found, we excluded 31 papers on the base of absence of a multi-department approach, or a lack of considering downstream effects of OR scheduling. Another reason for excluding the papers, was that some already assumed a given MSS. Therefore, those studies are more focused on the operational level. In the next step, we analyse these 17 papers.

Iteration 2: Of these 21 papers, 4 papers were literature reviews in the research field of operating room planning and scheduling. One of the literature reviews on operation scheduling has been done by Cardoen et al. (2010). They review 122 papers in the research field of operating room planning and scheduling, of which 47 studied the operating room along with other facilities (integrated operating room). Cardoen et al. (2010) found 7 of the reviewed papers to be focused on ward levelling. Four of them are already included in our start set and our additional papers found, two were not considered relevant to our research and one of these papers was added to our additional papers. The second review is the study of Vanberkel et al. (2010). In this review, health care models that include OR and downstream units are being reviewed. They argue that models that focus on single departments lead to sub-optimal results. Therefore, they reviewed papers that

used a holistic approach. They reviewed 88 papers found that consider more than one hospital department. In only twenty of these articles, departments surrounding and including the inpatient ward are modelled. Of these 88 papers, 7 papers included the modelling of the OR department and inpatient wards. However, 2 of these 7 papers were already included in our additional papers, the other five met our exclusion criteria. Vanberkel et al. (2010) furthermore contributed to the operating room literature by developing a model that related OR planning to workload at the nursing wards.
Guerriero and Guido (2011) conducted, in comparison to the other literature reviews, a more general review. The aim of their paper was to provide an overview on how operational research can be applied to surgical scheduling and planning processes. They categorized papers found on strategical, tactical, operational and mixed decision level. They particularly paid more attention to the published papers that presented mathematical models and solution approaches.

Article	**Goal**	**Solution Technique**
(Bekker and Koeleman, 2011)	Reducing variability in bed demand by determining optimal number of weekly elective patient admissions.	QPM
(Fügener et al., 2014)	Minimizing downstream cots of a MSS by optimizing the schedule with multiple stochastic approaches.	MP
(van Oostrum et al., 2008)	Constructing a MSS while maximizing OR utilization and level downstream requirements.	MP
(Vanberkel et al., 2011a)	Develop a method that evaluates a given MSS on downstream workload at nursing wards.	MP
(Adan et al., 2009)	Generate a MSS that realizes a given target of patient throughput and optimizes an objective function for utilization of resources.	MILP
(Beliën and Demeulemeester, 2007)	Build a MSS with levelled resulting bed occupancy.	ILP
(van Essen et al., 2014)	Comparing two approaches of optimizing and building an MSS.	MP
(Fügener et al., 2016)	A case study in which multiple MSSs are compared on downstream effects at nursing wards and ICUs.	MP and Simulation
(Adan and Vissers, 2002)	Develop a model to generate an admission profile for a specialty given patient throughput and utilization of resources.	ILP
(Santibáñez et al., 2007)	Develop a mixed integer programming model to schedule surgical blocks for each specialty considering OR time availability and post-surgical resource constraints	MIP
(Vanberkel et al., 2011b)	Use their developed model to evaluate proposed MSSs within a hospital.	MP
(Dellaert and Jeunet, 2017)	Tactical planning of surgeries while considering downstream resources. A variable neighborhood search is used to generate solutions.	MILP
(Beliën et al., 2009)	Providing a decision support system for building a master surgery schedule.	MILP
(Cappanera et al., 2014)	Compare three scheduling policies for the MSS. All three approaches maximize the number of scheduled surgeries and balance post-surgical beds.	MILP
(Yahia et al., 2014)	Compare two approaches of constructing MSS. One approach is based on balancing downstream requirements, the second based on surgeons' preferences.	MILP
(Min and Yih, 2010)	Stochastic optimization of a surgery schedule while accounting for downstream constraints and minimizing total costs	MP
(Chow et al., 2011)	A transparent and portable approach to improve scheduling practices. Scheduling both surgeon blocks and patient types to reduce peak bed occupancies.	MIP and Monte Care Simulation.

Table 4.2: Research papers regarding tactical OR planning and downstream effects

On the tactical level they found 17 papers of which 5 papers aimed at levelling of wards/bed occupancy, only one of these papers did not met our exclusion criteria and was therefore added to the additional papers.
The fourth literature review was also the most recent one. Samudra et al. (2016) conducted a large literature review on scheduling operating rooms and therefore also researched papers that aimed at levelling of the ward. Within this area they found 17 papers, of which 10 were already within our set of papers. Of the remaining seven papers, six did not meet our inclusion criteria. One paper was added to our additional papers. Upon the other papers found we conducted another iteration of backward and forward snowballing. We found 10 additional articles on the base of title, author and year. After screening their abstracts, we concluded that only one paper was relevant to our research objective and met our inclusion criteria. Therefore, we ended the second iteration with three more articles.

The final set of papers with their methodology and their objective are presented in Table 4.1. We have excluded the literature reviews out of this table. The abbreviations in the column solution technique stand for Quadratic Programming Modelling (QPM), Mathematical Programming (MP), Mixed Integer Linear Programming (MILP), Integer Linear Programming (ILP), Mixed Integer Programming (MIP).

4.2 Master Surgery Scheduling

Scheduling the OR can be divided into three different sets of problems. Yahia et al. (2014) referred to these problems as the Case-Mix Scheduling Problem (CMP), the Master Surgery Scheduling Problem (MSSP) and the Surgery Scheduling Problem (SSP). The CMP is the strategic decision of assigning the OR time to the different specialties. In the Master Surgery Schedule Problem, the total OR time is already assigned, but then ORs and so the OR days get assigned to the specialties. This is the tactical decision. The SSP is the operational decision of assigning a patient to a day, an OR and a start time. As we have mentioned, we focus on the tactical level and therefore the MSSP. The Master Surgery Schedule (MSS) is the block schedule that is being made in Stage 2 of the multiple stage process of OR scheduling that has been presented in Section 2.5. In the framework of Figure 2.5 the construction of a MSS belongs to the tactical level of resource capacity planning. Various definitions of MSS can be found. van Oostrum et al. (2008) define a MSS as a cyclical schedule of recurrent surgery types. Beliën and Demeulemeester (2007) and Vanberkel et al. (2010) define a MSS as a cyclical block of OR time dedicated to surgeons or specialties. Other authors use other terms than MSS. For example, Santibáñez et al. (2007) use surgical block schedule to refer to the distribution of operating room time amongst surgical specialties. In this report we will define a MSS as a cyclical schedule in which OR time is being allocated to specialties. Next to this definition, Beliën en Demeulemeester (2009) define three objectives while building a MSS:

1. The bed occupancy at hospitalization units must be levelled as much as possible.
2. An OR is best allocated exclusively to one group of surgeons having the same specialty.
3. A MSS is preferred to be as simple and repetitive as possible, with few changes from week to week.

The advantage of working with a MSS is that it structures the workload at the OR department. A disadvantage is that a MSS has little flexibility in resource capacity, since it assumes the same

resource level over time. A MSS is a fixed schedule for every cycle, and therefore making frequent changes to it conflicts with this cyclical nature.
The approach of constructing a MSS with a resulting levelled bed occupancy has been the topic of various studies. However, many different main objectives can be found between these studies. Cappanera et al. (2014) compared different policies of constructing a MSS on three criteria, namely efficiency (maximize throughput), balancing (level workload among department) and robustness (capability to prevent schedule disruptions caused by variability in LOS and surgery duration). However, with their proposed MIP approach (with three different objective functions, for three different policies) they did not find a superior policy that resulted in superior performance for one of their performance criteria.

4.3 Approaches for building the MSS

An approach with a mixed integer linear program (MILP) is done by Adan & Vissers (2002). Their objective function optimizes the utilization of resources and they specified this for the thoracic surgery department. They made up patient groups on the base of operation time, use of intensive care department and next to that, they distinguished groups in children or adults. They used a deterministic length of stay. With the deterministic MILP they were able to optimize the MSS on the patient mix. Adan & Vissers (2002) scheduled patients on the base of fixed capacities in the OR, the ICU and the wards. In a later study they improved their model by building a model with stochastic LOS, on which Adan et al. (2009) found better performance on target utilization. The study by Yahia et al. (2014) focussed on developing a MSS on the base of a MILP, their deterministic approach of the MILP did not include the uncertainty that comes along with the LOS of patients. Research done by Oostrum et al. (2008) aimed at minimizing the required OR capacity and to level hospital bed requirements by a two-phase approach. They use an integer linear programming (ILP) model to construct a MSS. In the first step of their approach, they came up with a generation of so-called ORDS (Operation Room Day Schedule). An ORDS is a list of surgery types assigned to an OR, that maximizes OR utilization. This phase is solved with column generation, an approach to solve complex optimization problems with a large amount of variables. In the second step they assign ORDS to OR days in order level the hospital bed demand. In this step they formulate a MILP. To linearize their complex model, they use deterministic variables.
Chow et al. (2011) also proposed an approach in which they combined a mixed integer programming model with a Monte Carlo simulation. They tried to improve the OR schedule in terms of reducing maximum expected bed occupancy. In order to determine the expected bed occupancy, they used expected LOS. Santibáñez et al. (2007) developed a deterministic mixed integer programming model to schedule surgical blocks for each specialty into ORs, for multiple hospitals. They developed this while considering OR time availability and surgical and post-surgical resources constraints. They attempted to reduce maximum bed utilization by reallocating specialties within the OR schedule, while keeping the same amount of ORs dedicated to the specialties. They constructed several scenarios for this reallocation, but they concluded that by reallocating the specialties in the block schedule it is possible to reduce resource requirements needed to care for patients after surgery. Nevertheless, these studies used deterministic approaches and are thereby ignoring the stochastic nature of healthcare processes. In comparison to that Min et al. (2010) proposed a more stochastic approach in which they consider uncertainty in elective surgery duration. Next to that, they consider capacity constraints of downstream resources. They formulate a stochastic

model for scheduling elective surgery patients and use a sample average approximation approach (SAA) method for obtaining an optimal surgery schedule, while minimizing the costs related to patients and overtime. Bekker and Koeleman (2011) aimed at reducing variability in bed demand by determining admission quota for elective patients, while considering the LOS. They used a Quadratic Programming model to determine the optimal number of elective patient admissions, such that a daily desired occupancy was achieved. They showed that reducing variability in bed occupancy is best achieved by smoothening the weekly admissions.

4.4 The link between the OR and the nursing wards

Within the literature reviews that were found, many studies were focused on only one department. In the literature review van Vanberkel et al. (2010) it is being argued that models that focus on single departments lead to sub-optimal results. In addition to that, they mention the importance of a multi-department view, a holistic approach. Beliën & Demeulemeester (2007) did this by using stochastic length of stay and stochastic number of patients. They used a combination of mixed integer programming and optimization with local search heuristics. They developed a number of mixed integer programming heuristic approaches and they used a meta heuristic (simulated annealing) approach to minimize total expected bed shortage. Their goal was to assign specialties to OR days in order to minimize their objective function. In a later extension they used this model to build a decision support system Beliën et al. (2009). On the base of the MSS, they visualised the resulting bed occupancy. Vanberkel et al. (2011b) also developed a tool to visualise downstream effects of a MSS. However, in contrast to the research by Beliën et al. (2009), they determine the complete probability distribution for bed occupancy in the complete time horizon. Therefore, they developed a method that evaluates the resulting workload of an MSS and with that, they make the link between the OR department and the nursing ward (Vanberkel et al., 2011b). They use binomial distributions and discrete convolutions to compute ward occupancy distributions, patient admissions and discharge distributions. The authors implemented their algorithm in a Dutch cancer institute (Antonie van Leeuwenhoek). Vanberkel et al. (2011a) constructed several MSSs and after consultation with various actors within the hospital they chose the MSS on the corresponding ward occupancy. Their approach does not produce an optimal MSS, but it evaluates a given MSS. Therefore, it requires a number of predetermined MSSs that need evaluation. Vanberkel et al. (2011b) initially used their algorithm as an evaluation tool to evaluate different MSSs, but their approach has thereafter been used as input by more authors. (Fügener et al., 2014; van Essen et al., 2014). Fügener et al. (2014) and Essen et al. (2014) combined the approach of Vanberkel et al. (2011a) with reallocating the surgical specialties within the block schedule to reduce resource requirements or downstream effects. These studies both gave promising results. An approach that used reallocation of OR blocks is the study by Van Essen et al. (2014). They acknowledged that determining the required number of beds and determining an objective function for a new OR schedule requires a lot of computational time. This is because the objective function requires the convolution of several probability distributions. Therefore, they came up with two approaches which are not fully search in the solution space or approximate the objective function. For the first approach they used a local search heuristic (Simulated Annealing) based on the given constraints and the objective function. In the second approach, they incorporated the approximation of the objective function in an ILP that included the given constraints of the OR schedule. By using their ILP approach they received better results and came up with a possible 20% reduction of hospital

beds.
The study that also used reallocation of specialties to optimize their objective function is done by Fügener et al. (2014). They did not only take the patient flow from the OR to the ward into account, but they also incorporated the patient stream from an ICU. In their research they consider the ICU as an important bottleneck in hospitals. They formulate a general assignment problem to calculate the downstream costs of a MSS instead of focusing on bed utilization. The costs within their generic model consist out of fixed costs, overcapacity costs, staffing and weekend staffing costs. They formulated two strategies to solve the master surgery scheduling problem. The first was exact objective function and heuristic solution method and the second strategy was approximated objective function and exact solution method. For the first strategy they applied an incremental improvement heuristic, a 2-Opt heuristic and simulated annealing. For the second strategy, the used two approximated objective functions. With the exact approximation approaches achieved the biggest improvements. In the scenario with nine ORs each weekday over two weeks, they found a maximum cost reduction of 9,2% after swapping 84% of the OR blocks. They later used their model to evaluate given MSSs on potential improvement in levelling workload and lowering weekend utilization (Fügener et al., 2016). In their solution they found that an adapted MSS decreased the maximum bed demand within a ward with 7%.

4.5 Optimization Heuristics

As mentioned, various heuristics or exact solution methods have been used within the papers that we have assessed. However, optimizing the proposed objective functions is not necessarily bounded by these set of heuristics. Frequently, we found studies that use a Simulated Annealing (SA) or Tabu Search (TS) approach to optimize their objective (Beliën et al., 2009; van Essen et al., 2014; Fügener et al., 2014). Besides SA or TS, various other heuristics are also applicable to optimizing the MSS to an objective (Fügener et al., 2014). Another example is the study by Dellaert and Jeunet (2017). They use Variable Neighbourhood Search (VNS) to optimize their objective function of an MILP that was initially formulated by Adan et al. (2009). Their proposed version of VNS provided high quality solutions in short computational time in comparison with CPLEX. Van Essen et al. (2014) acknowledged that determining the required number of beds requires a lot of computational time and that SA can requires a lot of computational time. An approach such as SA is known to be able to jump out of (poor) local optima (Kirkpatrick et al., 1983). However, if we use SA with a heuristic that swaps single specialties with each other, it searches its neighborhood and searching the total solution space computational extensive. On the other hand, if we use a heuristic that changes large parts of the solution, local improvements may not be found. Therefore, we want to use an approach that has the ability to jump out of (poor) local optima and has the ability to change a varying size of the solution.
In recent studies of optimization heuristics, the Adaptive Large Neighborhood Search approach (ALNS) is proposed (Lutz, 2015; Ropke and Pisinger, 2006; Pisinger and Ropke, 2010). This heuristic is composed of a number of sub-heuristics that are used with a frequency corresponding to their historical performance (Pisinger and Ropke, 2010). It can be used in combination with the acceptance procedure of SA, which gives it the ability to jump out of local optima. On the base of a degree of destruction, ALNS destroys a varying part of the solution. Therefore, we consider ALNS to be a suitable heuristic to use in our optimization. Furthermore, we found a literature gap in the combination of ALNS optimization and MSSP.

4.6 Conclusions

In this section we presented recent literature reviews that encompass recent literature about operating room scheduling on the tactical level. We explicitly searched for studies that linked the OR with downstream effects at nursing wards. The following research questions and answers conclude this chapter:

5: *What kind of approaches can be used to optimize the surgery scheduling?*

Many studies within this research field are focused on a single department and thereby ignore downstream effects of OR planning and scheduling. A single department approach leads to sub-optimal results and therefore we narrowed our literature research scope to multiple department approach. In the studies that remain, we found many deterministic approaches. By using a deterministic LOS or number of patients, uncertainty within healthcare processes is being ignored. In more recent studies we found studies that incorporate the stochasticity within their program.

6: *What approach or model is best applicable?*

A stochastic approach that has led to promising results is the approach by Vanberkel et al. (2011a).0 In various studies it has proven to lead to practical results (Vanberkel et al., 2011b; Fügener et al., 2014; van Essen et al., 2014). However, their approach is on itself an evaluation tool and it does not optimize the OR scheduling. We found two studies that used this approach and extended it to use it for optimization matters. Both studies compare and use exact approximation and local search approaches. Frequently, an SA approach is used to optimize an objective function. However, we have seen in recent literature that other heuristics are also applicable to solving the MSS problem. We want to be able to search the complete solution space within reasonable amount of computational time. Therefore, we want to use the ALNS heuristic in combination with an SA acceptance procedure. With this heuristic, we are able to search the complete solution space.

Chapter 5

Model Description

In this chapter we propose our approach to solve the Master Surgery Schedule Problem while considering the downstream effects of this planning. We structure this chapter on the base of the methodology by Law et al. (2007). Figure 5.1 shows a generalized flowchart of the steps the propose for a simulation study. We do not conduct a simulation study, but we consider the framework to be a good guideline for our research. The first two steps of the framework, the problem formulation and literature review, have been done in respectively Chapter 2 and Chapter 4. The conceptual model is presented in Section 5.1. In Section 5.2 we discuss how we gathered the data that is required for our model. In Section 5.3 we formulate our model. After that, a brief description of ward division in our model is given in Section 5.4. The verification and validation of the model is described in Section 5.5. We conclude this chapter in Section 5.6. The experimentation and implementation of the model are handled in Section 6.1 and Çhapter 7.

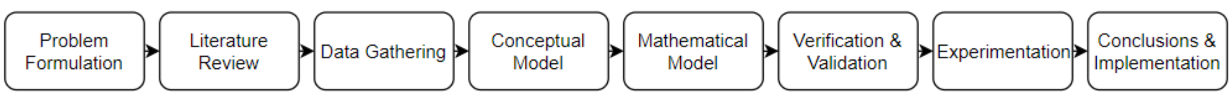


Figure 5.1: Steps in a simulation study. Law et al. (2007)

5.1 Conceptual Model

In the literature review of Chapter 4 we introduced the various managerial decisions that are made for OR scheduling. The MSSP that was introduced by Yahia et al. (2014) is the problem that we want to solve. It corresponds with Stage 2 of the multi-stage process of building the OR schedule (Vanberkel et al., 2011a; van Oostrum et al., 2008). We want to level the downstream effects of the MSS and more specifically level the workload at the nursing wards. Vanberkel et al. (2011a) defined to workload as the number of admissions, discharges and number of ongoing interventions. To control the downstream effects of the MSS, we use the model by Vanberkel to visualize the workload at the nursing wards. Similar to Vanberkel et al. (2011a) we assume stochastic length of stay upon which we determine the distribution for bed occupancy. In their case study, they evaluated several MSSs on the total bed occupancy within a hospital Vanberkel et al. (2011b). Since MST has a clear division in two floors for surgical patients we want to measure the bed occupancy and workload per floor. We want to measure the total bed occupancy and make an approximation of the occupancy per floor. As mentioned, the model by Vanberkel et al. (2011b) is an evaluation tool and does not optimize an OR schedule. Therefore, we need to formulate a model that can be optimized. For this model, we propose an approach based on (van Essen et al., 2014; Fügener et al., 2014). However, in their research they assigned surgeons and ORDS to ORs, which makes their approach more specialized. For the optimization of a given MSS, we propose an Adaptive Large Neighborhood Search approach.

5.2 Data Gathering

The input data we need for the model is extracted from the hospital systems SAP Business Objects (SAP) and XCare. From these systems we used the information about all the surgeries performed in 2017 and all the information about the patients at the ward in 2017. Other information was gathered by interviewing MST personnel. This information includes the strategic assignment of OR time to specialties and OR restrictions. For more information on data about the OR and the wards we refer to Section 3.1. Note, that Section 3.1 includes LOS for surgical and non-surgical patients and the admission and discharges at the nursing wards. However, our model only incorporates surgical patients and the total stay in the hospital. Therefore, LOS needed to be redetermined to the time between time of surgery and discharge (note that ICU/PACU LOS is also incorporated in this situation). Next to that, number of surgeries per specialty needed to be redetermined to only surgeries with clinical patients.

5.3 Mathematical Model

Our base model includes a couple of restrictions that we discuss within this section. Our main restrictions are derived from van Essen et al. (2014) and Fügener et al. (2014). As mentioned in Section 4.4, the study by van Essen et al. (2014) combined operational and tactical allocation with the assignment of ORDS to ORs. Next to that, Fügener et al. (2014) used a generic cost model to optimize the MSS. Since our focus is on the tactical level, we do not have to use all their restrictions. However, we include three restrictions in our model.

Every specialty has a number of sessions assigned and therefore all these sessions need to be planned within ORs. Fügener et al. (2014) refer to OR-blocks by binary variable $x_{i,q,j}$. It is 1 when specialty $j \in \{0, 1, 2, ..J\}$ is assigned to OR $i \in \{1, 2, ..I\}$ on day $q \in \{0, 1, 2.., Q\}$. Subsequently, it is zero otherwise. So, OR $i \in \{1, 2, ..I\}$ denotes all the surgical ORs of MST. Specialty $j \in \{0, 1, 2, ..J\}$ denotes all the surgical specialties and day $q \in \{0, 1, 2.., Q\}$ denotes every day of the MSS schedule. It follows, that $x_{i,q,j}$ is at most 1. Constraint 5.1 ensures this.

$$\sum_{j \in J} X_{i,q,j} \leq 1, \quad \forall i \in I, \forall q \in Q \tag{5.1}$$

In totally, every OR block is described by three parameters. i,q and j. An example of an OR block description is given in Figure 5.2.

$$
\begin{array}{cc|c|c|c|c|}
\multicolumn{6}{c}{\text{Days in MSS}} \\
 & \multicolumn{1}{c}{} & \multicolumn{1}{c}{q=1} & \multicolumn{1}{c}{q=2} & \multicolumn{1}{c}{} & \multicolumn{1}{c}{q=Q} \\
\cline{3-4}\cline{6-6}
 & i=1 & x_{1,1,j} & x_{1,2,j} & \multicolumn{1}{c|}{\cdots} & x_{1,Q,j} \\
\cline{3-4}\cline{6-6}
\text{Operating} & i=2 & x_{2,1,j} & x_{1,1,j} & \multicolumn{1}{c|}{\cdots} & x_{1,Q,j} \\
\cline{3-4}\cline{6-6}
\text{Rooms} & \multicolumn{1}{c}{} & \multicolumn{1}{c}{\vdots} & \multicolumn{1}{c}{\vdots} & \multicolumn{1}{c}{} & \multicolumn{1}{c}{\vdots} \\
\cline{3-4}\cline{6-6}
 & i=I & x_{I,1,j} & x_{I,2,j} & \multicolumn{1}{c|}{\cdots} & x_{I,Q,j} \\
\cline{3-4}\cline{6-6}
\end{array}
$$

Figure 5.2: Master Surgery Schedule description.

Every specialty has specific ORs in which they can perform their surgeries. The exact restrictions to which specialties can be performed in certain ORs is already presented in Section 2.5. The model needs to be able to assign certain sessions only to a specific subset of the ORs. Note, that this is a subset of OR $i \in \{1, 2, ..I\}$. To add this constraint to our model, we define the subset I_j that denotes the set of ORs in which specialty j can be planned. Furthermore, the number of OR-blocks is determined at this moment and given the time horizon all the OR-blocks need to be planned within ORs. Therefore, we define a decision variable that needs to ensure that the number of sessions per specialty planned, corresponds with the number of sessions per specialty that is derived from strategic planning. Therefore, Fügener et al. (2014) denoted d_j as the minimum number of sessions per specialty that needs to be planned. We define d_j as the number of sessions per specialty j that must be planned. Constraint 5.2 ensures this. The summation over all the ORs i and all the MSS days q give the exact number of sessions that is given by d_j.

$$\sum_{i \in I_j} \sum_{q \in Q} X_{i,q,j} = d_j, \quad \forall j \in J \tag{5.2}$$

Contrary to van Essen et al. (2014) we do not have to include any restrictions regarding instrument availability or surgeons that can perform a specific subset of surgeries. We do have to include a restriction that ensures that a maximum number of OR-blocks per specialty is at most performed per day. The numerical variable s_{jq} denotes the maximum number of sessions that can be performed by a certain specialty per day. Constraint 5.3 ensures that a solution is bounded by this limitation. Note, that this maximum amount is already limited by constraint 5.2.

$$\sum_{i \in I} X_{i,q,j} \leq s_{jq}, \quad \forall j \in J, \forall q \in Q \tag{5.3}$$

The constraints (5.1)-(5.3) limit the solution space of the starting solution. The objective we hereby use is to level workload at the nursing wards. We use the model of Vanberkel et al. (2011a) to link the MSS to workload at the nursing wards. The model consists out of three steps, that we describe step by step.

Vanberkel et al. (2011a) describes the MSS as the assignment of specialty j to OR-block $b_{i,j}$ for each day q and each OR i, where $i \in \{1, 2, .., I\}$ and $t \in \{1, 2, .., T\}$. The way specialty j fills the OR is determined by two factors, namely c^j and d_n^j. The input $c^j(k)$ is the probability distribution for the number of k surgeries that can be performed in an OR, where $k \in \left\{0, 1, .., C^j\right\}$. Note that, C^j is the maximum number of surgeries that can be performed by specialty j in one OR-block. The other input variable is the LOS of specialty j. The d_n^j parameter is the probability that a patient, who is still at the ward on day n, gets discharged on that day where $n \in \{0, 1, .., L^j\}$. L^j is the maximum LOS of specialty j. Note that parameter q only denotes the day within the MSS and that n denotes the LOS, which can be larger than q. Equation 5.4 shows the calculation of d_n^j, in which $P^j(n)$ is the probability that the LOS of specialty j is exactly n days long.

$$d_n^j = \frac{P^j(n)}{\sum\limits_{k=n}^{L^j} P^j(k)} \tag{5.4}$$

Note that, by using parameters c^j and d_n^j for the link between the OR and the nursing ward we generalize the patient flow of Figure 2.1. In our model, we only consider the stream from the OR department to the nursing wards. After the calculations of the d_n^j parameter we are able to calculate $h_n^j(x)$ which is the probability that n days after carrying out a block of specialty j, x patients of the block are still recovering on the wards. On day n = 0, the model assumes that a patient occupies a bed the whole day. From this assumption, the number of patients on recovery on day $n = 0$ equals the number of patients that undergo surgery on day $n = 0$. This means that on day $n = 0$, the number of recovering patients in the ward is $c^j(x)$. Recall, that d_n^j is the discharge probability and therefore (1 - d_n^j) is the probability that a patient stays on the ward, given that he/she is still at the ward on day n. In order to determine the probability $h_n^j(x)$, Vanberkel et al. (2011a) use the binomial distribution. Equation 5.5 computes the distribution of the probability of recovering patients on day n.

$$h_n^j(x) = \begin{cases} c^j(x) & when\, n = 0 \\ \sum\limits_{k=n}^{C^j} \binom{n}{k} (d_{n-1}^j)^{k-x} (1 - d_{n-1}^j)^x h_{n-1}^j(k) & otherwise. \end{cases} \tag{5.5}$$

We have mentioned the MSS as a cyclical schedule for surgical specialties that repeats after Q days. However, in this step we first look at one cycle of the MSS. We look at the influence of each OR-block on the total bed distribution. For specialty j is assigned to block $b_{i,q}$, we denote distribution $\bar{h}_m^{i,q}$ to be the number of recovering patients on day $m \in \{1, 2, .., Q, Q+1, Q+2, ..\})$ resulting from block $b_{i,q}$. So m can become larger than the set horizon of q and be at most L^j. Equation shows how this distribution can be computed.

$$\bar{h}_m^{i,q} = \begin{cases} h_{m-q}^j & if\, q \leq m < L^j + q \\ 0 & otherwise \end{cases} \tag{5.6}$$

By conducting the steps that are mentioned until thus far, we have computed $\bar{h}_m^{i,q}$, the distribution of the number of patients in the wards on day m that resulted from OR-block $b_{i,q}$. Vanberkel et al. (2011b) let H_m be the discrete distribution for the total amount surgical patients that are in the wards on day m resulting from a single MSS cycle. Until thus far, we showed how to compute the discrete distributions resulting from a single OR-block on a single day. All the independent discrete distributions can be added up by using discrete convolutions. Discrete convolutions are denoted with "$*$", and it is a method to add up two independent discrete distributions. The specialty distributions are independent because we assume the LOS of one patient does not influence the LOS of another patient. In Equation 5.7, A and B denote two independent discrete distributions and C is the convoluted distribution that comes forth out of A and B. In these equation τ denotes the maximum number that can come out of the convolution of A and B. So, suppose if the maximum value of A $= 3$ and the maximum value of B $= 4$, then τ is 7. In other words, if an OR A has a maximum number of 3 patients that can be operated on an OR day and OR B has a maximum number of 4 patients that can be operated on an OR day, then there is a chance that 7 patients flow to the nursing wards on that specific OR day.

$$C(x) = \sum_{k=0}^{\tau} A(k)B(x-k) \tag{5.7}$$

With these convolutions, we compute H_m. This method is given by Equation 5.8.

$$H_m(x) = \bar{h}_m^{1,1} * \bar{h}_m^{1,2} * ... * \bar{h}_m^{1,Q} * \bar{h}_m^{2,1} * ... * \bar{h}_m^{I,Q}. \tag{5.8}$$

Note, that we did not include the non-surgical patients. The model by Vanberkel et al. (2011b) only includes patient distributions from patients that have visited the OR department. We also include non-surgical patient distributions, which we denote with $\hat{H}_m(x)$. It is the probability distribution for non-surgical patients in the wards on day m. These distributions for non-surgical patients can be derived from patient management systems.

The probability distributions $H_m(x)$ and $\hat{H}_m(x)$ need to be convoluted in order to determine the total distribution of all the recovering patients in the wards on day m. We let $\bar{H}_m(x)$ denote this total distribution of all patients in the wards on day m. Equation 5.9 ensures this convolution.

$$\bar{H}_m(x) = H_m(x) * \hat{H}_m(x) \tag{5.9}$$

Note that the current model does not yet include the cyclical property of a MSS schedule. In the previous step we have only determined $\bar{H}_m$ for a single MSS. To incorporate this in the model, Vanberkel et al. (2011b) let $\hat{H}_q^{ss}$ denote the probability distribution of recovering patients on day q of the MSS cycle resulting from multiple MSSs. Note, that the MSS is a cyclic schedule and that we need to include this property. This is presented by Figure 5.3.

In equation 5.10, M denotes the last day where there is still a positive probability that a patient is recovering at the nursing wards. Therefore $M = max_j \left\{L^j + x_{i,q,j}\right\}$, where $x_{i,q,j}$ is last day that a block of specialty j is planned. Furthermore, [M/Q] consecutive MSS cycles need to be convoluted. Again, we used the convolution method to add up the distributions of multiple MSSs.

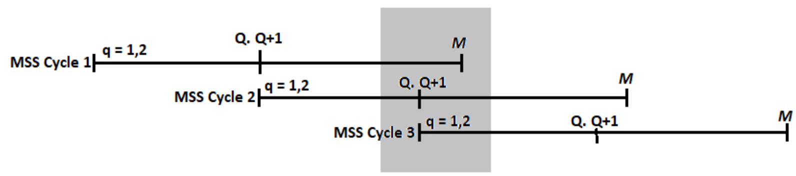


Figure 5.3: Cyclic schedule convolutions.

$$\bar{H}_q^{ss}(x) = \bar{H}_q * \bar{H}_{q+Q} * \bar{H}_{q+2Q} * ... * \bar{H}_{q+[M/Q]Q}. \tag{5.10}$$

Next, we let γ^k be the maximum number of required beds over the time horizon. Next to that, we want to denote the number of beds at occupied quantile β. For example, if quantile β denotes the 95^{th} percentile of demand of maximum required number of beds that need to be staffed. Then our objective function becomes:

$$min\ \gamma_\beta \tag{5.11}$$

Where the quantile β of the required number of beds is determined by Equation 5.12:

$$\gamma_\beta^k = max \left\{ \gamma^k | \bar{H}_q^{ss}(\gamma^k) \leq 0.95 \right\} \tag{5.12}$$

As mentioned, we also want to measure the bed occupation per floor and therefore group the nursing wards. Vanberkel et al. (2011b) propose a modification to their model for this. They let W_k be the set of specialties that are admitted to ward k, where $\{k \in 0, 1.., K\}$. Subsequently, in Equation 5.5 we only calculate the specialties that are assigned to those specific floor. We refer back to Table 2.2 for the description of which ward belongs to which floor. Note that we want three floors where we want to minimize the maximum bed occupation on a given time horizon. Our objective function then changes to:

$$min\ \gamma_\beta^k \tag{5.13}$$

In Equation 9.1, every γ_β is then replaced by γ_β^k.

Recall, that our main objective is to reduce the variability in bed occupation. Theoretically, lowering the maximum number of beds required does not necessarily mean that the variability reduces. In other words, if the high peaks in bed occupation are cut off, it can occur that low peaks become even lower. Therefore, we want to check another objective. We want to minimize the difference between the maximum required number of beds and the minimum required number of beds. Therefore, we let θ_β^k denote the minimum number of required beds for ward k at quantile β. Then our objective function becomes:

$$min\ (\gamma_\beta^k - \theta_\beta^k) \tag{5.14}$$

As mentioned in our literature search, the model by Vanberkel et al. (2011b) is initially meant as an evaluation tool for the workload of an MSS. Therefore, we include the admission rates and discharge rates within the schedule. Therefore, use some of the proposed extensions by Vanberkel et al. (2011b). To incorporate the admission rate, we replaced Equation 5.5 with:

$$h_n^j(x) = \begin{cases} c^j(x) & when\, n = 0 \\ h_n^j(0) = 1 & otherwise. \end{cases} \tag{5.15}$$

In this equation, every OR-block is only considered on the day of surgery. Afterwards, this block can be ignored. Therefore c_j is considered on day $n = 0$ and all the days, the probability for 0 patients is 100%.

