BACHELOR ASSIGNMENT

PREDICTING THE LENGTH OF STAY OF DAY CARE PATIENTS IN MEDISCH SPECTRUM TWENTE

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Management summary

In 2016 Medisch Spectrum Twente (MST) hospital will move to a new hospital building. The number of nursing beds at the new location is substantially reduced compared to the current site. In order to be able to house all patients with fewer beds, MST will gradually decrease its general bed capacity in the next few years.

A substantial reduction is expected for the day care and short stay ward, further referred to as day care ward. During daytime the average bed utilization of this ward is around 65 percent. By increasing this utilization the required bed capacity decreases, which could be realized by using a more efficient surgical scheduling method. Therefore, the post-surgery length of stay on the ward must be predictable. Because this is currently not the case, the goal of this project is to formulate a prediction model.

The majority of the literature on factors determining the length of stay only concerns medium and long stay inpatients, measuring the length of stay in the number of days. Martin & Smith (1996) provide an overview for this. Junger et al. (2001) studied the length of stay at the post anesthetic care unit for day care patients. We expected a major part of the factors of both studies are the same for the post-surgery length of stay of day care patients. We examined all factors derived from the literature whereof the data was available within MST. The studied period is from November 2012 until October 2013, resulting in 1997 surgeries after filtering out the unreliable and non-relevant data.

We use an univariate general linear model. Surgery type, surgery time, patient's gender and the number of surgeries performed per surgeon in the studied period were found as significant in predicting the post-surgery length of stay on the ward. Among others, anesthesia type, patient's age and planned surgery duration were found not significant. The fraction of explained variance is 0.212. The model predicts average values of the post-surgery length of stay on the ward well, but overestimates for values less than two and underestimate for values greater than four.

Our prediction model can be used in the surgical scheduling to take the bed utilization of the day care and short stay ward into account. The most accurate way is to implement the prediction model into the surgical scheduling software. However, this is not likely to be realizable within a short time period. Therefore we computed a table which provides for each combination of surgery type and gender the average predicted post-surgery length of stay and a 85%-prediction interval. Although it is difficult to estimate, we expect a bed capacity reduction of 48 percent when this approach is implemented, resulting in 17 beds needed instead of the current 33 at the day care and short stay ward.

We recommend a pilot period of three months wereby the post-surgery length of stay on the ward will be taken into account into the surgical scheduling. During this period, the surgical planning department and the day care ward both pretend as if there are 17 beds at the ward, using the remaining beds only if necessary.

Management samenvatting

In 2016 verhuist Medisch Spectrum Twente (MST) naar een nieuw gebouw. Het aantal bedden op de nieuwe locatie is aanzienlijk minder dan op de huidige locatie. Om met een gelijk aantal patiënten toch met minder bedden toe te kunnen, zal MST de komende jaren geleidelijk haar bedcapaciteit verminderen.

Verwacht wordt dat een aanzienlijke vermindering gerealiseerd kan worden voor de dagopname- en kort-verblijfafdeling. Op werkdagen is de gemiddelde bedbezetting overdag ongeveer 65 procent. Door het verhogen van de bedbezetting zal de benodigde bedcapaciteit logischerwijs afnemen. Dit kan gerealiseerd worden middels een efficiëntere manier voor het plannen van operaties. Hiervoor moet de post-operatieve ligduur op de afdeling voorspelbaar zijn. Omdat dit op dit moment niet het geval is, formuleren we een voorspellingsmodel hiervoor.

Het grootste deel van de literatuur over factoren die de ligduur bepalen gaat over middellange en langdurende klinische opnames, met de ligduur gemeten in dagen. Martin & Smith (1996) geven een overzicht daarvan. Junger et al. (2001) onderzochten de ligduur van dagbehandelingen op de *Post Anesthesia Care Unit*. We verwachten dat de factoren die de ligduur van dagbehandelingen bepalen voor een groot deel overeenkomen met de factoren uit de genoemde onderzoeken. We onderzoeken alle factoren uit de bovenstaande studies waarvan de data beschikbaar was in MST. De meegenomen dagbehandelingen vonden plaats in de periode november 2012 tot en met oktober 2013. Dit resulteerde in 1997 operaties nadat de onbetrouwbare en irrelevanta data eruit gefilterd waren.

We gebruiken een univariaat algemeen linair model. Operatietype, geslacht van de patiënt, operatietijdstip en het jaarlijks aantal uitgevoerde operaties door de desbetreffende chirurg bleken significant in het voorspellen van de post-operatieve ligduur op de verpleegafdeling. Onder andere anesthesievorm, leeftjid van de patient en geplande operatieduur bleken niet significant. De fractie verklaarde variantie is 0.212. Het model voorspelt gemiddelde waardes goed, maar overschat waardes kleiner dan twee en onderschat een ligduur langer dan vier uur.

Ons voorspellingsmodel kan gebruikt worden bij het plannen van operaties waardoor er rekening gehouden kan worden met de bedbezetting van de dagopname en kort-verblijf afdeling. De meest nauwkeurig manier is om het model te implementeren in de software voor het plannen van operaties. Dit is echter niet realiseerbaar op korte termijn. Daarom hebben we een tabel gemaakt dat voor iedere combinatie van operatietype en geslacht van de patiënt de gemiddelde voorspelde post-operatieve ligduur op de afdeling weergeeft. Daarnaast is er een 85%-voorspellingsinterval gegeven. We verwachten een vermindering van de benodigde bedcapaciteit van 48 procent als deze aanpak wordt geïmplementeerd, ondanks dat dit resultaat op voorhand moeilijk te schatten is. Er zullen dan naar verwachting 17 bedden nodig zijn in plaats van de huidige 33 bedden.

We bevelen een proefperiode aan van drie maanden waarbij de voorspelde post-operatieve ligduur op de afdeling wordt gebruikt bij het plannen van operaties. In deze periode doet zowel bureau Opname als de dagopvang en kort-verblijf afdeling alsof er slechts 17 bedden zijn, waarbij de resterende bedden alleen gebruikt worden indien het strikt noodzakelijk is.

Table of contents

Abbreviations

ARIMA	Autoregressive integrated moving average
ASA	American Society of Anesthesiologists
BMI	Body Mass Index
DC & ST	Day Care and Short Stay
ENT	Ear, Nose & Throat (surgery)
LASSO	Least Absolute Shrinkage and Selection Operator
LoS	Length of Stay
MA	Moving Average
MPSM	Management Problem Solving Method
MSS	Master Surgical Schedule
MST	Medisch Spectrum Twente
OR	Operating Room
PACU	Post Anesthetic Care Unit
PONV	Postoperative nausea and vomiting
PSLoSoW	Post Surgery Length of Stay on Ward

Preface

It took some time, but I am glad to present to you this research thesis which I wrote in the context of the completion of the bachelor study Industrial Engineering & Management at the University of Twente. As expected, the research study went not without struggle. I spent more time than planned on literature research, reading irrelevant articles. Furthermore, my tendency to perfectionism might improve the final results, but makes the process of achieving it more difficult.

I would like to thank Ingrid Vliegen and Irma de Vries for guiding me through the bachelor assignment and providing advices to improve my knowledge and skills. Furthermore, I would like to thank Alphons Vlierman who answered a lot of questions I had concerning the way of working at the nurse ward I studied.

This thesis is about formulating a prediction model for the length of stay after surgery of day care patients of Medisch Spectrum Twente hospital located in Enschede. I end this preface with for me an identifiable quote of Albert Einstein what I read beforehand. I am too stubborn to consider it true. While reading this thesis you may decide whether or not that was sensible of me.

“When the number of factors coming into play in a phenomenological complex is too large scientific method in most cases fails. One need only think of the weather, in which case the prediction even for a few days ahead is impossible.”

— Albert Einstein

Enschede, January 2013,

Nienke Gietema

1 Introduction

Healthcare costs in the Netherlands rise every year (CBS Statline, 2013). The percentage of the gross domestic product spent on healthcare is one of the highest in the world (WHO, 2013).These high costs led to a critical look at the current processes in healthcare. For example, in the past a clinical stay was financial more rewarding for Dutch hospitals than day surgery for the same procedure. Since 2004, this has changed resulting in more operations performed as day surgeries (Wasowicz-Kemps, 2008). Furthermore, due to improved or new technologies and treatments more surgeries can be performed as day surgery instead of a clinical admission (CBS Statline, 2013). Beside, efficient and effective use of the bed capacity is nowadays a key concern for hospitals (Harper & Shahani, 2002). This also applies for day admissions. However, bed capacity is often determined by simple spreadsheet-based calculations that are not very accurate (Marshall, Vasilakis, & El-Darzi, 2005).

In this research we study the bed capacity and the length of stay after surgery of day care and short stay patients. This introductory chapter first describes the context of the research in Section 1.1, then formulates the problem identification in Section 1.2, followed by the problem definition and relevant research questions in Section 0. The chapter ends with a description of the methodology used and the structure of the remaining chapters in Section 1.4.

1.1 Medisch Spectrum Twente

Top clinical care is highly specialized care that requires relatively expensive facilities such as cardiac and neurological surgery. In the Netherlands, 28 hospitals provide this top clinical care. With about 3700 employees, 1000 nursing beds, and around 32.000 clinical admissions Medisch Spectrum Twente (MST) in Enschede is one of the largest of these hospitals (Jaarimpressie MST, 2012).

In 2016 MST will move to a new hospital building currently being built. The number of nursing beds at the new location is substantially reduced compared to the current site. This raises the need for a more efficient way of working. In order to be able to house all patients with fewer beds MST will gradually decrease its bed capacity in the next few years.

To keep the research manageable in the limited time available, we focus on how to reduce the needed bed capacity of the day care and short stay department of MST. We concentrate on this department since we expect that a substantial bed capacity reduction can be realized here.

1.2 Problem identification

MST treats about 32.000 day care patients per year with a major part being cared for in the day care and short stay department. In the current situation there are 33 beds on this ward. Most of the time one patient per day per bed is scheduled. Nonetheless, at another ward in MST with day admissions and some other day care wards in the Netherlands (B.J. Dekker, Onze Lieve Vrouw Gasthuis) they can use a bed twice or more per day resulting in a lower number of beds needed. This gives rise to study the bed utilization of the day care and short stay department in MST. Figure 1 shows the average utilization per hour on working days for this department. During daytime the average bed utilization is around 65 percent. Bruin (2007) found that the desired bed utilization of wards with 30-40 beds is around 85 percent. However, it is questionable if this also applies to wards with day admissions.

By increasing the utilization the needed bed capacity decreases. This can be realized by decreasing the length of stay or by using a more efficient patient planning method. The first is a rather departmental focus whereas the second requires a fundamental approach that may be applied throughout the whole organization. Therefore MST prefers a study to patient planning.

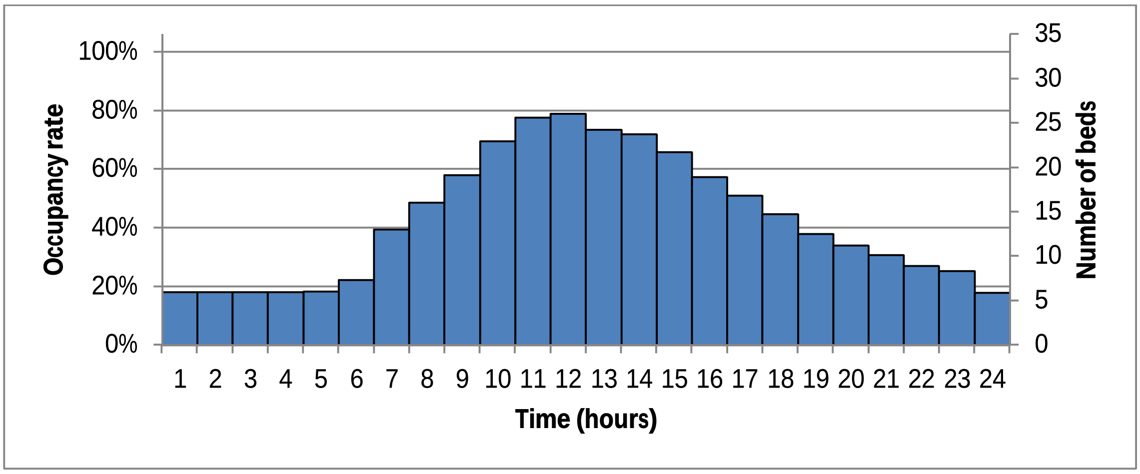


Figure 1.1Average bed utilization per hour on working days
(September & October 2013, 997 admissions, ward registration database X-Care)

The current day care patient planning method is purely based on the operating room department and does not allow for the length of stay on the ward afterwards. In order to be able to house more than one patient per bed per day this should be taken into account to avoid an overlapping hospital stay of consecutive patients.

1.3 Research objective & questions

As described above, the purpose of this study is to reduce the needed bed capacity through occupying the beds at the day care department twice when possible. The needed bed capacity for day admissions halves if it is possible to schedule consecutively two day care patients per bed per day instead of one. The day care admissions account for about 80 percent of the hospital admissions of the studied department, with on average 18-19 day admissions per day. Therefore the needed bed capacity of the day care and short stay department theoretically may be reduced to 10 when in all cases two day care patients per day per bed can be scheduled. However, it is questionable whether this reduction can be realized in practice.

In order to occupy the beds of the day care ward twice the length of stay after surgery must be predictable. We can use the length of stay as input for surgical scheduling in such a way that the recovery time at the ward of two consecutive patients will not overlap.

Unfortunately, the prediction of length of stay after surgery is not straightforward. The length of stay of day care patients is currently not taken into account in the surgical planning process of MST. Surgical and ward data are stored in different data systems. Hereby there is limited understanding of the length of stay after surgery of day care patients besides a sure instinct of the ward nurses. Hence, we first have to design a prediction model for the length of stay after surgery. We therefore formulate the following research questions:

How can the length of stay after surgery of day care and short stay patients of the hospital Medisch Spectrum Twente be predicted and what is the expected reduction of bed capacity of the corresponding ward when this is taken into account in the surgical planning process?

