DECISION SUPPORT FOR DESIGN, IMPLEMENTATION, AND FEASIBILITY OF AN ADMISSION LOUNGE

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PREFACE

Before you lies my master thesis, a document that marks the end of my time as a student at the University of Twente. A time that lasted seven years. After trying to pursue the career of an industrial designer for two years, I had to switch up my game five years ago. Apparently, industrial design was not my strong suit. Coming to the realisation that industrial engineering was more up my alley, I soon discovered that my interest belonged to the field of operations research in healthcare. Erwin, you may not know this, but you sparked this interest right at the beginning of my IEM bachelor's program. And now, I have reached the moment that I finish my master's program in that particular field of research, partially under your supervision. The past six months of my life have largely involved around this final part of my time as a student, and I want to thank those who have helped me getting to where I am now. Without selling anyone short, I want to thank several people in particular.

Gréanne, thank you for all the times you were available for giving me feedback. After our calls and meetings I always felt motivated and focussed. Without your supervision I would not have managed to go through this process as quick and confidently as I did. I admire your wordiness and capability to translate the streams of consciousness I produced every now and then. Erwin, as my second supervisor, you were not as much in the picture. However, during the last phase of this project, you helped me a great deal with bringing my research to its essence. Both during the preparation for my CHOIR presentation, and during the green light meeting.

Puck, I have been very lucky to have you as my supervisor at ChipSoft. During our meetings we switched back and forth between focussed, in-depth discussions, and making the weirdest, stupidest jokes. Yke, thank you for giving me the opportunity to do my research at ChipSoft, and for allowing me the freedom to find a project that both ChipSoft and the university saw great potential in. I also thank the other members of the capacity management team at ChipSoft, for the fun times, elaborate lunches, and useful discussions. And my fellow interns, thanks for our weekly meetings that allowed us to complain about the life of a thesis student every now and then.

Of course, I thank my family and friends for the love and support, in particular mom and dad. Jeroen, thank you for your patience and loving support, helping me to keep calm, and reminding me to enjoy the freedoms that the student life has to offer. I look forward to the adventures we will be facing together, especially now that I have successfully jumped this hurdle.

Wouter

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MANAGEMENT SUMMARY

Background Dutch hospitals are transforming the elective patient admissions process with a new type of ward: the Admission Lounge (AL). The AL facilitates elective patient admissions for relatively low-complex high-volume patient populations. With the AL, hospitals reduce the number of patient admissions that take place at the Clinical Ward (CW). Thereby improving the efficacy and efficiency of the perioperative process. In a preliminary field study we found that while many hospitals in the Netherlands have established or are establishing the AL, there is no systematic approach for its implementation. This raises the opportunity to improve the establishment of an AL through systematic strategic decision support. Potentially, this could lead to improved operational performances, better patient satisfaction, cost savings, and better care.

As the Dutch market leader in the field of hospital information systems, *ChipSoft* sees opportunities to implement methods from the field of operations research and management sciences into their hospital information system *HiX*. Part of their mission is to increase the efficiency and efficacy of hospitals. ChipSoft facilitates this research project to support hospital managers in the decision making process involved with the implementation process of an AL.

Goal and method The goal of this research is to facilitate systematic decision making regarding design, implementation and feasibility of an AL. We aim to quantify those decisions and give insights into the relations between the patient selection criteria, the potential bed reduction for the CW, and the required number of AL beds.

We use the taxonomic classification of planning decisions of Hulshof et al. (2012) to propose a five phase stepwise approach for strategic decision making. Using data visualisation we demonstrate the effects of inclusion and exclusion criteria for the AL on the volume and complexity of the AL's patient population. On the basis of the attributes *priority, age, ASA classification,* and *specialty,* patients are assigned to the AL or CW. Patients fall within a grey area when they could be assigned to both. With literature research, we find the Erlang loss model (see e.g., De Bruin et al. (2010)) as the most suitable model to determine the potential bed reduction for the CW. Inputs for the bed reduction are the patient assignments to the AL or CW, and a blocking probability of 5% for the CW. The potential bed reduction for the CW is determined for a risk pooling strategy. We assess the AL bed requirements and performance for a set service level, using our own deterministic model. By enumeration of the possible patient assignment rules for patients assigned to the grey area, we give suggestions for improved efficacy and efficiency of the AL and CW.