Next to the admission rate, we mention the discharge rate as a factor of the workload at nursing wards. This addition is also included in the study by Vanberkel et al. (2011b). In order to calculate the number of discharges per day resulting from a MSS, an addition must be made of the first step of the model. Recall, that this is the calculation of the distribution of recovering patients on day n, which we described with Equation 5.5. In Equation 5.5 we described this with $h_n^j(x)$. On each day n, every patient has the chance d_n^j of being discharged and chance $(1 - d_n^j)$ of staying in the ward. Vanberkel et al. (2011b) denote D_n^j to be the discrete distribution for the number of discharges from specialty j on day n. D_n^j is calculated by Equation 5.17

$$D_n^j(x) = \sum_{k=x}^{C^j} \binom{k}{x} (d_n^j)^x (1 - d_n^j)^{k-x} h_n^j(k) \tag{5.16}$$

By calculating the Equation 5.17, the discharge probabilities can replace $h_n^j(x)$ in Equation 5.5 and the next steps and the convolutions can be done in order to calculate the total number of discharges per day in the wards. For the admission rates and the discharges rates, the non-surgical probabilities need to be derived. After that, Equation 5.9 can be solved for both parameters.

5.3.1 Adaptive Large Neighborhood Search

In Section 5.3 we have presented our model and our objective function. In order to optimize the MSS and our objective function we use an optimization heuristic. As mentioned, we chose the ALNS procedure in combination with a SA accpetance procedure. In this section we describe the main steps of the algorithm and explain our choices. The ALNS approach we use is based on the studies by Lutz (2015) and Ropke and Pisinger (2006). For a detailed description of the ALNS heuristic we refer to the study by Lutz (2015). The ALNS approach is based on Large Neighborhood Search (LNS). The key idea behind this LNS heuristic is first removing instances from a solution with a destroy function and after that use a repair heuristic to create a new solution. In LNS, only one destroy and one repair function are used and an acceptance procedure is used to make a decision on accepting a new solution. The ALNS algorithm uses multiple destroy- and repair functions and gives them weights based on achieved improvement in the objective function. The ALNS approach exists of the following steps:

1. Create a starting solution $s_min = s \in S(I)$ that is feasible to constraints (5.1) - (5.3).
2. Set the ALNS parameters.
3. Select destroy heuristic d and repair heuristic r, where $r \in R$ and $d \in D$.
4. Generate new solution $s' = r(d(s))$.
5. Accept or reject new solution on the base of acceptance procedure.
6. Adjust the weights w and probabilities p of the heuristics.

Step 1: Create a starting solution.
As mentioned, our starting solution must be subject to (5.1) - (5.3). In other words, specialties must be planned into the ORs that are available (or dedicated) to them and the number of sessions that are allocated to each specialty must be assigned to the ORs. We used a greedy three step approach to generate this starting solution. In these loops we first fill the first days of all the weeks, before we fill the rest of the weekdays. The three steps of our approach are:

1. Plan all the specialties j that can only be planned in one OR.
2. Fill all the ORs o that only have one specialty dedicated to them.
3. Assign specialties on the base on difference between number of available spots for specialty j and OR-blocks that still need to be planned.

Table 5.3.1 shows the number of sessions per specialty that need to be planned in an MSS of 28 days. Within the 28-day horizon, some specialties have more than one session per day and therefore and requires ORs to be fully dedicated to them. This holds for CTC, GS and ORT which is incorporated in constraint 5.2. In the optimization heuristic we exclude these specific ORs, because these parts of the solution cannot differ between the start solution and the final solution.

Specialty	Number of sessions
PPA	1
CTS	5
CTS	47
ENT	15
GE	1
GS	93
GYN	20
MA	3
NEU	4
OPT	2
ORT	39
SDC	0
PS	14
URO	16

Table 5.1: Number of sessions per specialty in solution (based on a MSS in 2018)

Step 2: Set the ALNS parameters

The ALNS heuristic has a lot of tuneable input parameters and it would require a lot of experiments and lot of executions, which is not the goal of this study. Therefore, we base the parameter settings on the studies by Lutz (2015) and Ropke and Pisinger (2006). Table 5.2 shows the input parameters and their values.

The degree of destruction d is the part of the solution that will be destroyed or in other words the number of instances that are removed from the solution. This value d must be between 0 and 1. If it is close to 1 the complete solution is almost erased and when this value is close to 0 only a small part of the solution is destroyed. Lutz (2015) and Ropke and Pisinger (2006) both use a range with a d_{min} and d_{max} out of which in every iteration a random degree is picked. Their model performed best at a d_{min} and d_{max} of respectively $0.075n$ and $0.275n$. We let d_{min} be $0.01n$, since the possibility of destruction and repairment of a small part of the solution needs to be included to be able to reach the total solution space. Next, the update period stands for the number of iterations that are executed, before the weights and probabilities (that are given to the destroy and repair heuristics) are recalculated. This number must not be too low, since it can cause that some of the heuristic is left unused. Lutz (2015) and Ropke and Pisinger (2006) both used and substantiated a p_u of 100 iterations, we choose to use a lower p_u value since our solution space is smaller. Therefore, we choose to use a p_u value of 50.

The reaction factor ρ controls the influence of recent success on the weight of the heuristics.

The δ_i parameters denote the increase of the weight of the heuristics in three situations. The first situation is that the new solution is the best solution so far, for which the reward is δ_1. The second situation is that the new solution improves the current solution, which is rewarded with δ_2. The third case is that a new solution does not improve the solution but gets accepted. In this case a heuristic is rewarded with δ_3.

Input Parameters	Symbol	Value
Degree Of Destruction	d_{min}	$0.01n$
	d_{max}	$0.275n$
Update Period	P_u	100 iterations.
Success Factor	δ_1	135
	δ_2	70
	δ_3	25
Reaction Factor	ρ	0.35

Table 5.2: ALNS input parameters

Step 3 & 4: Select destroy and repair functions and generate a new solution: With the ALNS approach, multiple destroy- and repair heuristics are used. After using a destroy heuristic to remove instances from a given solution, repair heuristics are used to generate a new solution. Obviously, the set of these heuristics can be very large. However, within our model, solutions are heavily constrained. The destroy- and repair heuristics need to be able to access every solution possible. We choose to make sets of destroy- and repair heuristics. A set of a destroy- and a repair heuristic is weighted in this form. This approach is also proposed by Lutz (2015). Next, we discuss and explain the destroy- and repair heuristics that we use within our model.

Destroy- and Repair heuristics:

Random Removal: This procedure randomly removes assigned specialties from the given solution until the degree of destruction is reached. In this method, no cost function or objective is considered. Therefore, it is a method that can easily jump out of local optima. Table 5.3 presents the pseudo code for Random Removal.

Random Removal
Input: Current Solution s, Degree Of Destruction d,
while: degree of destruction is not reached **do**
Choose random day q and random OR i
Delete planned specialty on block *(i,q)* from solution
Update degree of destruction
result: Current Solution s'

Table 5.3: Pseudocode Random Removal

Related OR Removal: Lutz (2015) proposes a related removal heuristic. A specialty is deleted from the solution, along with related parts. As Lutz (2015) remarks, the challenge here is to find a reasonable relatedness measure which can be checked very fast. In case of the MSS, this is can be done by removing specialties from the same OR, but different day or weeks. This is under the assumption that specialties are not bounded to given weekdays. In our input data and our model, this is the case. Therefore, with related removal we delete specialties within an OR until the complete degree of destruction is reached.

Related Removal
Input: Current Solution s, Degree Of Destruction d,
initialize: choose random OR i
for $q = 0$ to d
Delete planned specialty on block *(i,q)* from solution s
result: Current Solution s'

Table 5.4: Pseudocode Related Removal

Basic Greedy Repair: Within our model we use a greedy approach to get to a start solution. This greedy approach is also used in to repair solutions resulting from the random removal and the related OR removal. In the starting solution, we checked which specialty has the highest priority of being planned. From there on, the specialty gets allocated to the first block available. To find this first block available in our start solution, we loop over the weekdays and after that over weeks. This approach resulted in feasible solutions, but note that if we use these same methods for reparation of the destroyed solution, ALNS stays in the same solution neighborhood. For example, if the Related OR Removal destroys the schedule of one OR for the second time and the solution within an OR has not changed in between, the repair method builds the same solution before destruction. Therefore, we use the following different looping methods so that the chance of repairing the new solution back to the initial solution is minimized:

1. Loop over all days (from low to high), loop over all ORs (from low to high)
2. Loop over all days (from high to low), loop over all ORs (from high to low)
3. Loop over all weekdays, loop over all weeks (from low to high), loop over all ORs (from low to high)
4. Loop over all weekdays, loop over all weeks (from high to low), loop over all ORs (from high to low)

Recall, that the MSS is a repetitive schedule that has the property of being as simple as possible. We assume that the last two looping methods provide a more repetitive schedule. Table 5.5 shows the pseudocode of the Basic Greedy Repair heuristic.

Basic Greedy Repair
Input: Current Solution *s'*, Degree Of Destruction d,
while: Solution is not repaired **do**
Find first empty OR i on day q
Find specialty j with highest plan priority
Plan specialty j on day q in OR i
Increase d
result: Current Solution s'

Table 5.5: Pseudocode Basic Greedy Repair

Swap Heuristic: A swap heuristic takes two OR-block within the OR schedule and swaps them. It needs to check for different specialties, because swapping the same specialty within an OR does not have any effect on the objective. Next to that it requires two specialties that can both be allocated to the same ORs. The search for two different specialties that can be swapped is already a computationally intensive operation. Therefore, we do not include the degree of destruction in this heuristic. Table 5.6 shows the pseudocode for the swap heuristic. This heuristic both destroys and repairs a solution in one iteration.

Swap Heuristic
Input: Current Solution s
while: neighbor solution is not found **do**
Select two OR-blocks
Check if swap is possible
Swap the OR-blocks
Neighbor solution is found
result: Current Solution s'

Table 5.6: Pseudocode Swap Heuristic

Step 5: Accept or reject new solution on the base of acceptance procedure: The ALNS heuristic requires a method to accept or reject a new solution. It has the purpose of deciding whether to continue with the newly generated solution *s'* or with the previous solution *s*. The ALNS heuristic does not contain a specified acceptance procedure. Therefore, practically every type of acceptance method can be used here, with each its advantages and disadvantages. If for example a *Greedy Acceptance* method is used in which a new solution is only accepted if it improves the cost function, the procedure can get stuck in a local optimum. With *Greedy Acceptance*, a solution with a promising neighborhood that seems less desirable at first sight is never accepted due to higher costs Lutz (2015). If a *Random Removal* destroy heuristic brings the ALNS into a promising neighborhood, we want to be able to accept it even if the new solution is not as good as the initial solution. In other words, we do not only want to accept improving solutions, but also worse solutions if they introduce a neighborhood with high potential. To ensure this, Lutz (2015) used *Threshold Acceptance*. Ropke and Pisinger (2006) used the acceptance procedure of Simulated Annealing (SA). Both procedures are comparable, since they both lower the probability of accepting worse solutions after every iteration. In our optimization model we use the acceptance procedure of Simulated Annealing, since this heuristic is frequently used in comparable studies and has proven to generate promising results (Fügener et al., 2014; van Essen et al., 2014).

For a complete and detailed description of the SA algorithm and its background we refer to Kirkpatrick et al. (1983). The acceptance procedure of SA is based on the physical annealing process of cooling down of metal. The SA approach starts with a high starting temperature T. In this state, the chance that a worse solution is accepted is still high. The temperature T decreases after every iteration. In the beginning of the annealing, more worse solutions are accepted. Every solution s' that improves the objective function is accepted. If a new solution is worse than the initial solution it is accepted with a decreasing probability. If $c(s') > c(s)$, then s' is accepted with probability $\exp^{\frac{c(s)-c(s')}{T}}$. After every iteration the temperature, and therefore the probability to accept a worse solution, is decreased with cooling down factor ϕ. Table 5.7 presents the values of the SA acceptance procedure we use in our model. These parameters are chosen so that, 100 p_u iterations are conducted.

Parameters	Symbol	Value
Start Temperature	T_{start}	100
Threshold Temperature	T_{stop}	0.6
Cool Down Factor	ϕ	0.95

Table 5.7: SA acceptance parameters

Step 6: Adjust the weights and probabilities of the heuristics: As mentioned, the ALNS algorithm uses multiple destroy and repair heuristics. In fact, the set of destroy of repair heuristics can be as large as the user wants. The algorithm assigns a weight to these heuristics based on the success of the algorithm. These weights determine how many times a heuristic is used within an iteration. Pisinger and Ropke (2010) state that the heuristic is chosen on the base of a *roulette wheel principle*. This principle means that a random number is generated on the interval $[0, 1]$. The probabilities p_j together denote this interval. For example, if random number r is generated and it falls in interval $[0, p_1]$, heuristic 1 is chosen to destroy- and repair the solution.

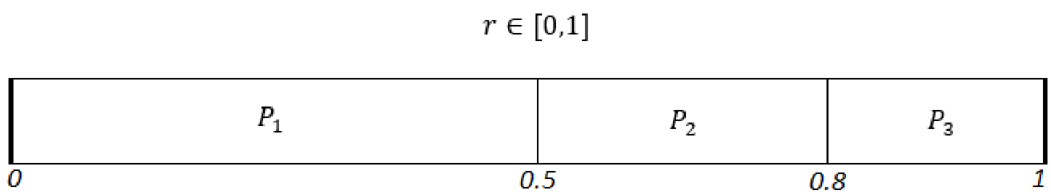


Figure 5.4: Roulette Wheel Principle

Initially, all the weights are set equal. The equation that is used for the calculation of weights is presented by Equation 5.17. In this equation, w denotes the weight of heuristic h. At every start of the p_u iterations, the success of the heuristic $s(h)$ is initialized as zero. Recall, that ρ denotes the influence of recent success. After using heuristic h in an iteration, the value of the success of the heuristic is increased with δ^i based on the corresponding scenarios that we have explained in the second step of ALNS. The number of times a heuristic is used within p_u is denoted by $u(h)$. And as mentioned in step 2, reaction factor ρ controls the influence of recent success of a heuristic on the weight. After p_u iterations the ratings of the heuristics are adjusted.

$$w(h) = \begin{cases} (1-\rho)w(h) + \rho\frac{s(h)}{u(h)}, & if\ u(h) > 0 \\ (1-\rho)w(h), & if\ u(h) = 0 \end{cases} \tag{5.17}$$

With the calculations of these weights, the probabilities are determined. This is presented by Equation 5.18. Lutz (2015) and Ropke and Pisinger (2006) both use weights and probabilities and for destroy- and repair heuristics. Since, we use sets of destroy and repair heuristics, we determine the weights and probabilities of the sets. In these equation $H = \{h_i | i = 1, .., k\}$ denotes the set of k heuristics. Lutz (2015) proposes an initial weight value for all the heuristics of 1000.

$$p(h_i) = \frac{w(h_i)}{\sum_{j=1}^{k} w(h_j)} \tag{5.18}$$

5.4 Ward and patient group inclusion

In MST, two of the three floors with wards are dedicated to surgical patients. These are the fourth-floor wards and the fifth-floor wards. Hereby, the fifth floor is partly dedicated to non-surgical patients. For example, surgical neurosurgery and non-surgical neurology patients are all dedicated to the ENEUVP ward. The sixth floor is dedicated to non-surgical patients which we therefore leave out of consideration. We mentioned to optimize on the base of specialty level, this means that sub-specialties are not incorporated and therefore our surgical specialties are only dedicated to one ward. In our model we analyse the influence of optimizing the MSS per floor on workload parameters. Therefore, we grouped wards together. Table 5.8 summarizes this grouping of nursing wards. On the fifth floor the nursing wards ETHOVP, ENEUVP and EGOUVP are located. ETHOVP and ENEUVP have a dedicated patient groups. CAR and CTS patient go to the ETHOVP ward and NEURO patients go from the OR department to the ENEUVP ward. The EGUOVP ward has a main dedication of URO. However, sub-specialties of GS, PS and ORT also go to the EGUOVP ward. For these sub-specialties it is referred to as the 'short-stay'-ward. However, short-stay versus long-stay is out of our scope and therefore we group this ward with the wards of the fourth floor: ECONVP, ECTVTP, EGYVNVP. Next to the long-stay versus short-stay patients division we also presented the surgical inflow of emergency patients. The inflow of emergency patients is incorporated in the number of surgeries probabilities. Recall, that non-surgical patients flow to the acute admission departments and that about 60% of these patients flow to the nursing wards. These patients are incorporated in the non-surgical patient distribution for both floors.

Model Division	MST Departments	Assigned specialties
5th Floor	ETHOVP, ENEUVP	PPA, CAR, CTC, NEURO
4th Floor	ECONVP, ECVTVP, EGYNVP, EGUOVP	ENT, CH, GYN, MA, MDL, OPT, ORT, SDC, PS, URO

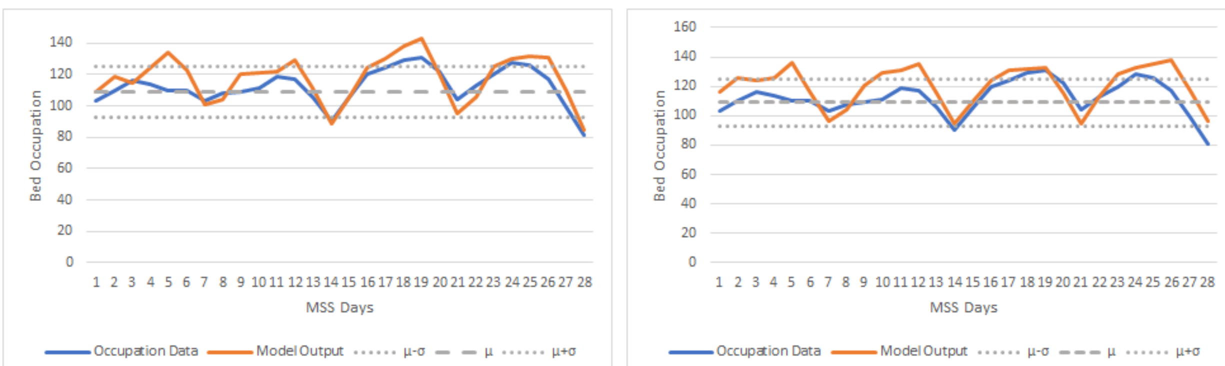
Table 5.8: Division of hospital departments in model.

5.5 Model Validation

We validate our model by comparing the model output with occupation, discharge and admission data of 2017. Therefore, we loaded the MSS of November 2017 in our model. We chose this MSS, because it had a relative low number of closed OR days. In multiple cases the planned MSS schedule differed from the realized MSS. Since, the realized MSS provides a better indication of bed occupation at the wards, we use the realized MSS schedules for our validation.

Figure 5.5 show the comparison of the model output and the occupation data of 2017 for the fourth floor. We loaded the MSS of November 2017 in our model and compared the occupation data with the output. For our bed occupation model, we compared the data with the 95th percentile of demand. This means that in 95% of the times, the bed demand is met. However, we concluded that on this percentile, our model overestimated the occupation, admission rates and the discharges rates. We found that 90th percentile resulted in a better fit to the data. Therefore, the figures and the results are based upon the 90th percentile.

In Figure 5.5 we calculated the surgical distribution for the period and added it up to the non-surgical data of the period. In Figure 5.5, we compared the occupation data with our model input including the empirical non-surgical distribution data. As mentioned, this non-surgical distribution is based on occupation data of 2017. The first situation in Figure 5.5 shows that our model overestimates the number of occupied beds for some of the weekdays. We assume this overestimation is caused by seasonality differences. The non-surgical occupation distribution is based on the yearly occupation per weekday. Figure 5.5 presents the model surgical patient output. Here, we added the surgical occupation output to the non-surgical occupation data. Next to that, it presents the total model output, which is the surgical patient output added to the non-surgical patient distribution. Figure 5.5 also shows, that the surgical distribution added up to the non-surgical occupation is a closer fit to the data compared to the total model output for the fourth floor. For the fifth-floor wards, the same effect is noticed. Since, the non-surgical distribution is a second variable, the model output has more fluctuations from the occupation data in comparison with the surgical distribution.

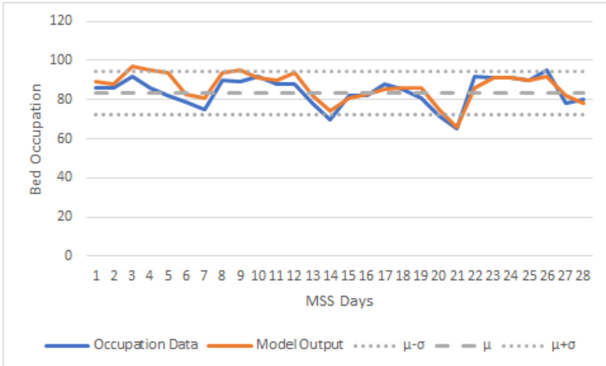


(a) Surgical Distribution 2017

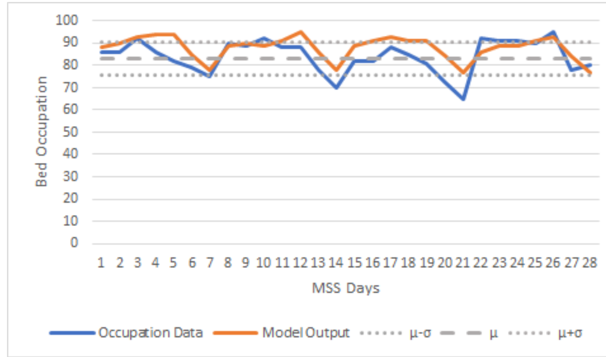
(b) Total Model Output 2017

Figure 5.5: Occupation Data 2017 versus Model Output 4th Floor.

Figure 5.6 shows the model output versus occupation data of 2017 of the fifth-floor wards. Figure 5.6 presents the surgical distribution added up to the non-surgical distribution of the period analysed. The second figure shows the model output that includes our empirical non-surgical bed occupation distribution. Again, it shows the same situation. The surgical patient distribution fits the occupation data, but for some days it underestimates the number of occupied beds. In the second situation, the model output overestimates the resulting bed occupation. Nevertheless, we consider our model output to be valid, because our model output data falls between $[\mu - \sigma, \mu + \sigma]$ which is $\pm$ 1 time the standard deviation from the mean occupation.



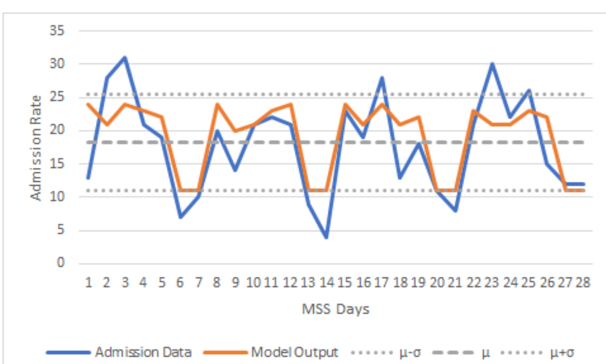
(a) Surgical Distribution 2017



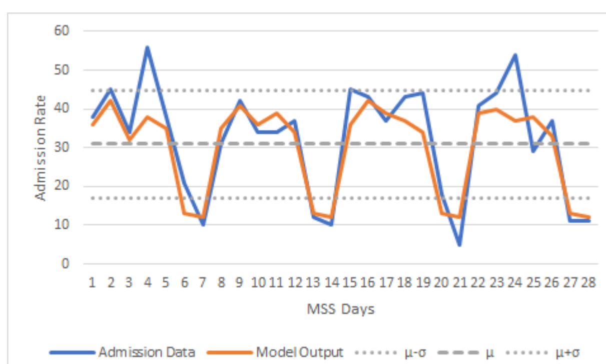
(b) Total Model Output 2017

Figure 5.6: Occupation Data 2017 versus Model Output 5th Floor.

Figure 5.7 presents the comparison of the admission rate output of our model and the data of 2017. Next to that, Figure 5.8 presents the comparison of the discharges rate output of our model and the data of 2017. At the 95th percentile of demand, our model overestimates the admission- and discharge rates, so that a large amount of the model output falls above $\mu + \sigma$. Therefore, we compared the data with the 90th percentile for the admission and discharge rates. For admissions, we see that the fourth floor distributions follow the admission data, but that the peaks are underestimated. Note, that these peaks fall outside the interval $[\mu - \sigma, \mu + \sigma]$. Therefore, we consider the analyzed period to have large variability in admission rates. Figure 5.8 presents the model output for discharge rates versus discharge data. It shows that for both floors, our model overestimates the number of discharges in weekend days and afterwards underestimates some peaks during weekdays. The overestimation in the weekend days is caused by discharge policies. It is common for patients to stay during weekend days. After the weekend, patients get discharges on Monday or Tuesday after the surgeon lets the patient discharge. In order to solve this limitation, we propose an addition to the model in Section 9.2.

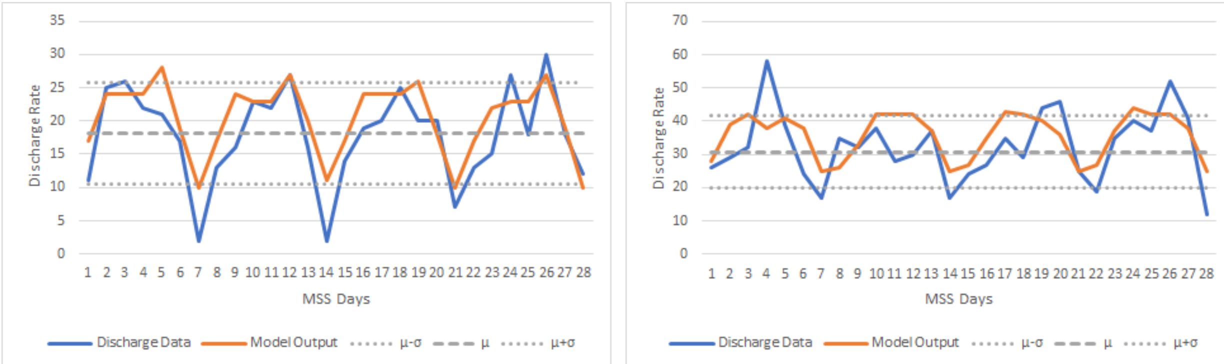


(a) Fifth Floor Admission Rates



(b) Fourth Floor Admission Rates

Figure 5.7: Admission Data 2017 versus Model Output.



(a) Fifth Floor Discharge Rates

(b) Fourth Floor Discharge Rates

Figure 5.8: Discharge Data 2017 versus Model Output.

5.6 Conclusion

In this chapter we formulated the model by Vanberkel et al. (2011b) and our additions to it. Furthermore, we described the ALNS approach that we use in conjunction with the model, to optimize a given MSS schedule. In Section 5.3.1 we described which heuristics we used within ALNS. In Section 5.4, we presented our choices for ward division in the model. In Section 5.5, we described the validation of our model. We showed that our tool is valid and gives valid results in bed occupation, admissions and discharges. We describe the results of MSS optimization in the next section.

Chapter 6

Results

In this chapter we answer research question 7: *What are the main findings and what are the effects of the model on the KPIs?* research question 8: *How can the main findings in the research be implemented in the organization?*. We describe the experiments in Section 6.1. In Section 6.2, we present the outcomes of optimization on peak minimization. In Section 6.3, we present the outcomes of optimization on range minimization. We compare and explain the corresponding results and conclude this chapter in Section 6.4.

6.1 Experimentation

In Section 6.2 and Section 6.3 we run the model for different MSSs of 2018. Note that, an MSS is a repetitive, cyclic schedule. However, within MST most MSSs have small differences in allocation of number of sessions. Therefore, we used four different MSSs. Table 6.1 shows the strategical allocation of sessions per specialty within the MSSs.

Specialty	MSS-5	MSS-25	MSS-37	MSS-45
PPA	1	1	0	0
CAR	4	5	4	5
CTC	46	47	48	47
CH	89	93	92	91
ENT	13	15	16	16
GYN	17	20	20	18
MA	4	3	3	3
MDL	1	1	1	1
NEURO	24	24	23	24
OPT	2	2	2	2
ORT	37	39	39	40
PS	17	14	15	16
SDC	7	0	1	1
URO	18	16	16	16

Table 6.1: Strategical session allocation for 2018 MSSs.

We ran the ALNS optimization for the four MSS scenarios in Table 6.1. The biggest bottleneck in running the model was the computational time. It took the model 11 hours to calculate 10000 iterations (100 runs of 100 p_u iterations) on a 2.5 GHz i7 core laptop. We incorporated 240 of the in total 280 OR-days (28 days horizon) within the optimization of the model, because the CTC ORs were left out of the swaps. Recall, that OR 14 and OR 15 are only dedicated and available for CTC and therefore exclusion does not influence the results of optimization.
We checked possible improvements of our model. Based on which, we used our model generated start solution for the optimization We used the session allocation of MSS-37 for the start solution, because this MSS is the standard MSS planned for 2018. The other MSSs are based on this schedule. Table 6.1 shows the outcomes of both optimization approaches in comparison with the start solution. It shows, that both approaches succeed in reduction of occupation peaks and the variability in bed occupation. Both approaches, lower the occupation peaks with 10 beds. The variability reduction is for both approaches respectively 14.68% and 19.26%.

Parameter	Start Solution	Peak optimization	Range optimization
Sum of Max. Required Beds	146	136	136
μ	121.25	121.45	121.9
σ	13.33	11.36	10.76
c_v	0.109	0.093	0.088

Table 6.2: Results of ALNS optimization (without non-surgical distribution)

We conducted both optimization approaches again and included the non-surgical distributions in the optimization. We conduct this, to determine the influence of the non-surgical patient distributions on the results. Table 6.3 presents the outcomes of this optimization run. It shows that both approaches reduce the occupation peaks with respectively 11 and 10 beds. Next to that, it shows that range occupation reduces the variability in bed occupation from c_v = 0.051 down to c_v = 0.040, which corresponds with a 19.61% reduction. Optimization on peak occupation resulted in a 9.80% variability reduction.

Table 6.1 and Table 6.3 show promising results, since both approaches reduce the occupation peaks and reduce the variance of the bed occupation. However, they increase the mean occupation. Furthermore, it shows peak optimization has the largest effect on the decrease of bed peaks. This confirms our assumption of Equation 5.14. The peak optimization only accepts solutions that lowers the sum of maximum required number of beds per floor, while the range optimization also accepts new solutions that increase the minimum required number of beds per floor. Therefore, we found larger reduction in variation of bed occupation with range optimization.

Parameter	Start Solution	Peak Optimization	Range Optimization
Sum of Max. Required Beds	243	232	233
μ	221.60	221.80	221.35
σ	11.37	10.25	8.93
c_v	0.051	0.046	0.040

Table 6.3: Results of ALNS optimization with start solution.

In the following sections, we perform the ALNS optimization with both objectives for the different MSS scenarios, as mentioned in Table 6.1.

6.2 Optimization on Maximum Bed Occupation:

Maximum Required Number Of Beds: For all the MSSs, we see that the maximum required beds and thereby occupation peaks are lowered by optimization with ALNS. In order evaluate the effect of the rescheduling, we plot the bed occupation output of all the MSSs used. We first analyse the maximum total required number of beds combined, because this was the objective function. Figure 6.1 shows the distribution for both floors combined. In this figure we excluded the weekend days, because we explicitly wanted to lower the variation in peaks in bed occupation on working days. Table 6.4 shows the numerical values that correspond to the output of Figure 6.1. It shows that the mean maximum required number of occupied beds increased after ALNS, but that the standard deviation decreased. The decreased standard deviation means that the data is less widely spread and the variation is lowered.

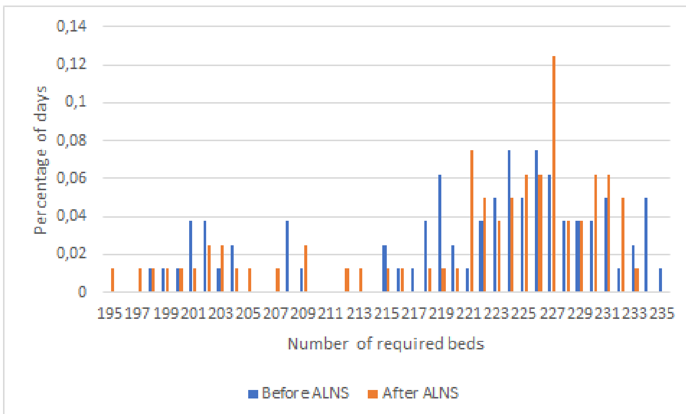
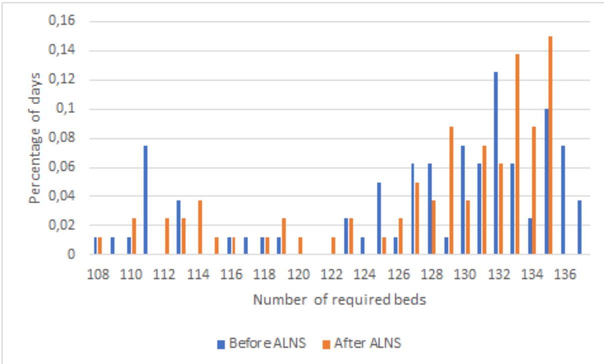


Figure 6.1: Output distribution before and after ALNS - 4th and 5th Floor.

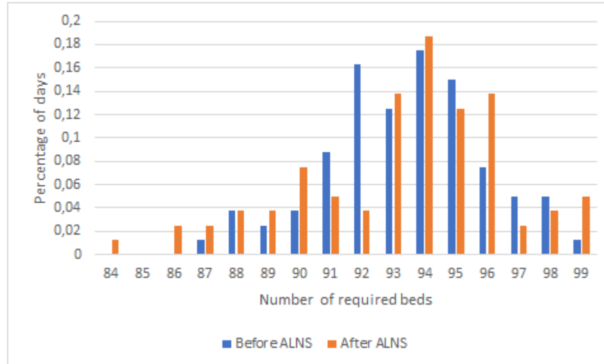
Parameters	Start Solutions	After ALNS
μ	220.87	221.10
σ	10.17	10.19
c_v	0.046	0.046

Table 6.4: Output distribution statistics before and after ALNS - 4th Floor.

Figure 6.6 shows the distribution for the fourth and the fifth floor that corresponds to the optimized MSSs. The figures show the total distribution of the 4th and the 5th floor bed occupation on the weekdays of the MSSs and in addition to that, they shows the bed occupation model output of the MSSs after they were optimized. Table 6.9 presents the numerical values that are derived from these output distributions. The table shows that the mean peak occupation for the fourth floor decreased and for the fifth floor, it shows that the mean occupation and the standard deviation slightly increased. Note, that the solution space here is smaller than for the fourth floor and the total bed occupation. As mentioned in Section 5.3, optimizing on peak occupation does not directly mean a lower standard deviation of the occupation.