I. Which factors significantly influence the length of stay after surgery?
II. How to predict the length of stay after surgery based on the influencing factors?
III. In what way can the expected length of stay after surgery be used in the surgical planning process in order to increase the bed utilization of the ward?
IV. What is the expected reduction in bed capacity when the changes in the surgical planning process will be implemented?

We focus on the first two research questions and investigate the last two research question in less detail. The remaining section of this chapter describes the methodology used to answer the stated problem definition and research questions and outlines briefly the content of the rest of the report.

1.4 Methodology and structure of the report

In order to do structured research we use the Management Problem Solving Method (MPSM) (Heerkens & Winden, 2012). The MPSM is a common sense based, generally applicable and systematic approach taking into account the context of the organization in order to generate solutions that fit the company. The main steps are identification of problems, analysis of the core problem, design solutions, implementation of the chosen solution and evaluation of the results.

The problem identification is already set out in this introductory chapter. In Chapter 1 we describe the processes concerning surgical admissions in order to place the study in context. We outline the relevant literature regarding bed capacity and forecasting the length of stay in Chapter **Error! Reference source not found.**. Then, in Chapter 4, we examine the relevant factors determining the length of stay after surgery and formulate a prediction model for this. In Chapter 5, we generate adjustments in the surgical scheduling process based on the prediction model and we calculate the expected reduction in bed capacity. Chapter 6 is devoted to the future implementation of the planning adjustments. We omit the evaluation step of the MPSM because the adjustments are not implemented yet. The report ends with a conclusion and discussion of the study and some recommendations to further improve the bed utilization of the day care and short stay ward.

2 Patient flow processes

In the previous chapter we explained the purpose of this research study being to investigate if it is possible to occupy a bed twice a day at the day care and short stay ward. This chapter describes the processes concerning surgical day and short stay admissions to provide insight into the current state of affairs within the hospital MST. In Section 2.1 we describe the case mix of the day care and short stay department. Figure 2.1 shows the patient flow process that we explain in the subsequent sections. In Section 2.2 we describe the preoperative process, followed by the admission process in Section 2.3. The chapter ends with a description of the recovery process in Section 2.4. Appendix 1 shows these processes more detailed.

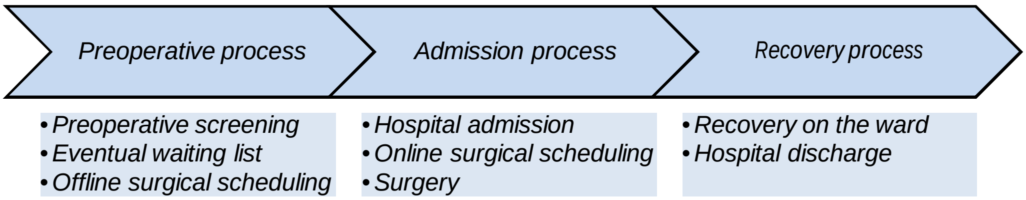


Figure 2.1 Patient flow process

2.1 Case mix

The day care and short stay (DC & ST) ward hospitalized about 4600 admissions in the period from November 2012 until October 2013. Approximately 78 percent of the admissions are day admissions. Table 2.1 shows the relative admission frequency per specialty; general surgery, orthopedic surgery and plastic surgery are the major specialties making use of the DC & ST ward.

Table 2.1 Admission frequency per specialty for the DC & ST ward
(November 2012 – October 2013, 4719 admissions, ward registration database X-Care)

Specialty	***Relative frequency (%)***
General surgery	43
Orthopedic surgery	27
Plastic surgery	12
Oral surgery	5
Ophthalmologic surgery	3
Neurological surgery	7
Other specialties	4

Error! Reference source not found. shows that most of the patients are in the age between 21 and 70. Children are normally cared for at a pediatric ward, but there are some exceptional cases in which they are cared for at the DC & ST ward.

Figure 2.2 Admission frequencies per year of the day care and short stay ward

(November 2012 – October 2013, 4719 admissions, ward registration database X-Care)

MST follows guidelines to decide whether a patient can be treated in day of short stay admission. For this, they make use of the American Society of Anesthesiologists (ASA) Physical Status Classification System. This system classifies patients into one of the five categories according to their physical condition (ASA Physical Status Classification System - American Society of Anesthesiologists, 2013). A normal healthy patient falls within ASA I whereas a declared brain-dead patient belongs to ASA V. Appendix 2 shows the ASA classification system in further detail. MST carries out day-treatments for patients with ASA I and II, because no complications during surgery and recovery are expected which is an indication for a longer length of stay. Nevertheless, there are exceptions whereby an ASA III-patient may undergo day care surgery. Table 2.2 shows the relative frequencies of the ASA status of patients cared for at the DC & ST ward.

Table 2.2 Relative frequencies of ASA status of patients at the DC & ST ward
(April 2013 – October 2013, 526 clinical admissions, 1791 day admissions,
ward registration database X-Care & anesthesia registration database Metavision)

Patient's ASA Status	***Day admissions***	***Clinical admissions***
ASA I	63%	53%
ASA II	36%	46%
ASA III	1%	1%

2.2 Preoperative process

The process starts when during an outpatient appointment the specialist decides that surgery is needed. In this case the patient goes to the preoperative screening where the anesthetist looks at the medical history and health status of the patient. Thereupon the majority of the clinical patients have to visit a nurse who provides additional information about the hospital admission, surgery and aftercare (Opname - MST, 2013). After the screening, the surgery can be planned. For ear, nose & throat (ENT) and orthopedic surgery, patients may make an appointment for surgery at the surgical planning department right after the screening, but in most cases the planning department calls the patient later on.

The period between the preoperative screening and surgery depends on the waiting list per surgery type. The current waiting time is short for the specialties ENT, gynecology, neurosurgery and general surgery. As a consequence, the planning department currently does not use a master surgical schedule (MSS) which have been used in the past (Apenhorst, 2010). The MSS ensures that all patients receive a surgery date right after the preoperative screening. This is useful for patients as well for the hospital itself, because the MSS allows for leveling the bed occupation through a cyclic scheme with fixed times for the different surgery types (Van Berkel, et al., 2011). Hereby the bed utilization increases. MST wants to use a MSS again when waiting lists are larger or when they are able to still efficiently schedule surgeries when waiting lists are small. The next section describes how the planning department currently schedules the surgeries.

2.2.1 Offline surgical scheduling

The planning department uses the software OR-Suite for offline surgical scheduling which is done based on historic data. In general, the average surgery duration of the surgeries of the last three months of the particular surgery type is taken as the required length of the next one. However, surgeons can inform the planning department about individual deviating surgery durations which will be taken into account in order to schedule more accurately. Once a week the planning department discusses the surgical schedule for the upcoming week with the operating coordinator of the operating room (OR) department to ensure realistically planned surgery durations.

Besides the historic data the planning department uses a fixed four weekly block scheme showing the allocated OR time to the specialties for the eleven operating rooms. One OR is mainly reserved for emergencies. However, there is no operating room dedicated to day care surgery. Therefore, the day care surgeries are scheduled between clinical surgeries in the ten remaining operating theaters.

In a quarterly meeting between the planning department and the surgeons the staff planning of the specialists is discussed. Therefore the schedulers know at what particular times certain surgeries may be planned. Every week the planning department and the surgeons discuss the personnel planning and surgery schedule in order to identify trends and adjust for particularities.

Due to urgent surgeries and emergencies the surgery schedule may change up to one day in advance. The surgery duration of day care surgeries is generally shorter compared to clinical surgeries. Therefore, day care surgeries are regularly used to fill last minute gaps in the schedule. This results in an unbalanced number of day care surgeries throughout the week. Therefore, the variability of the number of day care surgeries increases and the needed bed capacity at the DC & ST ward becomes more irregular (Hopp & Spearman, 2001). This irregularity is exacerbated through the decentralized way of scheduling. Each specialty has its own scheduler and there is limited communication between them. Chapter 3.4 describes the influence of OR scheduling on the ward in more detail. Because of the ad hoc scheduling the nurse informs the patient one day before surgery about the actually planned hospital admission and surgery times.

2.3 Hospital admission

In this section we describe the process of hospital admission. Figure A1.2 of Appendix 1 shows this process more detailed. On the day of admission the patient reports to the front desk of the ward two hours before the planned surgery or 45 minutes before if it is the first surgery of the day in the corresponding OR. A nurse assigns a bed to the patient according to the bed planning manually made the day before. Thereafter the nurse checks if the patient meets the conditions to undergo surgery such as being sober and not having fever. If not, there will be examined if the surgery still can be done later that day; otherwise the surgery needs to be rescheduled. In the positive case, the nurse reports to the OR department that the patient is ready for surgery. When ready, the OR department reports to the ward that the patient may come to the holding for anesthesia. After surgery the patient stays at the recovery room as long as necessary. The nurse transports the patient to the ward after a call from the OR department that the patient is sufficiently recovered to be further cared for on the ward. Due to the variability of surgery durations the surgical schedule regularly needs to be adjusted.

2.3.1 Online surgical scheduling

The day coordinator of the OR department adjust the OR schedule in such a way that as much surgeries as possible can take place within regular working hours (8:00-16:00). Therefore surgeries may be rescheduled to another operating room or deferred to another day if the prior surgery is delayed. The day coordinator changes the sequence of surgeries when not properly scheduled by the planning department. Usually day surgeries are planned in the morning. An exception is made when block anesthesia is needed. This anesthesia type relatively takes a long time to perform. Therefore, surgeons have to wait longer before they can start operating. The anesthesia of the second surgery can be done in parallel with the first surgery. It is thus preferred to start with a surgery with a anesthesia type that can be quickly performed.

In order to ensure a bed for every patient the ward managers discuss the expected bed utilization every morning. Patients could be cared for at another ward if a shortage of bed capacity of the initial ward is expected.

2.4 Recovery process

The discharge criteria are different for day and clinical admissions. A day care patient will be discharged by the nurses when the patient meets certain criteria such as a normal body temperature and appetite. A clinical patient will be discharged only by the surgeon who makes his ward round every morning. When a clinical patient is not discharged during the ward round he/she has to stay until the next ward round of the surgeon the next day.

3 Theoretical framework

In this chapter we discuss the literature concerning modeling the length of stay (LoS) in order to provide us with the knowledge and tools to formulate a prediction model for the length of stay of day care and short stay patients. First we place the study in context in Section **Error! Reference source not found.**, followed by a description of factors influencing the length of hospital stay in Section 3.2. Thereafter, we describe several patient flow models in order to determine the required bed capacity in Section 3.3, ending the chapter with literature concerning operating room scheduling with leveling ward capacity in Section 3.4.

3.1 Research field

Hans, van Houdenhoven, & Hulshof (2012) provide a framework for healthcare planning and control that distinguishes four hierarchical levels and four managerial areas. Figure 3.1 shows that bed capacity planning falls within resource capacity planning. MST already determined the aggregated bed capacity for the new hospital building and therefore the bed capacity at strategic level. The tactical level includes the bed capacity per ward and the planning of gradually bed reduction whereas the surgical scheduling belongs to the offline operational level. This study examines how to predict the length of stay of day care and short stay patients in order to use it in the surgical scheduling process. This presumably reduced the needed bed capacity of the related ward. Therefore this research falls within the offline operational level of resource capacity planning of the hospital. It is a bottom up approach to improve the determined bed capacity at tactical level.

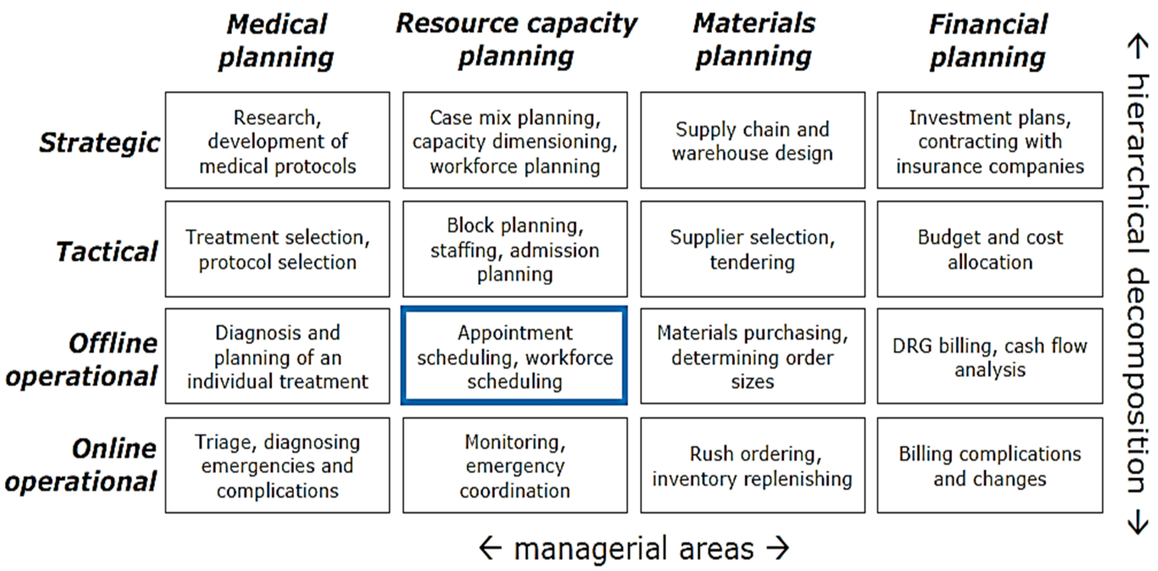


Figure 3.1 Example application of the framework for healthcare planning and control to a general hospital according to Hans et al. (2012)

3.2 Factors influencing the length of stay

The majority of literature on factors determining the length of stay concerns medium and long stay inpatients, measuring the LoS in days. Although our research focuses on day care patients we discuss the significant factors related to this inpatient LoS, because we expect that a major part of the factors are the same. Martin & Smith (1996) provide an overview of determinants of the LoS, which can be divided into two categories: patient characteristics and hospital characteristics, see Table 3.1. Chen & Naylor (1994) studied the length of stay for acute heart attack in 187 Canadian hospitals and found that patient characteristics explain only twelve percent of the variation of the LoS.