Our proposed five phase stepwise approach and the described algorithms are integrated into a decision support system (DSS) and we provide a mock-up design of the DSS in the HiX environment. For validation purposes, we perform two case studies: the first to verify and validate our algorithms, and the second to validate interpretability and use of the DSS at the strategic level.

Results The proposed stepwise approach consists of the following phases:

1. *Set up inclusion and exclusion criteria for the AL*
2. *Determine appropriate staff, equipment, and supporting processes for the AL and CW*
3. *Analysis of potential bed reductions for the CW and required capacity for the AL*
4. *Analysis of feasibility within the facility layout*
5. *Optimisation: assignment of the grey area patients to the AL or CW*

In the first case study we provide the inputs for Phase 1. In the second case study, the case hospital's representatives provide the input. The visualisation of the inclusion and exclusion criteria for the

AL provides insights about the impact of the criteria for each attribute on the distribution of AL, CW, and grey area patients. In the first case study, the patient population contains 19% AL patients, and 12% grey area patients. In the second case study, the population contains 44% AL patients, and 35% grey area patients. During Phase 2, hospital management derives the appropriate staff, equipment, and supporting process in correspondence with the complexity profiles of AL and CW patients.

In Phase 3 of the first case study, the CW can potentially reduce its capacity by 4 beds while the AL requires 2 required beds, resulting in an overall reduction of 2 beds. For the second case study, the CW bed reduction amounts 2 while the AL requires 3 beds, resulting in an overall increase of 1 bed. Hospital management assesses the feasibility of the AL requirements in Phase 4.

During Phase 5, we enumerate the assignment of patients of 1 specialty, 1 ASA class, and 3 age ranges from the grey area to the AL. In both case studies, the outcomes of the enumeration indicate potential for improved performance of the AL and CW by assigning patients from the grey area to the AL. For the first case study, we find a solution that reduces the CW capacity by 5 beds, while the AL requires 3 beds. For the second case study, we find a solution that reduces the CW's capacity by 3 beds while the AL requires 4 beds. In both case studies, the AL gets assigned a bigger patient population. This indicates a bigger effect on the hospital's efficiency than the solution before enumeration. The runtime of the DSS, performing the enumeration for 12 assignment combinations, is shorter than one minute. The results of the first case study are presented in a mock-up design in the ChipSoft's HiX environment.

Conclusions and recommendations The DSS facilitates systematic strategic decision making by following the developed five phase stepwise approach. The visualisation of the results successfully provides insights into the relations between patient selection and capacity requirements for both the AL and CW. The optimisation method in our DSS enumerates AL assignment rules successfully and is able to indicate a solution that is effective and efficient for both the AL and the CW. Insights generated by the DSS are well interpretable and useful, according to hospital management. Moreover, ChipSoft sees potential in the developed tool.

In our case studies we consider one specialty for assignment to the AL. Consideration of more (sub)specialties or a variety of other patient selection criteria for the AL can exponentially increase the solution space and runtime for the enumeration method. However, the current short runtime allows enumerating relatively large solution spaces. This indicates potential for application of our algorithms to bigger instances.

We recommend ChipSoft to relate the DSS to the tools that are currently developed for forecasting the outflow of the operating room to the clinical wards and other hospital units, as a result of the master surgery schedule. Our model is capable of determining the expected inflow of the AL with a relatively simple method. This method could be refined with more accurate forecasts that are related to the outflow of the OR as a results of the MSS. Another recommendation is to include a field within the preoperative screening form of the anaesthesiologist which automatically indicates whether a patient is suitable for AL admission in compliance with the patient's characteristics.

For further research, we recommend to explain the variability of the load on the AL and CW using discrete event simulation. We also see potential in applying a time-dependent Erlang loss model to determine the potential bed reduction at the CW. For AL patients, arrival at the CW is prolonged, meaning that the peak load is potentially reduced. The time-dependent loss model allows to incorporate peak and off peak arrival rates for the CW and thereby the effect of the AL on the CW can be explained further.