(a) Occupation on 4th Floor



(b) Occupation on 5th Floor

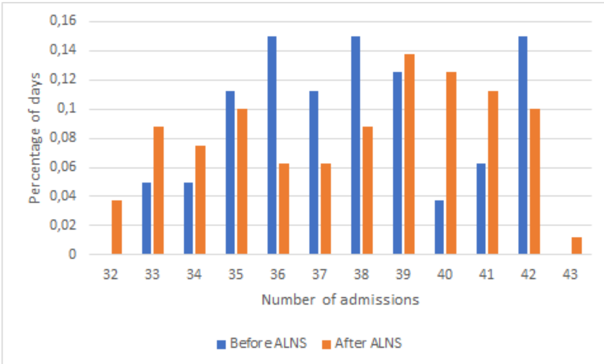
Figure 6.2: Occupation distribution before and after ALNS procedure

Parameters	Start Solutions	After ALNS
4th Floor μ	127.46	127.80
4th Floor σ	8.32	7.63
4th Floor c_v	0.065	0.059

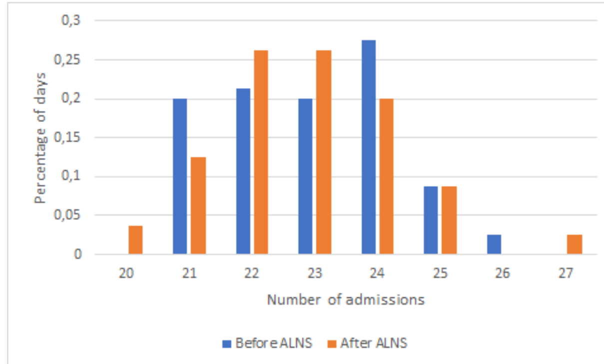
Parameters	Start Solutions	After ALNS
5th Floor μ	93.41	93.30
5th Floor σ	2.54	3.27
5th Floor c_v	0.027	0.035

Table 6.5: 4th and 5th Floor occupation statistics

Admission Peaks: The second factor we analysed in our model is the number of admissions. Figure 6.3 presents the figures that correspond with the MSSs analysed. It shows that the peak admissions increased for that the fifth-floor wards after ALNS. Table 6.10 presents the corresponding values to the figures. For both floors it shows that the variability of admissions increases slightly. Differences in peaks are only found for the fifth-floor wards.



(a) Admission peaks on 4th Floor



(b) Admission peaks on 5th Floor

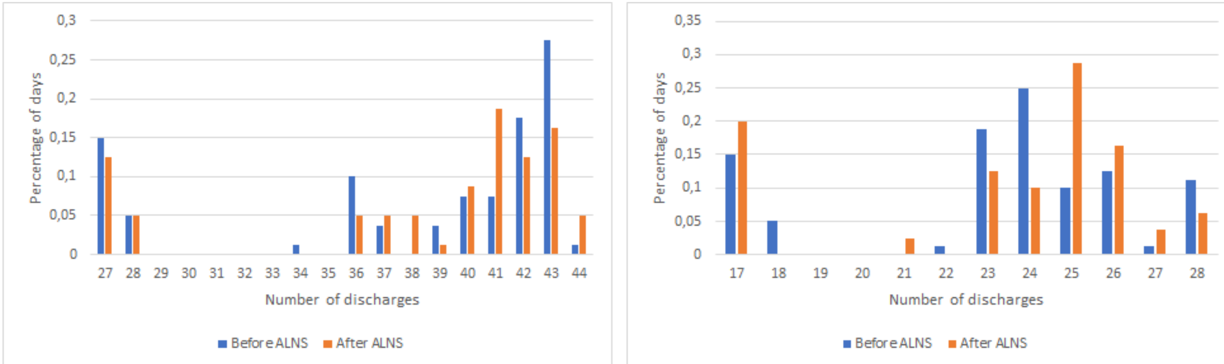
Figure 6.3: Admission output distribution before and after ALNS procedure

Parameters	Start Solutions	After ALNS
4th Floor μ	37.78	37.73
4th Floor σ	2.65	3.09
4th Floor c_v	0.070	0.081

Parameters	Start Solutions	After ALNS
5th Floor μ	24.76	22.85
5th Floor σ	2.01	1.43
5th Floor c_v	0.081	0.062

Table 6.6: 4th and 5th Floor Admission statistics

Discharge Peaks: The third workload factor that we analysed within our model is the discharge rate. In the tables corresponding to the optimized MSSs, it is shown that the maximum discharge rate did not show large difference from the initial values. Figure 6.4 shows the output distribution. Next to that, Table 6.7 presents the output parameters. Again, we see that the mean values increase, but that the standard deviation decreases.



(a) Discharge rates on 4th Floor

(b) Discharge rates on 5th Floor

Figure 6.4: Discharge output distribution before and after ALNS procedure

Parameters	Start Solutions	After ALNS
μ	38.12	38.22
σ	5.94	5.97
c_v	0.155	0.156

Parameters	Start Solutions	After ALNS
μ	23.27	23.37
σ	3.39	3.49
c_v	0.145	0.149

Table 6.7: 4th and 5th Floor Discharge statistics

6.3 Optimization on Occupation Range

In Section 5.3, we mentioned that minimization on the maximum required number of beds does not directly lower the variation in bed occupation. Theoretically, a slightly lowered range does not necessarily mean a decreased variation. However, we assume that if the improvement is large enough, this will lead to a lower variation. Therefore, we conducted the ALNS procedure again for the MSSs of 2018. However, in this case the optimization was conducted with objective 5.14. Appendix J shows the MSS outputs that were generated out of the ALNS runs. Next to that, Appendix K presents the MSS specific outcomes.

Bed Occupation: Again, we conducted the ALNS procedures for all the 2018 MSSs. Figure 6.5 presents the total output distribution for the week days. In addition to that, Table 6.8 shows the numbers corresponding to the output distribution. It shows that the variation in bed occupation reduces for both wards combined. Next to the total bed distribution, we compared the individual floor distributions. Figure 6.5 shows these distributions for both floors. Table 6.8 shows the variance parameters that corresponds to the distribution. It shows that after ALNS, the variability in bed occupation decreases at the fourth-floor wards, but that the mean occupation increases. Furthermore, it shows that variability in bed occupation increases at the fifth-floor wards, but that the mean occupation decreases. We explain this effect in Section 6.4.

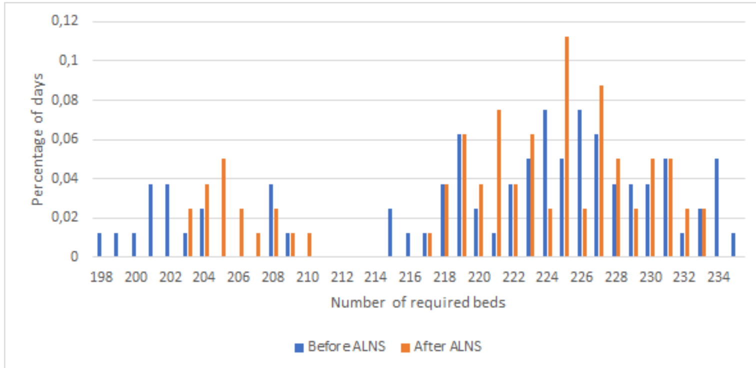
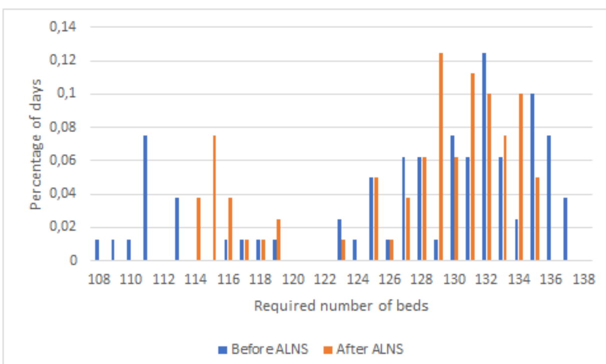


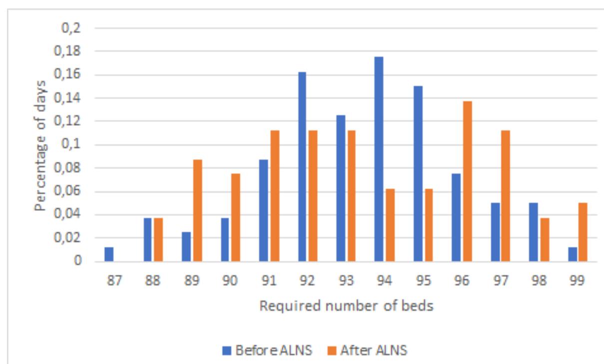
Figure 6.5: Output distribution before and after ALNS - 4th and 5th Floor. (Range optimization)

Parameters	Start Solutions	After ALNS
μ	220.87	221.03
σ	10.17	8.65
c_v	0.046	0.039

Table 6.8: Total distribution output before and after ALNS. (Range optimization)



(a) Occupation on 4th Floor



(b) Occupation on 5th Floor

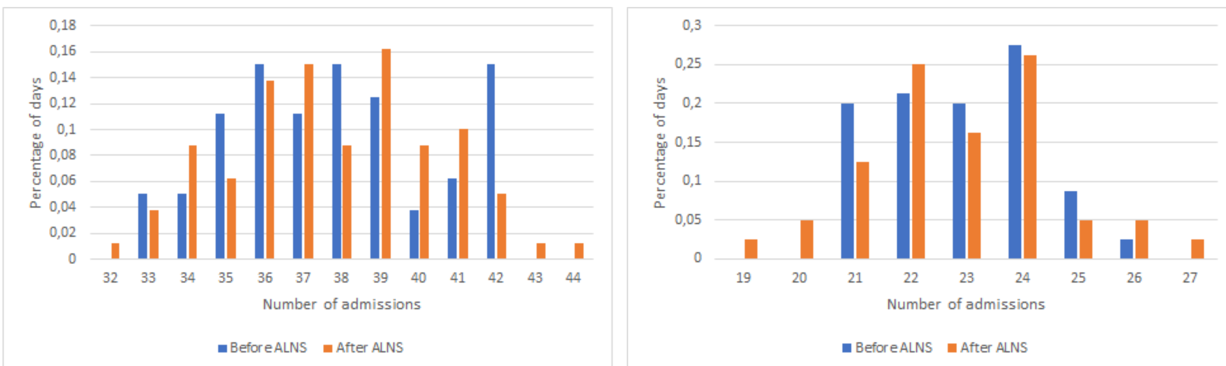
Figure 6.6: Occupation distribution before and after ALNS procedure. (Range optimization)

Parameters	Start Solutions	After ALNS
4th Floor μ	127.46	127.60
4th Floor σ	8.32	6.50
4th Floor c_v	0.065	0.051

Parameters	Start Solutions	After ALNS
5th Floor μ	93.41	93.43
5th Floor σ	2.55	3.09
5th Floor c_v	0.027	0.033

Table 6.9: 4th and 5th Floor occupation output. (Range optimization)

Admission Rate: Figure 6.7 presents the output distributions for the admission rates. It shows that the admission rates do not change largely from the start solutions values. For the fourth floor we see a slight decrease in mean and variability and for the fifth floor we see a slight increase in mean and variability.



(a) Admission rate on 4th Floor

(b) Admission rate on 5th Floor

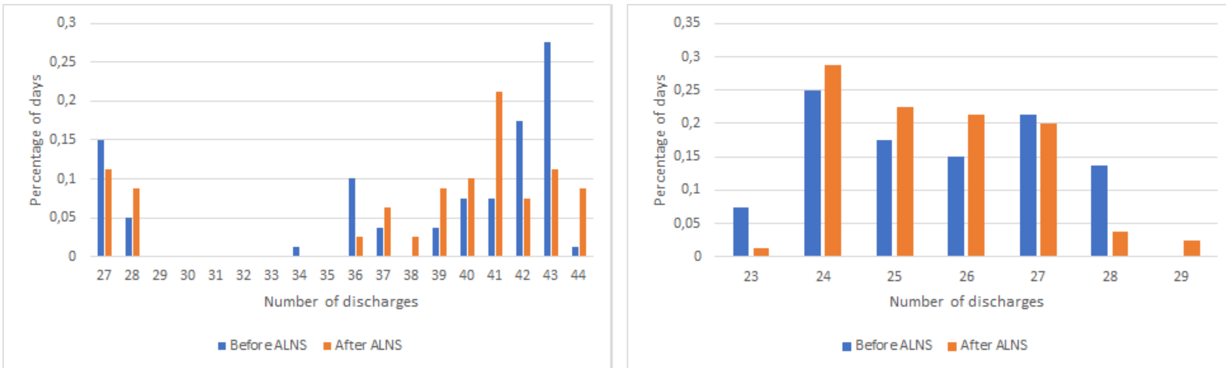
Figure 6.7: Admission distribution before and after ALNS procedure. (Range optimization)

Parameters	Start Solutions	After ALNS
4th Floor μ	37.78	37.75
4th Floor σ	2.65	2.65
4th Floor c_v	0.070	0.070

Parameters	Start Solutions	After ALNS
5th Floor μ	22.91	22.86
5th Floor σ	1.37	1.71
5th Floor c_v	0.059	0.074

Table 6.10: 4th and 5th Floor Admission Output (Range Optimization)

Discharge Rate: The output data for the discharge rates are presented in Figure 6.8 and Table 6.11. Figure 6.3 we see that the output discharge peaks became higher after the ALNS procedure. For the fifth-floor output parameters, we do not see large differences.



(a) Discharge rate on 4th Floor (b) Discharge rate on 5th Floor

Figure 6.8: Discharge distribution before and after ALNS procedure. (Range optimization)

Parameters	Start Solutions	After ALNS	Parameters	Start Solutions	After ALNS
th Floor μ	38.12	38.17	5th Floor μ	25.58	25.51
4th Floor σ	5.94	5.75	5th Floor σ	1.57	1.35
4th Floor c_v	0.155	0.150	5th Floor c_v	0.061	0.053

Table 6.11: 4th and 5th Floor Discharge Output (Range Optimization)

6.4 Conclusions

Section 6.1 described our choices for the optimization experiments. Furthermore, it presented the outcomes of optimizing our model generated MSS. In Section 6.2 and Section 6.3 we conducted the ALNS heuristic for four different MSSs. In these sections we presented the outcomes of these optimization approaches. In this section, we analyze and conclude these outcomes.

Bed Occupation: In Section 6.1 we showed the potential variability reduction of MSS optimization. Range optimization and peak optimization showed a potential peak reduction of 6.85% less required beds in occupation peaks for surgical beds.

We saw that both approaches resulted in MSSs with lower variation in total bed occupation. Table 6.12 presents these found reductions. Note, that we were not able to find large reductions in peaks. This is because the input MSSs have already repetitive schedules, where specialties that are allocated to the fifth or the fourth floor are spread over the MSSs. The difference with our starting solution is caused by a more equal spread of CH ORs over the MSS in the planned MSS. Furthermore, Table 6.12 shows that the largest peak reduction was 5 beds. Note that, this reduction was found for MSS-5. This MSS has the largest amount of SDC ORs and SDC ORs is the OR that has the lowest clinical outflow. Therefore, replacement of these ORs resulted in peak reduction. Besides peak occupation reduction, we showed that our optimization approaches resulted in reduction of variability in bed occupation. In all the experiments, we saw that range optimization resulted in the largest reduction in variation of bed occupation. We conclude that range optimization is a more effective approach than peak occupation, because range optimization does actively increase the minimum occupation. An overview of the results of optimizing each MSS can be found within Appendix K. Table 6.12 summarizes the outcomes of the goal functions.

MSS	Start Peak	New Peak	Improvement	Approach
MSS-5	236	231	2.12%	Peak
MSS-25	235	231	1.70%	Range
MSS-37	233	232	0.42%	Range
MSS-45	234	231	1.28%	Peak

Table 6.12: Table Occupation Reduction

MSS	Start Range	New Range	Improvement	Approach
MSS-5	[198,235]	[203,232]	21.62%	Range
MSS-25	[201,234]	[204,231]	18.18%	Range
MSS-37	[201,233]	[204,233]	9.38%	Range
MSS-45	[201,234]	[203,233]	9.09%	Range

Table 6.13: Table Range Reduction

MSS	Start c_v	New c_v	Improvement	Approach
MSS-5	0.051	0.039	23.52%	Range
MSS-25	0.045	0.039	13.33%	Range
MSS-37	0.045	0.040	11.11%	Range
MSS-45	0.046	0.040	13.04%	Range

Table 6.14: Table Range Reduction

The reduction of variance for the total number of beds is presented in Table 6.14. We saw that both procedures resulted in a lower variance for the total number of beds and the fourth-floor wards. However, the fifth-floor wards increased their variance. We assume this results from a lower solution space (values that the bed occupation can take) for the fifth-floor wards. This space is larger for the fourth-floor wards. Appendix J shows the starting and output solutions. Note, that the MSSs all have at least two CTC ORs per day and most of the times have one NEURO OR per day. The solution space for the fifth floor wards is then built by adding a NEURO, PPA, CAR or CTC OR to the days. Therefore, it is difficult to decrease the occupation range for the fifth floor wards. An improvement is much more likely to happen for the fourth floor. Therefore, the model will optimize the fourth-floor wards for the cost of more variance for the fifth-floor wards. In Section 9.2 we propose a model adjustment to solve this problem.

Admissions: In Section 6.2 and Section 6.3 we presented the outcomes of the optimization approaches and we presented the effect on the admission rates. We saw that for both approaches, the effect on admission rates is minimal. The output MSSs in Appendix J show that most of the OR days consist out of at least 5 CH ORs, 2 CTC ORs, 1 NEURO OR, 1 ORT OR. The other five ORs do not have the specialties of the fifth-floor wards, because this heavily increases the occupation. Therefore, we conclude that the resulting effect on admission rates minimal.

Discharges: In Section 6.2 and Section 6.3 we presented the outcomes of the optimization approaches and we presented the effect on the discharge rates. We saw that the effect on discharge rates is minimal. For the peak optimization approach we saw a slight increase in average and variation of discharge rates. Range optimization resulted in a lower average and a lower variance in discharge rates. Note, that this approach brings up the minimal number of occupied beds. We assume that this minimal number of occupied beds is caused by a peak in discharges. Therefore, bringing up the minimal number of occupied beds results in less variability in discharge rates.

The main differences between the initial MSSs and the optimized MSSs are that specialties with the lowest resulting clinical outflow are placed at the end of the week. These specialties are SDC and OPT. Furthermore, we see more variation in the number of CH ORs per day. In the initial MSSs this is 4 or 5 CH ORs per day, in the optimized MSSs this is 3 to 6 CH ORs per day.

Chapter 7

Implementation

In this chapter we discuss the implementation of our tool in MST and the tactical process of building the MSS.

At the moment, a four weekly MSS is generated for 28 days. These schedules are made after strategical allocation of total case time per specialty. After this managerial decision, our model should be used to align the new MSS with the downstream effects. This tactical decision is made by supporting departments and it is made at least once a year. By April 2018, this decision is proposed to be placed at the OR department. Therefore, the model needs to be used by personnel of the OR department. OR personnel can easily implement surgical preferences and operational adjustments. The operational adjustments to the MSS schedule are not in the scope of this research and our model, but the tactical decision of building a robust MSS can be supported by our model. Our model has three main purposes which are part of the tactical decision phase:

1. Build a feasible schedule on the base of strategical allocation of OR days to specialties.

2. Evaluate an MSS on downstream effects.

3. Optimize an MSS on resulting bed occupancy.

After the strategical allocation of OR capacity to specialties, our model generates a feasible start solution for a given time horizon. In order to incorporate the second and third purposes of our model, adjustments to the input distributions are required. In order to use and to update our model, we have made a manual that supports these steps and the use of the model. The following steps are required at least once a year:

Update LOS and Surgeries Per Specialty:
The main input files are the LOS probabilities and the distribution for the number of surgeries per specialty. These probabilities need to be updated yearly and need to include the probabilities based on a year of total data. Note, that more LOS and surgery per specialty data does not directly give better results. In case of new treatment or procedures, these number can quickly vary from old data and therefore not represent the new data anymore.

Update Non-Surgical Distributions:

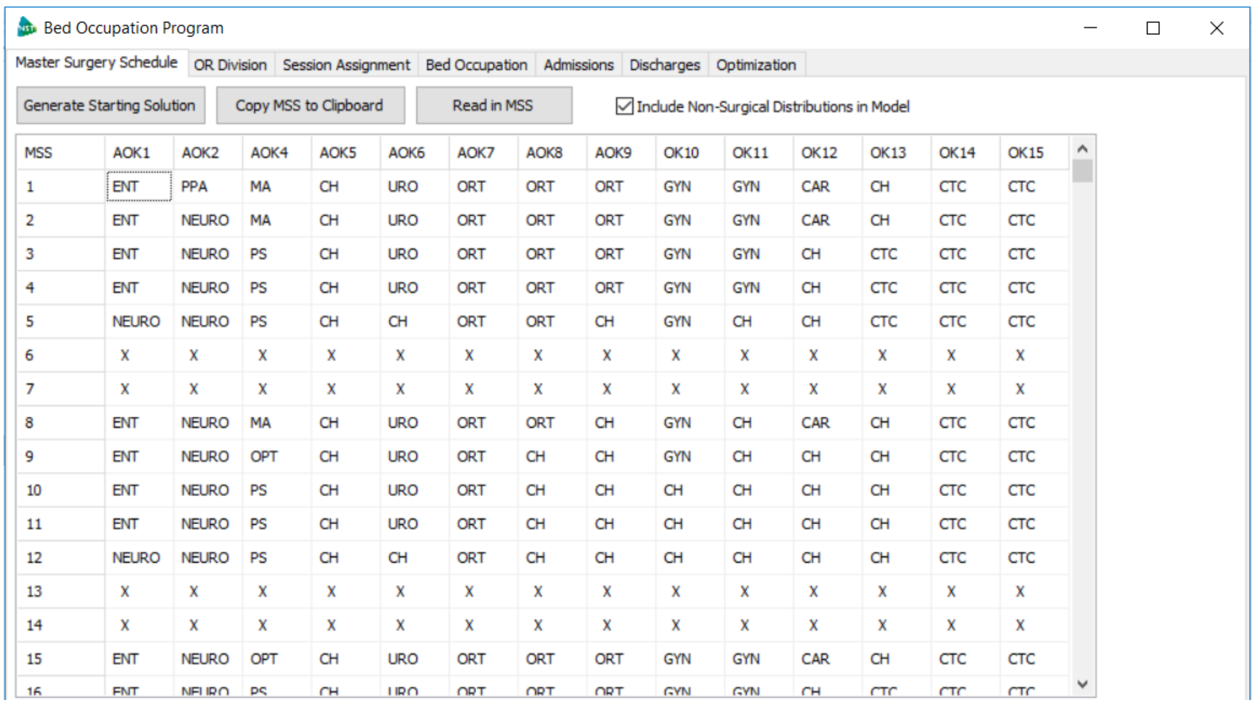
The used non-surgical distributions are based on occupation data of 2017. For every ward, we have checked whether dedicated patients directly came from the OR department. This means non-surgical patients, boarded patients and patients from smaller sub-specialties are taken into account in this distribution. These distribution are all set in txt. files and serve as an input file for the Delphi model. In order to give a clear view on the effects of the MSS on downstream resources, non-surgical distributions need to be updated yearly. Recall, that besides the bed occupation, we have non-surgical distributions admission and discharges. This data can be distracted from patient management systems. The patient data at the nursing wards needs to be compared with the patient data at the OR department.

OR Division and Ward Dedication:

Figure 7.1 shows a screenshot of the Delphi program user interface. Within the model some parameters and constraints can be changed. The OR division (so which specialty can be planned in which OR on which weekday) can be adjusted. In case ORs are changed so that other surgical specialties can be performed in these certain ORs, this needs to be adjusted in the OR Division tab. This division is saved in a .txt file.

Next to the OR division, changes in ward dedication do occur. For example, at the end of 2017 a large relocation of wards took place within MST. Therefore, it is important to allow changes in which specialty is assigned to which floor. In order to incorporate these changes in our model, we build in a check that assigns surgical specialties to specific wards.

Furthermore, the number of sessions assigned to a certain specialty can be changed. However, the number of sessions need to be an equivalent of, at most the number of the available ORs in the time horizon. Therefore, 14 ORs and 28 days make 280 available sessions (no sessions can be planned on weekend days).



MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	ENT	PPA	MA	CH	URO	ORT	ORT	ORT	GYN	GYN	CAR	CH	CTC	CTC
2	ENT	NEURO	MA	CH	URO	ORT	ORT	ORT	GYN	GYN	CAR	CH	CTC	CTC
3	ENT	NEURO	PS	CH	URO	ORT	ORT	ORT	GYN	GYN	CH	CTC	CTC	CTC
4	ENT	NEURO	PS	CH	URO	ORT	ORT	ORT	GYN	GYN	CH	CTC	CTC	CTC
5	NEURO	NEURO	PS	CH	CH	ORT	ORT	CH	GYN	CH	CH	CTC	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	ENT	NEURO	MA	CH	URO	ORT	ORT	CH	GYN	CH	CAR	CH	CTC	CTC
9	ENT	NEURO	OPT	CH	URO	ORT	CH	CH	GYN	CH	CH	CH	CTC	CTC
10	ENT	NEURO	PS	CH	URO	ORT	CH	CH	CH	CH	CH	CH	CTC	CTC
11	ENT	NEURO	PS	CH	URO	ORT	CH	CH	CH	CH	CH	CH	CTC	CTC
12	NEURO	NEURO	PS	CH	CH	ORT	CH	CH	CH	CH	CH	CH	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	ENT	NEURO	OPT	CH	URO	ORT	ORT	ORT	GYN	GYN	CAR	CH	CTC	CTC
16	ENT	NEURO	PS	CH	URO	ORT	ORT	ORT	GYN	GYN	CH	CTC	CTC	CTC

Figure 7.1: Screenshot of the Delphi Model.

Chapter 8

Conclusions and Recommendations

In this chapter we describe the conclusions of our research. Section 8.1 concludes this research. In Section 8.2 we discuss our main recommendations for Medisch Spectrum Twente. Chapter 9 describes the discussion of our research.

8.1 Conclusions

Our research considers the tactical OR planning. Our research objective is to reduce variability in bed utilization. In the remainder of this section, we repeat and answer our research questions.

What is the path in which the patients flow through the hospital?

We showed that the patient streams are divided in the elective and emergency patient streams. Emergency patients enter the hospital at the emergency department and flow into the acute admission department or flow directly to the OR department. From the acute admission department, they flow to the OR department, or they flow to the nursing wards or they get directly discharged. From the OR department patients flow to the nursing wards. The elective surgery patients start their path through the hospital at the outpatient clinic. After consult with a physician and pre-operative screening, they flow to the OR department. After surgery, when patients need intensive care or extra monitoring, they enter the PACU, ICU or recovery. From there on, they flow to the nursing wards. Furthermore, we described all the departments that are relevant in the patient flow process and we presented the process at the nursing wards and the ORs that take place for one elective patient.

How is the system organized at the planning department, OR department and the nursing wards?

We showed process flow charts from processes for a single patient at the OR department and the nursing wards. Furthermore, we presented the process of OR planning and constructing the OR schedule and thereby showed which actor in the process make the managerial decision in the four-staged OR planning process. The tactical and the strategical phase of OR planning are currently made by supporting departments and the board in consult with the specialty managements. From Section 2.5 we conclude that at the tactical level of OR planning, no downstream effects are considered. Only for patients that flow to PACU and ICU units, bed availability is taken into account. The operational phase of the OR planning process is made by the planning department. Furthermore, we showed that the planning department is partly centralized and decentralized. We conclude that in the organization, the downstream effects are partly taken into account, but that they are only visible for a short time horizon.

What are relevant key performance indicators of the nursing wards, OR department and the planning department?

We formulated multiple performance indicators to measure the performance for both the OR department and the nursing wards. For performance measurement of the OR department and the planning department, we analyzed the OR utilization of the specialties. The number of surgeries per session show the total throughput per operating specialty and thereby the throughput of each surgical specialty.

The main KPI for the nursing ward was initially the bed utilization, because lowering the variance in bed utilization at nursing wards is our research objective. However, we showed that bed utilization was not monitored sufficiently in 2017 at MST. Next to that, we have showed that it is an indicator that is difficult to measure. Therefore, we have proposed our definition of bed utilization and measured this KPI at all nursing wards. Bed utilization does not show everything about the performance of a nursing ward and therefore we presented the bed occupation per ward. However, the bed occupation and bed utilization heavily depend on other criteria and therefore we have also presented patient admissions and discharges per ward and the LOS of patients of all the elective clinical patients. As mentioned, we consider occupation, admission and discharges as the total workload at the nursing wards.

What is the performance of the planning department, OR department and the nursing wards?

We presented the outcomes of every performance indicator for the OR department and the nursing wards. We showed that some specialties never reached the threshold for OR utilization in 2017. In this chapter we also showed that for most of the specialties the planned OR utilization was already lower than the target OR utilization. Therefore, it is impossible for some of the specialties to even reach the target utilization. Therefore, we conclude that over 2017, the planned OR utilization was too low for most of specialties. Subsequently, we conclude that the realized OR utilization was also too low for most of the specialties. However, a side note must be made that the planned and realized OR utilization showed an increasing line after August for most of the specialties. Furthermore, we see no differences in OR utilization target. As mentioned, this can lead to a larger amount of overtime. Next to that, we discussed the most common disruptions in their OR schedule, the total overtime and the OR throughput.

For the nursing wards, we conclude that the variability of bed utilization is high throughout the year. We showed that in periods where less OR sessions are performed, the bed utilization decreases. This period is for example in summer months and in the last weeks of December and the beginning of January. We concluded that the surgical patient wards had a average bed utilization rate of 70%, which we consider to be a high utilization rate. Besides utilization, we also analyzed the occupation, admission and discharges rates of the specialties and the wards. We showed that all the ward showed lower bed occupation and patient admissions on weekend days. The specialties especially showed significant lower patient occupation and admissions on Sundays, even though many patients get admitted on the day before surgery. For most of the specialties, we found no significant difference in patient admission between week days and weekend days. For patient discharges, this is comparable. Patient discharges are significantly lower on Sundays throughout 2017, for all the specialties. However, we showed that discharge rates are significantly high on Saturdays.

What kind of approaches can be used to optimize the surgery scheduling?

Many studies within this research field are focused on a single department and thereby ignore downstream effects of OR planning and scheduling. A single department approach leads to suboptimal results and therefore we narrowed our literature research scope to multiple department approach. In the studies that remain, we found many deterministic approaches. By using a deterministic LOS or number of patients, uncertainty within healthcare processes is being ignored. In more recent studies we found studies that incorporate the stochasticity within their program.

What approach or model is best applicable?

A stochastic approach that has led to promising results is the approach by Vanberkel et al. (2011a) In various studies it has proven to lead to practical results (Vanberkel et al., 2011b; Fügener et al., 2014; van Essen et al., 2014). However, their approach is on itself an evaluation tool and it does not optimize the OR scheduling. We found two studies that used this approach and extended it to use it for optimization matters. Both studies compare and use exact approximation and local search approaches. Frequently, an SA approach is used to optimize an objective function. However, we have seen in recent literature that other heuristics are also applicable to solving the MSS problem. We want to be able to search the complete solution space within reasonable amount of computational time. Therefore, we want to use the ALNS heuristic in combination with an SA acceptance procedure. With this heuristic, we are able to search the complete solution space.

What are the main findings and what are the effects of the model on the KPIs?

In Section 3.3.1 we showed that bed utilization is a difficult KPI to measure and to optimize on. Furthermore, we showed that clear definitions lack for bed utilization and bed occupation. Therefore, we optimize on the base of bed occupation which we defined as the daily usage of a bed. We developed a Master Surgery Scheduling tool that builds and evaluates an MSS on the base of the model by Vanberkel et al. (2011b). Next to that, it optimizes an input MSS on the base of minimization of occupation peaks and on the base of minimization of the range of between minimum and maximum week day occupation. This optimization is done on the base of Adaptive Large Neighborhood Search as described by Pisinger and Ropke (2010) and Lutz (2015). On the base of discrete convolutions and binomial distributions, the model determines the resulting bed occupation, admissions rates and discharge rates of an MSS.
We performed experiments on four different planned MSSs from 2018. Thereby, we conducted the Adaptive Large Neighborhood search with the range minimization objective and the peak minimization objective. We showed that both approaches have the potential to decrease the variation in bed occupation. On the base of our feasible starting solution, we found that the procedure minimizes the peak occupation with 10 beds (6.8% peak reduction) without non-surgical patient distribution and 11 beds (4.52%) with non-surgical patient distribution. The experiments showed

that range minimization gave the best results in reducing the variability of bed occupation. Optimizing the 2018 MSSs resulted in peak reductions between 0.42% - 2.12%, which we consider to be a minimal effect. However, the optimization approaches resulted in lower variances per MSS. The variance reductions per MSS were 11.11% - 23.52%. Optimization of the MSS showed small effects on the admission- and discharge- rates. Based on these results, we conclude that our model helps to evaluate workload of a specific MSS. Next to that, we conclude that relocation of specialties within the MSS helps to reduce variation in bed occupation at the nursing wards. In the optimized MSSs we explicitly saw that if surgical specialties with a small clinical outflow (SDC and OPT) are relocated to the end of the week, this helps to reduce the variation in bed occupation. Furthermore, we saw that variation in the number of CH ORs per day helps to reduce the variation in bed occupation. In the initial MSSs this was 4 or 5 CH ORs per day and in the optimized MSSs this is 3 to 6 CH ORs per day.

How can the main findings in the research be implemented in the organization?

Our MSS optimization tool should be used to align the MSSs with the downstream effects. This tactical decision is made by supporting departments and it is made at least once a year. By April 2018, this decision is proposed to be placed at the OR department. Therefore, the tool needs to be used by personnel of the OR department. OR personnel can easily implement surgical preferences and operational adjustments. The operational adjustments to the MSS schedule are not in the scope of this research and our model, but the tactical decision of building a robust MSS can be supported by our model. The input data (LOS and number of surgeries per session) needs to be yearly updated.

8.2 Recommendations

We have several recommendations for MST, which we discuss in this section.

Bed Occupation Model: Our main recommendation is to implement our MSS optimization tool in the tactical decision of building a new MSS. As mentioned it can be used for multiple decision. For a 28-days horizon it can build a feasible start solution and optimize on minimum peaks in bed occupation. Next to that, it can also be used to load in given MSSs to make a decision on the base of balanced workload. Furthermore, it can be used to visualize the decision for a certain MSS.

Closed- and idle- OR days: In this research we did not handle the fact that sometimes the ORs are closed or not in use by surgical specialties. This can be caused by several reasons, but we assume that this is most of the times, a decision made by surgical specialties. Our model can be used in determining when the 'closed OR-days' should take place. For example, by rescheduling the closed-OR days within the realized MSS of November 2017, we were able to reduce the calculated peak capacity in bed occupation by at most 5 beds for both floors combined and that minimization of a specific floor might even lower the achieved peak occupation. Figure 8.1 shows this achieved change in bed occupation. Again, note that we tried to minimize the bed occupation of both floors combined.