Table 3.1 Determinants of length of stay according to Martin & Smith (1996)

Factors related to patient characteristics	***Factors related to hospital characteristics***
Age	Hospital characteristics
Severity of illness	Workload of staff
Socio-economic status	Surgeon characteristics
Type of admission (emergency or elective)	Waiting list

In contrast to the literature concerning medium stay inpatient LoS, Junger et al. (2001) researched factors influencing the length of stay in the post anesthetic care unit (PACU) of day care patients and their eventually unanticipated admission to the ward. They differentiate in factors related to patient characteristics, anesthesia, surgery, and factors related to logistics and organization. Gender and age are significant factors for unanticipated admission and therefore for the length of stay. Body mass index (BMI) and American Society of Anesthesiologists (ASA) physical status do not significant influence the length of postoperative stay. This may be due to the majority of the studied patients having an ASA status I or II and only a small part has an ASA-III status or higher. Factors related to anesthesia that have a significant impact on the length of postoperative stay are the type of anesthesia, used drugs for anesthesia and postoperative nausea and vomiting (PONV). With respect to surgery characteristics the surgery duration, intraoperative blood loss, intraoperative hemoglobin concentration and the volume of infused colloids and crystalloids are the most influencing factors predicting the length of stay. Factors related to logistics and organization that have a significant impact are preoperative waiting time and the time of day of admission to the day-care unit.

The studies discussed by Martin & Smith (1996) and the study of Junger et al. (2001) do not exactly match our research to the length of stay of day care patients. However, they provide a valuable insight in which factors might be relevant for our prediction model.

3.3 Modeling length of hospital stay

In the previous chapter we described the day care and short stay patient flow through the hospital. Patient flow models describe the movement of (groups) of patient throughout the hospital. Hereby, the durations of medical tests and admission to the ward can be determined. Therefore, patient flows are commonly used to model the length of hospital stay. Harper & Shahani (2002) state that patient flow models are generally based on Markov chain models, queueing models, integer programming, forecasting or simulation techniques. In this section we therefore describe these approaches. Marshall, et al. (2005) describe the common approaches for Markov chain models, queuing models and simulation regarding patient flows which we summarize in respectively Section **Error! Reference source not found.** and Section 3.3.2, followed by a brief description of an integer programming approach by Akcali, Côté, & Lin (2006) in Section 3.3.3. The section ends with forecasting techniques to predict the required bed capacity based on the length of stay as described by Lin (1989).

3.3.1 Markov chain models

Patient flow can be described by using Markov chains. Discrete-time Markov chains describe a system with different states and stepwise transitions between them. The next state only depends on the current state and does not depend on the states the chain passed through before (Winston, 2003). This memorylessness property is useful, because only information about the present is needed. It turns out that the hospital stay of a patient can be formulated as a Markov chain. From an operational view the states represent the movement of patients through a set of locations in the hospital. When looking from a clinical view perspective, the states represent the changes of the patient's health status (Harper & Shahani, 2002). However, precise knowledge about the different states is required in order to develop an accurate model. A Markov chain model based on Coxian phase-type distributions obviates this disadvantage. Hereby there is one finite absorbing state where patients get to with certainty - leaving the hospital. All other states are transient, meaning (groups of) patients will be there a finite time and then move to a next state. The Coxian property ensures an explicit ordering of the transient states whereby only a transition to the next transient state or to the absorbing state is allowed. For example, states could represent diagnosis, surgery and recovery. The model can be further expanded by using a Bayesian network in order to include discrete variables.

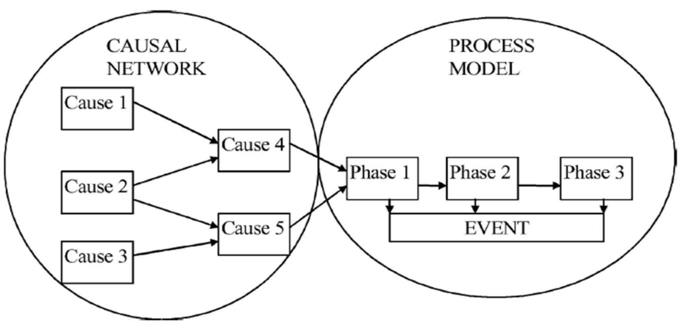


Figure 3.2 shows such a model where the causal nodes may represent characteristics determining the length of stay which influences the transitions probabilities of the states in the process model.

Figure 3.2 A Coxian phase-type model using Bayesian network

3.3.2 Queuing models and simulation

Patient flow may also be described by a queuing model (Marshall et al., 2005). An operational view is common to formulate the queuing model whereby each location is modeled with a possible waiting queue (Harper & Shahani, 2002). Due to the complexity of these models, developing the queuing system as discrete event simulation model is usually preferred to analytic approximations (Marshall et al., 2005). In discrete event simulation, the state variables change at separate time points, called events. Queuing models have extensive capabilities for modeling patient flow. For example, bed capacity constraints and bed blocking (delayed transfer from hospital) can be taken into account (Marshall et al., 2005). However, simulation requires a long execution time and is more complex to develop.

3.3.3 Integer programming

A more static method to describe patient flow is by using integer programming (IP) techniques. These techniques solve optimization problems maximizing or minimizing a function of decision variables with subject to certain constraints with at least one variable being integer (Winston, 2003). Akcali et al. (2006) use this method to minimize the cost of operating beds, expected patient waiting cost and cost of changing bed capacity. Restrictions are a maximum expected patient delay before admission, limited budget and maximum periodically increase in capacity. In contrast to the previous models IP models are used to determine the bed capacity using the average length of stay instead of modeling the length of stay itself. This method can be applied to determine the required bed capacity at strategic level, but it might be used to determine the needed ward capacity at tactical level as well.

3.3.4 Forecasting

The forecasting techniques discussed next use historic data. This in contrast with the above described models whereby also knowledge concerning the context and linkages between variables is required. A simple method to forecast patient flows is exponential smoothing. The (generalized) patient's state of the next period F_{t+1} is forecasted using the actual (A_t) and predicted state (F_t) of the current period and a smoothing constant (α) that determines the weight of actual or predicted state (Winston, 2003):

$$F_{t+1} = \alpha\, A_t + (1 - \alpha)\, F_t. \tag{1}$$

The formula can be extended to include trends and seasonality. Since it is a simple method it is not very accurate. Another simple forecasting method is by moving average (MA(n)). Hereby the average of the n previous actual values is taken as the forecast for the next period (Winston, 2003):

$$F_{t+1} = \frac{1}{n}\sum_{i=0}^{n-1} A_{t-i}. \tag{2}$$

A more detailed time series forecasting model is the Box-Jenkins univariate time series approach described by Lin (1989). Hereby a given set of time series data is fitted to a mixed autoregressive integrated moving average (ARIMA). (Chatfield & Prothero, 1973). An ARIMA model is a mixture of an auto regression model (AR), adjusted factor to account for trends (I) and a moving average model (MA) (Poortema, 2011). The exponential smoothing model described above is a simplified variant of the ARIMA model (Gardner Jr., 2005). The Box-Jenkins method is used when it is hard to find the explanatory variables for the variable being forecasted or when they are not observable. The first is the case for patient movements, because there are many influencing factors.

Regression analysis is another method to model the length of hospital stay and thereby the patient flow throughout the hospital. This method explains the variable to be predicted in terms of explanatory variables plus an error term (Poortema, 2011). Among others, Martin & Smith (1996) and Junger et al. (2001) both performed a regression analysis to examine the signficant factors in predicting the length of stay. A general linear model is a simple regression model. Equation (1) shows this model:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \beta_{k+1} x_1 x_2 + \cdots + e \tag{1}$$

with Y the variable to be predicted, β_0 the y-intercept, the terms $\beta_k x_k$ the influence of the predictor variables, interaction terms like $\beta_{k+1} x_1 x_2$, and a normally distributed random error e.

3.3.5 Link to research study

In this section we discussed several patient flow models in order to define the bed capacity. With patient flow models the bed capacity per ward can be determined at a tactical level. With most of the described models the length of stay can be determined accurately for certain groups of patients. However, some of them are insufficient to determine the length of stay at an individual level.

3.4 Operating room scheduling with leveling bed capacity

In the previous section we considered modeling the length of stay and the determination of bed capacity throughout the hospital. However, these models do not allow for the influences of the operating room schedule. Van Berkel et al. (2011) show that a reduction in bed capacity of around four percent can be achieved by taking the ward occupancy into account in the OR scheduling. Van Essen, Bosch, Hans, van Houdenhoven, & Hurink (2012) provide a overview of models that provide operating room schedules with leveling bed capacity. Most of the models are at the tactical level, scheduling OR blocks within a cyclic schedule, that for each day allocate a specialty to a particular OR. We describe the model of van Berkel et. al (2011) at the tactical level in Section 3.4.1. Van Essen et al. (2012) discuss two models at the operational level, which are discussed in Section 3.4.2.

3.4.1 Tactical level

Van Berkel et al. (2011) provide one of the more detailed models at tactical level to schedule OR blocks. They developed a master surgical schedule (MSS), which allocate specialties to ORs. They improved the MSS in a iterative way until the MSS was acceptable to operating room staff and leveled the ward occupancy. For each specialty they compute the probability distribution of the required number of beds based on the probability distribution of the number of surgeries per day and the hospital discharge probabilities for that particular specialty. Next they calculate for each OR block the impact on the number of recovering patients in the hospital during the scheduling cycle. Operation research methods then can be used to determine the optimal OR block schedule (Van Essen et al., 2012).

3.4.2 Operational level

Van Essen et al. (2012) mention two models at an operational level. Cardoen, Demeulemeester, & Beliën (2009) consider the sequence of surgeries per day minimizing the peak use of recovery beds. However, they assume the length of stay to be deterministic. Fei, Meskens, & Chu (2010) assume a fixed bed capacity using it as a constraint in their OR scheduling in order to optimize the utilization of beds.

3.4.3 Link to research study

These operating room scheduling models level the bed capacity for inpatient wards with a longer hospital stay than the day care and short stay patients that are the subject of this study. Therefore it is questionable whether these models can be applied to the day care and short stay ward.

4 Prediction model for length of stay after surgery

In this chapter we formulate a model to predict the length of stay of stay after surgery of day care patients. In Section 4.2, we describe the relevant factors regarding the length of stay we examine, followed by the data set we use in Section 4.1. The chapter ends with the development of the prediction model and its applicability and generalizability in Section 4.

4.1 Relevant factors

In the previous chapter we described possible relevant factors influencing the length of hospital stay. Table 4.1 repeats the relevant factors according to Martin & Smith (1996) from the previous chapter and Table 4. summarizes the previous described factors mentioned by Junger et al. (2001). We expect that a major part of these factors are relevant for our prediction model. Therefore we examine these factors in case the data thereof is available within MST. Table 4.3 shows the factors which we will investigate whether they are significant in predicting the length of stay after surgery. Data concerning patient's age and gender is provided by the data system X-Care. Although Junger et al. (2001) found ASA status not being significant, we expect that ASA status is a good indicator of severity of illness which is a relevant factor according to Martin & Smith (1996). BMI is not a significant predictor as well according to Junger et. al (2001). Nevertheless, we would examine this factor if the data were available in the data systems of MST, which is not the case. Because emergency patients are not cared for at the day care and short stay ward the type of admission (elective of emergency) is irrelevant. Hospital characteristics are irrelevant as well, because we gather data from one hospital only. The factor workload of nursing staff of the DC & ST ward is represented by the number of day care surgeries per day. We assume a higher workload of personnel if there are more surgeries performed that day. Surgeon, specialty and number of surgeries per surgeon together represent the surgeon characteristics. Factors related to surgery we take into account are surgery type, planned surgery duration, number of surgeries per surgery type, starting time of surgery and surgery date. All other factors mentioned by Junger et al. (2001) or Martin & Smith (1996) are omitted, because the data herefore is not available in the data systems of MST. There are certain other factors not mentioned by Martin & Smith (1996) or by Junger et al. (2001) such as patient's weight, mental disorders and comorbidity that might be significant based on common sense. However, we do not have data concerning this factors.

Table 4.1 Determinants of length of stay according to Martin & Smith (1996)

Factors related to patient characteristics	***Factors related to hospital characteristics***
Age	Hospital characteristics
Severity of illness	Workload of staff
Socio-economic status	Surgeon characteristics
Type of admission (emergency or elective)	Waiting list

Table 4.2 Determinants of length of stay according to Junger et al. (2001)

Factors related to patient characteristics	***Factors related to hospital characteristics***
Gender	Type of anesthesia
Age	Used drugs for anesthesia
BMI (not significant)	Postoperative nausea and vomiting (PONV)
ASA status (not significant)	Surgery duration
	Intraoperative blood loss
	Intraoperative hemoglobin concentration
	Volume of infused colloids and crystalloids
	Preoperative waiting time
	Time of day of admission to the day-care unit

Table 4.3 Examined factors

Factors related to patient characteristics	**Factors related to hospital characteristics**
Age	Surgery type
Gender	Planned surgery duration
ASA class	Surgeon
	Specialty
	Starting time of surgery
	Season of surgery date
	Anesthesia type
	Number of surgeries per surgery type
	Number of surgeries per surgeon
	Number of surgeries per surgeon and surgery type
	Number of surgeries per day
	Similarity of planned and actual surgery type

4.2 Data

In order to formulate a prediction model we collect data concerning day admissions. This section describes how we collect the data, prepare them to develop the model and we formulate the underlying assumptions.