CONTENTS

LIST OF ACRONYMS

AL	Admission Lounge
ALOS	Average Length of Stay
ASA	American Society of Anaesthesiologists (ASA classification)
CW	Clinical Ward
DSS	Decision Support System
ED	Emergency Department
FTE	Full Time Equivalent
GDP	Gross Domestic Product
HIS	Health Information System
HiX	Health Information Exchange. HIS of ChipSoft.
ICU	Intensive Care Unit
IP	Input Parameter
KPI	Key Performance Indicator
LOS	Length of Stay
LB	Lower Bound
LPN	Licensed Practical Nurse
LT	Logistics Team
MSS	Master Surgery Schedule
NP	Nurse Practitioner
OR	Operating Room
OT	Operating Theatre
PAC	Pre Assessment Clinic
PACU	Post Anaesthesia Care Unit
POS	Preoperative Screening
SN	Specialised Nurse
UB	Upper Bound

Specialties			
BAR	Bariatric	**MDL**	Gastroenterology
CHI	General surgery	**NCH**	Neurosurgery
GYN	Gynaecology	**NEU**	Neurology
INT	Internal medicine	**ORT**	Orthopaedics
KAA	Jaw surgery	**PLA**	Plastic surgery
KNO	Ear nose throat	**URO**	Urology
LON	Lung surgery		

CHAPTER 1
INTRODUCTION

Hospitals are addressing the efficacy and efficiency of the admission process with the new policy *admissions without beds* which is done in a new type of ward: the *Admission Lounge* (*AL*). We introduce a decisions order for systematic decision making in setting up the AL. This first chapter serves as a general introduction for the rest of this thesis. Section 1.1 describes the research context. This is followed by the problem description in Section 1.2, which is based on semi-structured interviews with three hospitals. Section 1.3 contains the research objective for solving the core problem and Section 1.4 sets the scope for the research. The chapter closes with Section 1.5, which gives the research questions and a reading guide for the thesis.

1.1. Context description

The pressure on healthcare systems rises as both the demand for healthcare and expenditures are increasing (Hulshof, Kortbeek, Boucherie, Hans, & Bakker, 2012). In 2017, health and welfare costs in the Netherlands totalled 97.5 billion euros, which was 13.3% of the Dutch GDP. Hospitals and care institutes alike account for 28% of all Dutch health expenditures, therefore it is possible to significantly reduce healthcare costs through increased efficacy and efficiency of their processes (CBS, 2018).

1.1.1. ChipSoft and HiX

ChipSoft is an IT company that develops IT solutions for health institutes. ChipSoft is the Dutch market leader in the field of *Health Information Systems and Electronic Patient Records* (abbreviated *HIS*). ChipSoft's innovative software supports care and facilitates the delivery of the right care to the patient. The ambition of ChipSoft is to make care more efficient, such that care providers optimally utilise their limited time and resources.

The main product of ChipSoft is their HIS, called *HiX*, which stands for *health information exchange*. HiX is a comprehensive solution for a wide range of care institutes such as hospitals, general practitioners, and pharmacies. There are three core components to HiX: the electronic patient record, administration, and patient logistics.

Through each of the core components of HiX and other HISs, care institutes register a substantial amount of patient data that can be utilised to make care more efficient, in particular in hospitals. Currently, ChipSoft sees opportunities to implement methods from the operations management and logistics field that help hospitals utilise their own data and increase efficiency and efficacy of care (ChipSoft, 2019).

1.1.2. Admission Lounge

Within hospitals, there is a promising development termed *admissions without beds*. The new approach addresses both efficacy and efficiency of care through physical separation of the preoperative and postoperative *elective patient* processes and by letting elective patients spend less time in bed before surgery. Elective patients are patients with a planned admission and surgery, unlike emergency patients. The new admission process takes place at a new type of ward: the *Admission Lounge (AL)*. The process replaces elective patient admissions at the *Clinical Ward*

(CW), which also situates recovering postoperative patients. Figure 1A depicts the traditional patient admission process. Introduction of the AL goes along with the introduction of the admission process in Figure 1B. The lighter coloured process arrows depict steps in the process where the patient is in an assigned bed.

Figure 1A – Traditional admission process.

Figure 1B – Admission Lounge (AL) admission process.