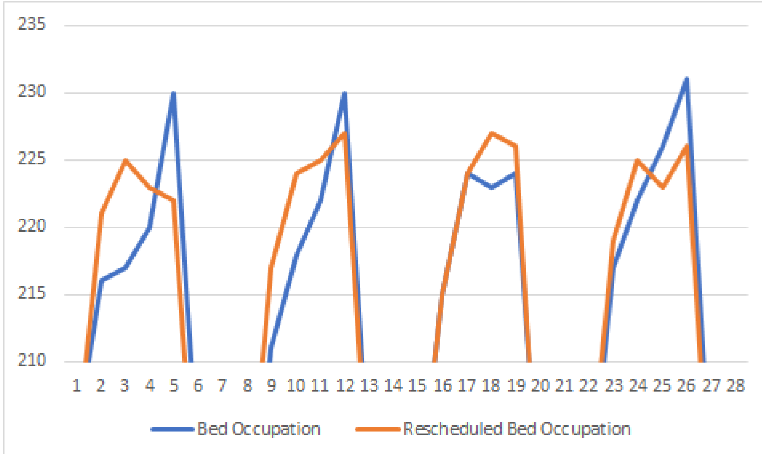


Figure 8.1: 90th percentile bed occupation after rescheduling closed OR days.

Data quality: As mentioned in Chapter 3, about 10% of the OR data is not usable. This can come forth out of a lack of registration of surgical data. Therefore, we recommend MST to pay close attention to the registration of data. MST is an hospital that has a lot of ongoing projects on improving their efficiency. On data-driven projects especially, the starting point is good quality of data.

Definitions of ward KPIs: In Section 3.3 we presented the definitions MST uses for bed occupation and bed utilization. Next to that we have presented our definitions for bed occupation and bed utilization. In order to run projects that aim at reduction of variability in these performance indicators it is necessarily that clear definition are maintained. We recommend MST to use our proposed definition. For an overview of our proposed definitions of bed utilization and bed occupation we refer to Section 3.3.

Chapter 9

Discussion

This chapter describes the study limitations and the possibilities for further research. Section 9.1 describes the study limitations and Section 9.2 describes the possibilities for further research.

9.1 Study Limitations

This study has several limitations. We discuss this limitations in this section.

Data Availability: As mentioned in Section 3.1 in 10.31% of the OR patient data, no indication was is available on surgical specialty, operating surgeons or surgery. This can influence our results and therefore our results need to be interpreted carefully. Furthermore, within MST a large relocation and reduction of beds and nursing wards took place in November 2017. Therefore, the data occupation and utilization data showed differences between the begin and the end of 2017. Note, that the shift to different wards also effects the data. In addition to that, the data had to be drawn from different systems to determine the input distributions. This increases the difficulty of determining the input distributions. Furthermore, it causes for example that LOS distribution differ between different projects.

Patient inclusion: In the LOS distributions and the number of surgeries per OR distributions we did not include day-treatment or polyclinical patients. These patients heavily increase the number of admissions and discharges. However, the LOS and number of surgeries input distribution can be adjusted to generate an only surgical patient distribution.

Time-depended distributions: As mentioned in Section 5.5, our model overestimates the weekend discharges. This is caused by the discharge distributions by Vanberkel et al. (2011b) that are not related to day type. In MST, the discharge policy differs in weekdays from weekend days. Therefore, discharge policy is neglected in our model.

9.2 Further Research

Schedule on sub-specialties: In our model, variation between the model output and the historical data in 2017 comes forth out differences between sub-specialties. In Appendix B the number or surgeries per session is presented where, for example the ENT specialty, has a large spread of possible number of surgeries within a session. A session of only one patient can take place and a session of 20 patients can take place. A division in sub-specialties can possibly ensure that larger improvements can be generated in the optimization part. In order to do so, validation has to take place for all the surgeries. It must be validated which surgery belongs to which sub-specialty. Next to that, this type of scheduling also requires inclusion of instrument- and surgeon availability constraints. Note, that it also needs to be known in the model which surgeon performs which surgical (sub-)specialty at the OR.

As mentioned, lack of indication about surgery, specialty and operating surgeon is not uncommon in the data. On sub-specialty level this can become a problem, because the patient population is too low for less frequent sub-specialties to generate a representative distribution for the number of surgeries on an OR-day. Next to that, the ward patient data structure does not give an indication about sub-specialty. We can link the unique admission number to the admission number at the wards. By incorporating these new constraints, the model loses flexibility.

Patient Flow: In our model, we did not consider patient flow from the OR to the ICU/PACU and from the ICU/PACU to the nursing wards. This can influence the outcomes of our model. We did not incorporate this patient flow, because our data set did not include patient streams from and to ICU/PACU beds. If this data is available within MST, this can be an interesting addition to our model. This model addition have been described by Fügener et al. (2014).

Operational level modeling: In this research, we have built a model that is focused on planning on the tactical level. An interesting extended research topic, is the consequences of planning on the operational level. If more patient specific information is known and taken into account in the model, a more short term ward specific bed occupation can be determined. Ultimately, planning software that directly shows the downstream effects of scheduling surgical patients will most likely have the most effects on ward balancing.

Ward specific weighted optimization objective: The optimization by using the ALNS procedure showed that the total standard deviation decreased for the wards. Furthermore, it also decreased the standard deviation of the 4th floor wards. However, the 5th floor wards did not decrease their standard deviation in bed occupation. The solution space for bed occupation at the fifth-floor wards is smaller than the solution space at the fourth-floor wards. An improvement for the fifth floor can also mean a larger decrease in objective for the fourth floor. Therefore, it is useful to set weights on improvements per floor. For example, a lowered range of bed occupation of one bed at the fifth floor can be valued as much as a lowered bed occupation range of two beds at the fourth floor.

Total workload optimization: In our model we calculated the total occupation, admission and discharge distributions following from an MSS. In our optimization approach we optimized on bed occupation. In further research it would be interesting to optimize on total workload. However, note that solely minimizing the sum of the peaks of occupation, discharge and admission is not a correct method because in that case discharge, admission and occupation is all given the same weights. In practice, these three factors determine the workload in a different way. In other words, the admission of a patient may take more time than the discharge of a patient. Therefore weight factors should be incorporated in a total workload objective. In our model, we denoted the maximum required number beds with γ. In order to find a total workload optimization objective, let γ^d and γ^a respectively denote the maximum number of discharges and admissions. The workload objective is then denoted by Equation 9.1, where α_d and α_w denote the workload weights given to admissions and discharges:

$$min\ \gamma_\beta + \alpha_d \gamma_\beta^d + \alpha_w \gamma_\beta^a \tag{9.1}$$

Reduce computational time: The computational time of the optimization approach we used implemented is large, since 10000 iterations of ALNS heuristic were computed in 11,5 hours. This is caused by the large number of convolutions that is calculated in every iteration. To reduce the computational time, the number of convolutions needs to be brought down. van Oostrum et al. (2008) did their optimization on the base of ORDS, which are all possible combinations of surgeries within a specific OR. This approach can be used to lower the computational time of our model. By incorporating this approach, all possible combinations of ways the complete OT is filled can be determined before starting the ALNS heuristic. Instead of ORDS, complete OT-days are calculated. We assume that this heavily increases the computational time of initialization of the bed distribution. For example, in our default OR division an OT day can have 1,152,000 possible combinations of specialties. A more constrained OR division lowers this number of combinations. The disadvantage of this approach is that initialization time is heavily increased. However, the total bed distribution as a result of every possible OT-day is already calculated. Therefore, new solutions only need to execute the convolutions for the bed distributions between total OT-days.

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Appendix A

OR Utilization Per Specialty

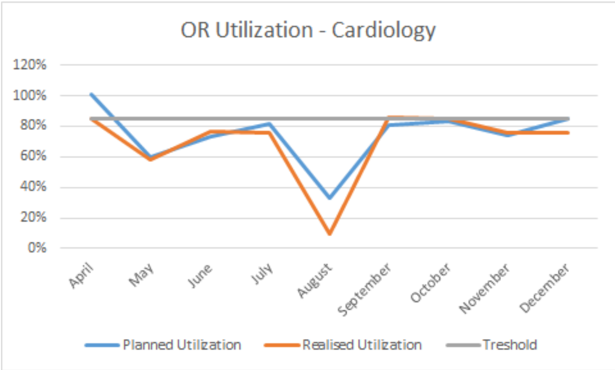


Figure A.1: OR Utilization Cardiology in 2017. Source: SAP Business Objects.

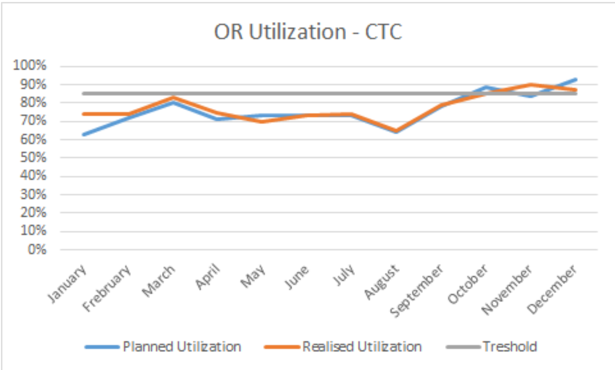


Figure A.2: OR Utilization Cardio-Thoracic Surgery in 2017. Source: SAP Business Objects.

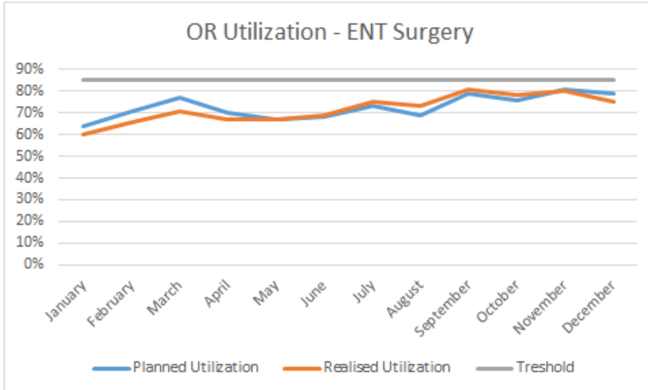


Figure A.3: OR Utilization Ear, Nose and Throat Surgery in 2017. Source: SAP Business Objects.

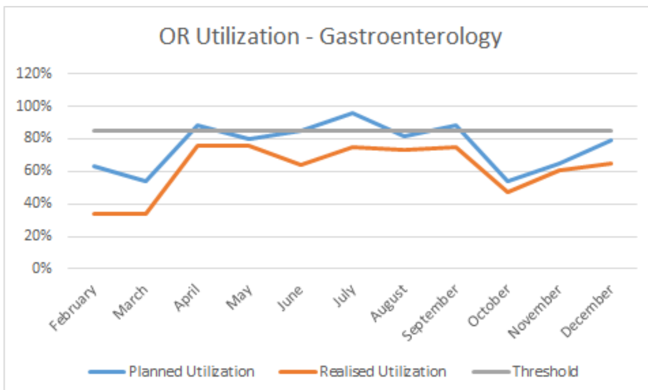


Figure A.4: OR Utilization Gastroenterology in 2017. Source: SAP Business Objects.

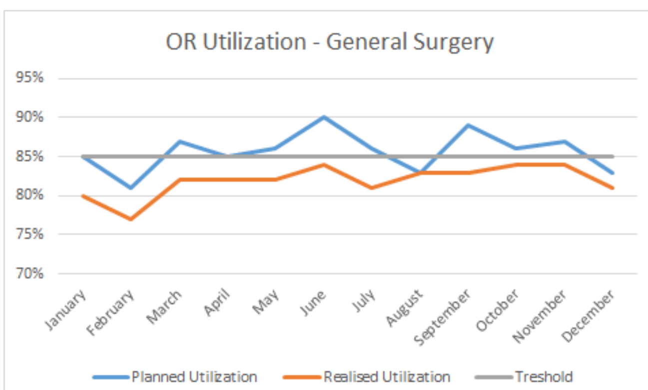


Figure A.5: OR Utilization General Surgery in 2017. Source: SAP Business Objects.

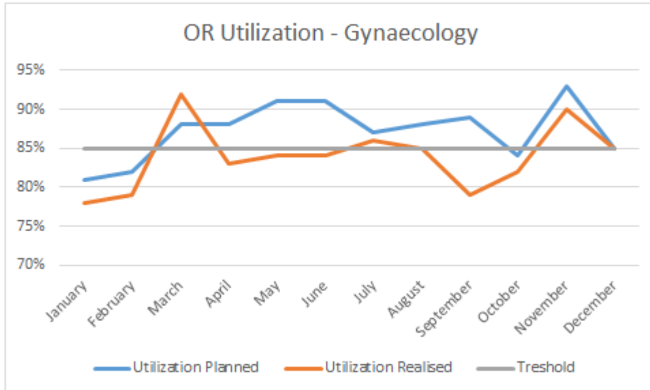


Figure A.6: OR Utilization Gynaecology in 2017. Source: SAP Business Objects.

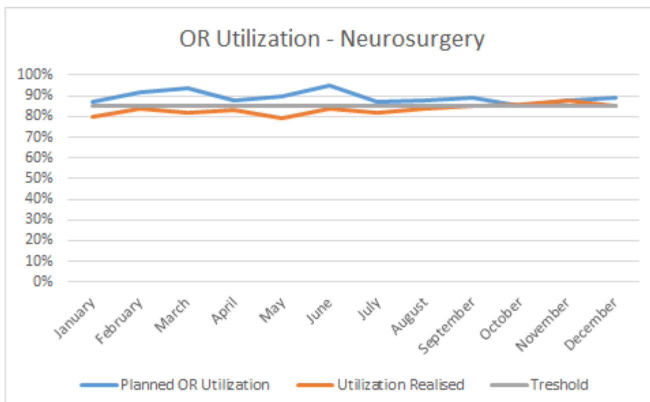


Figure A.7: OR Utilization Neurosurgery in 2017. Source: SAP Business Objects.

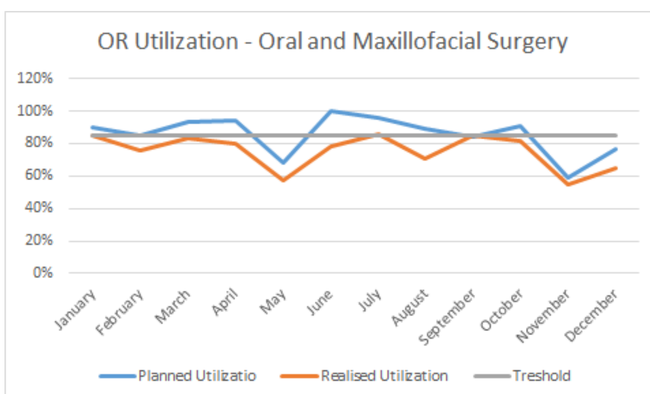


Figure A.8: OR Utilization Oral and Maxillofacial Surgery in 2017. Source: SAP Business Objects.

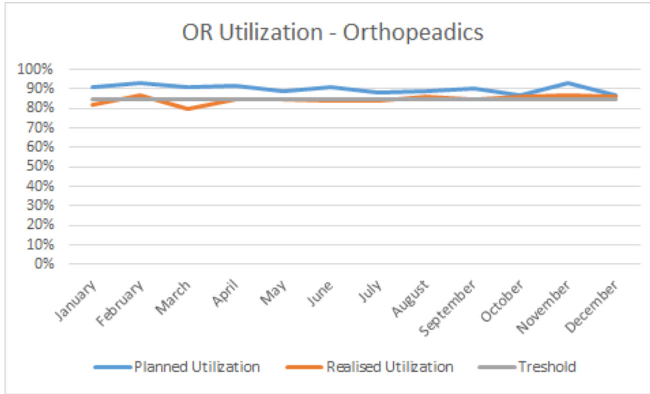


Figure A.9: OR Utilization Orthopaedics in 2017. Source: SAP Business Objects.

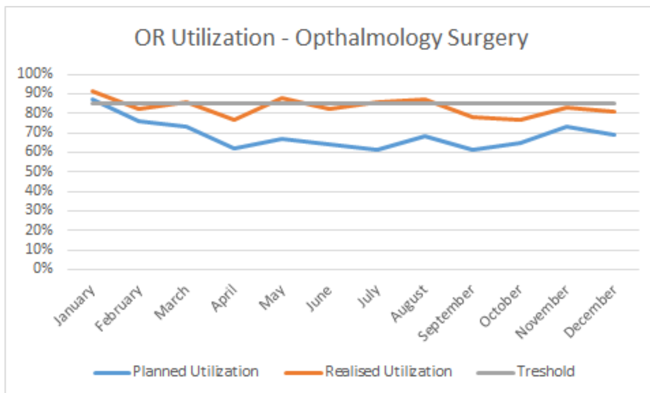


Figure A.10: OR Utilization Opthalmology in 2017. Source: SAP Business Objects.

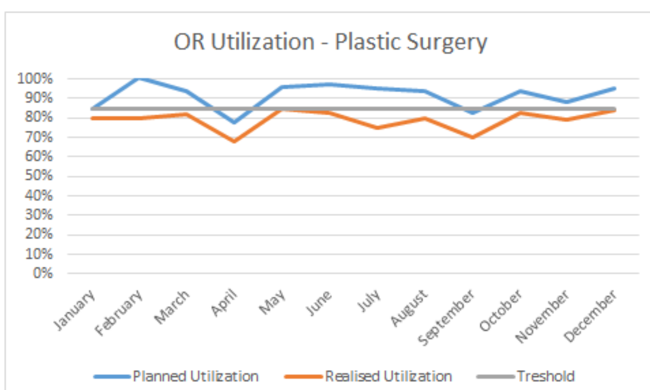


Figure A.11: OR Utilization Plastic Surgery in 2017. Source: SAP Business Objects.

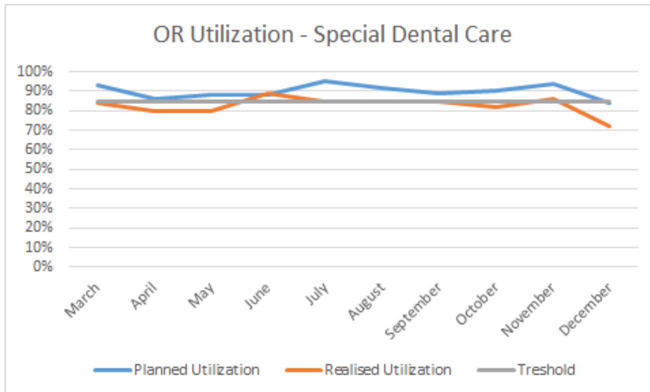


Figure A.12: OR Utilization Special Dental Care in 2017. Source: SAP Business Objects.

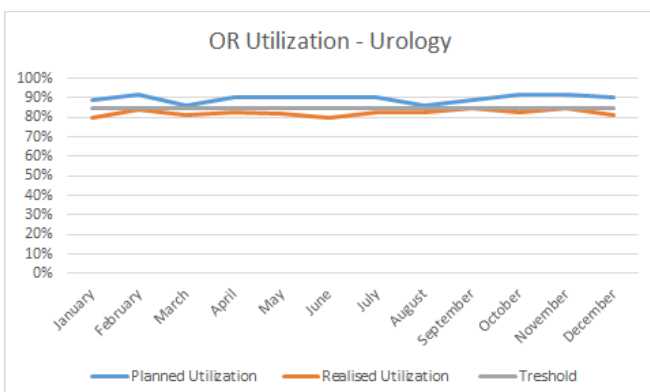


Figure A.13: OR Utilization Urology in 2017. Source: SAP Business Objects.

Appendix B

Surgeries Per Session Per Specialty

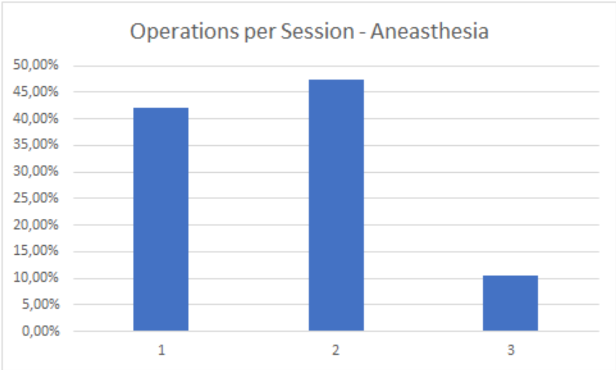


Figure B.1: Operations Per Session Anesthesia during 04-01-2016 to 05-10-2017. N = 32. Source: ORSuite.

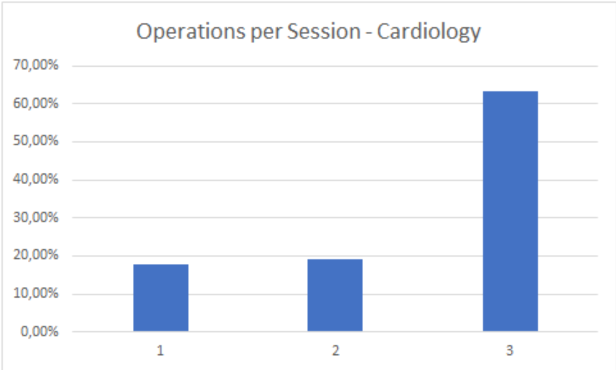


Figure B.2: Operations Per Session Cardiology during 04-01-2016 to 05-10-2017. N = 334. Source: ORSuite.

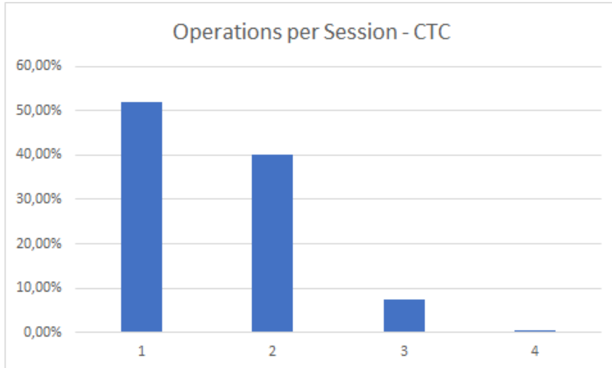


Figure B.3: Operations Per Session Cardio-Thoracic Surgery during 04-01-2016 to 05-10-2017. N = 2222. Source: ORSuite.

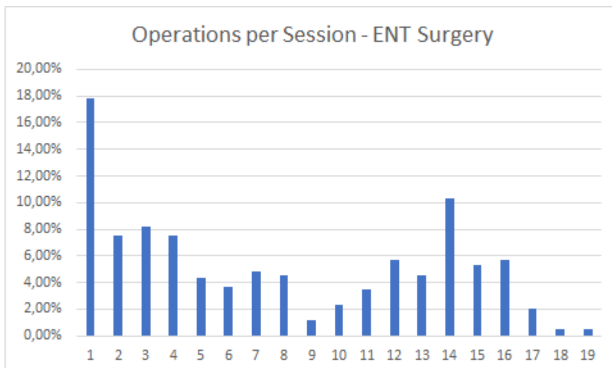


Figure B.4: Operations Per Session Ear, Nose and Throat Surgery during 04-01-2016 to 05-10-2017. N = 3354. Source: ORSuite.

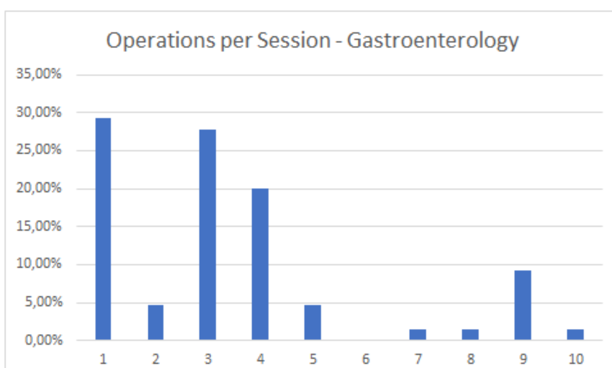


Figure B.5: Operations Per Session Gastroenterology during 04-01-2016 to 05-10-2017. N = 225. Source: ORSuite.

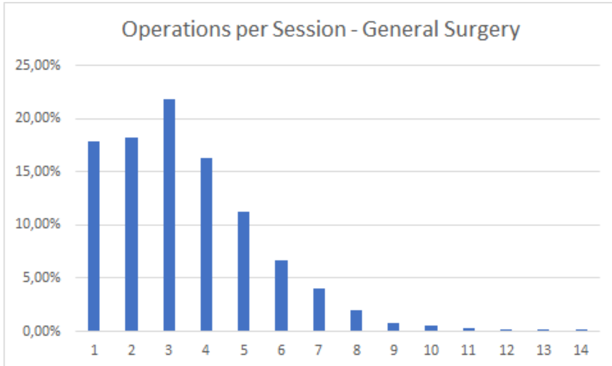


Figure B.6: Operations Per Session General Surgery during 04-01-2016 to 05-10-2017. N = 7803. Source: ORSuite.

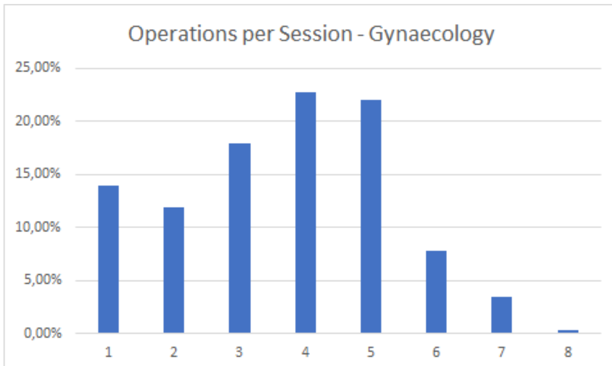


Figure B.7: Operations Per Session Gynaecology during 04-01-2016 to 05-10-2017. N = 2223. Source: ORSuite.

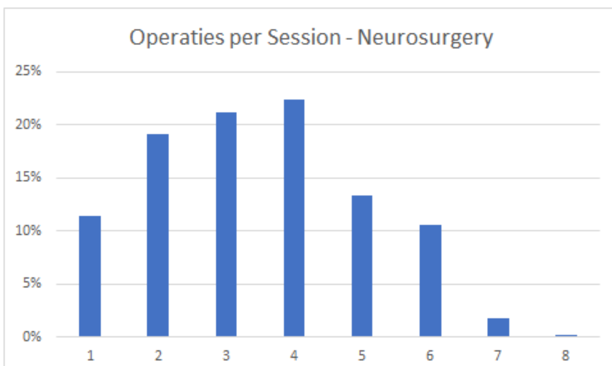


Figure B.8: Operations Per Session Neurosurgery during 04-01-2016 to 05-10-2017. N = 1739. Source: ORSuite.

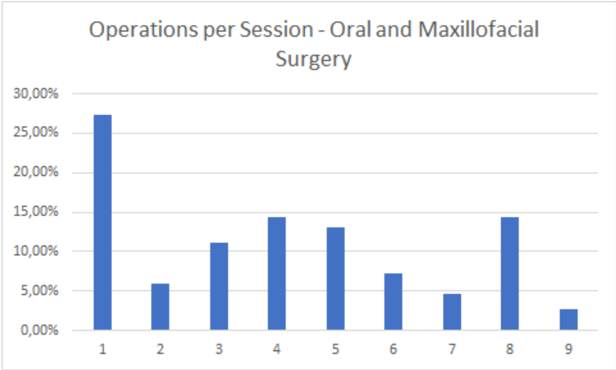


Figure B.9: Operations Per Session Oral and Maxillofacial Surgery during 04-01-2016 to 05-10-2017. N = 626. Source: ORSuite.

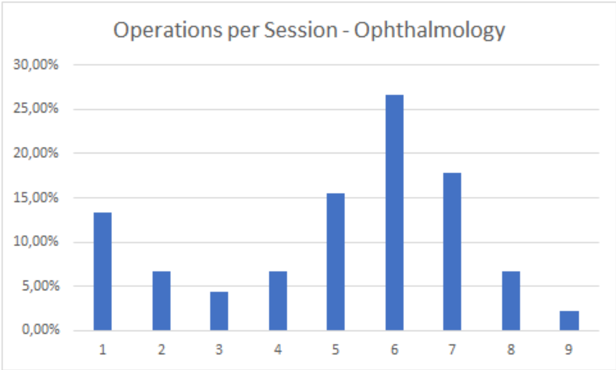


Figure B.10: Operations Per Session Ophthalmology during 04-01-2016 to 05-10-2017. N = 226. Source: ORSuite.

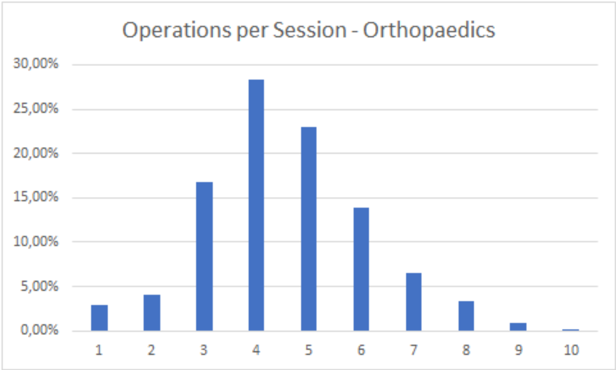


Figure B.11: Operations Per Session Orthopaedics during 04-01-2016 to 05-10-2017. N = 3501. Source: ORSuite.

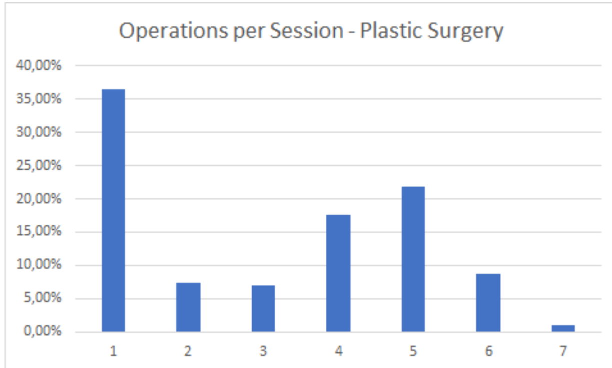


Figure B.12: Operations Per Session Plastic Surgery during 04-01-2016 to 05-10-2017. N = 1279. Source: ORSuite.

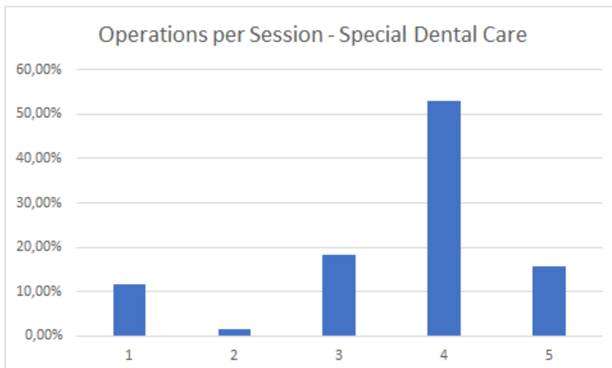


Figure B.13: Operations Per Session Special Dental Care during 04-01-2016 to 05-10-2017. N = 435. Source: ORSuite.

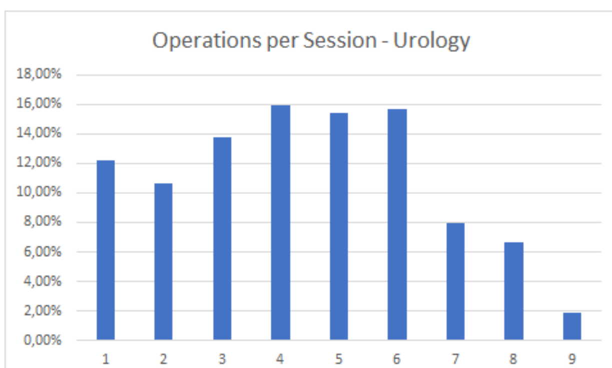
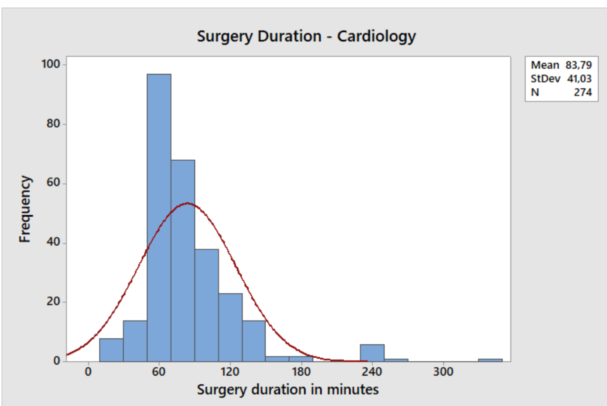


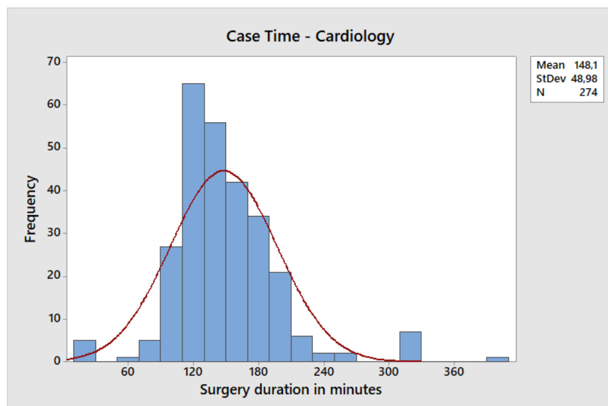
Figure B.14: Operations Per Session Urology during 04-01-2016 to 05-10-2017. N = 1639. Source: ORSuite.

Appendix C

Surgery Duration and Case Time Per Specialty

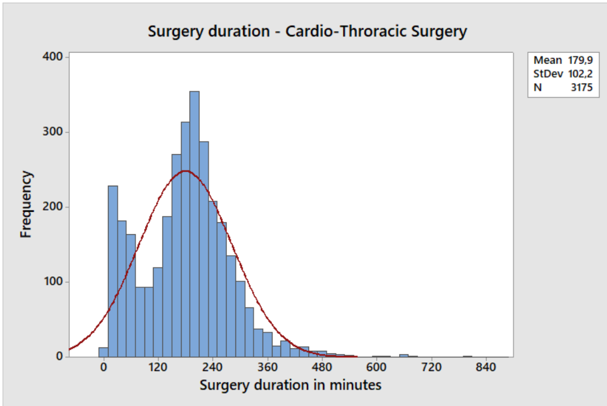


(a) Surgery duration CAR patients.

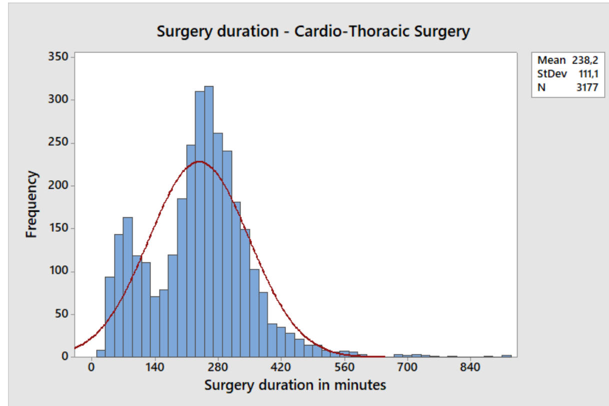


(b) Case Time CAR patients.