4.2.1 Data collection

Three data systems store the patient data of MST. Data regarding surgery is stored in OR-Suite, data related to the wards is stored in X-Care and data related to anesthesia is stored in Metavision. Table 4.4 shows for each data system the data categories we use. We gather data of about 3.500 day care surgeries in the period from November 2012 to October 2013.

Table 4.4 Data gathered from the three data systems

OR-Suite	X-Care	Metavision
Patient ID	Patient ID	Patient ID
Surgery date	Surgery date	Surgery date
Admission type	Admission date and time	Anesthesia type
• day admission	Discharge date and time	ASA class
• clinical admission	Patient's gender	
Surgery type (planned)	Patient's date of birth	
Arrival time OR	Ward	
Starting time surgery	Surgery specialism	
Ending time surgery		
Departure time OR		
Arrival time recovery room		
Departure time recovery room		

We use the patient ID and surgery date to link the data from the different systems together.

4.2.2 Unreliable and non-relevant data

We cannot automatically assume all the data being reliable. In agreement with MST we decide data being unreliable if the admission duration is less than two hours, surgery duration is less than ten minutes, cutting length of surgery (ending time minus starting time surgery) is less than 5 minutes or the length of stay after surgery is less than 30 minutes. In such cases it unrealistic that a surgery or admission actually took place. Furthermore, we remove data regarding acute surgeries, because they cannot be scheduled and therefore they are not relevant for the prediction model. Since patients with clinical admission stay at least one day then we do not take them into account, because they are not relevant for our research. This because occupying a bed twice is only possible when the first patient per bed and day is a day care patient. Beside we only use data from surgeries whereby data is stored from X-Care and OR-Suite. If data of one of those systems is missing, we cannot determine the length of stay after surgery which is the variable to be predicted. Finally, we remove surgeries with surgery types that occur less than ten times and/or surgeons who performed less than five surgeries in the period studied. This because we cannot draw statistical conclusions of them.

4.2.3 Outliers

Our data concerning the post-surgery length of stay on ward ($PSLoSoW$) is positively skewed with a skewness factor of 17.38 and a kurtosis of 450.18. Detectecting outliers by taking the third quartile plus one and a half times the interquartile range results in length of stay greater than seven hours being outlier (Poortema, 2011). However, a $PSLoSoW$ of seven hours is common for certain surgeries. Hence, we decide to consider a $PSLosoW$ of more than eighteen hours as being an outlier. This is the case in 1.3 percent of the cases. A patient with such a length of stay has to stay overnight even if the surgery takes place at the beginning of the day. When in these cases a day care surgery is planned, it is evident that a shorter length of stay was expected; otherwise it would have been a clinical admission. Figure 4.1 shows the frequencies of the $PSLoSoW$ after removing the outliers.

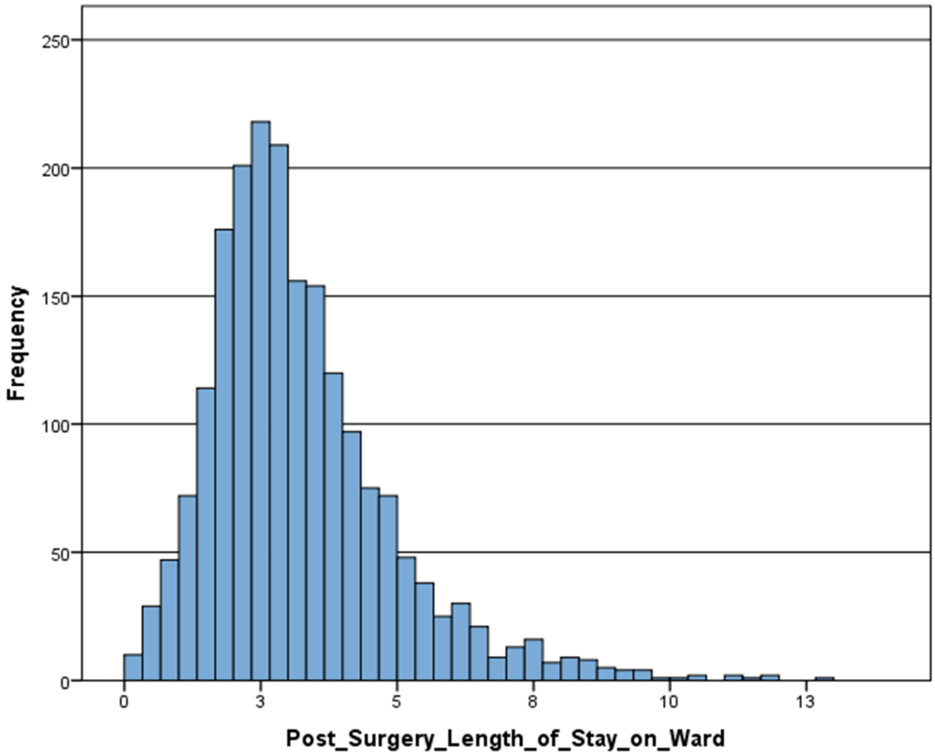


Figure 4.1 Frequencies of post-surgery length of stay on ward (in hours)
(November 2012 – October 2013, 1997 admissions, registration databases X-Care, OR-Suite & Metavision)

4.2.4 Assumptions and requirements

We assume that the staff registers the data veraciously. If this is not the case, the data would be unreliable and therefore the prediction model would not be useful. However, we can imagine that for example time registration may not always be done according to the precise reality. Besides we assume that the nurses discharge a patient when he or she meets the discharge criteria and therefore that a patient will not stay longer than medically needed. In order to develop an useful prediction model it is required that surgery durations, patient case mix and surgery methods do not change significantly for the future period. However, Wasowicz-Kemps (2008) shows that there are trends in day surgery in the Netherlands such as new surgery techniques which may influence the length of stay. Finally, it is necessary that surgeries are performed according to the OR schedule and that the surgery duration can be predicted well.

4.3 Prediction model

In this section we formulate a model in order to predict the post-surgery length of stay on ward of day care patients on the DC & ST ward of MST. In Section 4.3.1 we formulate the prediction model. We describe the residuals in Section 4.3.2, followed by the Section 4.3.3, 4.3.4 and 4.3.5 concerning results, applicability and generalizability.

4.3.1 Model

We use a univariate general linear model, because of multiple ordinal variables in our dataset. Our model will be of the following form:

$$PSLoSoW = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \beta_{k+1} x_1 x_2 + \cdots + e \tag{1}$$

with $PSLoSoW$ the post-surgery length of stay on the ward which is the variable to be predicted, β_0 the y-intercept, the terms $\beta_k x_k$ the influence of the predictor variables, interaction terms like $\beta_{k+1} x_1 x_2$, and a normally distributed random error e.

With stepwise forward model selection we find surgery type, patient's gender, surgery time and the number of surgeries per surgeon as the best combination of significant predictors for the $PSLoSoW$. We use an $\alpha_{to\ enter}$ of 0.15 and an $\alpha_{to\ remove}$ of 0.20. This means that factors with a P-value of 0.15 or less are included in the model, and will be removed when a new factor increases the P-value of a already present factor to more than 0.20. Appendix 3 shows a scatterplot for each predictor variable. The variables surgery type, patient's gender, surgery time and number of surgeries per surgeon all shows a correlation with the post-surgery length of stay on ward in contrast to the surgery date. The correlation between surgery time and $PSLoSoW$ is which is -0.253. However, this might be caused by the OR scheduling whereby certain surgeries are typically scheduled in the morning, whereas other surgeries might normally be performed in the afternoon. Therefore we also investigate the influence of surgery time for arthroscopic knee surgeries. Hereby the correlation between surgery time and $PSLoSoW$ is -0.255, which in the same range as the correlation when all surgery types are included.

Table 4.5 shows the significance, mean and scale of the used predictor variables. Surgery type is a binary variable. For example, an arthroscopic knee surgery is associated with surgery type 4. In this case $S_{type\ 4}$ has a value of one; all other $S_{type\ i}'s$ will be zero. The starting time of surgery is between 7:54 A.M. and 3:40 P.M. If the patient is a male P_{gender} is one, if it is a female patient P_{gender} is zero. The number of performed surgeries per surgeon is between 5 and 159 with on average 86 performed surgeries in the studied period. The significance is indicated by the P –value which is for all the predictor variables smaller than 0.02.

Table 4.1 P-values of predictor variables

Variable name	**Predictor**	**P-value**	**Measuring scale**	**Values**
$S_{type\ i}$	Surgery type	0.000	Nominal	i = 0..48
S_{time}	Starting time of surgery	0.000	Interval	[7.90 – 15.67], μ = 10.78
P_{gender}	Patient's gender	0.004	Nominal	0 = female, 1 = male
$Sg_{surg\ num}$	Number of surgeries per surgeon	0.019	Interval	[5 – 159], μ = 86

Equation (2) shows the prediction model:

$$Predicted\ PSLoSoW = 5.138 + \sum_{i=1}^{48} \beta_i\ S_{type\ i} - 0{,}181 S_{time} + 0{,}338 P_{gender\ j} + 0{,}002 Sg_{surg\ num} + \gamma_{i,P_{gender}} S_{type\ i} + e \quad (2)$$

with

β_i = parameter coefficient corresponding to surgery type i

$S_{type\ i} = \begin{cases} 1\ if\ surgery\ type\ numberis\ i \\ 0\ otherwise \end{cases}$

$\gamma_{i,P_{gender}}$ = interaction coefficient corresponding to surgery type i and patient's gender

$P_{gender} = \begin{cases} 1 \text{ if male} \\ 0 \text{ if female} \end{cases}.$

e = normally distributed error ~ $N(0; 2.135)$

The parameter coefficients corresponding to the surgery types and the interaction coefficients can be found in Appendix 4.

Suppose we want to predict the post-surgery length of stay on the ward of a male patient, undergoing an arthroscopic surgery of the knee by a surgeon that performed 148 surgeries last year. The surgery is scheduled at 9:51 a.m. Our model predicts a post-surgery length of stay on the ward of 3.26 hours. In the studied period there was a patient that met this conditions whereby the actual length of stay was 2.97 hours. In this case we overestimated the length of stay with 0.29 hours. In practice this means that this patient would have been discharged 20 minutes earlier than we expected. Table 4.6 shows the calculation of the predicted $PSLoSoW$ of this example.

Table 4.2 Example of predicting PSLoSoW

Parameter	***Value***	***Coefficient***	***Value * Coefficient***
Constant	n/a	5.138	5.138
Gender	1 (male)	0.338	0.338
Surgery type 4 (arthroscopy knee)	1	-0.459	-0.459
Surgery time	9,85 (9:51 a.m.)	-0.181	-1.783
Number of surgeries per surgeon	148	0.002	0.362
Interaction term surgery type 4 * male	1	-0.334	-0.334
Total (= $PSLoSoW$)			3.262

4.3.2 Results

The fraction of explained variance, denoted adjusted R^2, indicates how well the model fits the data. Our prediction model has an adjusted R^2-value of 0.212 whereas a perfect fitted model would have a value of 1. Our value of the adjusted R^2 might seem small, indicating that our model does not fit the data well. However, it is about as expected, since Chen & Naylor (1993) could not explain a substantial amount of the variation as well. **Error! Reference source not found.** shows a scatter plot whereby the predicted values are plotted against the actual values. When all values are perfectly predicted, all the dots would lie around the equation line $y = x$. The majority of the dots indeed lie around the diagonal through the origin.

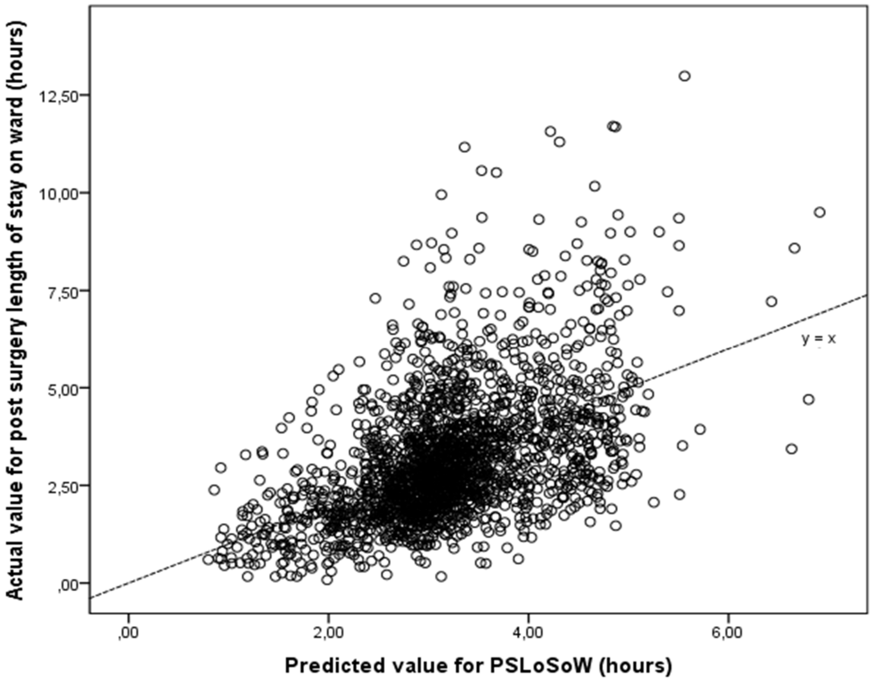


Figure 4.2 Predicted values against actual values

However, the model seems to overestimate for small values and underestimate for large values. Table 4.3 shows the average prediction error per time interval. In 94 percent of the cases we overestimate a length of stay between zero and two hours. We predict the best for a post-surgery length of stay on the ward between two and four hours. On average, our prediction model underestimates when the length of stay exceeds four hours.