Hospitals generally require patients to arrive approximately 2 hours before surgery is scheduled. Both processes above start at the moment the patient is called from the waiting room. Figure shows that traditional admissions take place at the CW, where, after the patient intake, a staff member assigns a patient to a bed. The patient waits in bed until the *Operating Theatre (OT)* is ready for that patient. The OT refers to the complex with the *holding*, *Operating Rooms* (*ORs*), and the *Post Anaesthesia Care Unit (PACU).* When the OT is ready, the patient is transferred to the *holding*. At the holding, the OT staff performs a last check with the patient. When the OR is ready, an OT staff member transfers the patient to the OR where the OR staff puts the patient on the operating table. Then the patient undergoes surgery. After surgery, the OR staff puts the patient back in bed again. Next, the patient is transferred to the PACU to wake up from anaesthesia. Finally, the patient is transferred to the CW, where the CW staff monitors the patient until the patient is discharged from the hospital. Figure 1B shows that the first two process steps for AL admissions differ from those in the traditional admission process. After intake, the patient is not assigned to a bed until shortly before the transfer to the holding. As a result, the patient spends less time in bed and more beds are available.

There are differences within the nomenclature of the AL, as Dutch hospitals come up with their own name for this department themselves, such as *Electieve Opname Afdeling* or *Nuchtere Opname Afdeling*, which translate to *Elective Admission Department* and *Sober Admission Department*, respectively. The absence of a single nomenclature is not the only problem with the AL. While many hospitals in the Netherlands have established, or are establishing, the AL, there is no indication that there is one systematic approach for doing so. This raises an opportunity to improve the establishment of an AL through systematic strategic decision support. More systematic implementation of an AL could lead to improved operational performances, better patient satisfaction, cost savings, and most importantly, better care.

1.2. Problem description

In a preliminary field study, we conducted semi-structured interviews (see Appendix A) with three hospitals to identify their expected effects of the AL, and their strategic decisions. Two hospitals were about to start a pilot for the AL and the other hospital was using the AL for approximately one year already. Each of the hospitals noted that there are three main desired effects of the AL:

- lower workload on the CW staff through separation of the preoperative and postoperative elective patients;
- lower staffing costs through the reduction of bed reservations and separation the aforementioned processes;
- increased patient friendliness through a more comfortable admission environment.

Strategic decisions in setting up the AL have an influence on whether the desired effects occur.

Hulshof et al. (2012) introduced a taxonomic classification for planning decisions in healthcare, including inpatient care services. Hulshof et al. (2012) suggest that when the regional coverage and service mix offered by a hospital is determined, management ideally decides on *case mix selection*, *care unit partitioning*, *capacity dimensioning*, and *facility layout* (Figure 2). We clarify these concepts in the context of the AL and the CW. First, case mix selection refers to the types and volumes of patients that the AL serves (and the types of volumes of patients that are admitted via the CW accordingly). Second, care unit partitioning refers to the decision upon the medical care units in which the complete admission facility, so the AL and the CW, is divided. It addresses both the creation of the AL and CW, and the question which patient groups to consolidate in either the AL or CW. Thereby, affecting the decisions on designated staff, equipment and beds for each unit. Third, in conjunction with care unit partitioning, capacity dimensioning decisions consider the size of the AL and CW. The capacity is usually expressed in staffed beds, but equipment and staff are also considered. Then lastly, the facility layout concerns the positioning of the AL and the CW, based on which facilities should be close to each of the units.

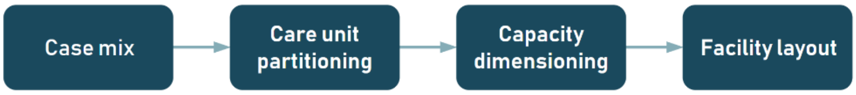

Figure 2 – Ideal strategic decision order in planning the AL and CW.

The strategic decisions are ideally taken in the order depicted in Figure 2, but it is undeniable that decisions on care unit partitioning and capacity dimensioning should be taken in conjunction with each other. Furthermore, restrictions within the facility layout may lead to new insights related to the other strategic decisions. This implies that the decision-making process may consist of several iterations and that decisions can be taken in a different order at various stages of the process. Figure 3 shows all possible decision orders.