Figure C.1: Surgery duration and case time CAR. Source: ORSuite

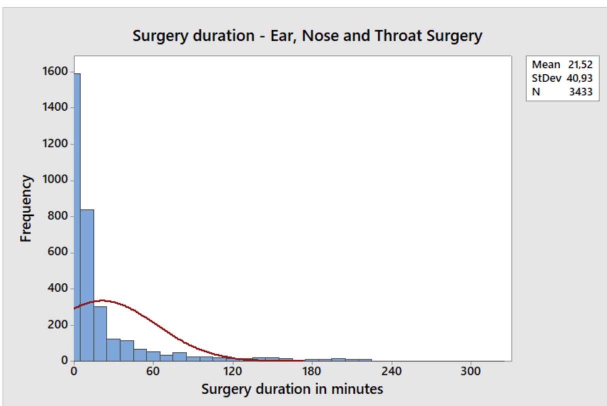


(a) Surgery duration CTC Surgery patients.

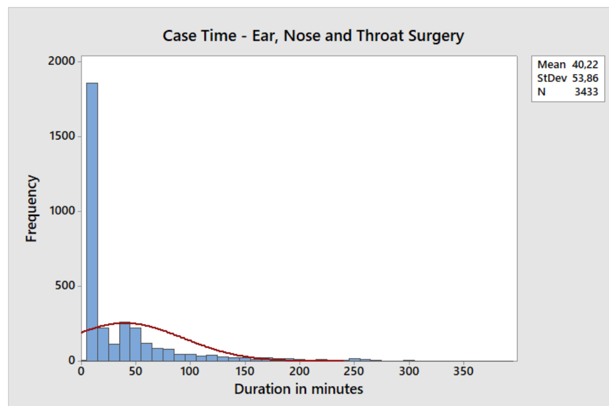


(b) Case Time CTC Surgery patients.

Figure C.2: Surgery duration and case time Cardio-Thoracic Surgery. Source: ORSuite

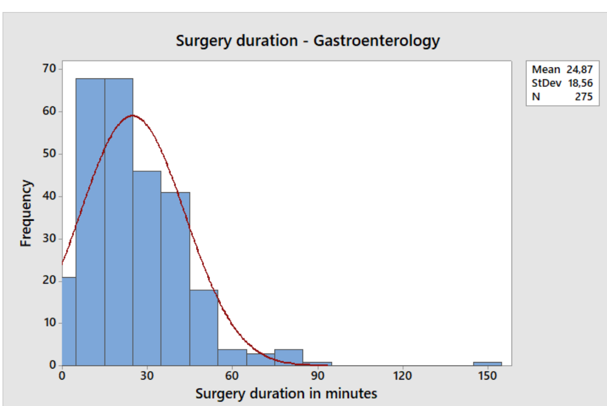


(a) Surgery duration ENT patients.

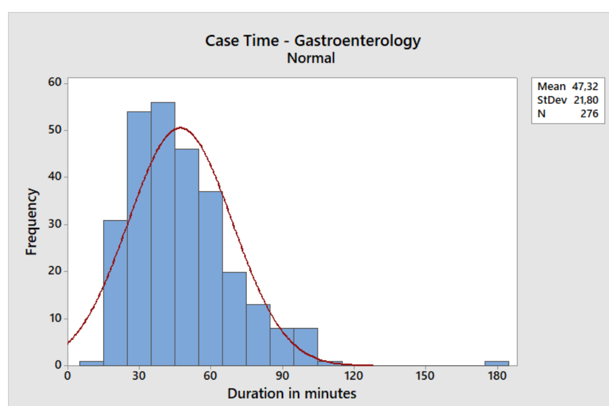


(b) Case Time ENT patients.

Figure C.3: Surgery duration and case time ENT Surgery. Source: ORSuite

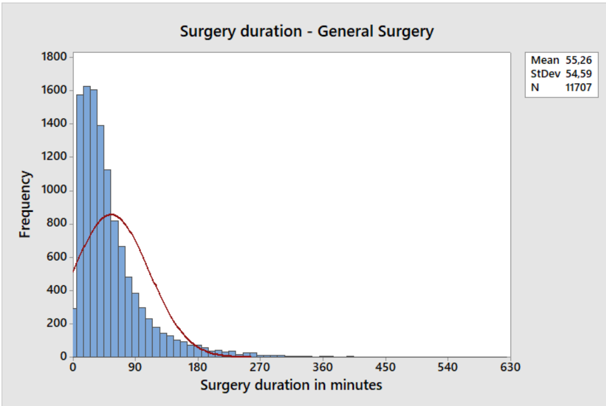


(a) Surgery duration GE patients.

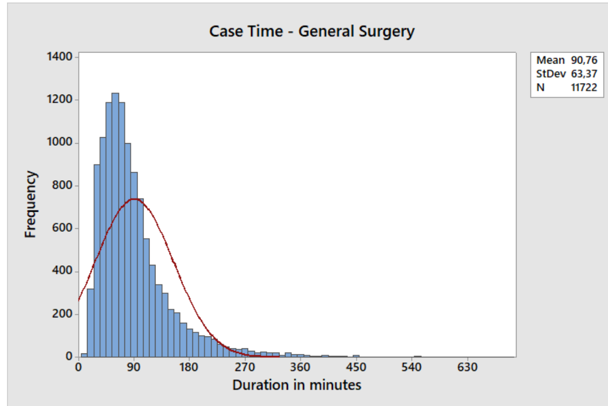


(b) Case Time GE patients.

Figure C.4: Surgery duration and case time GE Surgery. Source: ORSuite

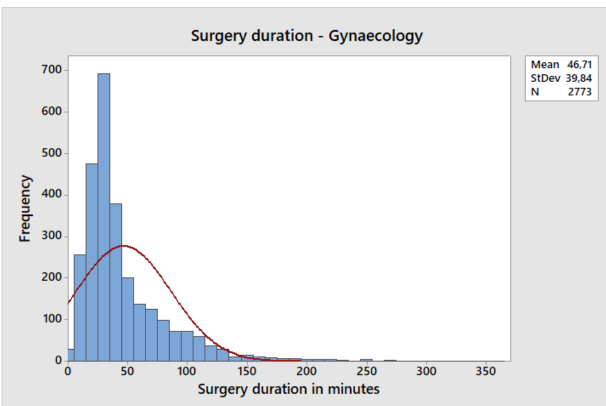


(a) Surgery duration GS patients.

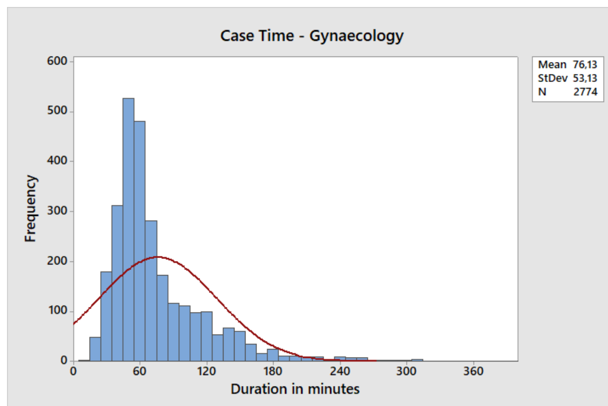


(b) Case Time GS patients.

Figure C.5: Surgery duration and case time GS Surgery. Source: ORSuite

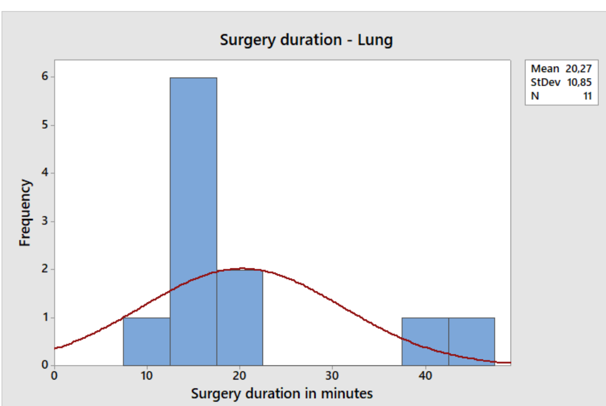


(a) Surgery duration GYN patients.

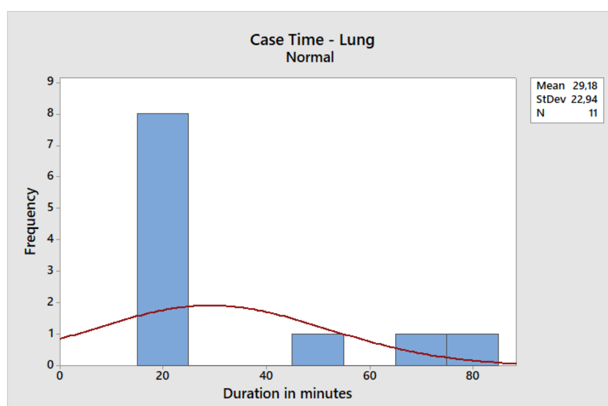


(b) Case Time GYN patients.

Figure C.6: Surgery duration and case time GYN Surgery. Source: ORSuite

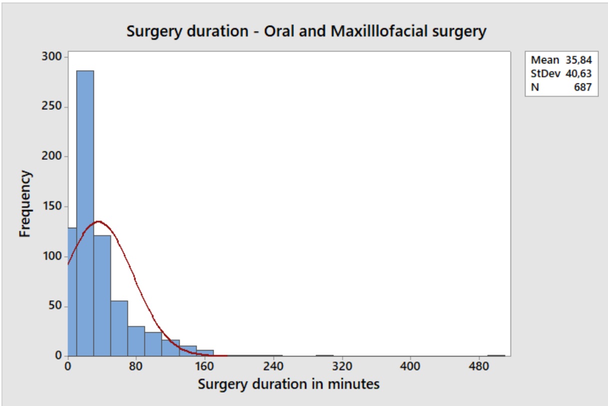


(a) Surgery duration Lung patients.

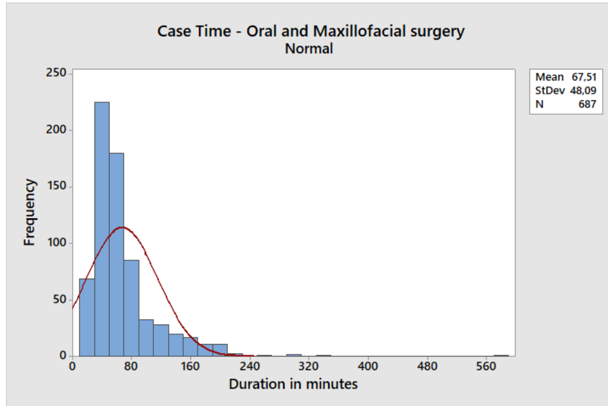


(b) Case Time Lung patients.

Figure C.7: Surgery duration and case time Lung Surgery. Source: ORSuite

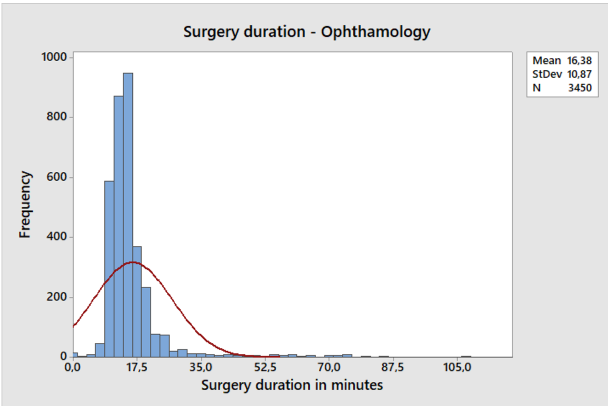


(a) Surgery duration OM patients.

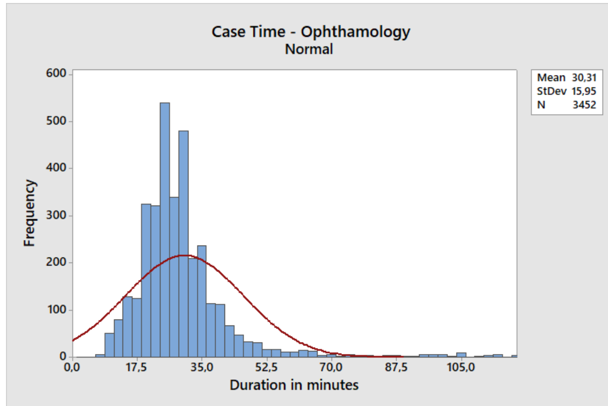


(b) Case Time OM patients.

Figure C.8: Surgery duration and case time OM Surgery. Source: ORSuite

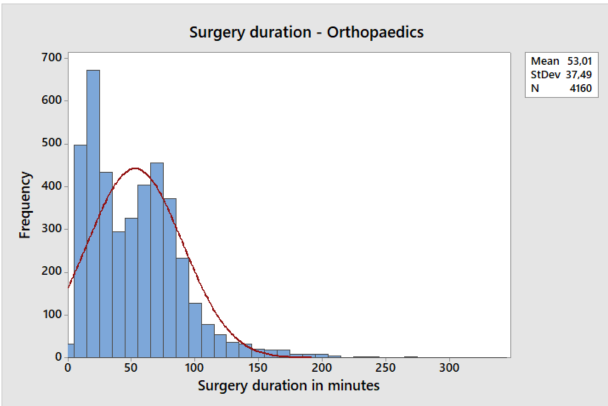


(a) Surgery duration OPT patients.

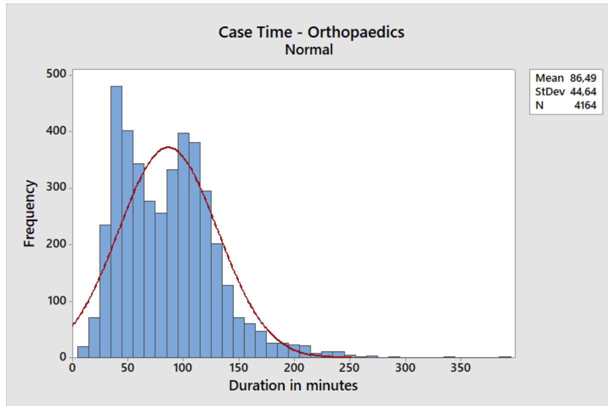


(b) Case Time OPT patients.

Figure C.9: Surgery duration and case time OPT Surgery. Source: ORSuite

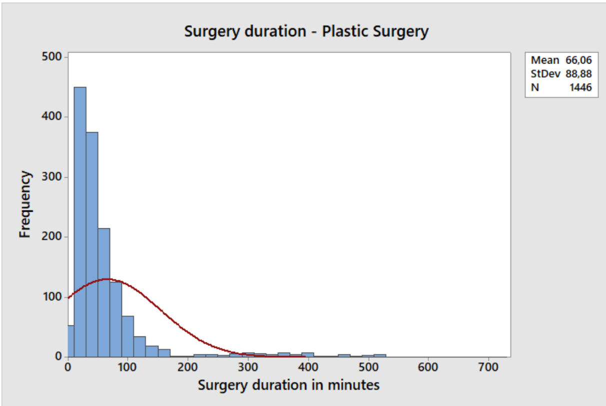


(a) Surgery duration ORT patients.

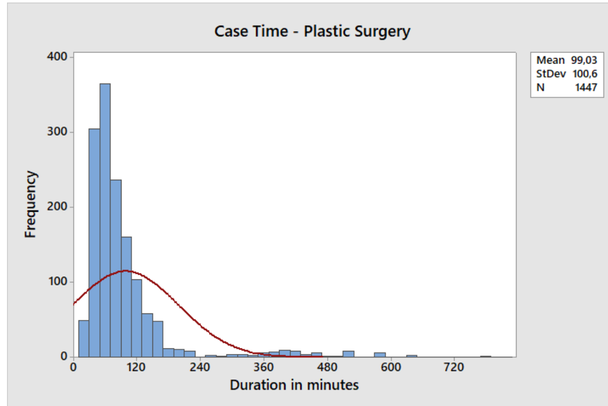


(b) Case Time ORT patients.

Figure C.10: Surgery duration and case time ORT Surgery. Source: ORSuite

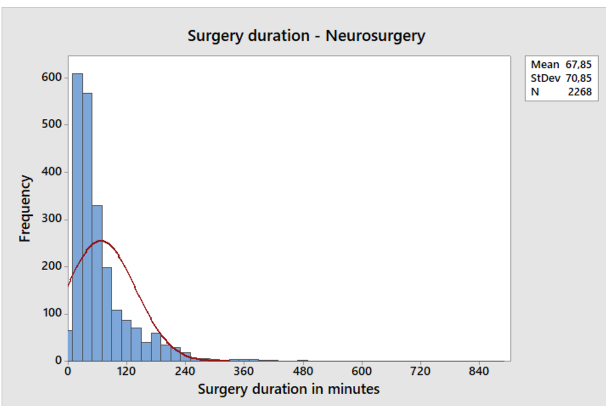


(a) Surgery duration PS patients.

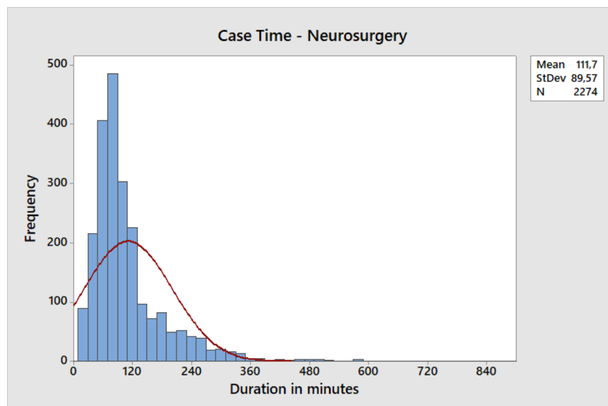


(b) Case Time PS patients.

Figure C.11: Surgery duration and case time PS Surgery. Source: ORSuite

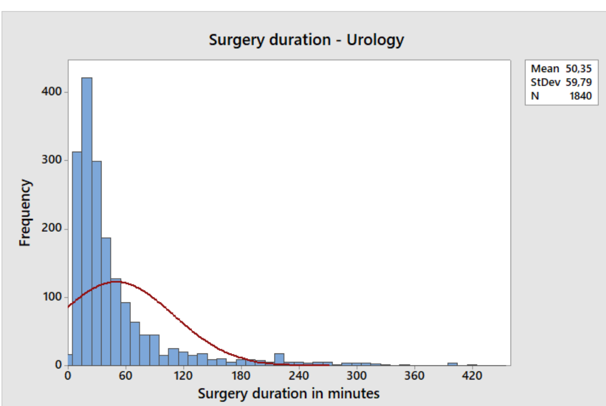


(a) Surgery duration NEU patients.

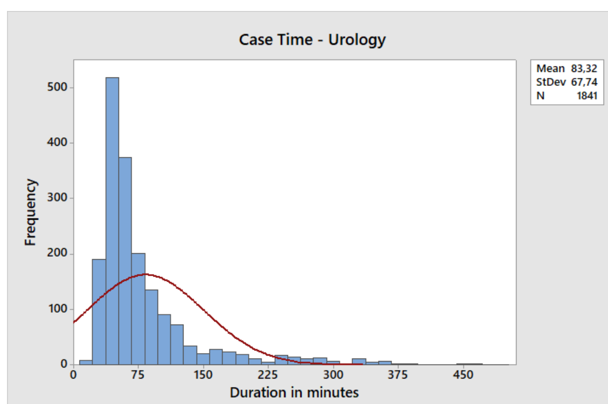


(b) Case Time NEU patients.

Figure C.12: Surgery duration and case time NEU Surgery. Source: ORSuite



(a) Surgery duration URO patients.

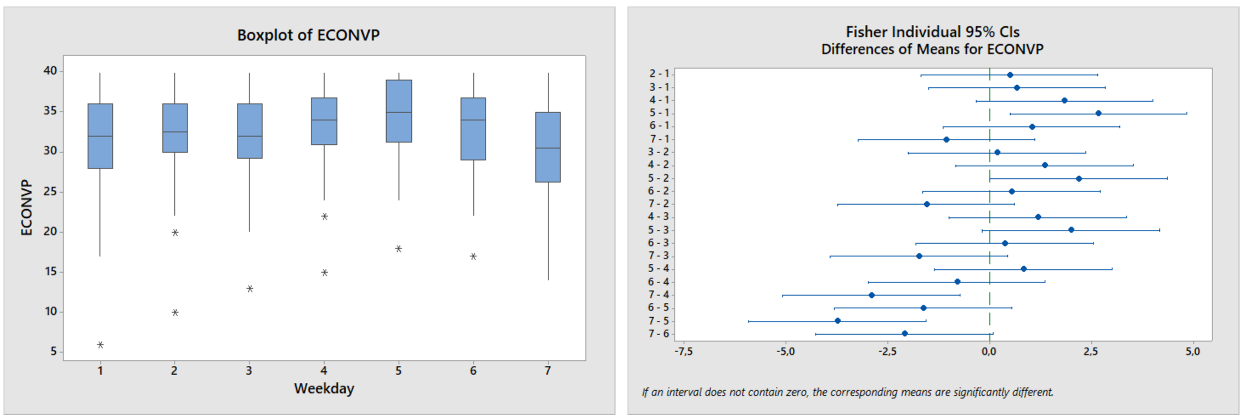


(b) Case Time URO patients.

Figure C.13: Surgery duration and case time URO Surgery. Source: ORSuite

Appendix D

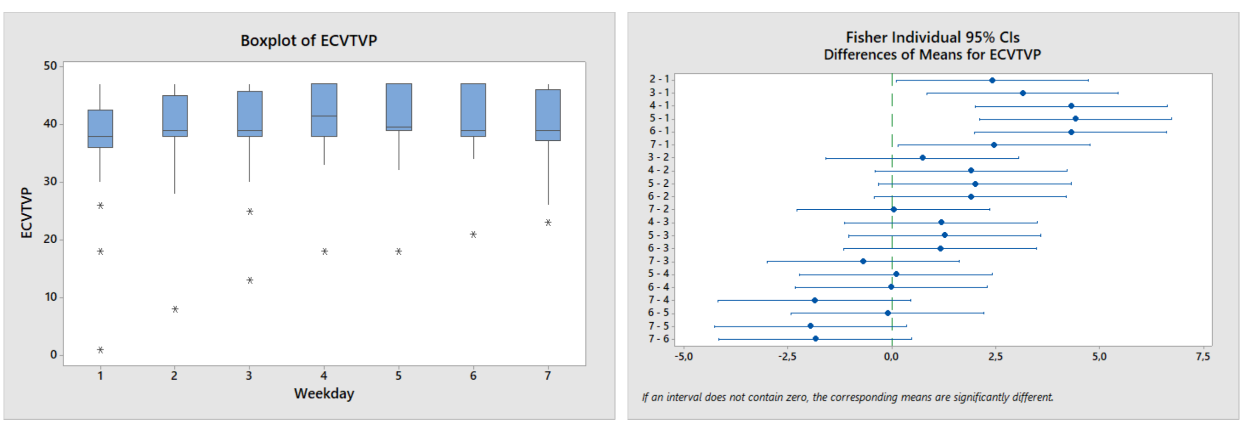
Bed Occupation Per Ward



(a) Bed Occupation ECONVP

(b) F-Test for Bed Occupation ECONVP

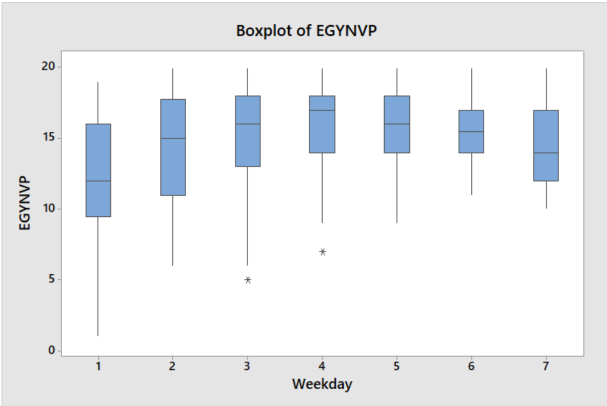
Figure D.1: Bed Occupation in 2017 and F-test ECONVP. N = 1786. Source = XCare.



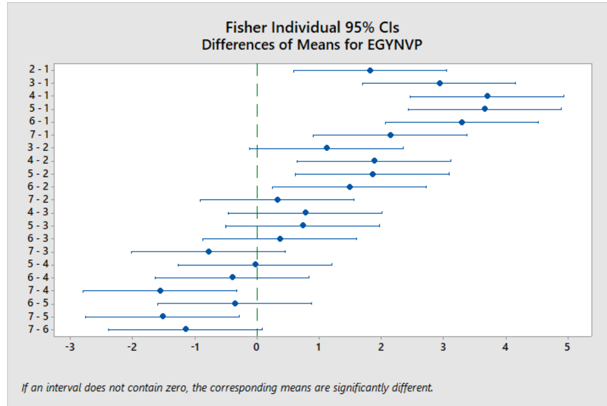
(a) Bed Occupation ECVTVP

(b) F-Test for Bed Occupation ECVTVP

Figure D.2: Bed Occupation in 2017 and F-test ECVTVP. N = 2495. Source = XCare.

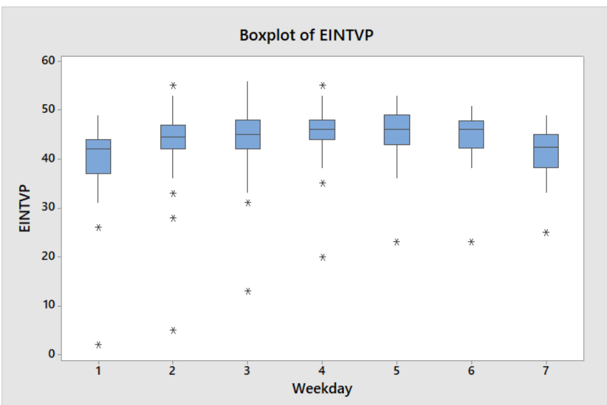


(a) Bed Occupation EGYNVP

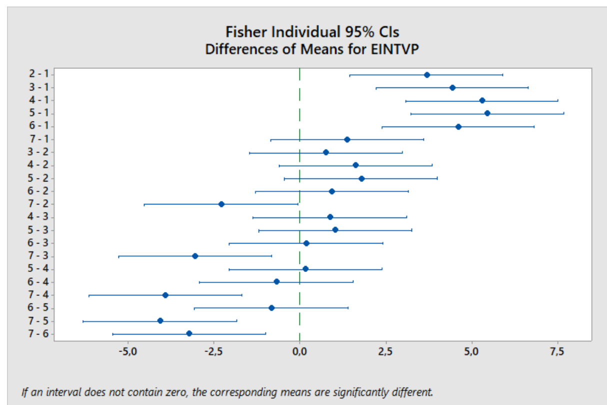


(b) F-Test for Bed Occupation EGYNVP

Figure D.3: Bed Occupation in 2017 and F-test EGYNVP. N = 3347 . Source = XCare.

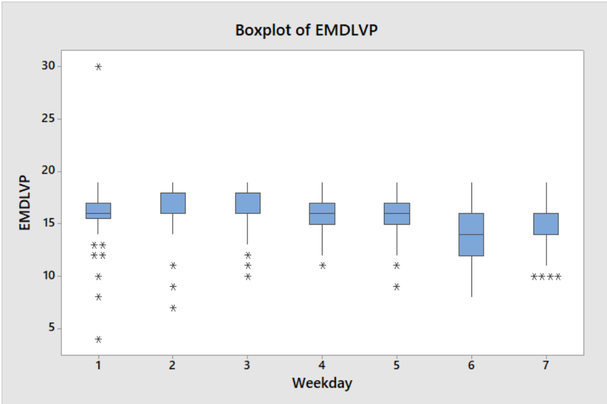


(a) Bed Occupation EINTVP

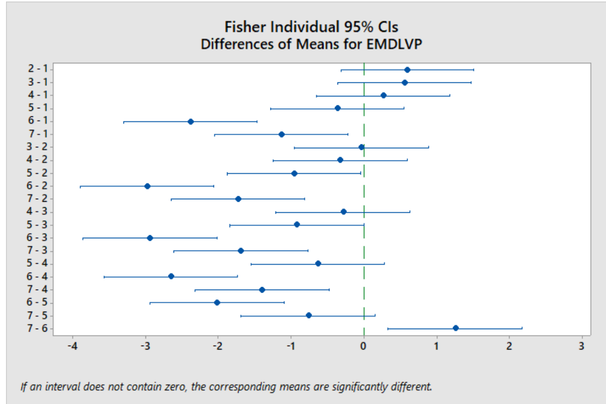


(b) F-Test for Bed Occupation EINTVP

Figure D.4: Bed Occupation in 2017 and F-test EINTVP. N = 1712. Source = XCare.

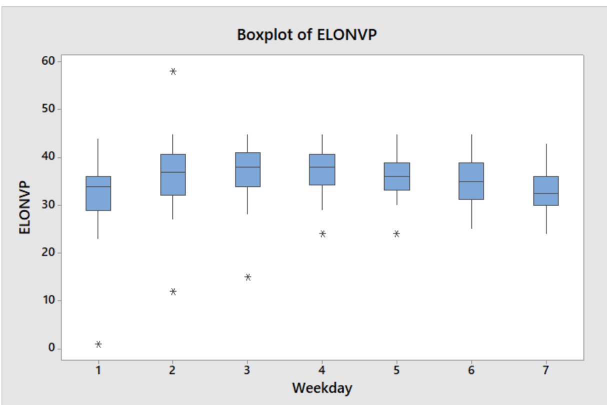


(a) Bed Occupation EMDLVP

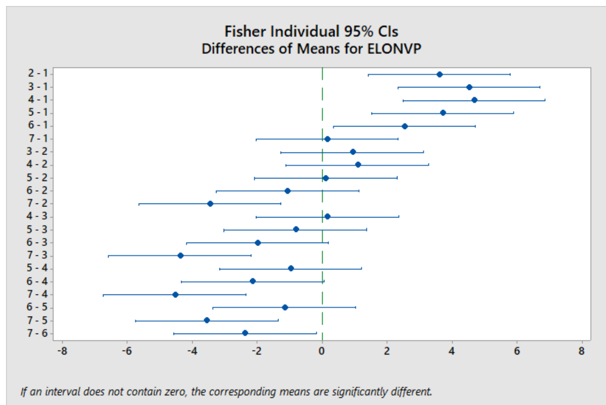


(b) F-Test for Bed Occupation EMDLVP

Figure D.5: Bed Occupation in 2017 and F-test EMDLVP. N = 1186. Source = XCare.

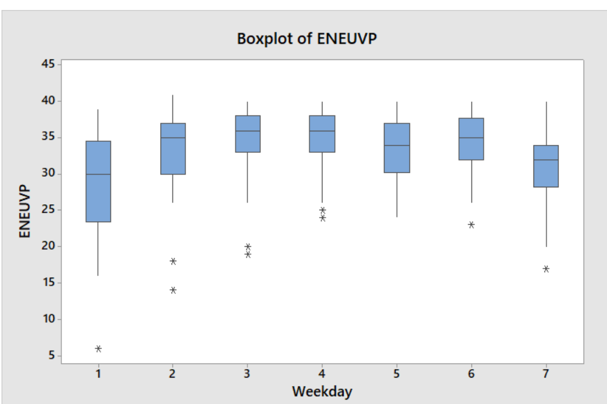


(a) Bed Occupation ELONVP

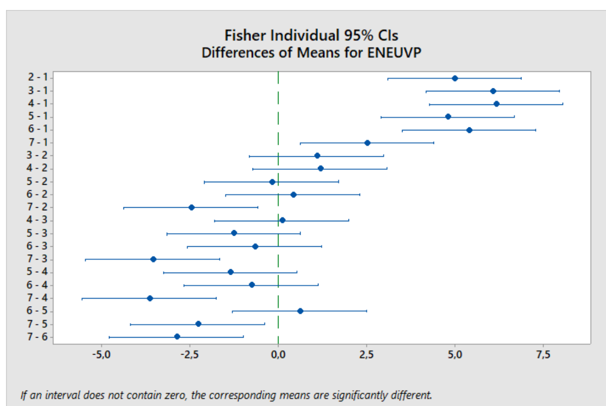


(b) F-Test for Bed Occupation ELONVP

Figure D.6: Bed Occupation in 2017 and F-test ELONVP. N = 2370 . Source = XCare.

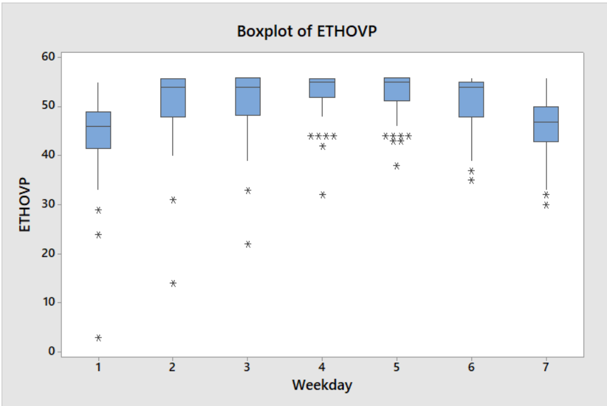


(a) Bed Occupation ENEUVP

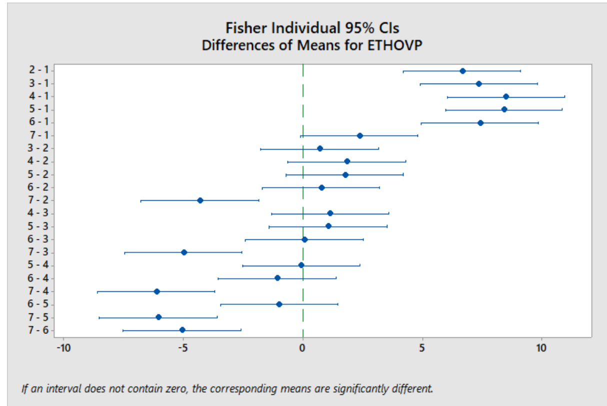


(b) F-Test for Bed Occupation ENEUVP

Figure D.7: Bed Occupation in 2017 and F-test ENEUVP. N = 2512. Source = XCare.

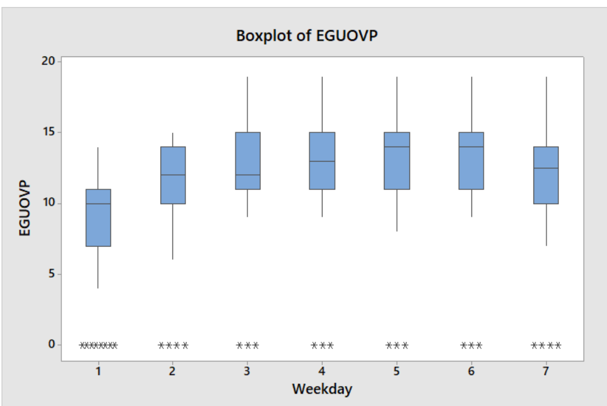


(a) Bed Occupation ETHOVP

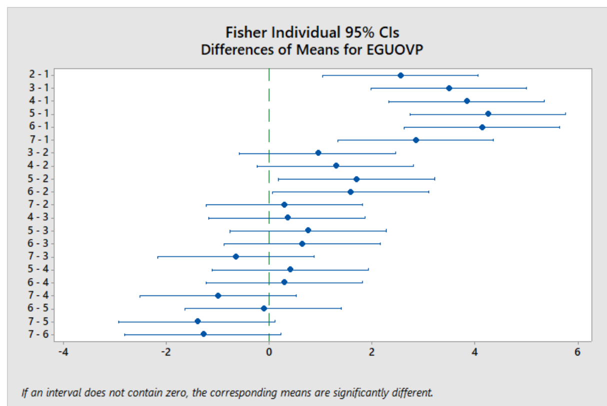


(b) F-Test for Bed Occupation ETHOVP

Figure D.8: Bed Occupation in 2017 and F-test ETHOVP. N = 3306. Source = XCare.