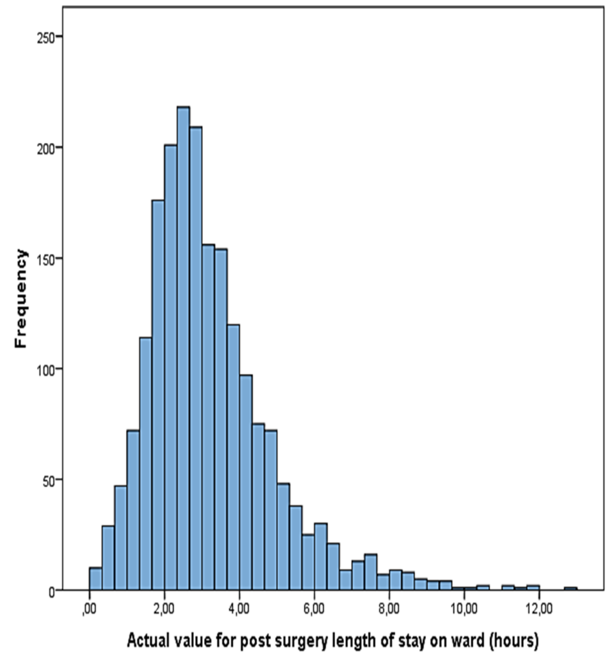
Table 4.3 Average prediction errors per time interval

Actual PSLoSoW (hours)	*0-2*	*2-4*	*4-6*	*6-8*	*8-10*	*>10*	*Total*
Frequency	454	1053	355	95	31	9	1997
Average absolute prediction error (hours)	1.16	0.67	1.22	2.89	4.41	6.94	1.04
Relative frequency of underestimates	6%	33%	85%	100%	100%	100%	40%
Relative frequency of overestimates	94%	67%	15%	0%	0%	0%	60%

Error! Not a valid bookmark self-reference.5 below shows a statistical summary of the actual and predicted value for the post-surgery length of stay on the ward. Our prediction model has about the same mean as the actual data, but predicts extreme values less accurate, resulting in a lower standard deviation. The distribution of the predicted values is less skewed and more flat than the distribution of actual values which is shown by
Figure 4.3.

Table 4.4 Statistical summary of actual and predicted PSLoSoW

Variable	***Mean***	***Standard deviation***	***Minimum***	***Maximum***	***Skewness***	***Kurtosis***
Actual value	3.208	1.689	0.083	12.983	1.394	3.144
Predicted value	3.208	0.848	0.800	6.910	0.214	0.654



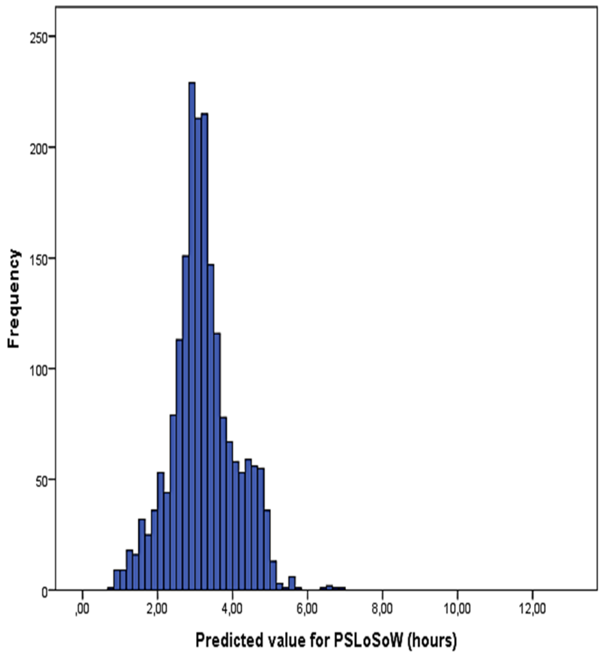


Figure 4.3 Histograms of actual and predicted values for the PSLoSoW

4.3.3 Residuals

The residual value, or prediction error, is the actual value of the post-surgery length of stay on the ward minus the predicted value. They can be seen as actually estimates of the random error e from the general linear model. In order to estimate the length of stay well, the residuals need to be normally distributed with a zero mean. Our residuals do indeed have a zero mean. However, Figure 4.5 shows that the residuals do not fit the normal distribution completely. Figure 4.4 supports this, because if the data is normally distributed, than all the values would be located at the diagonal through the origin. A statistical analysis is given in Table 4.5. The residuals are positively skewed, whereas the normal distribution is symmetrically. The kurtosis is 3.186 which mean that the distribution of residuals is thinner than a normal distribution. This might indicate that we miss an explanatory variable in the prediction model.

Table 4.5 Statistical summary of the residual values

Variable	***Mean***	***Standard deviation***	***Minimum***	***Maximum***	***Skewness***	***Kurtosis***
Residual value	0.000	1.461	-3.400	7.810	1.318	3.186

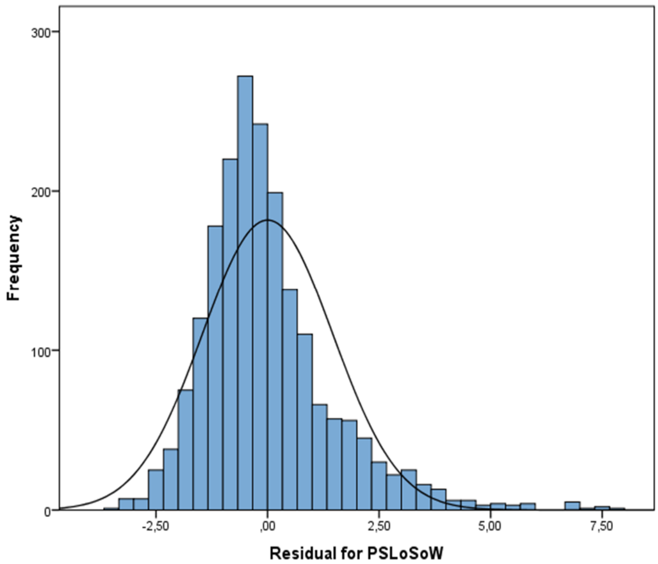


Figure 4.5 Histogram of residual values for the PSLoSoW

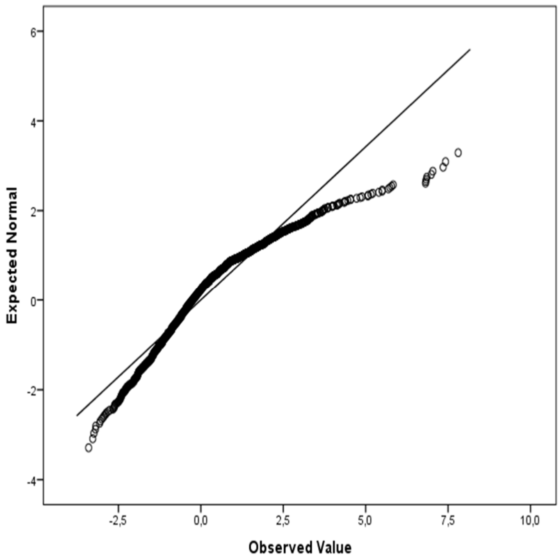


Figure 4.4 Normal Q-Q plot of residual values for the PSLoSoW

4.3.4 Applicability

The fraction of explained variance is 0.212, which means that about 80 percent of the variance remains unexplained. Besides, the residuals are not precisely normally distributed, indicating we probably miss one or more explanatory variables. However, our model predicts average length of stay well, but estimates extreme values less accurate. We expect our model to be applicable if a proper margin is used to compensate for the underestimation of large values.

4.3.5 Generalizability

This model predicts the length of stay on the ward after surgery for day care patients. Therefore, the model cannot be automatically applied for clinical patients or for admissions without surgery. However, we expect similar significant factors for the post-surgery length of stay on the ward for clinical admissions. The parameter coefficients will be different, because the time scale is different, measuring the length of stay in days instead of hours. Beside, one or more of the significant factors found by Martin & Smith (1996) like age, severity of illness or surgeon characteristics are likely to be significant for prediction the clinical length of stay for MST as well. Finally, it is questionable whether the prediction model is applicable for clinical admissions. The aim of this model is to gain insight in the length of stay of day care patients, in order to investigate if a bed capacaity reduction can be achieved by occupying the beds twice. This is not the case for clinical admissions. This model can also not be applied without modifications to other hospitals, because the hospital characteristics of MST are implicitely included in the model. However, a fittable prediction equation is easily to compute if similar data is available within the hospital.

5 Surgical scheduling based on prediction model and expected reduction in bed capacity

In the previous chapter we formulated a model to predict to post-surgery length of stay on the ward ($PSLoSoW$) for day care patients. This chapter describes how this model can be used in the surgical scheduling process. The purpose for this is to achieve a bed capacity reduction for the day care and short stay ward. This is possible through occupying the beds twice instead of once. The surgical planning department can take the length of stay into account in the surgical scheduling to forestall overlapping length of stay of two consequtive patients at the DC & ST ward. Section 5.1 describes how this can be done. In Section 5.2 we examine the expected bed capacity reduction as a result of the adjusted surgical scheduling. The chapter ends with a section concerning the implementation of the prediction model.

5.1 Surgical scheduling

This section describes how our prediction model can be used in the surgical scheduling process. The most accurate way is to implement the model into the surgical scheduling software. However, this is not likely to be realizable within a short time period. Therefore we describe an alternative simplified approach. For each combination of surgery type and gender we calculate the average predicted $PSLoSoW$. If the number of surgeries is less than six we use the average predicted $PSLoSoW$ of both male and female patients of that surgery type. This because we cannot draw statistical conclusions of five or less surgeries. Furthermore, we calculate the average error for all the combinations. As described in Section 4.3.2, our prediction model predicts average length of stay well, but estimates extreme values less accurate. Therefore, we calculate prediction intervals. Equation (3) and (4) show the lower and upper bound per surgery type and gender:

$$\text{Lower bound} = \text{average predicted } PSLoSoW - 1.8 \text{ average error} \tag{3}$$

$$\text{Upper bound} = \text{average predicted } PSLoSoW + 1.8 \text{ average error} \tag{4}$$

We use a scaling factor 1.8, because this is the best trade-off between interval width and percentage of actual $PSLoSoW$ that falls within the interval. A percentage of 85 of the actual post-surgery length of stay on the ward falls within the predicted intervals. The upper bound is exceeded in 9 percent of the cases. The average interval width is 3.82. Table A.5.1 of Appendix 5 shows the average predicted $PSLoSoW$ and the lower and upper bound per surgery type and gender.

Table 5.1 Part of Table A.5.1

Surgery type	***Patient's gender***	***Freq.***	***AVG Predicted PSLoSoW***	***Lower bound***	***Upper bound***	***Interval width***	***Actual PSLoSoW in prediction interval (%)***
Perianal fistula	male	21	4,15	1,25	7,25	6,00	95%
	female	14	4,01	2,50	5,75	3,25	79%
Phaco cataract + implantant	male	21	1,27	0,75	2,00	1,25	67%
	female	33	1,64	0,50	3,25	2,75	82%
Proctoscopy	male	18	3,40	1,75	5,50	3,75	83%
	female	13	3,45	2,00	5,00	3,00	77%
Release trigger finger	male	4	2,10	1,00	3,50	2,50	100%
	female	6	2,33	1,00	4,00	3,00	100%

The surgical planning department can use the average predicted post-surgery length of stay on the ward and the corresponding prediction interval in the surgical scheduling. Surgeries with a small expected interval width and a small average predicted $PSLoSoW$ are preferred to schedule in the morning. This in contrast for surgeries with a larger interval width or larger average predicted $PSLoSoW$ which are preferred to schedule later on the day. For example, a male patient undergoing a release trigger finger surgery has a expected length of stay of 2.10 hours. In all likelihood the length of stay will be between 1.00 and 3.50 hours. It is possible to allocate a second day care or clinical surgery for the same bed that day and therefore the surgery is preferred to be scheduled early on the day. Surgeries with clinical admissions are preferably scheduled in the afternoon, because they occupy a bed the rest of the day.

Consider for example the surgeries of February 8th 2013. There were four day care surgeries that day which are shown by

Table 5.2 Example of surgical scheduling We use average surgery duration and average time spent at the recovery room. There were four beds needed in the actual situation. If we would schedule them with taking the post-surgery length of stay on the ward into account, we need two beds instead of four. The ganglion removal and the Dupuytren surgeries are scheduled as the first surgery of the day. Both have a relatively small predicted length of stay and a relatively small prediction interval width. The proctoscopy and perianal fistula surgeries have a longer expected length of stay. Therefore they are scheduled in the afternoon in such a way that they are expected to be discharged from the recovery room after the two patients in the morning are expected to be discharged from the hospital.

Table 5.2 Example of surgical scheduling

Surgery type	***Patient's gender***	***Surgeon***	***AVG Predicted PSLoSoW***	***Time interval***	***Starting time of surgery***	***Expected arrival time at ward***	***Expected discharge time interval***
Ganglion removal	Female	A	2.34	[0.50-4.50]	8:00	9:45.	10:15 – 14:15
Dupuytren	Female	B	2.82	[1.50-4.50]	8:00	10:00	11:30 – 14:30
Proctoscopy	Male	C	3.40	[1.75-5.50]	12:45	14:15	16:00 – 19:45
Perianal fistula	Female	C	4.01	[2.50-5.75]	13:00	14:30	17:00 – 20:15

However, in practice it might not be as simple as the previous example. Anesthesia type, agenda of surgeons, and clinical surgeries must be taken into account. This might cause the actual surgical schedule to turn out to be less efficient for the day care and short stay ward. Furthermore, the used bed has to be stripped down and made up again. This approach does not explicitly reserves time for this. Finally, we deleted cases in our data set with a length of stay of more than eighteen hours which happens 1.3 percent of the time. Because we schedule the second patient after the upper bound of the prediction interval of the first patient, we expect that we have enough margin to handle this extreme length of stays within the regular bed capacity.