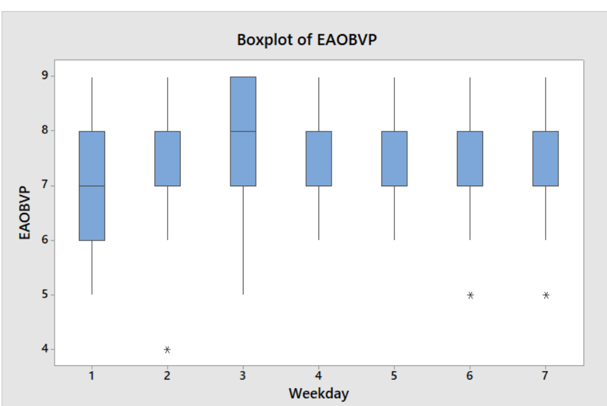


(a) Bed Occupation EGUOVP

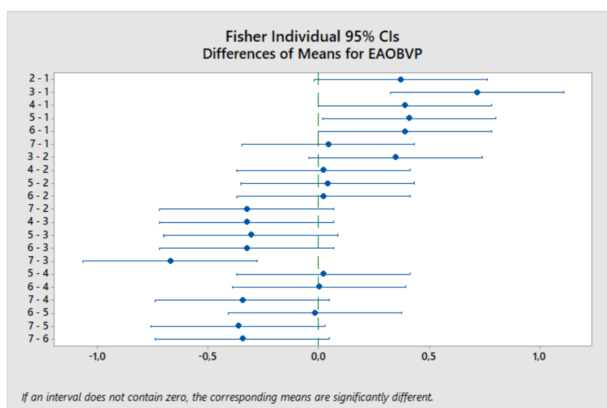


(b) F-Test for Bed Occupation EGUOVP

Figure D.9: Bed Occupation in 2017 and F-test EGUOVP. N = 2666. Source = XCare.

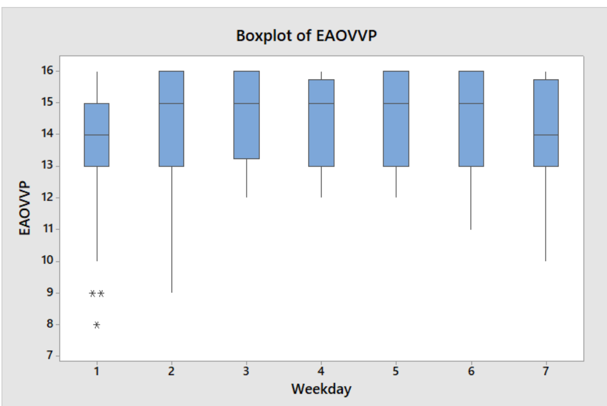


(a) Bed Occupation EAOBVP

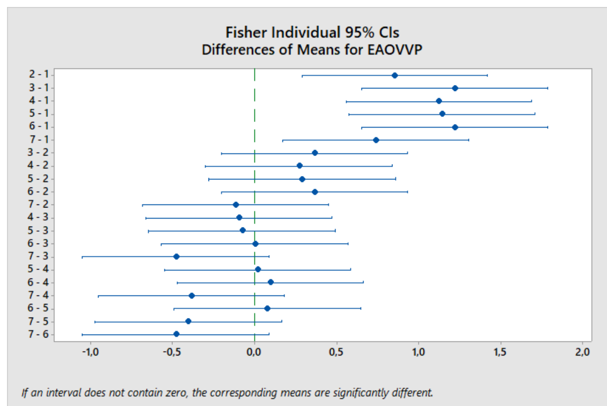


(b) F-Test for Bed Occupation EAOBVP

Figure D.10: Bed Occupation in 2017 and F-test EAOBVP. N = 5870. Source = XCare.



(a) Bed Occupation EAOVVP



(b) F-Test for Bed Occupation EAOVVP

Figure D.11: Bed Occupation in 2017 and F-test EAOVVP. N = 2985 . Source = XCare.

Appendix E

Bed Utilization Per Specialty

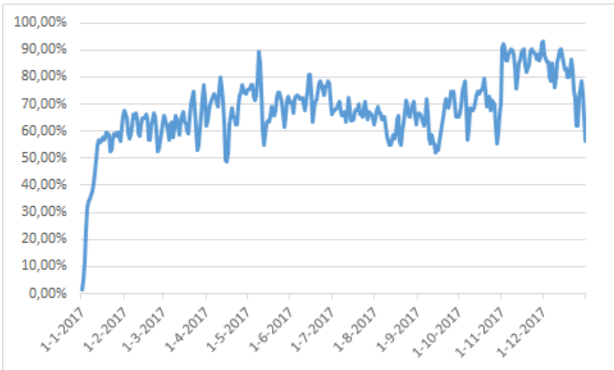


Figure E.1: Bed Utilization EINTVP ward in 2017. Source: ORSuite.

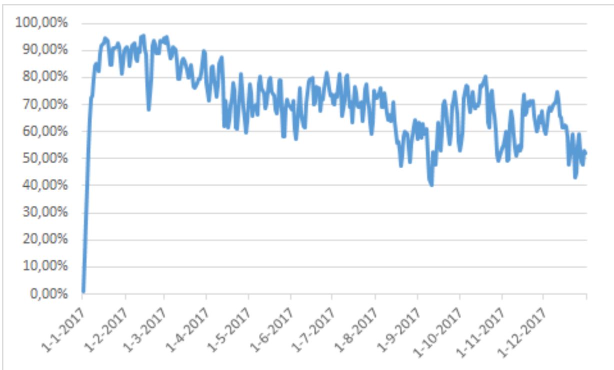


Figure E.2: Bed Utilization ELONVP ward in 2017. Source: ORSuite.

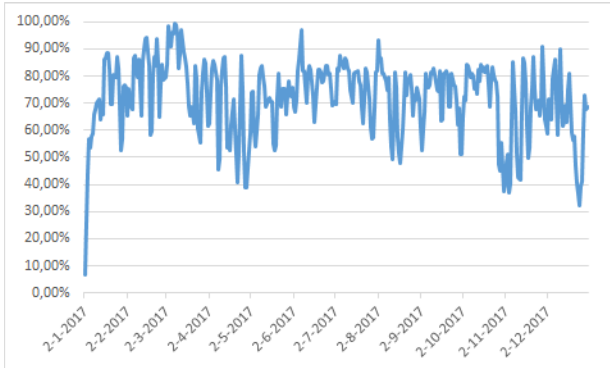


Figure E.3: Bed Utilization EMDLVP ward in 2017. Source: ORSuite.

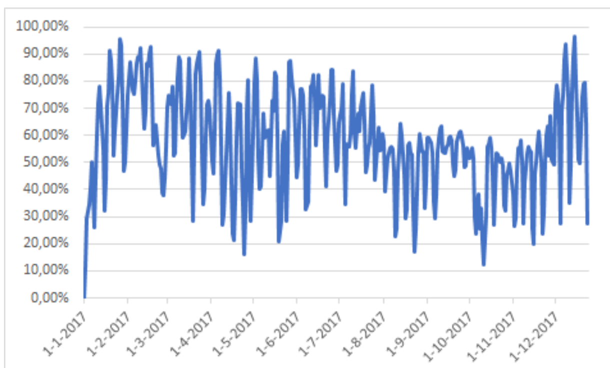


Figure E.4: Bed Utilization EGUOVP ward in 2017. Source: ORSuite.

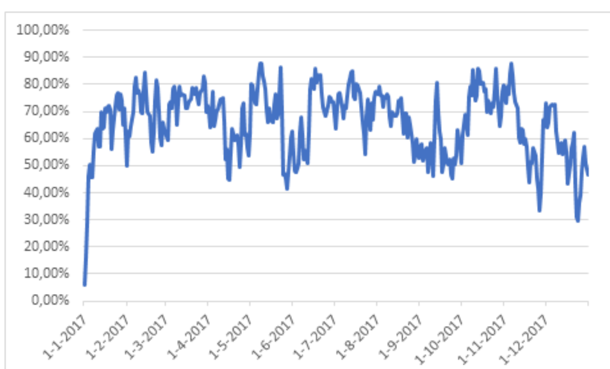


Figure E.5: Bed Utilization ENEUVP ward in 2017. Source: ORSuite.

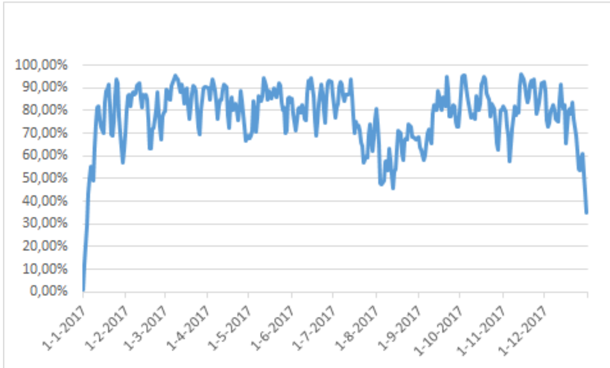


Figure E.6: Bed Utilization ETHOVP ward in 2017. Source: ORSuite.

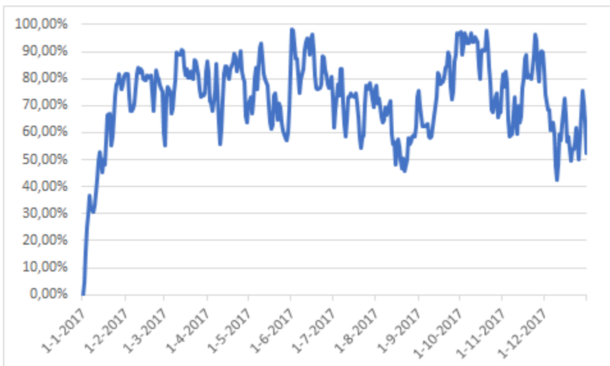


Figure E.7: Bed Utilization ECONVP ward in 2017. Source: ORSuite.

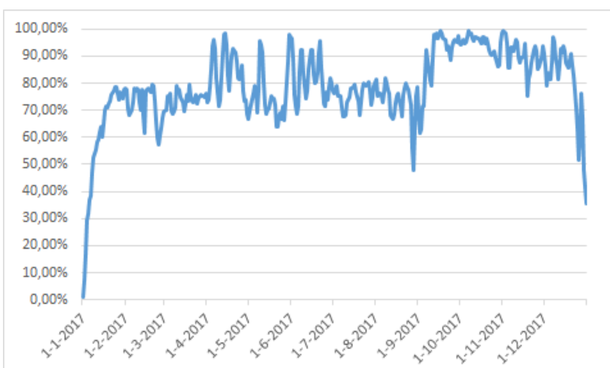


Figure E.8: Bed Utilization ECVTVP ward in 2017. Source: ORSuite.

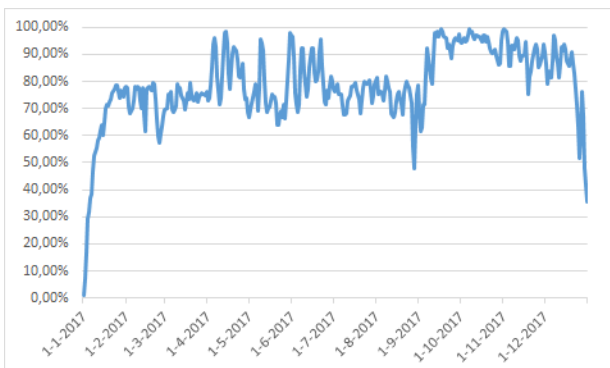


Figure E.9: Bed Utilization ECVTVP ward in 2017. Source: ORSuite

Appendix F

Bed Occupation and Utilization variances

	ETHOVP	ENEUVP	EGUOVP	EGYNVP	ECVTVP	ECONVP
μ_{week}	27.83	33.54	21.21	18.66	41.15	32.68
$\mu_{weekend}$	21.96	33.07	17.15	15.07	38.65	31.51
σ_{week}	4.30	5.49	5.61	4.12	5.79	5.72
$\sigma_{weekend}$	4.60	4.75	6.29	4.60	6.62	5.61
$c_{v,week}$	0.155	0.163	0.264	0.221	0.140	0.175
$c_{v,weekend}$	0.209	0.144	0.366	0.305	0.171	0.178

Table F.1: Variance parameters for (surgical patient) ward occupation .

	EMDLVP	EINTVP	ELONVP	EAOVVP	EAOBVP	ESNYDV
μ_{week}	16.15	44.76	36.74	10.25	18.67	12.27
$\mu_{weekend}$	14.38	40.75	33.01	2.25	15.18	-
σ_{week}	2.40	5.72	5.51	8.11	4.36	5.09
$\sigma_{weekend}$	3.33	5.92	6.13	2.22	3.73	-
$c_{v,week}$	0.148	0.128	0.150	0.219	0.233	0.415
$c_{v,weekend}$	0.232	0.145	0.185	0.274	0.246	-

Table F.2: Variance parameters for (non-surgical patient) ward occupation.

	ETHOVP	ENEUVP	EGYNVP	EGUOVP	ECVTVP	ECONVP
μ	0.780	0.665	0.529	0.610	0.790	0.727
σ	0.129	0.116	0.178	0.210	0.137	0.149
c_v	0.165	0.174	0.336	0.350	0.174	0.205

Table F.3: Variance parameters for surgical ward utilization.

	EMDLVP	EINTVP	ELONVP	EAOVVP	EAOBVP
μ	0.721	0.680	0.727	0.675	0.572
σ	0.144	0.120	0.132	0.210	0.119
c_v	0.199	0.176	0.181	0.350	0.209

Table F.4: Variance parameters for non-surgical ward utilization.

Appendix G

Length Of Stay Per Specialty

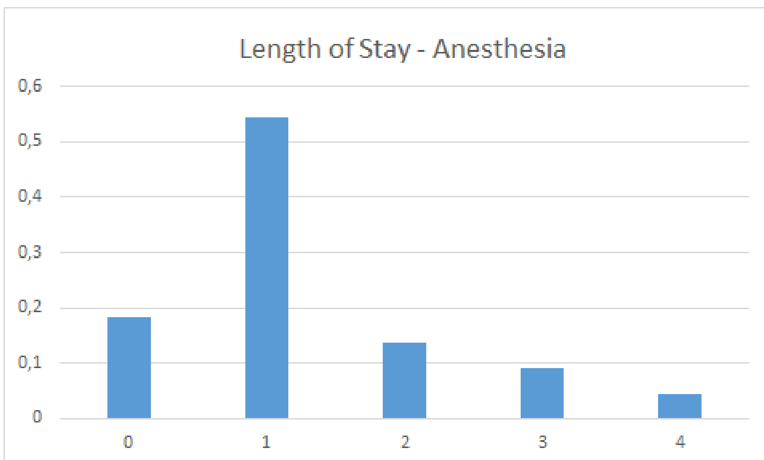


Figure G.1: Length Of Stay PPA in 2017. N = 22 . Source: XCare

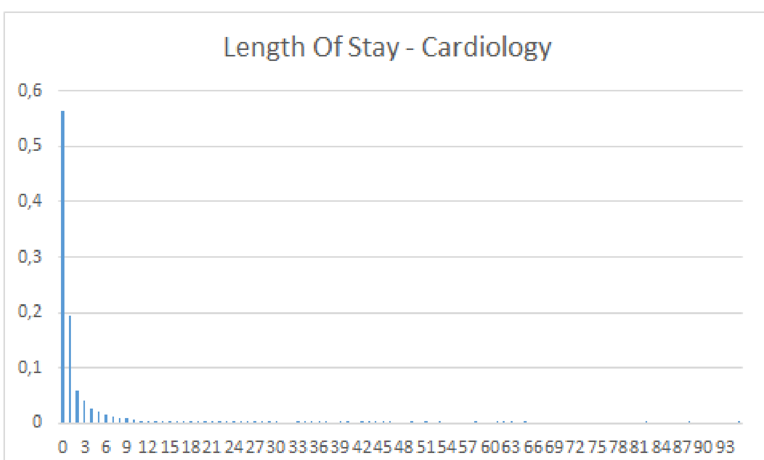


Figure G.2: Length Of Stay CAR in 2017. N = 8790 . Source: XCare

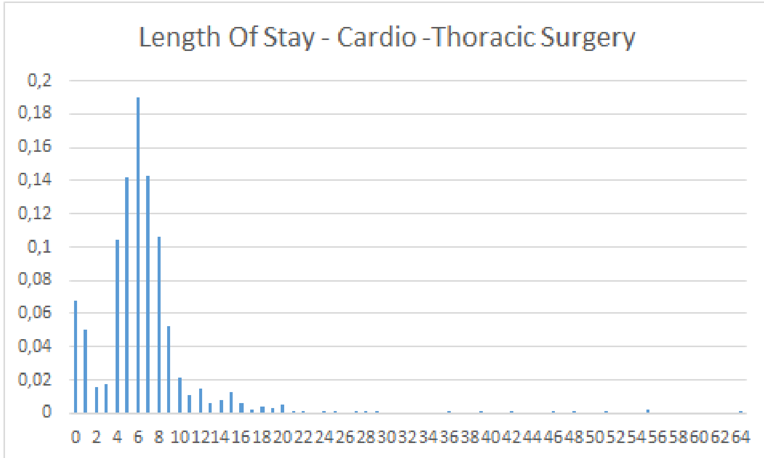


Figure G.3: Length Of Stay CTC in 2017. N = 972. Source: XCare

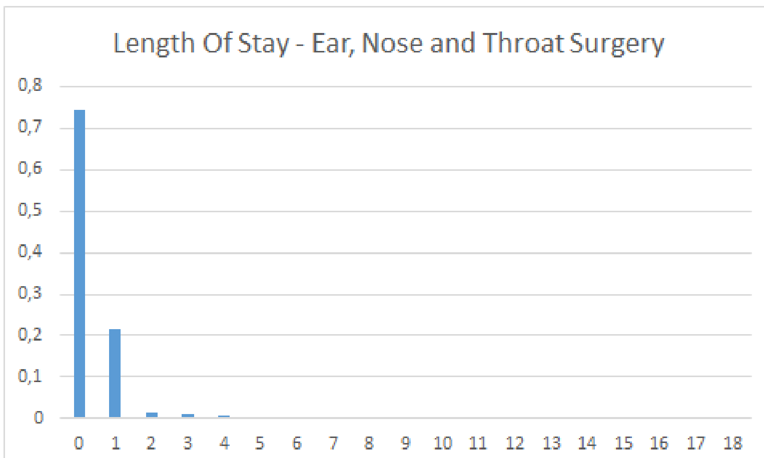


Figure G.4: Length Of Stay ENT in 2017. N = 1981. Source: XCare

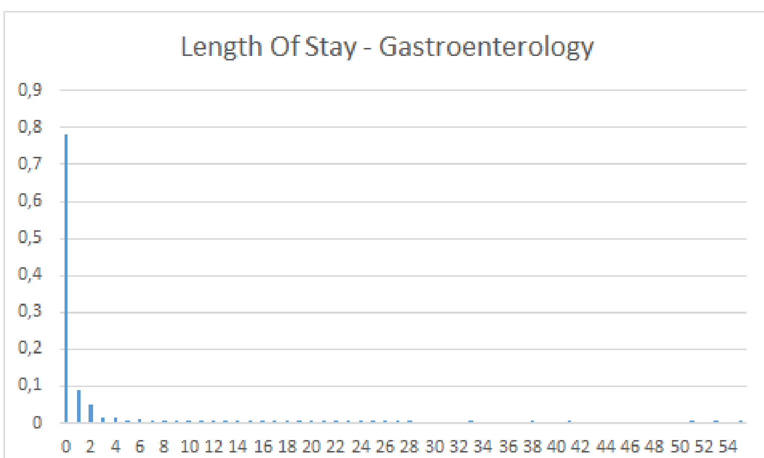


Figure G.5: Length Of Stay GE in 2017. N = 9197. Source: XCare

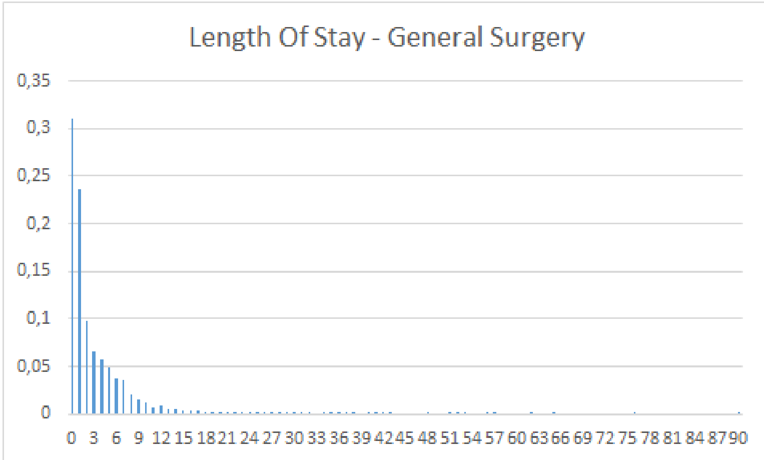


Figure G.6: Length Of Stay GS in 2017. N = 7190. Source: XCare

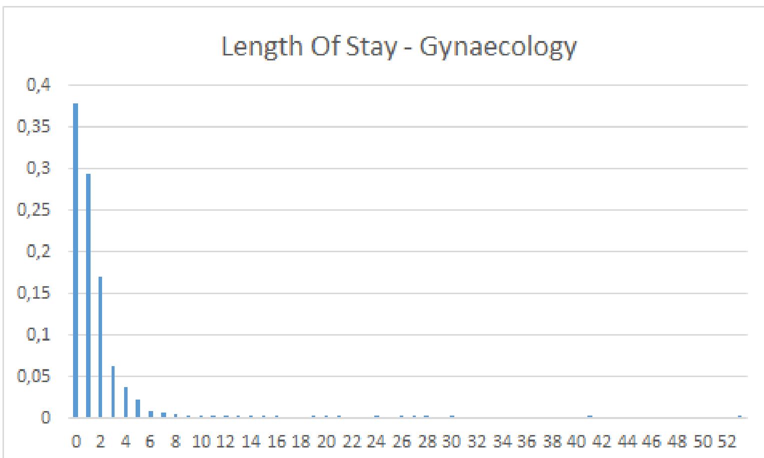


Figure G.7: Length Of Stay GYN in 2017. N = 4359. Source: XCare

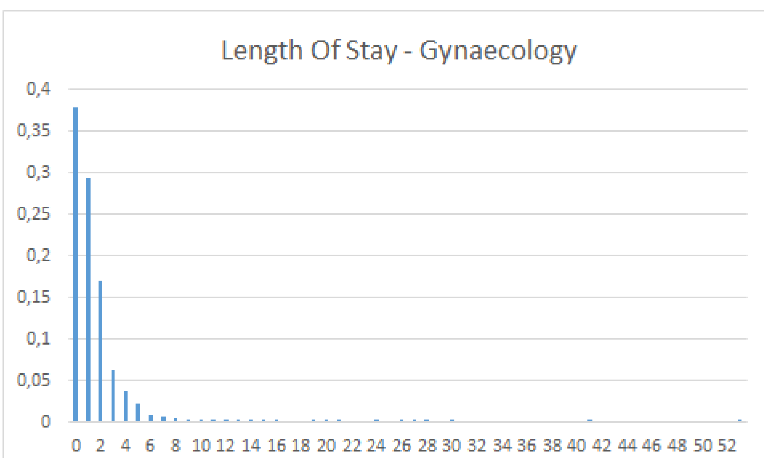


Figure G.8: Length Of Stay MA in 2017. N = 413. Source: XCare

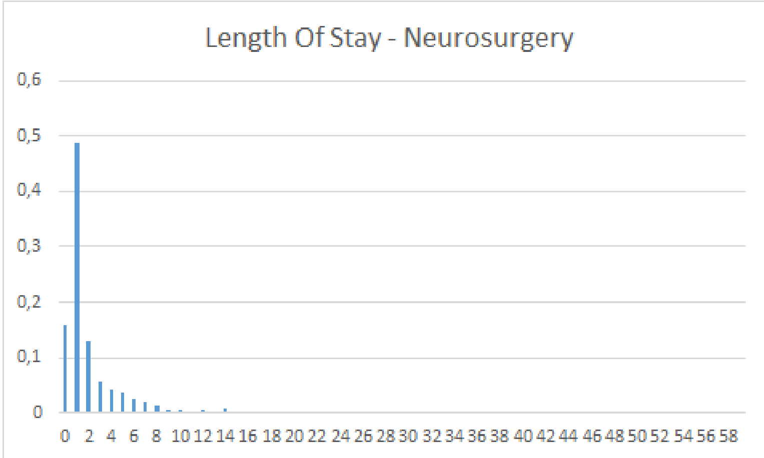


Figure G.9: Length Of Stay NEURO in 2017. N = 1221. Source: XCare

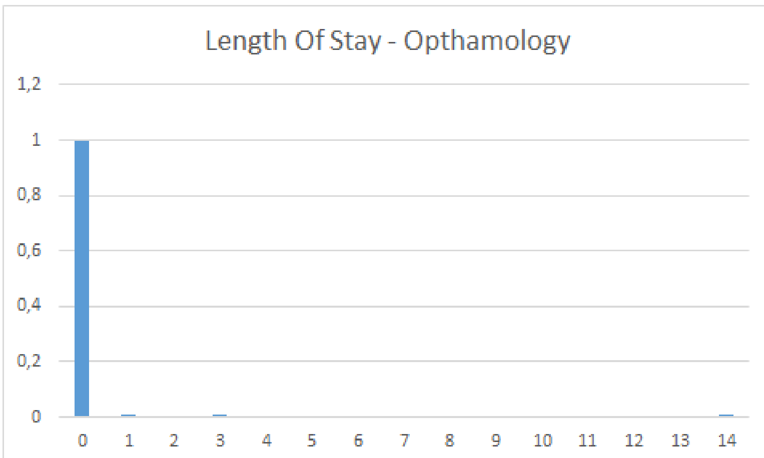


Figure G.10: Length Of Stay OPT in 2017. N = 1263. Source: XCare

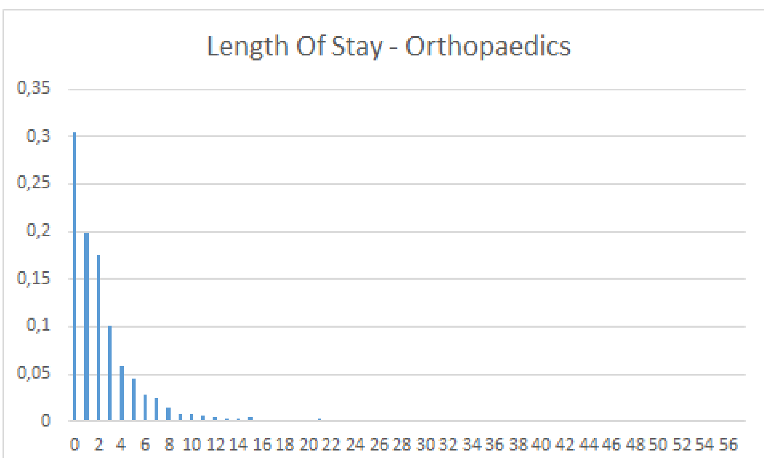


Figure G.11: Length Of Stay ORT in 2017. N = 2361. Source: XCare

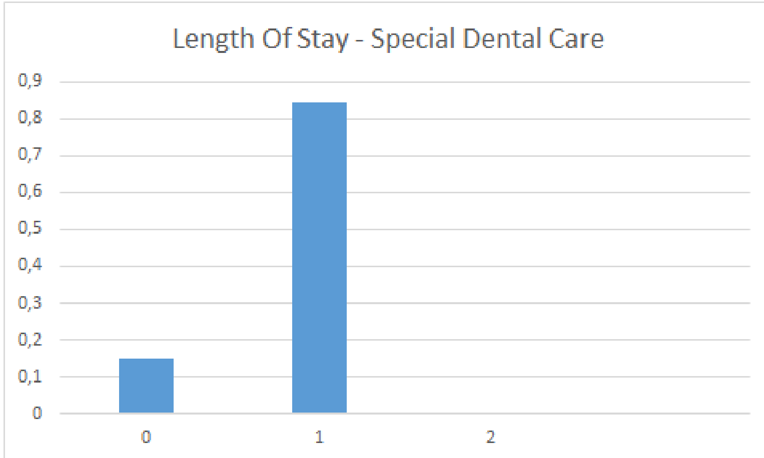


Figure G.12: Length Of Stay SDC in 2017. N = 239. Source: XCare

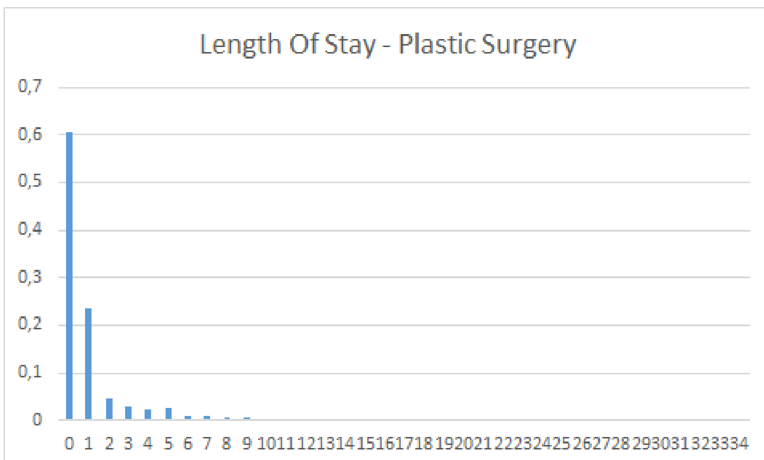


Figure G.13: Length Of Stay PS in 2017. N = 761. Source: XCare

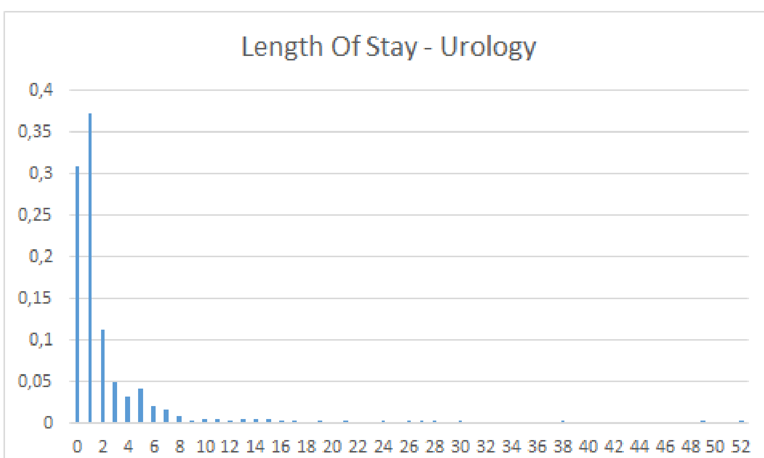


Figure G.14: Length Of Stay URO in 2017. N = 1508. Source: XCare

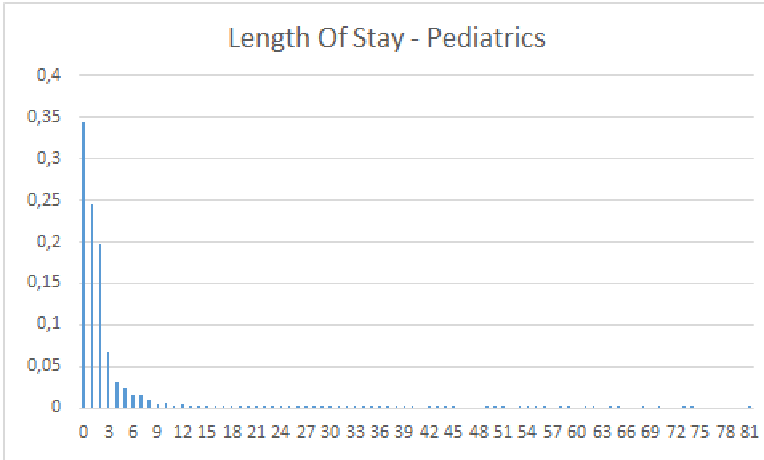


Figure G.15: Length Of Stay Pediatrics in 2017. N = 6335. Source: XCare

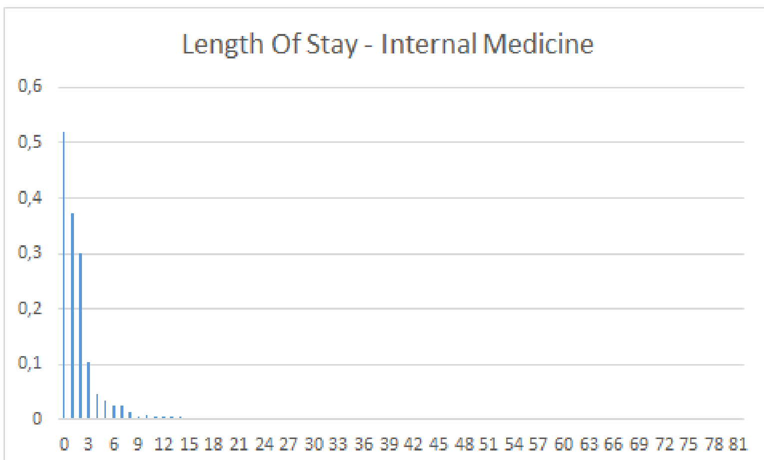


Figure G.16: Length Of Stay Internal Medicine in 2017. N = 4165. Source: XCare

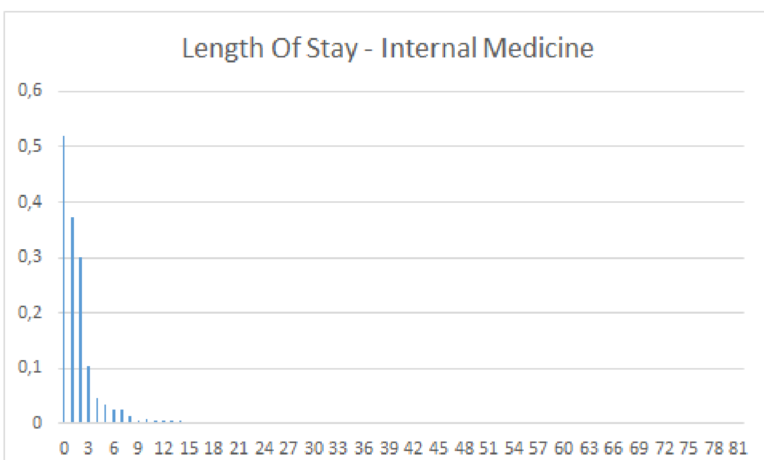
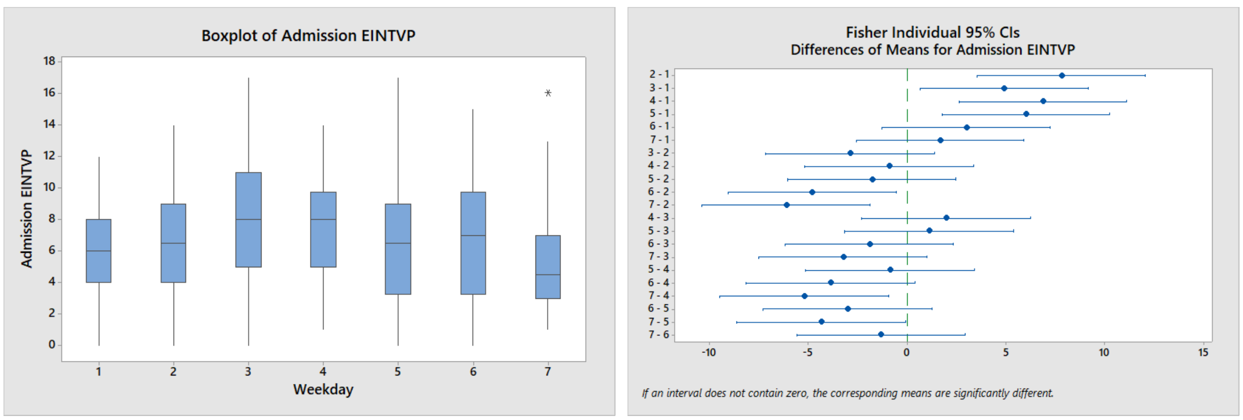


Figure G.17: Length Of Stay Neurology in 2017. N = 3069. Source: XCare

Appendix H

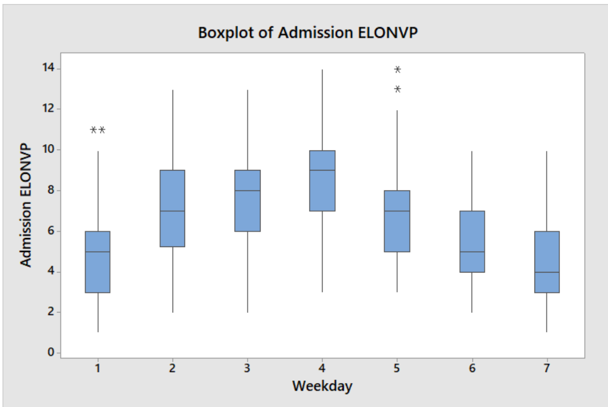
Admission Rate Per Ward



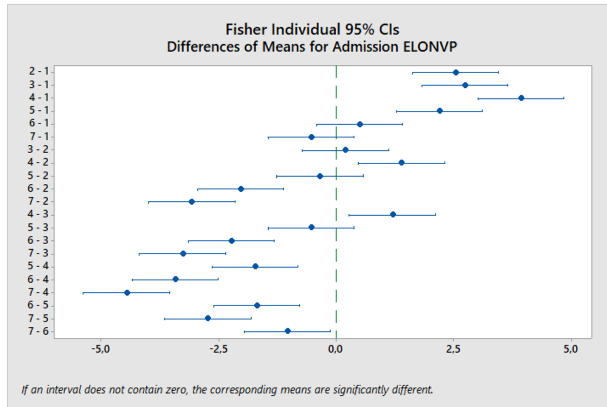
(a) Patient Admissions EINTVP

(b) F-Test for EINTVP Patient Admission

Figure H.1: Patient Admission EINTVP and F-Test for comparing means. N = 4476 . Source = XCare.