A requirement for the application of the prediction model is that patients are not be allocated to a bed prior to surgery if capacity is insufficient at that moment. In such cases patients will have to wait in the waiting room until the nurse take them to the operating room department. The reason for this is that in most cases it is impossible to schedule two consecutive patients per day for one bed when the pre-surgery time is spent in bed.

5.2 Expected bed capacity reduction

It is difficult to estimate the bed capacity reduction, because we did not implement this approach yet. However, we determine the expected reduction by reason logically. We assume that the surgery duration and duration at the recovery room are fixed and both one hour. Regular working hours of the operating room department are between 8:00 and 16:00. Therefore, surgeries are scheduled at the latest at 14:00 and thus the patient will return at the ward at latest at 16:00. The first patient has to be expected to be discharged at that time. If the surgery of the first patient is scheduled as the first surgery of the day, say at 8:00, the patient will return to the ward at 10:00. The expected post-surgery length of stay on the ward of the first patient has to be utmost six hours. The upper bound of our predicted $PSLoSoW$ is in 77 percent six hours or less. In September and October 2013 there were 997 admissions at the day care & short stay ward; about 800 of them were day admissions. These months have a total of 44 working days with on average 18-19 day admissions and 4-5 clinical admissions per day. On average, 14 of the day admissions have a predicted $PSLoSoW$ six hours or less. This is more than half of the total admissions per day. Therefore, we conclude that is is possible to schedule two patients at the same bed per day. This results in a needed bed capacity for day admissions of ten. However, surgery duration and duration at the recovery room are not deterministic. We did not take into account scheduling restrictions. Furthermore, the admissions may be unevenly distributed over the days. Nevertheless, we expect that a bed capacity for day admissions of twelve is sufficient to house all the day care patients at the day care & short stay ward. There are five bed needed for the clinical patients. This results in a total of seventeen beds for the DC & ST ward which is a reduction of 48 percent compared to the current 33 beds.

5.3 Implementation

In Chapter 4 and Section 5.1 we formulated a prediction model and designed an approach to use the model in order to reduce the needed bed capacity at the day care and short stay ward. This section describes how this previous described approach described can be implemented at MST. We recommend a pilot period of three months wereby the $PSLoSoW$ will be taken into account in the surgical scheduling. In this period, the surgical planning department and the day care and short stay ward should both pretend as if there are 17 beds at the ward, using the remaining beds only if necessary. After this period, the effects will be evaluated among the OR-planning department, the day care and short stay ward, involved surgeons and eventually involved patients.

6 Conclusion, discussion & recommendations

This chapter starts with a conclusion of the performed research. Then we discuss the used approach and results and we end with recommendations to further reduce the bed capacity at Medisch Spectrum Twente.

6.1 Conclusion

In this research we formulated a model to predict the post-surgery length of stay on the ward ($PSLoSoW$) for day care patients of Medisch Spectrum Twente. The purpose for this is to use it in the surgical scheduling process to allow for occupying the beds of the day care and short stay ward twice. We expect a bed capacity reduction as a result.

The majority of the literature on factors determining the length of stay only concerns medium and long stay inpatients, measuring the LoS in the number of days. Martin & Smith (1996) provide an overview for this. Junger et al. (2001) studied the LoS at the PACU for day care patients. We expected a major part of the factors of both studies are the same for the post-surgery LoS of day care patients. We examined all factors derived from the literature whereof the data was available within MST. The studied period is from November 2012 until October 2013, resulting in 1997 surgeries after filtering out the unreliable and non-relevant data.

We found that surgery type, surgery time, patient's age and the number of surgeries performed per surgeon per year are significant in predicting the post-surgery LoS. The fraction of explained variance, denoted adjusted R^2 has a value of 0.212. This indicates that our model might not fit the data well. The model predicts average LoS well, but seems to overestimate for a LoS of less than two hours and underestimate for a length of stay greather than four hours. Nevertheless, we expect our model to be useful in practice.

The bed utilization of the day care and short stay ward is strongly influenced by the surgical scheduling. Our prediction model can be used in the scheduling of surgeries to take this bed utilization into account and to avoid overlapping stay of two consequtive patients of the same bed. The most accurate way is to implement the prediction model into the surgical scheduling software. However, this is not likely to be realizable within a short time period. Therefore we computed a table which provides for each combination of surgery type and gender the average predicted post-surgery length of stay and a 85%-prediction interval. Although it is difficult to estimate, we expect a bed capacity reduction of 48 percent when this approach is implemented, resulting in 17 beds needed instead of the current 33 at the day care and short stay ward.

6.2 Discussion

The first matter of discussion is the small value of fraction of explained variance, which is 0.212. It is questionable of the model can be applied at all, because the majority of the variance remains unexplained. We might miss one or more explanatory variables. The non-normality of the residuals supports this. We used a general linear model, because of multiple ordinal variables. Perhaps we would gain better results if we transformed the ordinal variables into nominal variables so that we could apply a regression model. The selection of predictors is done by forward stepwise model selection. Hesterberg, Choi, Meier, & Fraley (2008) showed that this method not always gives the best model, because it is a greedy algorithm, selecting the best variables at each step, but neglecting the future effects. They mention that selecting predictors by the Least Absolute Shrinkage and Selection Operator (LASSO) generally results in better prediction models. However, due to the research scope and limited time available we decided to use a more simple selection method.

The second discussion point is whether the variables are representative. Our model showed that surgeries that take place early on the day results in a smaller post-surgery length of stay on the ward. That does not seem logical. There might be un underlying cause, like the possibility that more standardized surgeries are scheduled in the morning, or that the nurses earlier discharge patients earlier on the day. Therefore, it is questionable if time is a reliable predictor voor the $PSLoSoW$. However, Junger et al. (2001) found a similar correlation. Against our expectations, the type of anesthesia showed being not significant. This may be caused by the way the data is registerd. The data system concerning anesthesia distinguishes between general anesthesia, local anesthesia, sedation, or a combination of them. If this data would been more detailed, with anesthesia types like spinal puncture, laryngeal mask or block anesthesia, the type of anesthesia is more likely to be a significant predictor.

Prior to the model we did some assumptions. We assumed that the staff registers the data veraciously and that the nurses discharge a patient when he or she meets the discharge criteria and therefore that a patient will not stay longer than medically needed. Beside we required that surgery durations, patient case mix and surgery methods do not change significantly for the future period. Finally, it is necessary that surgeries are performed according to the OR schedule and that the surgery duration can be predicted well. For all those assumptions and requirements it is doubtful whether or not these are met in the current situation.

The last point of discussion is about the consequences for the rest of the hospital. Scheduling the day care surgeries in such a way that the bed capacity at the day care and short stay ward reduces, may cause an increase in bed capacity for other wards or inefficient schedules for the surgeons. The consequences for the nurses at the DC & ST ward are not clear as well as the impact on the patients. Perhaps they have to deal with more peaks in the bed occupancy, although we expect the contrary. The impact on patients is not entirely clear as well, but the hospital stay remains the same if overlapping stay do not occur which we expect.

6.3 Recommendations

We end this chapter with some recommendations to further reduce the bed capacity or to improve the working methods. The main recommendation is a pilot period of three months wereby the $PSLoSoW$ will be taken into account in the surgical scheduling. In this period, the surgical planning department and the day care and short stay ward both pretend as if there are 17 beds at the ward, using the remaining beds only if necessary. If the prediction of the length of stay at the ward is useful in practice, we recommend to integrate the prediction model in the surgical scheduling software or to develop a software tool that calculates the expected length of stay. The parameter coefficients of the prediction model need to be renewed after a certain period of time due to trends in day surgery (Wasowicz-Kemps, 2008). We advise to check each year if the model still complies and to renew the data and the parameter coefficients if this is not the case.

One of points of discussions described in Section 6.2 is that is it questionable if the assumptions regarding the prediction model hold. We recommend examining whether this is the case, thus whether staff register the data veraciously and whether a patient will not stay longer than medically needed. If not, stricter procedures might be needed. This increases the predictability of the length of stay as well, which improves the prediction model. Strict procedures also might be useful for anesthesia, resulting in the same type of anesthesia per surgery type as much as possible. We suggest more standardization of the ward rounds of the surgeons, with a predictable starting time as early as possible in de day. In this way clinical patients can be discharged at the start of the day, resulting in more available beds in the morning.

A requirement for the prediction model is that surgeries are performed according to the OR-schedule. Currently, surgery changes on the day itself are not uncommon. Therefore we advise to investigate how these changes can be kept at a minimum. Furthermore, it is useful to research if the number of surgeries per day can be leveled more than in the current situation. On some days only four day care surgeries are performed whereas on other days this reaches up to twenty day care surgeries. The studied ward hospitalizes both day care and short stay patients. Day care patients are cared for at several wards within MST. We recommend to investigate whether or not it is more efficient to centralize all the day admissions on one ward without short stay admissions. A requirement for the application of the prediction model is that patients are not allocated to a bed prior to surgery if capacity is insufficient at that moment. In such cases patients will have to wait in the waiting room until the nurse take them to the operating room department. We suggest to examine if this is a reasonable requirement and how this can be realized in practice. Finally, we recommend to explore and learn from comparable hospitals that occupy day care beds more than once per day.

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Appendix 1: Patient processes

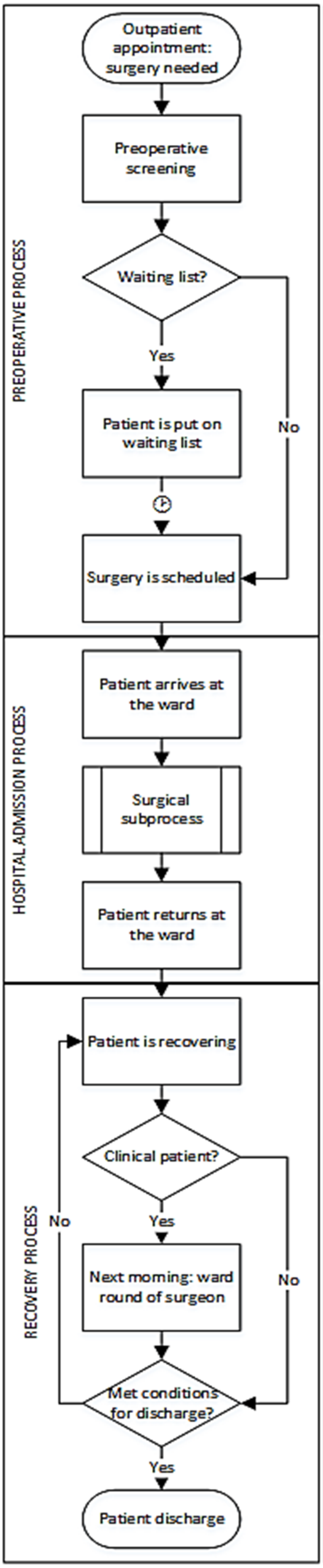

Figure A1.1 Patient flow process

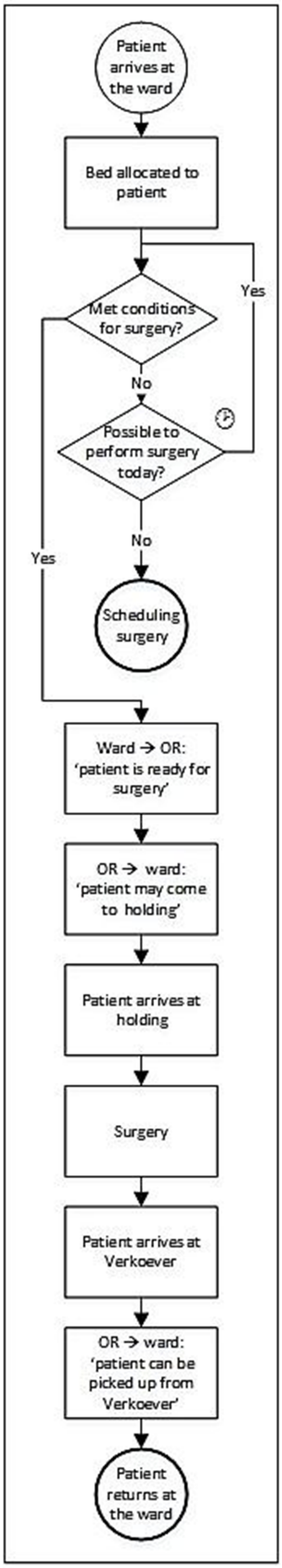

Figure A1.2 Surgical sub process

Appendix 2: ASA Physical Status Classification System

Table A.2: ASA Physical Status Classification System

ASA Physical Status	Description
ASA I	A normal healthy patient
ASA II	A patient with mild systemic disease
ASA III	A patient with severe systemic disease
ASA IV	A patient with severe systemic disease that is a constant threat to life
ASA V	A moribund patient who is not expected to survive without the operation
ASA VI	A declared brain-dead patient whose organs are being removed for donor purposes

(ASA Physical Status Classification System - American Society of Anesthesiologists, 2013)