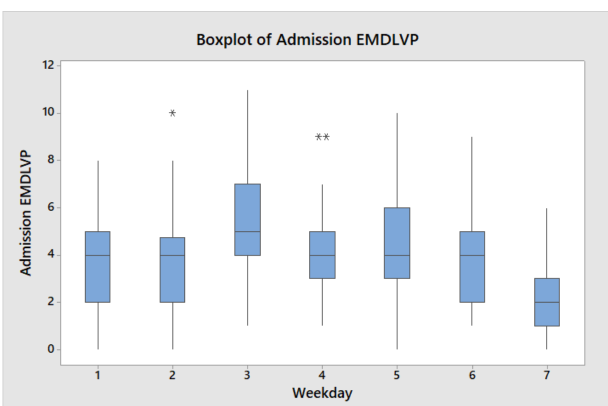


(a) Patient Admissions at ELONVP

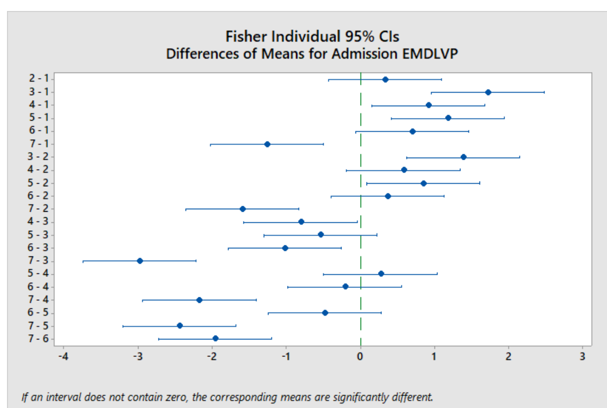


(b) F-Test for ELONVP Patient Admission

Figure H.2: Patient Admission ELONVP and F-Test for comparing means. N = 4361 . Source = XCare.

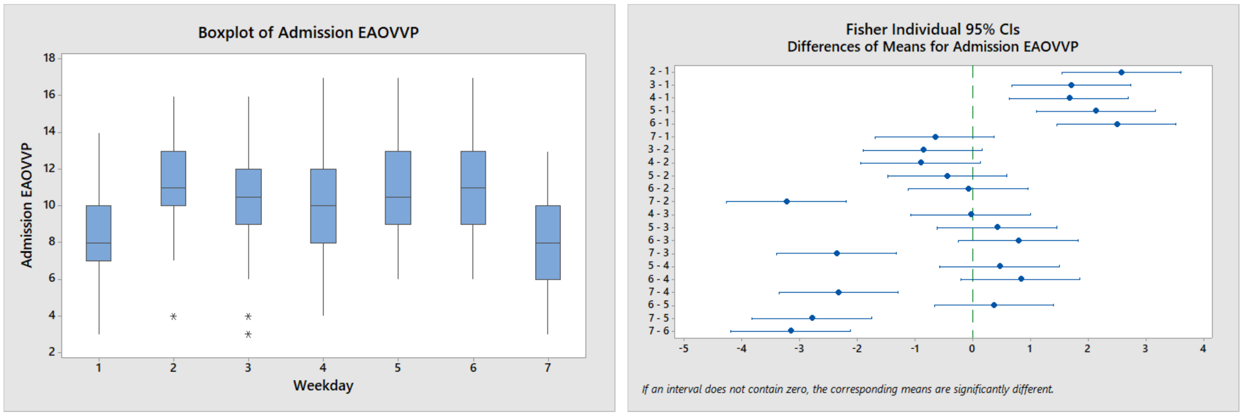


(a) Patient Admissions at EMDLVP



(b) F-Test for EMDLVP Patient Admission

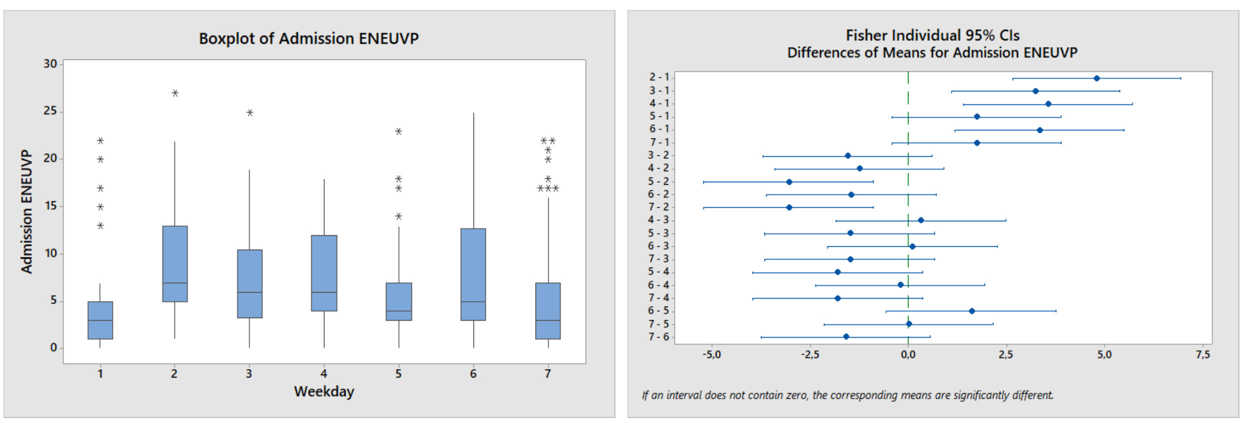
Figure H.3: Patient Admission EMDLVP and F-Test for comparing means. N = 2727. Source = XCare.



(a) Patient Admissions at EAOVVP

(b) F-Test for EAOVVP Patient Admission

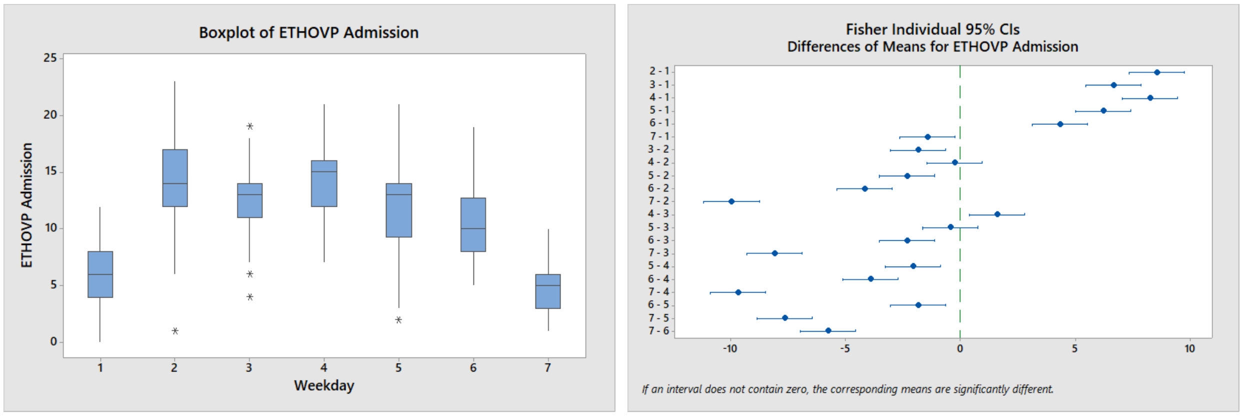
Figure H.4: Patient Admission EAOVVP and F-Test for comparing means. N = 4288. Source = XCare.



(a) Patient Admissions at ENEUVP

(b) F-Test for ENEUVP Patient Admission

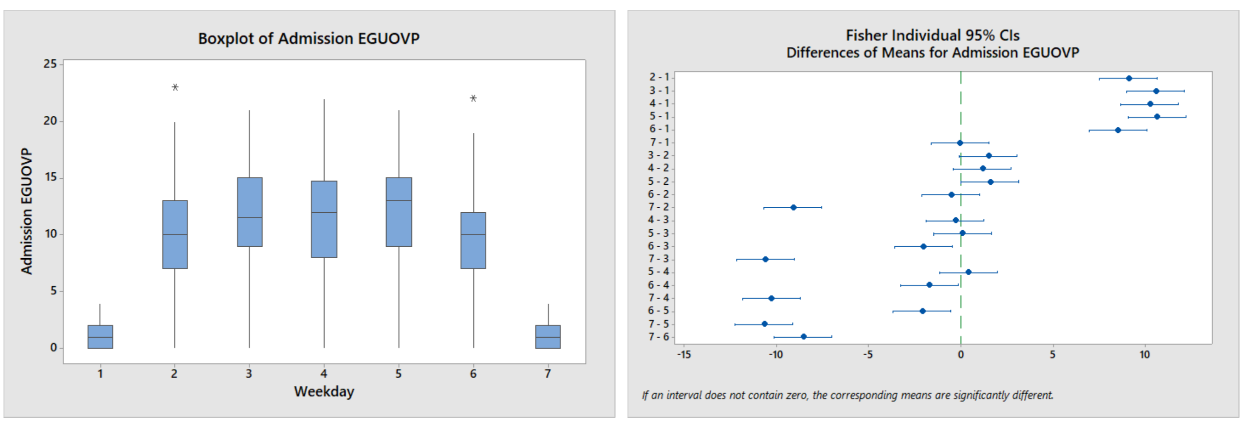
Figure H.5: Patient Admission ENEUVP and F-Test for comparing means. N = 5125. Source = XCare.



(a) Patient Admissions at ETHOVP

(b) F-Test for ETHOVP Patient Admission

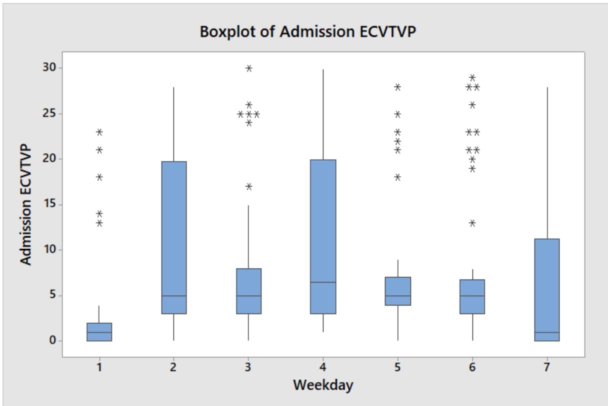
Figure H.6: Patient Admission ETHOVP and F-Test for comparing means. N = 6324. Source = XCare.



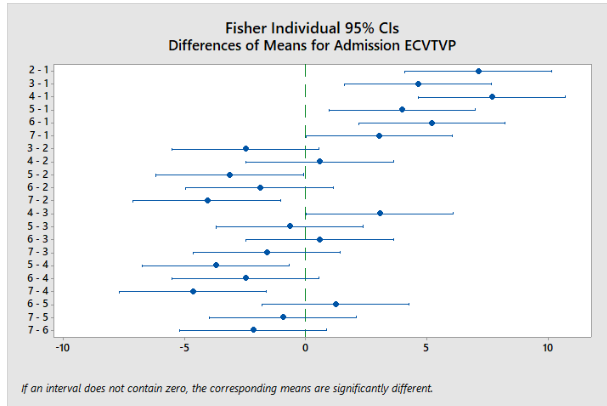
(a) Patient Admissions at EGUOVP

(b) F-Test for EGUOVP Patient Admission

Figure H.7: Patient Admission EGUOVP and F-Test for comparing means. N = 3452. Source = XCare.

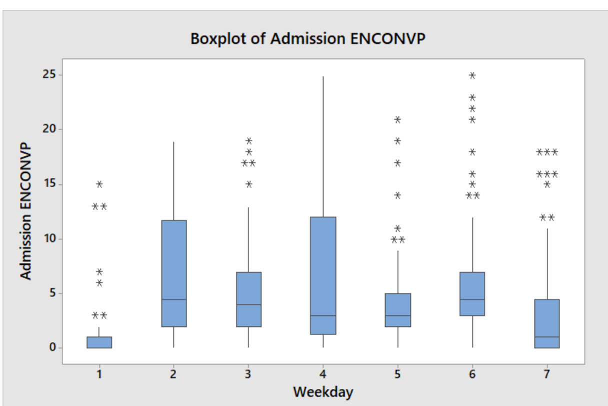


(a) Patient Admissions at ECVTVP

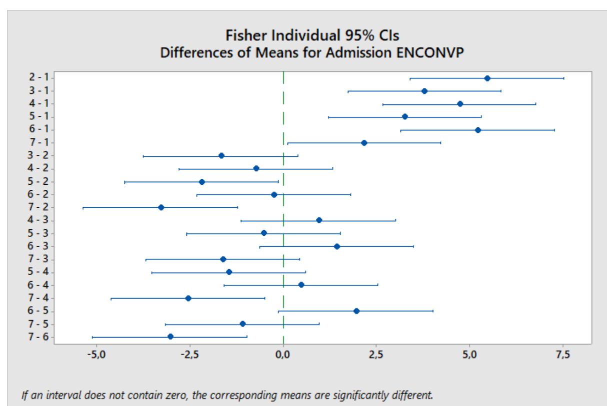


(b) F-Test for ECVTVP Patient Admission

Figure H.8: Patient Admission ECVTVP and F-Test for comparing means. N = 3410. Source = XCare.

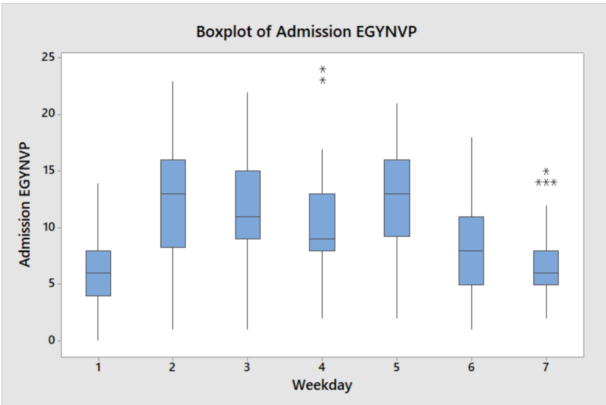


(a) Patient Admissions at ECONVP

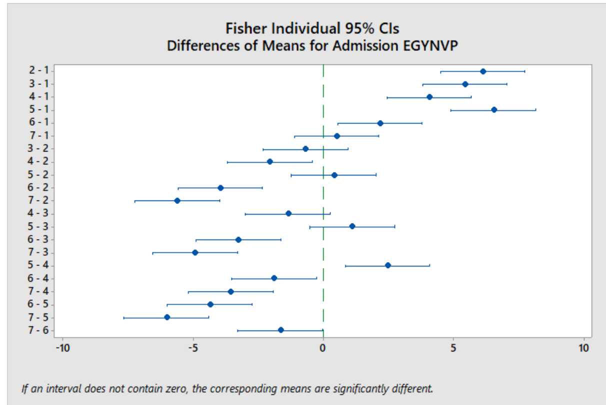


(b) F-Test for ECONVP Patient Admission

Figure H.9: Patient Admission ECONVP and F-Test for comparing means. N = 2401 . Source = XCare.

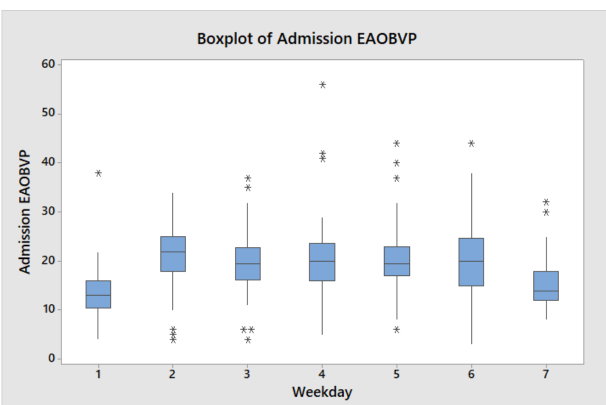


(a) Patient Admissions at EGYNVP

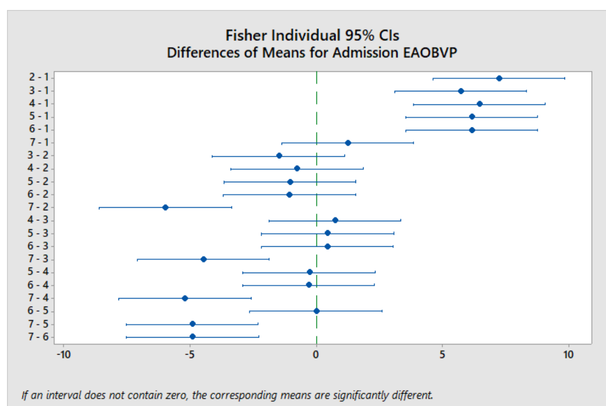


(b) F-Test for EGYNVP Patient Admission

Figure H.10: Patient Admission EGYNVP and F-Test for comparing means. N = 4591 . Source = XCare.



(a) Patient Admissions at EAOBVP

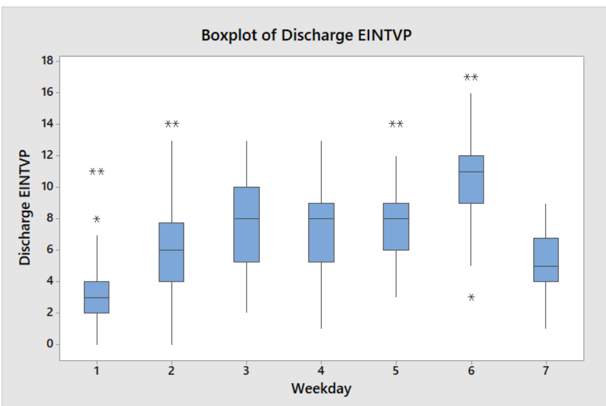


(b) F-Test for EAOBVP Patient Admission

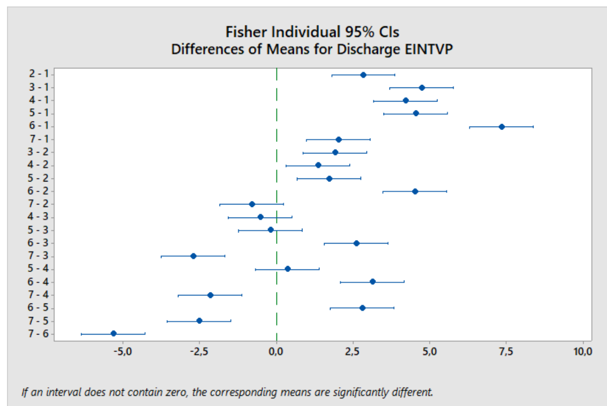
Figure H.11: Patient Admission EAOBVP and F-Test for comparing means. N = 8053. Source = XCare.

Appendix I

Discharge Rate Per Ward

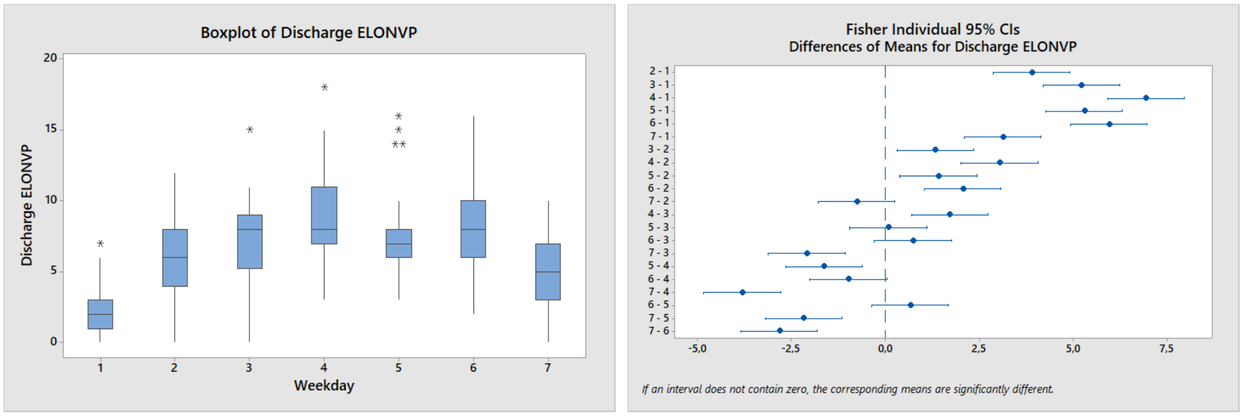


(a) Patient Discharge EINTVP



(b) F-Test for EINTVP Patient Discharge

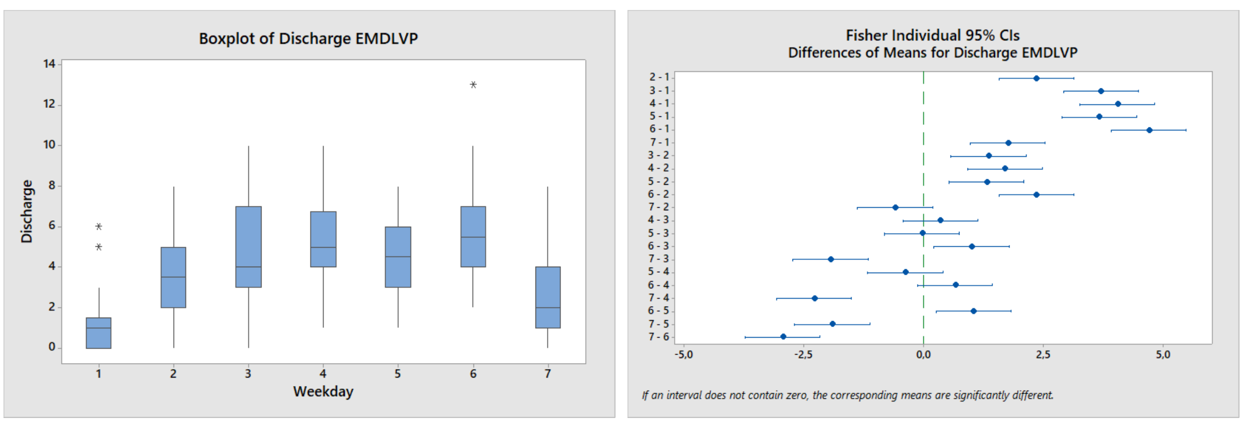
Figure I.1: Patient Discharge EINTVP and F-Test for comparing means. N = 4452. Source = XCare.



(a) Patient Discharge ELONVP

(b) F-Test for ELONVP Patient Discharge

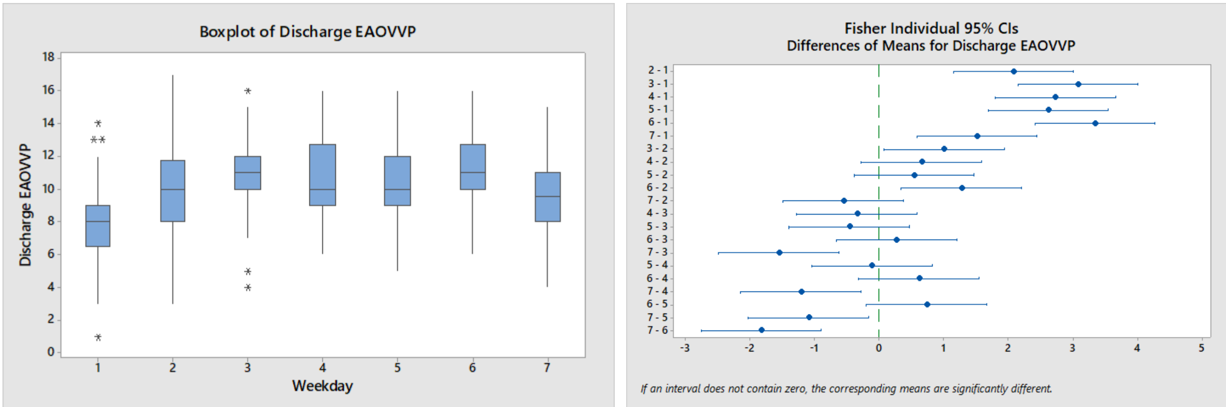
Figure I.2: Patient Discharge ELONVP and F-Test for comparing means. N = 4360. Source = XCare.



(a) Patient Discharge EMDLVP

(b) F-Test for EMDLVP Patient Discharge

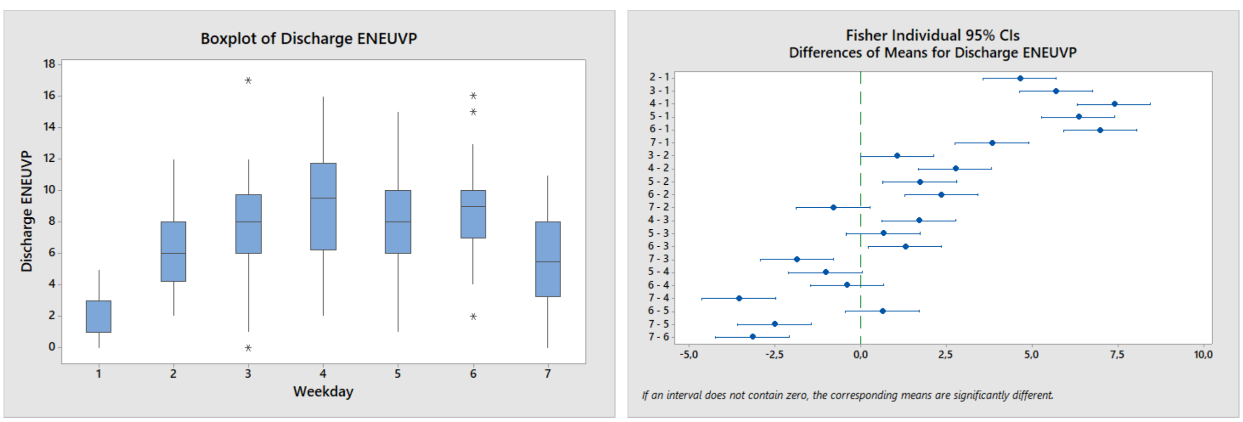
Figure I.3: Patient Discharge EMDLVP and F-Test for comparing means. N = 2715. Source = XCare.



(a) Patient Discharge EAOVVP

(b) F-Test for EAOVVP Patient Discharge

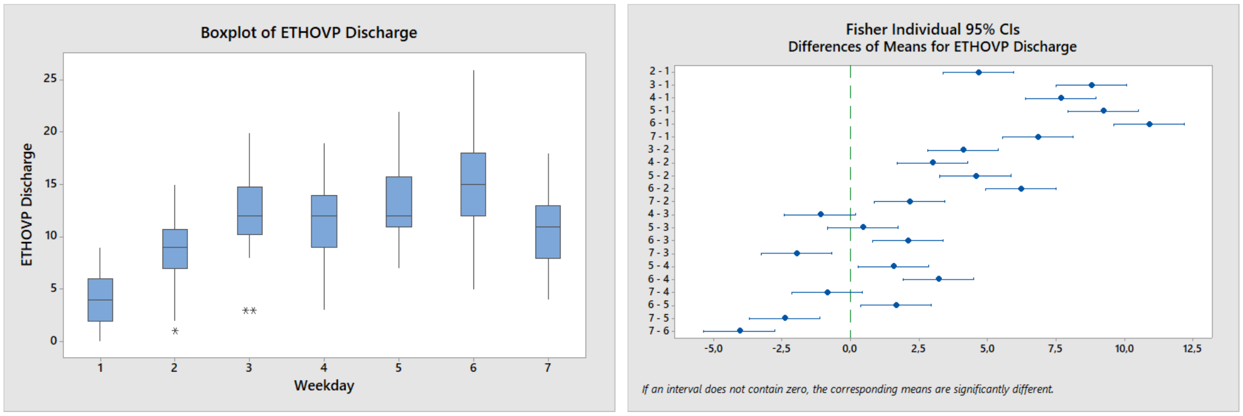
Figure I.4: Patient Discharge EAOVVP and F-Test for comparing means. N = 4282. Source = XCare.



(a) Patient Discharge ENEUVP

(b) F-Test for ENEUVP Patient Discharge

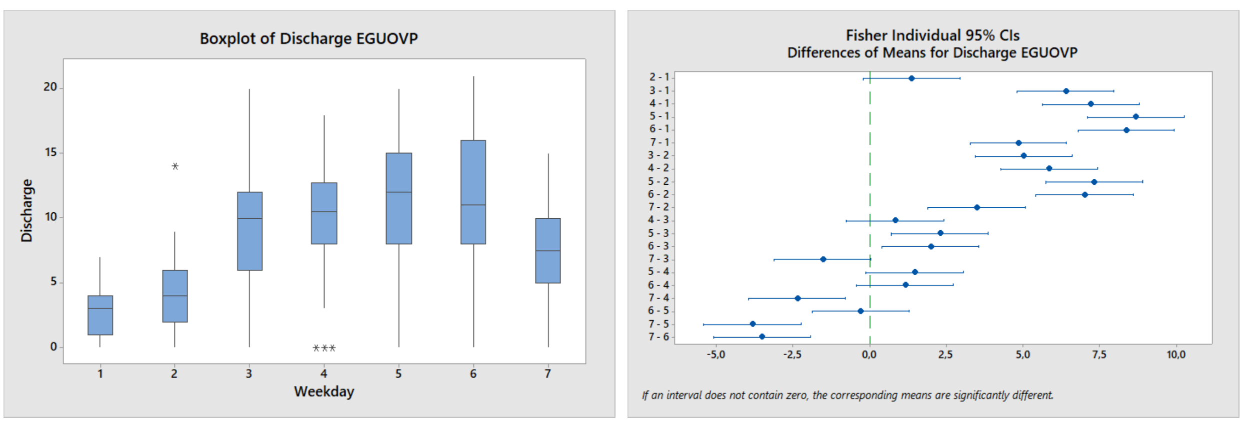
Figure I.5: Patient Discharge ENEUVP and F-Test for comparing means. N = 5095. Source = XCare.



(a) Patient Discharge ETHOVP

(b) F-Test for ETHOVP Patient Discharge

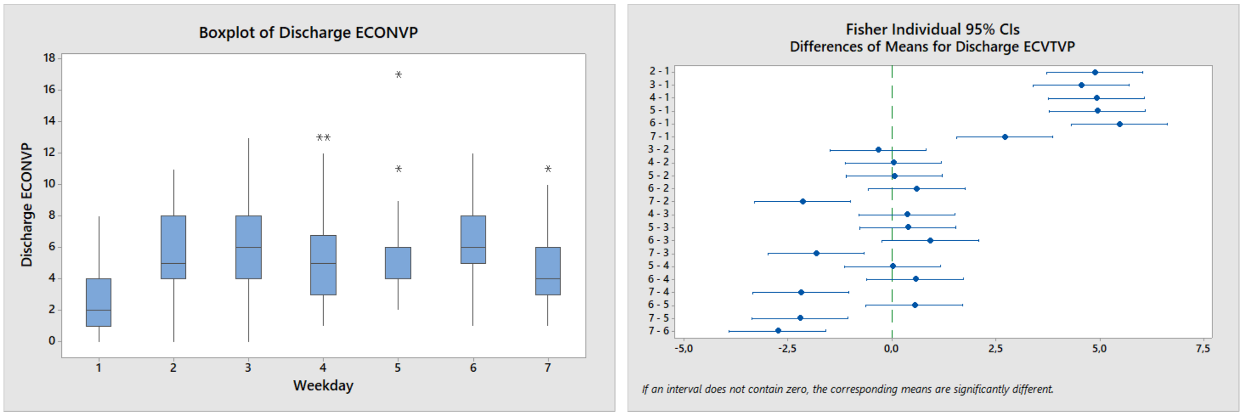
Figure I.6: Patient Discharge ETHOVP and F-Test for comparing means. N = 6305. Source = XCare.



(a) Patient Discharge EGUOVP

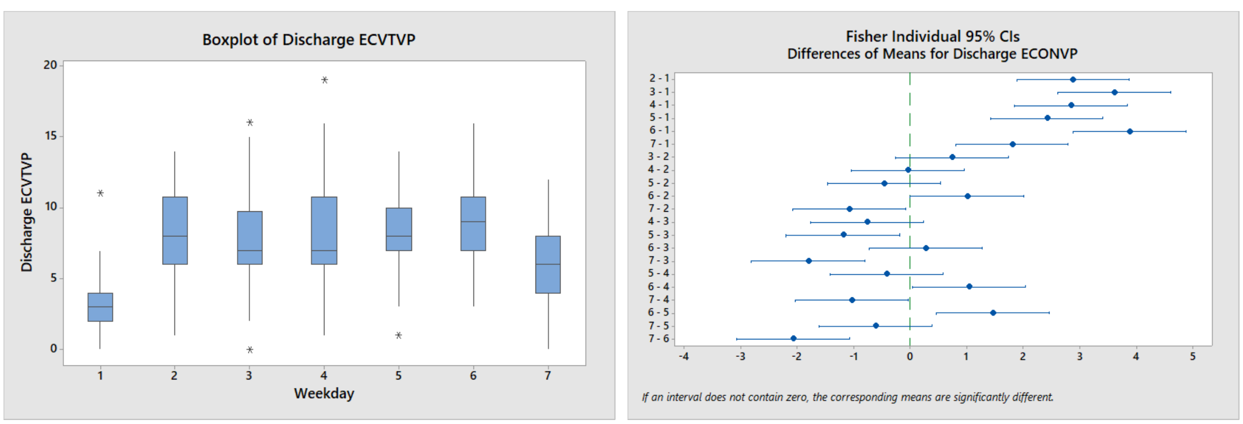
(b) F-Test for EGUOVP Patient Discharge

Figure I.7: Patient Discharge EGUOVP and F-Test for comparing means. N = 3452. Source = XCare.



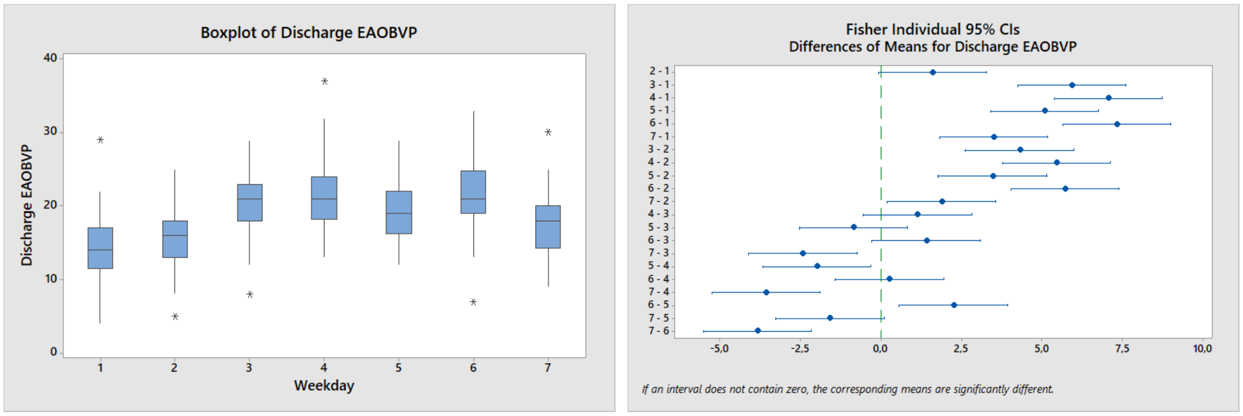
(a) Patient Discharge ECONVP (b) F-Test for ECONVP Patient Discharge

Figure I.8: Patient Discharge ECONVP and F-Test for comparing means. N = 2385. Source = XCare.



(a) Patient Discharge ECVTVP (b) F-Test for ECVTVP Patient Discharge

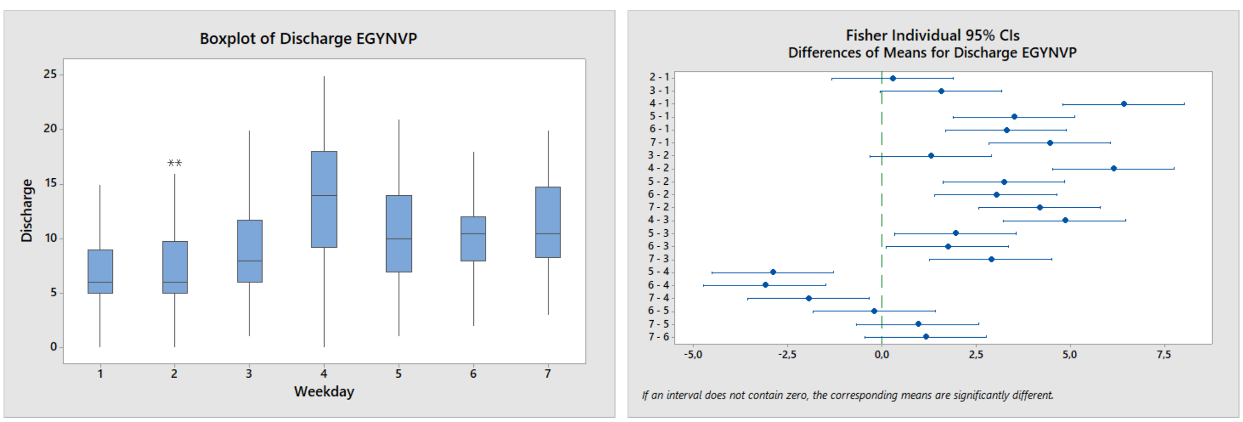
Figure I.9: Patient Discharge ECVTVP and F-Test for comparing means. N = 3398. Source = XCare.



(a) Patient Discharge EAOBVP

(b) F-Test for EAOBVP Patient Discharge

Figure I.10: Patient Discharge EAOBVP and F-Test for comparing means. N = 8042. Source = XCare.



(a) Patient Discharge EGYNVP

(b) F-Test for EGYNVP Patient Discharge

Figure I.11: Patient Discharge EGYNVP and F-Test for comparing means. N = 4575. Source = XCare.

Appendix J

Output MSSs after ALNS procedure

MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	CH	NEURO	OPT	CH	URO	ORT	ORT	ORT	CH	URO	CH	PS	CTC	CTC
2	ENT	NEURO	MDL	CH	CH	CH	ENT	ORT	CH	ORT	CH	PS	CTC	CTC
3	NEURO	NEURO	CH	CH	URO	ORT	ORT	ORT	GYN	ORT	CH	PS	CTC	CTC
4	ENT	NEURO	CH	CH	URO	ORT	CH	ORT	GYN	GYN	CH	CTC	CTC	CTC
5	CH	NEURO	PS	CH	CH	CH	SDC	ORT	GYN	CH	CH	CTC	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	SDC	NEURO	NEURO	CH	URO	PS	ORT	ORT	GYN	URO	CH	SDC	CTC	CTC
9	CH	NEURO	CH	MA	URO	ORT	ORT	ORT	CH	CH	CH	PS	CTC	CTC
10	CH	NEURO	CH	CH	CH	PS	CH	ORT	GYN	GYN	CH	SDC	CTC	CTC
11	SDC	NEURO	CH	CH	URO	ORT	ENT	ORT	CH	CH	CAR	PS	CTC	CTC
12	NEURO	NEURO	CH	MA	CH	CH	CH	ORT	GYN	CH	CH	PS	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	ENT	NEURO	CH	CH	CH	PS	ORT	ORT	CH	CH	CH	CTC	CTC	CTC
16	ENT	NEURO	NEURO	CH	URO	ORT	ENT	ORT	GYN	CH	CH	PS	CTC	CTC
17	ENT	NEURO	CH	MA	URO	ORT	ORT	ORT	GYN	GYN	CH	SDC	CTC	CTC
18	ENT	NEURO	PS	CH	CH	CH	CH	ORT	CH	CH	CAR	CH	CTC	CTC
19	NEURO	SDC	CH	MA	URO	PS	ENT	CH	GYN	CH	CH	CTC	CTC	CTC
20	X	X	X	X	X	X	X	X	X	X	X	X	X	X
21	X	X	X	X	X	X	X	X	X	X	X	X	X	X
22	ENT	CH	PS	CH	URO	CH	CH	CH	GYN	URO	CAR	CH	CTC	CTC
23	NEURO	CH	OPT	CH	CH	ORT	CH	ORT	GYN	GYN	CH	PS	CTC	CTC
24	CH	NEURO	NEURO	CH	URO	ORT	PS	ORT	GYN	URO	CH	PS	CTC	CTC
25	NEURO	NEURO	CH	CH	URO	ORT	ENT	ORT	CH	URO	CH	CTC	CTC	CTC
26	CH	PPA	CH	CH	URO	ORT	ENT	ORT	GYN	CH	CAR	CTC	CTC	CTC
27	X	X	X	X	X	X	X	X	X	X	X	X	X	X
28	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Figure J.1: MSS-5 after ALNS optimization with peak minimization.

MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	CH	NEURO	NEURO	CH	URO	ORT	MDL	ORT	GYN	PS	CH	SDC	CTC	CTC
2	NEURO	CH	CH	CH	URO	PS	ENT	ORT	GYN	CH	CH	PS	CTC	CTC
3	ENT	NEURO	CH	CH	URO	CH	CH	CH	GYN	GYN	CH	PS	CTC	CTC
4	NEURO	NEURO	CH	CH	CH	ORT	ENT	ORT	CH	CH	CH	SDC	CTC	CTC
5	CH	NEURO	PS	CH	CH	CH	ORT	ORT	GYN	CH	CAR	CH	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	NEURO	NEURO	CH	CH	URO	ORT	ORT	ORT	CH	ORT	CAR	CTC	CTC	CTC
9	ENT	NEURO	CH	MA	URO	ORT	CH	ORT	GYN	PS	CH	CH	CTC	CTC
10	NEURO	SDC	NEURO	CH	URO	CH	CH	ORT	GYN	GYN	CH	SDC	CTC	CTC
11	ENT	NEURO	OPT	CH	URO	ORT	CH	ORT	CH	CH	CH	CTC	CTC	CTC
12	ENT	SDC	CH	CH	URO	ORT	ORT	ORT	CH	ORT	CAR	CTC	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	ENT	NEURO	CH	CH	URO	CH	ORT	ORT	CH	CH	CH	CTC	CTC	CTC
16	ENT	NEURO	CH	CH	URO	CH	PS	ORT	GYN	GYN	CH	PS	CTC	CTC
17	NEURO	NEURO	CH	CH	CH	CH	ORT	ORT	GYN	CH	CH	CH	CTC	CTC
18	NEURO	NEURO	CH	MA	URO	CH	PS	ORT	GYN	CH	CH	PS	CTC	CTC
19	ENT	NEURO	CH	CH	URO	PS	PS	ORT	GYN	URO	CH	CTC	CTC	CTC
20	X	X	X	X	X	X	X	X	X	X	X	X	X	X
21	X	X	X	X	X	X	X	X	X	X	X	X	X	X
22	ENT	NEURO	CH	MA	URO	ORT	ORT	ORT	GYN	URO	CH	CH	CTC	CTC
23	ENT	NEURO	PS	CH	URO	CH	ORT	ORT	CH	CH	CH	CTC	CTC	CTC
24	ENT	NEURO	NEURO	MA	URO	ORT	CH	ORT	CH	SDC	CH	PS	CTC	CTC
25	CH	PPA	OPT	CH	CH	ORT	SDC	ORT	GYN	GYN	CH	PS	CTC	CTC
26	ENT	CH	CH	CH	URO	PS	PS	ORT	GYN	CH	CAR	CH	CTC	CTC
27	X	X	X	X	X	X	X	X	X	X	X	X	X	X
28	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Figure J.2: MSS-5 after ALNS optimization with range optimization

MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	ENT	NEURO	CH	MA	URO	CH	ORT	ORT	GYN	CH	CAR	CH	CTC	CTC
2	ENT	NEURO	NEURO	CH	URO	ORT	ORT	ORT	GYN	CH	CH	PS	CTC	CTC
3	ENT	NEURO	CH	CH	URO	CH	CH	ORT	GYN	CH	CH	CH	CTC	CTC
4	ENT	NEURO	OPT	CH	URO	ORT	ORT	ORT	GYN	CH	CH	CTC	CTC	CTC
5	ENT	NEURO	PS	CH	URO	CH	CH	ORT	GYN	CH	CH	CTC	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	ENT	NEURO	OPT	CH	URO	ORT	CH	ORT	GYN	CH	CAR	CH	CTC	CTC
9	ENT	NEURO	CH	MA	URO	ORT	ORT	ORT	GYN	GYN	CH	CH	CTC	CTC
10	ENT	NEURO	PS	CH	URO	ORT	CH	ORT	CH	CH	CH	CH	CTC	CTC
11	ENT	NEURO	PS	CH	CH	CH	CH	ORT	GYN	CH	CAR	CH	CTC	CTC
12	NEURO	NEURO	PS	CH	URO	ORT	CH	ORT	GYN	CH	CH	CTC	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	ENT	PPA	CH	CH	URO	ORT	ORT	ORT	GYN	CH	CH	CTC	CTC	CTC
16	ENT	NEURO	PS	CH	URO	ORT	CH	ORT	CH	CH	CH	CH	CTC	CTC
17	ENT	NEURO	PS	CH	URO	ORT	CH	ORT	GYN	CH	CAR	PS	CTC	CTC
18	NEURO	NEURO	PS	CH	URO	ORT	CH	ORT	GYN	CH	CH	PS	CTC	CTC
19	CH	NEURO	PS	CH	URO	CH	CH	CH	GYN	CH	CAR	CTC	CTC	CTC
20	X	X	X	X	X	X	X	X	X	X	X	X	X	X
21	X	X	X	X	X	X	X	X	X	X	X	X	X	X
22	NEURO	NEURO	CH	MA	URO	ORT	CH	ORT	GYN	CH	CH	CH	CTC	CTC
23	ENT	NEURO	PS	CH	CH	ORT	CH	ORT	GYN	GYN	CH	CH	CTC	CTC
24	ENT	NEURO	PS	CH	CH	CH	CH	ORT	GYN	CH	CH	CTC	CTC	CTC
25	ENT	NEURO	MDL	CH	CH	ORT	CH	ORT	GYN	CH	CH	CTC	CTC	CTC
26	NEURO	NEURO	PS	CH	URO	ORT	ORT	ORT	GYN	CH	CH	CH	CTC	CTC
27	X	X	X	X	X	X	X	X	X	X	X	X	X	X
28	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Figure J.3: MSS-25 after ALNS optimization with peak optimization

MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	CH	NEURO	MA	MA	CH	ORT	CH	ORT	CH	ORT	CH	CTC	CTC	CTC
2	ENT	NEURO	CH	CH	URO	CH	CH	ORT	GYN	ORT	CH	CH	CTC	CTC
3	ENT	NEURO	MDL	CH	URO	CH	ENT	CH	GYN	URO	CH	CH	CTC	CTC
4	NEURO	NEURO	NEURO	CH	CH	CH	PS	ORT	GYN	GYN	CH	CH	CTC	CTC
5	ENT	NEURO	PS	CH	URO	ORT	ORT	ORT	GYN	CH	CH	CH	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	CH	NEURO	NEURO	CH	URO	ORT	ORT	ORT	CH	ORT	CAR	CTC	CTC	CTC
9	ENT	CH	PS	CH	URO	CH	CH	CH	GYN	GYN	CH	CH	CTC	CTC
10	ENT	CH	PS	CH	CH	ORT	PS	ORT	GYN	CH	CAR	CTC	CTC	CTC
11	ENT	NEURO	CH	CH	URO	CH	CH	ORT	GYN	GYN	CH	CH	CTC	CTC
12	NEURO	NEURO	PS	CH	CH	CH	ENT	ORT	GYN	ORT	CH	PS	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	ENT	NEURO	CH	CH	URO	ORT	CH	ORT	CH	URO	CH	CTC	CTC	CTC
16	NEURO	SDC	OPT	CH	CH	PS	ORT	ORT	GYN	CH	CH	CH	CTC	CTC
17	ENT	NEURO	CH	CH	CH	CH	ENT	ORT	GYN	GYN	CH	PS	CTC	CTC
18	CH	NEURO	PS	CH	URO	ORT	ENT	ORT	GYN	ORT	CH	CTC	CTC	CTC
19	ENT	NEURO	CH	MA	URO	CH	ORT	ORT	CH	CH	CAR	CTC	CTC	CTC
20	X	X	X	X	X	X	X	X	X	X	X	X	X	X
21	X	X	X	X	X	X	X	X	X	X	X	X	X	X
22	CH	NEURO	CH	CH	URO	CH	ORT	ORT	GYN	URO	CAR	CH	CTC	CTC
23	NEURO	NEURO	PS	CH	URO	ORT	CH	ORT	GYN	CH	CH	PS	CTC	CTC
24	ENT	NEURO	PS	CH	URO	CH	PS	ORT	GYN	CH	CH	CH	CTC	CTC
25	ENT	NEURO	OPT	CH	URO	ORT	ORT	ORT	GYN	CH	CH	CTC	CTC	CTC
26	ENT	NEURO	PS	CH	CH	ORT	ORT	ORT	GYN	CH	CH	CTC	CTC	CTC
27	X	X	X	X	X	X	X	X	X	X	X	X	X	X
28	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Figure J.4: MSS-25 after ALNS optimization with range optimization

MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	ENT	NEURO	CH	MA	URO	ORT	CH	ORT	CH	URO	CH	CTC	CTC	CTC
2	ENT	NEURO	OPT	CH	URO	ORT	CH	ORT	GYN	CH	CH	CH	CTC	CTC
3	ENT	NEURO	PS	CH	CH	OPT	CH	CH	GYN	CH	CH	PS	CTC	CTC
4	ENT	NEURO	PS	CH	URO	ORT	ORT	ORT	GYN	CH	CH	PS	CTC	CTC
5	NEURO	NEURO	CH	CH	URO	ORT	ENT	ORT	GYN	GYN	CH	PS	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	CH	NEURO	CH	MA	URO	ORT	ORT	ORT	CH	ORT	CH	CTC	CTC	CTC
9	ENT	NEURO	PS	CH	URO	ORT	CH	ORT	GYN	CH	CH	CTC	CTC	CTC
10	ENT	NEURO	NEURO	CH	URO	ORT	ORT	ORT	CH	CH	CAR	CH	CTC	CTC
11	ENT	NEURO	PS	CH	CH	CH	CH	ORT	GYN	CH	CAR	PS	CTC	CTC
12	ENT	NEURO	CH	CH	URO	ORT	CH	ORT	GYN	CH	CAR	PS	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	CH	NEURO	CH	CH	URO	CH	CH	ORT	GYN	CH	CH	CTC	CTC	CTC
16	NEURO	NEURO	NEURO	CH	URO	CH	PS	ORT	CH	ORT	CH	CH	CTC	CTC
17	ENT	NEURO	CH	CH	URO	CH	MDL	CH	GYN	GYN	CH	CH	CTC	CTC
18	ENT	SDC	CH	MA	URO	ORT	ORT	ORT	GYN	GYN	CH	CTC	CTC	CTC
19	ENT	NEURO	CH	CH	CH	ORT	CH	ORT	GYN	URO	CH	CTC	CTC	CTC
20	X	X	X	X	X	X	X	X	X	X	X	X	X	X
21	X	X	X	X	X	X	X	X	X	X	X	X	X	X
22	ENT	CH	CH	CH	CH	ORT	CH	ORT	GYN	GYN	CH	CH	CTC	CTC
23	ENT	NEURO	PS	CH	URO	CH	CH	ORT	GYN	CH	CH	CH	CTC	CTC
24	NEURO	NEURO	PS	CH	URO	ORT	CH	ORT	GYN	CH	CAR	PS	CTC	CTC
25	ENT	NEURO	PS	CH	CH	ORT	CH	ORT	GYN	GYN	CH	CTC	CTC	CTC
26	ENT	NEURO	CH	CH	CH	ORT	ORT	ORT	CH	PS	CH	CTC	CTC	CTC
27	X	X	X	X	X	X	X	X	X	X	X	X	X	X
28	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Figure J.5: MSS-37 after ALNS optimization with peak optimization

MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	CH	NEURO	NEURO	CH	URO	PS	ORT	ORT	CH	URO	CH	CH	CTC	CTC
2	ENT	NEURO	MDL	CH	CH	PS	CH	ORT	GYN	GYN	CH	PS	CTC	CTC
3	ENT	NEURO	NEURO	CH	URO	PS	CH	ORT	GYN	ORT	CH	PS	CTC	CTC
4	ENT	NEURO	PS	CH	URO	CH	CH	ORT	GYN	GYN	CH	PS	CTC	CTC
5	NEURO	NEURO	PS	CH	URO	ORT	ENT	CH	CH	URO	CAR	CH	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	CH	NEURO	CH	CH	CH	ORT	ORT	ORT	CH	CH	CAR	CH	CTC	CTC
9	ENT	CH	CH	CH	URO	CH	CH	ORT	GYN	GYN	CH	CH	CTC	CTC
10	ENT	NEURO	CH	CH	CH	ORT	ORT	ORT	GYN	GYN	CH	CTC	CTC	CTC
11	ENT	NEURO	PS	CH	URO	OPT	ORT	ORT	GYN	CH	CAR	CH	CTC	CTC
12	ENT	CH	MA	CH	CH	ORT	ORT	ORT	GYN	GYN	CH	CTC	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	NEURO	CH	NEURO	CH	URO	ORT	ORT	ORT	CH	CH	CH	PS	CTC	CTC
16	NEURO	NEURO	PS	CH	URO	CH	ORT	ORT	GYN	CH	CAR	CH	CTC	CTC
17	ENT	NEURO	MA	CH	URO	ORT	ORT	ORT	GYN	CH	CH	CTC	CTC	CTC
18	CH	NEURO	NEURO	CH	CH	CH	ORT	ORT	GYN	CH	CH	CTC	CTC	CTC
19	ENT	NEURO	CH	CH	CH	PS	ORT	ORT	GYN	CH	CH	CTC	CTC	CTC
20	X	X	X	X	X	X	X	X	X	X	X	X	X	X
21	X	X	X	X	X	X	X	X	X	X	X	X	X	X
22	CH	NEURO	CH	CH	CH	CH	CH	ORT	GYN	CH	CH	CH	CTC	CTC
23	NEURO	NEURO	CH	CH	URO	OPT	ENT	ORT	CH	URO	CH	PS	CTC	CTC
24	ENT	PPA	MA	CH	CH	CH	CH	ORT	GYN	ORT	CH	PS	CTC	CTC
25	ENT	NEURO	CH	CH	URO	CH	ORT	ORT	GYN	CH	CAR	CTC	CTC	CTC
26	ENT	NEURO	CH	CH	URO	ORT	ENT	ORT	GYN	URO	CH	CTC	CTC	CTC
27	X	X	X	X	X	X	X	X	X	X	X	X	X	X
28	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Figure J.6: MSS-37 after ALNS optimization with range optimization

MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	ENT	NEURO	NEURO	CH	URO	NEURO	ORT	ORT	GYN	CH	CH	CH	CTC	CTC
2	ENT	CH	MA	CH	URO	ORT	PS	ORT	GYN	ORT	CH	PS	CTC	CTC
3	NEURO	NEURO	PS	CH	URO	PS	PS	CH	GYN	GYN	CH	PS	CTC	CTC
4	CH	NEURO	PS	CH	CH	CH	CH	ORT	CH	GYN	CH	CH	CTC	CTC
5	NEURO	NEURO	PS	CH	URO	ORT	ORT	ORT	GYN	GYN	CH	CH	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	ENT	NEURO	PS	CH	URO	CH	CH	ORT	CH	CH	CAR	CTC	CTC	CTC
9	ENT	NEURO	MA	CH	URO	ORT	ORT	ORT	CH	CH	CH	CTC	CTC	CTC
10	ENT	NEURO	MA	CH	URO	ORT	ENT	ORT	GYN	GYN	CH	CTC	CTC	CTC
11	ENT	CH	CH	CH	URO	ORT	ORT	ORT	CH	GYN	CAR	PS	CTC	CTC
12	ENT	NEURO	OPT	CH	CH	ORT	ORT	ORT	CH	CH	CAR	CH	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	ENT	NEURO	PS	CH	URO	ORT	ORT	ORT	CH	ORT	CH	CTC	CTC	CTC
16	ENT	NEURO	PS	CH	URO	ORT	CH	ORT	CH	URO	CH	PS	CTC	CTC
17	ENT	NEURO	PS	CH	URO	ORT	CH	ORT	GYN	CH	CAR	CTC	CTC	CTC
18	ENT	NEURO	CH	CH	URO	ORT	CH	ORT	GYN	GYN	CH	CH	CTC	CTC
19	CH	NEURO	NEURO	CH	URO	OPT	CH	ORT	GYN	CH	CH	CH	CTC	CTC
20	X	X	X	X	X	X	X	X	X	X	X	X	X	X
21	X	X	X	X	X	X	X	X	X	X	X	X	X	X
22	ENT	NEURO	CH	CH	URO	CH	ENT	ORT	GYN	GYN	CH	PS	CTC	CTC
23	NEURO	NEURO	CH	CH	URO	ORT	ORT	ORT	CH	CH	CH	CH	CTC	CTC
24	ENT	CH	PS	CH	CH	ORT	CH	ORT	GYN	CH	CAR	CTC	CTC	CTC
25	ENT	NEURO	MDL	CH	CH	CH	CH	ORT	CH	CH	CH	CH	CTC	CTC
26	NEURO	SDC	NEURO	CH	CH	ORT	CH	ORT	GYN	CH	CH	CTC	CTC	CTC
27	X	X	X	X	X	X	X	X	X	X	X	X	X	X
28	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Figure J.7: MSS-45 after ALNS optimization with peak optimization

MSS	AOK1	AOK2	AOK4	AOK5	AOK6	AOK7	AOK8	AOK9	OK10	OK11	OK12	OK13	OK14	OK15
1	ENT	NEURO	MA	CH	URO	NEURO	CH	ORT	CH	CH	CH	CTC	CTC	CTC
2	ENT	NEURO	CH	CH	CH	ORT	PS	ORT	GYN	ORT	CAR	CH	CTC	CTC
3	ENT	NEURO	MA	CH	URO	ORT	ORT	ORT	CH	CH	CH	PS	CTC	CTC
4	ENT	NEURO	OPT	CH	URO	CH	ORT	ORT	GYN	GYN	CAR	CTC	CTC	CTC
5	ENT	NEURO	CH	CH	URO	ORT	ORT	ORT	GYN	CH	CH	CH	CTC	CTC
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	ENT	NEURO	PS	CH	URO	ORT	ORT	ORT	CH	CH	CAR	CH	CTC	CTC
9	ENT	CH	CH	CH	URO	CH	ENT	ORT	GYN	ORT	CH	CTC	CTC	CTC
10	ENT	NEURO	MA	CH	URO	CH	PS	ORT	CH	CH	CAR	CH	CTC	CTC
11	ENT	NEURO	NEURO	CH	URO	NEURO	CH	ORT	GYN	CH	CH	PS	CTC	CTC
12	CH	NEURO	CH	CH	URO	ORT	PS	ORT	CH	GYN	CH	CTC	CTC	CTC
13	X	X	X	X	X	X	X	X	X	X	X	X	X	X
14	X	X	X	X	X	X	X	X	X	X	X	X	X	X
15	NEURO	NEURO	CH	CH	URO	ORT	ORT	ORT	CH	URO	CH	CH	CTC	CTC
16	ENT	CH	PS	CH	URO	CH	ENT	ORT	GYN	URO	CAR	CH	CTC	CTC
17	NEURO	SDC	PS	CH	URO	CH	ENT	ORT	GYN	GYN	CH	CH	CTC	CTC
18	CH	NEURO	PS	CH	CH	ORT	ORT	ORT	GYN	CH	CH	CTC	CTC	CTC
19	NEURO	NEURO	CH	CH	CH	ORT	ORT	ORT	GYN	CH	CH	CTC	CTC	CTC
20	X	X	X	X	X	X	X	X	X	X	X	X	X	X
21	X	X	X	X	X	X	X	X	X	X	X	X	X	X
22	NEURO	NEURO	MDL	CH	CH	ORT	CH	ORT	CH	CH	CH	CH	CTC	CTC
23	ENT	NEURO	OPT	CH	URO	PS	CH	ORT	GYN	CH	CH	CTC	CTC	CTC
24	CH	NEURO	CH	CH	CH	CH	ORT	ORT	GYN	GYN	CH	PS	CTC	CTC
25	ENT	CH	PS	CH	CH	PS	ENT	ORT	GYN	GYN	CH	PS	CTC	CTC
26	NEURO	NEURO	PS	CH	URO	ORT	CH	ORT	GYN	CH	CH	PS	CTC	CTC
27	X	X	X	X	X	X	X	X	X	X	X	X	X	X
28	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Figure J.8: MSS-45 after ALNS optimization with range optimization

Appendix K

Output Parameters before and after ALNS procedure

MSS-5				
Before ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	219,70	11,21	198	235
4th Occupation	126,70	8,95	108	137
5th Occupation	93,00	2,94	87	99
4th Admission	37,75	2,55	33	42
5th Admission	22,90	1,25	21	25
Discharge 4th	38,00	6,07	27	43
Discharge 5th	23,35	3,45	17	28
After ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	220,15	10,39	198	231
4th Occupation	126,76	7,88	110	135
5th Occupation	92,76	2,96	86	96
4th Admission	37,86	3,01	32	43
5th Admission	22,76	1,15	21	25
Discharge 4th	37,67	6,18	26	44
Discharge 5th	23,19	3,62	17	28

(a) ALNS peak optimization

MSS-5				
Before ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	219,70	11,21	198	235
4th Occupation	126,70	8,95	108	137
5th Occupation	93,00	2,94	87	99
4th Admission	37,75	2,55	33	42
5th Admission	22,90	1,25	21	25
Discharge 4th	38,00	6,07	27	43
Discharge 5th	23,35	3,45	17	28
After ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	220,65	8,74	203	232
4th Occupation	127,05	6,39	115	135
5th Occupation	92,95	3,21	88	97
4th Admission	37,95	2,33	34	41
5th Admission	22,90	1,53	20	27
Discharge 4th	37,81	5,99	27	44
Discharge 5th	23,05	3,48	17	28

(b) ALNS range optimization

Figure K.1: MSS-5 before and after ALNS optimization

MSS-25				
Before ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,30	9,96	201	234
4th Occupation	127,65	8,24	111	137
5th Occupation	93,65	2,46	88	98
4th Admission	37,80	2,65	33	42
5th Admission	23,00	1,49	21	26
Discharge 4th	38,15	6,04	27	43
Discharge 5th	23,35	3,47	17	28
After ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,55	10,60	199	233
4th Occupation	127,67	8,26	110	135
5th Occupation	93,29	3,03	86	98
4th Admission	37,71	3,05	32	42
5th Admission	22,95	1,29	21	25
Discharge 4th	37,76	6,11	27	44
Discharge 5th	23,14	3,61	17	28

(a) ALNS peak optimization

MSS-25				
Before ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,30	9,96	201	234
4th Occupation	127,65	8,24	111	137
5th Occupation	93,65	2,46	88	98
4th Admission	37,80	2,65	33	42
5th Admission	23,00	1,49	21	26
Discharge 4th	38,15	6,04	27	43
Discharge 5th	23,35	3,47	17	28
After ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	220,70	8,65	204	231
4th Occupation	126,95	6,75	114	134
5th Occupation	93,00	2,65	88	97
4th Admission	37,81	3,18	32	43
5th Admission	22,76	1,80	20	27
Discharge 4th	37,67	5,97	27	44
Discharge 5th	22,95	3,51	17	29

(b) ALNS range optimization

Figure K.2: MSS-25 before and after ALNS optimization

MSS-37				
Before ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,05	9,94	201	233
4th Occupation	127,70	8,13	110	135
5th Occupation	93,35	2,46	88	98
4th Admission	37,90	2,83	33	42
5th Admission	22,80	1,32	21	25
Discharge 4th	38,15	6,06	27	44
Discharge 5th	23,05	3,44	17	28
After ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	220,90	10,20	197	232
4th Occupation	127,38	6,56	113	133
5th Occupation	92,95	4,42	84	99
4th Admission	37,81	2,94	33	42
5th Admission	22,76	1,68	20	27
Discharge 4th	37,57	5,86	27	43
Discharge 5th	22,95	3,63	17	28

(a) ALNS peak optimization

MSS-37				
Before ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,05	9,94	201	233
4th Occupation	127,70	8,13	110	135
5th Occupation	93,35	2,46	88	98
4th Admission	37,90	2,83	33	42
5th Admission	22,80	1,32	21	25
Discharge 4th	38,15	6,06	27	44
Discharge 5th	23,05	3,44	17	28
After ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,45	8,94	204	233
4th Occupation	127,33	6,60	114	135
5th Occupation	93,52	3,57	89	99
4th Admission	37,71	2,72	33	44
5th Admission	23,00	1,88	19	26
Discharge 4th	37,62	5,65	27	44
Discharge 5th	23,24	3,72	17	28

(b) ALNS range optimization

Figure K.3: MSS-37 before and after ALNS optimization

MSS-45				
Before ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,45	10,24	201	234
4th Occupation	127,80	8,55	111	137
5th Occupation	93,65	2,46	88	98
4th Admission	37,70	2,79	33	42
5th Admission	22,95	1,50	21	26
Discharge 4th	38,20	6,07	27	43
Discharge 5th	23,35	3,47	17	28
After ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,80	10,30	195	231
4th Occupation	127,71	8,28	108	135
5th Occupation	93,62	2,60	87	96
4th Admission	37,76	3,58	32	42
5th Admission	23,14	1,64	20	27
Discharge 4th	37,95	6,20	27	46
Discharge 5th	23,00	3,37	17	26

(a) ALNS peak optimization

MSS-45				
Before ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,45	10,24	201	234
4th Occupation	127,80	8,55	111	137
5th Occupation	93,65	2,46	88	98
4th Admission	37,70	2,79	33	42
5th Admission	22,95	1,50	21	26
Discharge 4th	38,20	6,07	27	43
Discharge 5th	23,35	3,47	17	28
After ALNS	**Average**	**Std.Dev**	**Min**	**Max**
Total	221,35	8,93	203	233
4th Occupation	127,05	6,79	114	135
5th Occupation	93,52	3,10	89	99
4th Admission	37,62	2,52	34	42
5th Admission	23,00	1,74	19	26
Discharge 4th	37,67	5,84	27	45
Discharge 5th	23,29	3,69	17	29

(b) ALNS range optimization

Figure K.4: MSS-45 before and after ALNS optimization