Appendix 3: Scatterplot of predictor variables

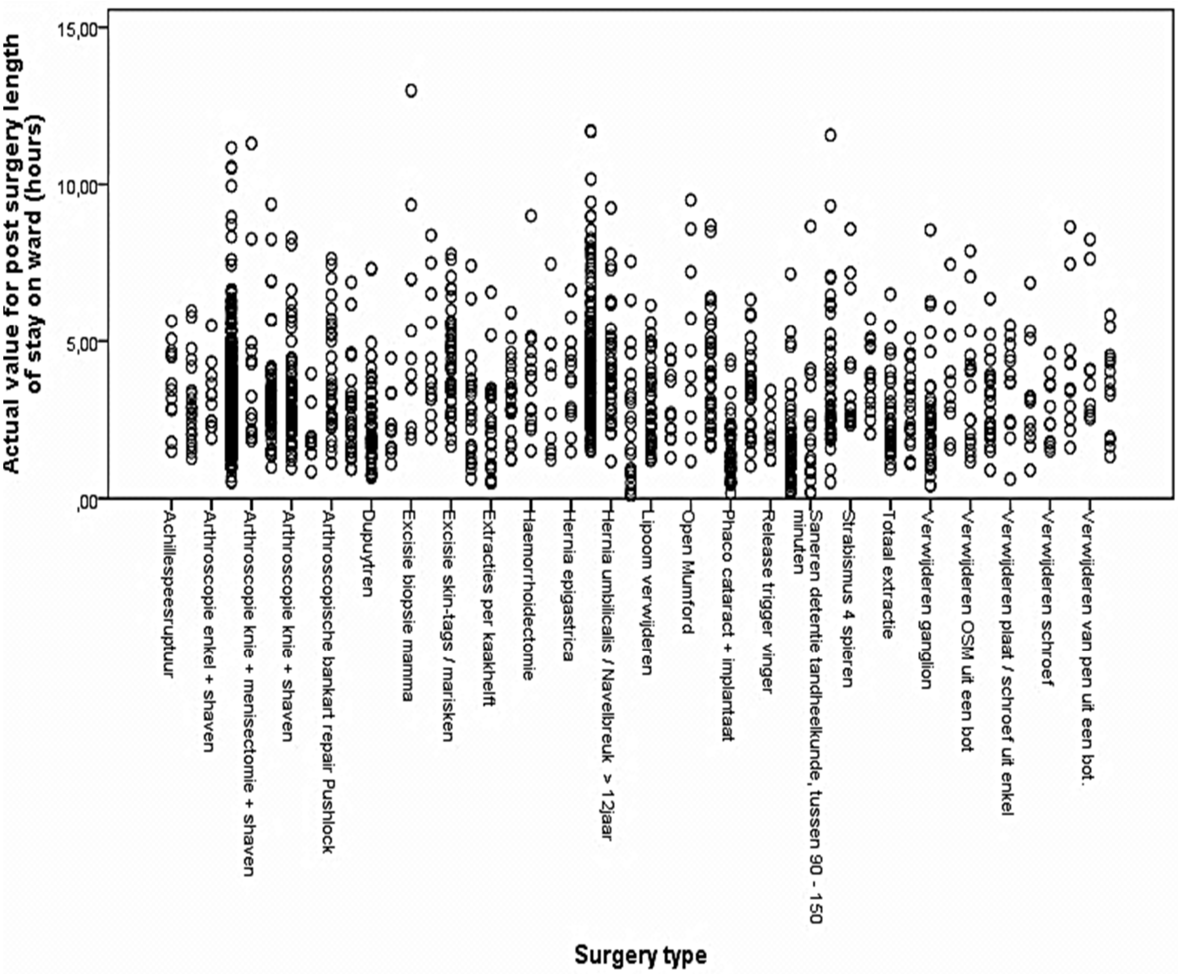

Figure A3.1 Correlation between surgery type and PSLoSoW

(November 2012 – October 2013, 1997 admissions, registration databases X-Care, OR-Suite & Metavision)

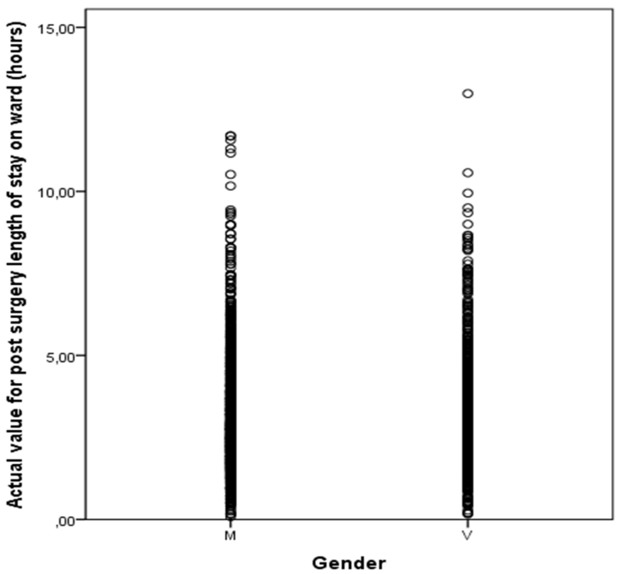

Figure A3.2 Correlation between patient's gender and PSLoSoW

(November 2012 – October 2013, 1997 admissions, registration databases X-Care, OR-Suite & Metavision)

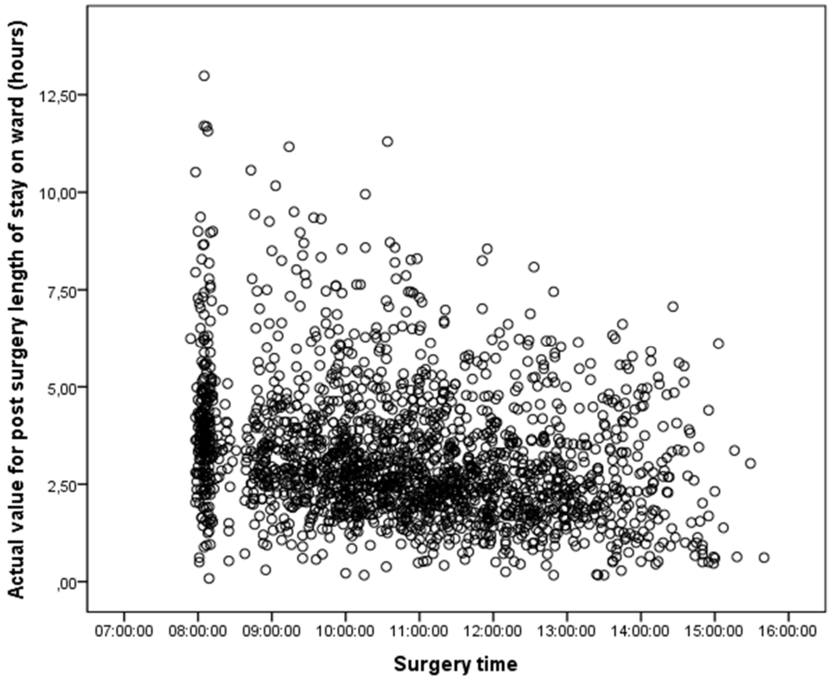

Figure A3.3 Correlation between surgery time and PSLoSoW

(November 2012 – October 2013, 1997 admissions, registration databases X-Care, OR-Suite & Metavision)

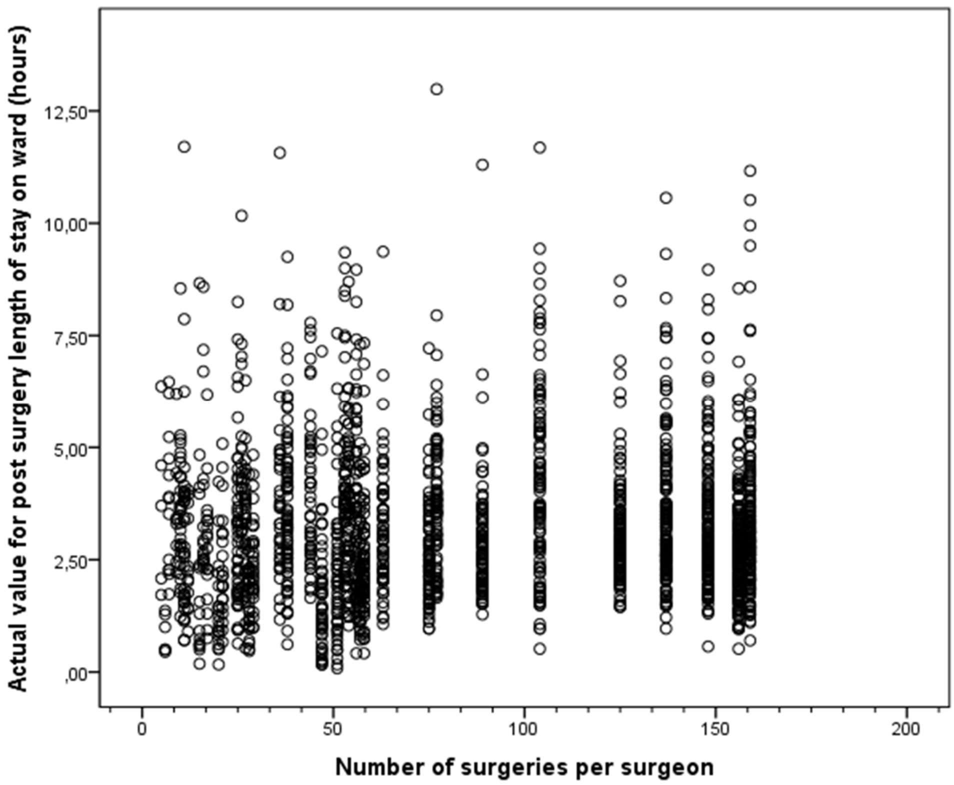

Figure A3.5 Correlation between number of surgeries yearly performed per surgeon and PSLoSoW

(November 2012 – October 2013, 1997 admissions, registration databases X-Care, OR-Suite & Metavision)

Appendix 4: Prediction parameters estimates

Table A4.1 Prediction parameters estimates

(November 2012 – October 2013, 1997 admissions, registration databases X-Care, OR-Suite & Metavision)

Parameter		Estimate	Std. Err.	T-value	Sig.	95% Conf. Int. Low. bnd.	95% Conf. Int. Upp. bnd.
Y-intercept		-43,892	13,084	-3,355	,001	-69,552	-18,232
Surgery time		-4,385	,491	-8,936	,000	-5,347	-3,422
Surgery date		,001	,000	3,753	,000	,001	,002
Number of surgeries per surgeon		,002	,001	2,324	,020	,000	,004
Gender	Male	,427	,853	,500	,617	-1,246	2,099
	Female	0^a					
Surgery type	*Achillespeesruptuur*	,463	1,252	,370	,711	-1,992	2,919
	Arthroscopie enkel	,987	,948	1,042	,298	-,871	2,846
	Arthroscopie enkel + shaven	,118	1,007	,117	,907	-1,857	2,092
	Arthroscopie knie	-,381	,678	-,563	,574	-1,710	,948
	Arthroscopie knie + menisectomie + shaven	-,164	1,092	-,150	,881	-2,306	1,979
	Arthroscopie knie + partiële menisectomie	-,273	,731	-,374	,709	-1,707	1,161
	Arthroscopie knie + shaven	-,488	,711	-,685	,493	-1,883	,908
	Arthroscopie pols	-1,232	,852	-1,446	,148	-2,903	,439
	Arthroscopische bankart repair Pushlock	1,268	,771	1,644	,100	-,245	2,781
	Carpaal tunnel syndroom / CTS	,036	,748	,048	,961	-1,430	1,502
	Dupuytren	-,465	,766	-,606	,544	-1,967	1,038
	Dupuytren straalsgewijs	-1,445	1,638	-,882	,378	-4,657	1,767
	Excisie biopsie mamma	1,867	,796	2,346	,019	,306	3,427
	Excisie fibro-adenoom	,834	,773	1,079	,281	-,682	2,349
	Excisie skin-tags / marisken	,926	,711	1,302	,193	-,469	2,321
	Extracties / M	-,363	,761	-,477	,633	-1,856	1,130
	Extracties per kaakhelft	-,142	,853	-,167	,868	-1,814	1,530
	Fissura ani	,297	,766	,387	,699	-1,206	1,800
	Haemorrhoidectomie	1,483	,946	1,568	,117	-,372	3,338
	Hall procedure	-1,244	1,637	-,760	,447	-4,455	1,967
	Hernia epigastrica	,663	,819	,810	,418	-,943	2,269
	Hernia inguinalis	1,489	,946	1,575	,115	-,365	3,344
	Hernia umbilicalis / Navelbreuk > 12jaar	,821	,819	1,002	,316	-,786	2,427
	Kleine verrichtingen	-,314	,787	-,399	,690	-1,858	1,230
	Lipoom verwijderen	,141	,747	,189	,850	-1,325	1,607
	Lymfeklier extirpatie / biopsie regionaal	,140	,947	,148	,883	-1,718	1,997

	Open Mumford	3,156	,948	3,328	,001	1,296	5,015
	Peri-anale fistel	,555	,780	,712	,476	-,974	2,085
	Phaco cataract + implantaat	-1,150	,719	-1,598	,110	-2,560	,261
	Proctoscopie	,151	,787	,192	,847	-1,391	1,694
	Release trigger vinger	-,703	,906	-,776	,438	-2,480	1,074
	Saneren detentie tandheelkunde, maximaal 90 minuten	-1,022	,735	-1,391	,165	-2,464	,420
	Saneren detentie tandheelkunde, tussen 90 - 150 minuten	-,854	,807	-1,058	,290	-2,436	,729
	Sinus pilonidalis	-,541	1,003	-,539	,590	-2,508	1,427
	Strabismus 4 spieren	,234	,876	,267	,789	-1,484	1,953
	THD procedure	,342	,946	,361	,718	-1,513	2,196
	Totaal extractie	-,432	,807	-,536	,592	-2,015	1,150
	Verlengen, verkorten of uitsnijden van pezen, fascien of spieren	,016	,905	,017	,986	-1,760	1,791
	Verwijderen ganglion	-,948	,756	-1,255	,210	-2,430	,534
	Verwijderen k-draad of cerclage	-,559	1,251	-,447	,655	-3,011	1,894
	Verwijderen OSM uit een bot	,632	,854	,739	,460	-1,044	2,307
	Verwijderen osteosynthese materiaal	-,060	,779	-,077	,938	-1,589	1,468
	Verwijderen plaat / schroef uit enkel	,361	,876	,412	,680	-1,357	2,078
	Verwijderen plaat en schroeven	-,388	,945	-,411	,681	-2,242	1,465
	Verwijderen schroef	,286	,947	,302	,763	-1,572	2,144
	Verwijderen schroeven	1,670	,946	1,766	,078	-,185	3,525
	Verwijderen van pen uit een bot.	1,145	,875	1,307	,191	-,572	2,862
	Verwijderen zwelling uitgaande van de cutis, de subcutis en/of het onderhuids vet- en bindweefsel	0[a]					
Interaction terms							
*Surgery type * gender*	*Achillespeesruptuur * Male*	-,569	1,443	-,395	,693	-3,399	2,260
	*Arthroscopie enkel * Male*	-2,103	1,139	-1,846	,065	-4,338	,131
	*Arthroscopie enkel + shaven * Male*	-1,047	1,251	-,837	,403	-3,501	1,407
	*Arthroscopie knie * Male*	-,441	,861	-,512	,609	-2,130	1,248
	*Arthroscopie knie + menisectomie + shaven * Male*	,776	1,302	,596	,551	-1,778	3,330
	*Arthroscopie knie + partiële menisectomie * Male*	-,503	,930	-,541	,588	-2,327	1,321
	*Arthroscopie knie + shaven * Male*	-,038	,915	-,042	,966	-1,833	1,756

*Arthroscopie pols * Male*	-,785	1,206	-,652	,515	-3,150	1,579
*Arthroscopische bankart repair Pushlock * Male*	-1,926	,995	-1,935	,053	-3,879	,026
*Carpaal tunnel syndroom / CTS * Male*	-1,817	1,043	-1,742	,082	-3,862	,228
*Dupuytren * Male*	-,833	,953	-,874	,382	-2,703	1,037
*Dupuytren straalsgewijs * Male*	,284	1,785	,159	,874	-3,217	3,784
*Excisie skin-tags / marisken * Male*	-,038	1,016	-,037	,970	-2,032	1,956
*Extracties / M * Male*	-,154	1,110	-,139	,889	-2,332	2,023
*Extracties per kaakhelft * Male*	-1,438	1,075	-1,338	,181	-3,546	,670
*Fissura ani * Male*	-1,166	1,072	-1,088	,277	-3,267	,936
*Haemorrhoidectomie * Male*	-1,776	1,183	-1,501	,134	-4,095	,544
*Hall procedure * Male*	1,260	1,791	,704	,482	-2,252	4,773
*Hernia epigastrica * Male*	-1,789	1,304	-1,371	,171	-4,347	,770
*Hernia inguinalis * Male*	-,817	1,091	-,749	,454	-2,956	1,323
*Hernia umbilicalis / Navelbreuk > 12jaar * Male*	-,401	1,010	-,397	,692	-2,381	1,579
*Kleine verrichtingen * Male*	-1,819	1,071	-1,697	,090	-3,920	,283
*Lipoom verwijderen * Male*	-1,276	,969	-1,316	,188	-3,177	,626
*Lymfeklier extirpatie / biopsie regionaal * Male*	-1,474	1,223	-1,205	,228	-3,873	,925
*Open Mumford * Male*	-3,640	1,274	-2,858	,004	-6,138	-1,142
*Peri-anale fistel * Male*	-,106	,998	-,107	,915	-2,063	1,851
*Phaco cataract + implantaat * Male*	-,658	,949	-,693	,489	-2,519	1,204
*Proctoscopie * Male*	-,467	1,012	-,461	,645	-2,451	1,518
*Release trigger vinger * Male*	-1,131	1,289	-,877	,380	-3,658	1,397
*Saneren detentie tandheelkunde, maximaal 90 minuten * Male*	-,928	,944	-,984	,325	-2,779	,922
*Saneren detentie tandheelkunde, tussen 90 - 150 minuten * Male*	-,818	1,143	-,716	,474	-3,059	1,423
*Sinus pilonidalis * Male*	,719	1,157	,621	,535	-1,551	2,988
*Strabismus 4 spieren * Male*	,057	1,138	,050	,960	-2,174	2,288
*THD procedure * Male*	-,163	1,175	-,138	,890	-2,467	2,141
*Totaal extractie * Male*	-,613	1,021	-,600	,548	-2,615	1,390
*Verlengen, verkorten of uitsnijden van pezen, fascien of spieren * Male*	-,527	1,127	-,467	,640	-2,738	1,684
*Verwijderen ganglion * Male*	,027	,988	,027	,979	-1,911	1,964
*Verwijderen k-draad of cerclage * Male*	,844	1,458	,579	,563	-2,015	3,703
*Verwijderen OSM uit een bot * Male*	-1,276	1,122	-1,137	,256	-3,476	,924
*Verwijderen osteosynthese materiaal * Male*	-,725	1,080	-,671	,502	-2,844	1,393

*Verwijderen plaat / schroef uit enkel * Male*	-,610	1,222	-,499	,618	-3,006	1,787
*Verwijderen plaat en schroeven * Male*	,363	1,243	,292	,770	-2,075	2,801
*Verwijderen schroef * Male*	-2,264	1,243	-1,821	,069	-4,703	,175
*Verwijderen schroeven * Male*	-2,500	1,245	-2,008	,045	-4,942	-,059
*Verwijderen van pen uit een bot. * Male*	-1,166	1,471	-,793	,428	-4,050	1,719

Appendix 5: Durations of surgery, recovery room and PSLoSoW per surgery type

Table A5.1 Durations of surgery, recovery room and PSLoSoW per surgery type

Surgery type	**Patient's gender**	**Freq.**	**AVG Predicted PSLoSoW**	**Lower bound**	**Upper bound**	**Interval width**	**Actual PSLoSoW in prediction interval (%)**
Achillespeesruptuur	M	10	3,57	1,25	6,00	4,75	100%
	F	2	3,64	1,50	6,00	4,50	100%
Arthroscopie enkel	M	18	2,62	1,50	4,00	2,50	83%
	F	5	2,97	1,50	4,50	3,00	60%
Arthroscopie enkel + shaven	M	8	2,92	2,00	4,25	2,25	100%
	F	4	3,20	2,00	4,50	2,50	50%
Arthroscopie knie	M	414	3,05	1,50	4,75	3,25	85%
	F	270	3,04	1,50	4,75	3,25	86%
Arthroscopie knie + menisectomie + shaven	M	10	4,55	0,75	8,50	7,75	90%
	F	3	4,18	0,75	7,75	7,00	100%
Arthroscopie knie + partiële menisectomie	M	43	3,20	1,75	5,00	3,25	84%
	F	26	3,14	1,25	5,25	4,00	85%
Arthroscopie knie + shaven	M	40	3,32	1,25	5,75	4,50	83%
	F	41	2,97	1,75	4,50	2,75	85%
Arthroscopie pols	M	5	1,94	1,00	3,00	2,00	80%
	F	8	2,14	1,00	3,50	2,50	88%
Arthroscopische bankart repair Pushlock	M	18	3,16	1,25	5,25	4,00	72%
	F	16	4,61	2,00	7,50	5,50	88%
Carpaal tunnel syndroom / CTS	M	9	1,81	0,75	3,00	2,25	100%
	F	20	3,14	1,25	5,25	4,00	85%
Dupuytren	M	54	2,24	0,75	3,75	3,00	81%
	F	16	2,82	1,50	4,50	3,00	88%
Dupuytren straalsgewijs	M	10	2,42	1,00	4,00	3,00	90%
	F	1	2,34	1,00	3,75	2,75	100%
Excisie biopsie mamma	M	0					
	F	12	5,27	1,00	10,00	9,00	92%
Excisie fibro-adenoom	M	0					
	F	15	4,26	1,75	7,00	5,25	87%
Excisie skin-tags / marisken	M	9	4,74	2,50	7,25	4,75	100%
	F	38	4,22	2,25	6,50	4,25	82%
Extracties / M	M	6	2,91	0,50	6,00	5,50	83%
	F	17	2,90	1,25	4,75	3,50	76%
Extracties per kaakhelft	M	15	2,05	0,50	4,00	3,50	87%
	F	8	3,10	1,50	5,00	3,50	75%

Surgery type	**Patient's gender**	**Freq.**	**AVG Predicted PSLoSoW**	**Lower bound**	**Upper bound**	**Interval width**	**Actual PSLoSoW in prediction interval (%)**
Fissura ani	M	8	2,85	1,25	4,75	3,50	88%
	F	16	3,39	1,75	5,25	3,50	88%
Haemorrhoidectomie	M	10	3,30	1,50	5,25	3,75	100%
	F	5	3,85	1,75	6,25	4,50	80%
Hall procedure	M	9	3,60	1,00	6,50	5,50	89%
	F	1	3,43	1,25	6,00	4,75	100%
Hernia epigastrica	M	3	3,83	1,75	6,00	4,25	100%
	F	10	4,08	2,00	6,50	4,50	80%
Hernia inguinalis	M	147	4,50	2,00	7,25	5,25	84%
	F	5	4,51	2,00	7,25	5,25	80%
Hernia umbilicalis / Navelbreuk > 12jaar	M	32	4,19	1,75	7,00	5,25	88%
	F	10	4,18	3,25	5,25	2,00	80%
Kleine verrichtingen	M	9	1,73	0,50	4,25	3,75	67%
	F	13	3,03	0,50	6,25	5,75	69%
Lipoom verwijderen	M	22	2,54	1,25	4,25	3,00	77%
	F	20	3,43	1,50	5,75	4,25	90%
Lymfeklier extirpatie / biopsie regionaal	M	7	2,37	1,00	4,00	3,00	86%
	F	5	3,01	1,75	4,50	2,75	80%
Open Mumford	M	5	4,87	1,75	8,25	6,50	80%
	F	5	4,87	1,75	8,25	6,50	60%
Peri-anale fistel	M	21	4,15	1,25	7,25	6,00	95%
	F	14	4,01	2,50	5,75	3,25	79%
Phaco cataract + implantaat	M	21	1,27	0,75	2,00	1,25	67%
	F	33	1,64	0,50	3,25	2,75	82%
Proctoscopie	M	18	3,40	1,75	5,50	3,75	83%
	F	13	3,45	2,00	5,00	3,00	77%
Release trigger vinger	M	4	2,10	1,00	3,50	2,50	100%
	F	6	2,33	1,00	4,00	3,00	100%
Saneren detentie tandheelkunde, maximaal 90 minuten	M	32	1,44	0,50	3,00	2,50	81%
	F	24	2,13	0,50	4,25	3,75	79%
Saneren detentie tandheelkunde, tussen 90 - 150 minuten	M	6	1,68	0,50	3,75	3,25	67%
	F	11	2,48	0,50	5,50	5,00	82%
Sinus pilonidalis	M	43	3,88	1,25	6,75	5,50	86%
	F	4	3,79	1,25	6,75	5,50	100%
Strabismus 4 spieren	M	9	3,99	1,50	6,75	5,25	89%
	F	7	3,44	1,00	6,25	5,25	86%
THD procedure	M	11	3,90	2,00	6,00	4,00	100%
	F	5	3,75	2,00	5,75	3,75	100%
Totaal extractie	M	20	2,57	0,75	4,75	4,00	90%
	F	11	2,70	1,00	4,75	3,75	100%

Surgery type	Patient's gender	Freq.	AVG Predicted PSLoSoW	Lower bound	Upper bound	Interval width	Actual PSLoSoW in prediction interval (%)
Verlengen, verkorten of uitsnijden van pezen, fascien of spieren	M	13	2,95	1,50	4,75	3,25	77%
	F	6	3,05	1,75	4,50	2,75	83%
Verwijderen ganglion	M	18	2,80	0,50	5,25	4,75	78%
	F	18	2,34	0,50	4,50	4,00	83%
Verwijderen k-draad of cerclage	M	8	4,15	1,50	7,00	5,50	88%
	F	2	3,86	1,25	6,50	5,25	100%
Verwijderen OSM uit een bot	M	9	2,91	1,00	5,00	4,00	100%
	F	8	4,19	0,75	8,00	7,25	100%
Verwijderen osteosynthese materiaal	M	8	2,72	0,50	5,25	4,75	88%
	F	14	3,29	1,75	5,00	3,25	93%
Verwijderen plaat / schroef uit enkel	M	5	3,60	1,50	6,00	4,50	80%
	F	7	3,72	2,00	5,75	3,75	86%
Verwijderen plaat en schroeven	M	6	3,59	0,75	6,75	6,00	83%
	F	5	3,26	1,00	5,75	4,75	100%
Verwijderen schroef	M	6	1,99	1,25	3,00	1,75	100%
	F	5	2,75	2,00	3,75	1,75	60%
Verwijderen schroeven	M	6	3,43	1,75	5,50	3,75	83%
	F	5	4,14	1,50	7,00	5,50	60%
Verwijderen van pen uit een bot.	M	2	4,29	1,50	7,25	5,75	100%
	F	7	4,50	1,25	8,00	6,75	86%
Verwijderen zwelling uitgaande van de cutis, de subcutis en/of het onderhuids vet- en bindweefsel	M	8	3,70	2,00	5,50	3,50	63%
	F	5	3,53	1,75	5,75	4,00	80%