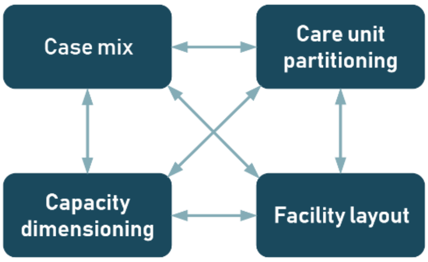

Figure 3 – All possible strategic decision orders.

We found that the reference hospitals' order of decision making does not correspond with the ideal order that Hulshof et al. (2012) suggest. Alternatively, these hospitals let physical characteristics of their facility constraint the capacity dimensioning, case mix selection and care unit partitioning, respectively; in the complete opposite order compared to Hulshof et al., (2012). That is, when hospital management decides to set up an AL, they look for a free or rarely used area in the hospital, preferably near the OT, to locate the AL. This decision restricts the number of beds that the AL can situate, and thereby the capacity dimensioning decision. Following, there is a restriction on both the number of patients due to the capacity, and the types of patients due to the location, which means that there is a restriction on the case mix selection as well. Following from the case mix selection and the capacity dimensioning, the hospitals determine the size and required skills of the staff for both the AL and CW. While this line of decision making appears logical, it could lead to multiple problems. The variability of AL and CW utilisation due to sub-optimal case mix selection, causes sub-optimal care unit partitioning and capacity dimensioning, as a result of the restrictive facility layout decision.

From our preliminary field study, we conclude that resource utilisation variability could either result in overutilisation or underutilisation of beds and staff at the AL, CW, or both. Overutilisation of the facilities causes patient dissatisfaction and a workload that is too high. Additionally, it leads to a bed shortage at either the AL or the CW. This bed shortage reinforces the high workload on nursing staff. A too high workload brings along the risk of situations that are unsafe for patients, which must be avoided as much as possible. Ultimately, the staff is prone to make more mistakes when the workload is too high, and together with low patient satisfaction, the positive effects of the AL might be unnoticeable.

Underutilisation of the facilities, and mainly the AL, leads to a bed surplus, meaning that too many patient admissions take place at the CW instead of the AL. It also leads to overstaffing, because a high *nurse to patient ratio* occurs. Another example of underutilisation is a staff skill imbalance when overqualified staff treats preoperative patients. One of the incentives for the AL is a financial advantage, which has decreased effect when management fails to utilise its resources in a balanced manner.

One of the hospitals in our preliminary field study explained that the CW staff experienced a higher workload after the introduction of the AL. This higher workload occurred because the nurse to patient ratio for the CW remained the same as before the introduction of the AL, while a large fraction of all patient admissions did not take place at the CW anymore. As a result, CW staff treated relatively more postoperative patients, which require more care than preoperative patients. On the other hand, for the AL the perceived workload is significantly lower, another hospital claimed. Because preoperative patients require less care and monitoring, there are fewer care activities for the AL staff, compared to the CW staff. The experiences described by both hospitals, reaffirm the earlier introduced effects of overutilisation and underutilisation. This leads us to the core problem:

There is a lack of insight into the relations between the expected performance of the Admission Lounge and the Clinical Ward, and decisions on case mix selection, capacity dimensioning, care unit partitioning and the facility layout.

By solving the core problem, we enable hospitals to make planning decisions in the ideal order of Hulshof et al. (2012). As a result, hospitals can systematically decide what strategic decisions to the desired effects related to efficacy and efficiency. In this thesis, we use the decision order depicted by Figure 4. The proposed order respects the ideal order of Hulshof et al. (2012) but allows for feedback loops within the decision-making process when new information becomes available and for making decisions on care unit partitioning and capacity dimensioning in conjunction with each other.

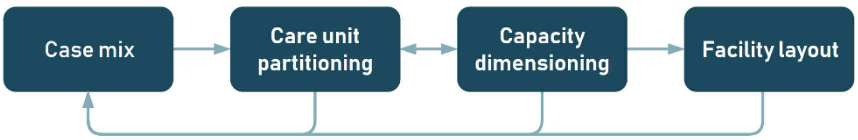

Figure 4 – Iterations in the ideal order for strategic decision making.

1.3. Research objective

The objective of this research is to solve the core problem. We propose the following research objective:

To design a decision support system for case mix selection, capacity dimensioning, care unit partitioning and the facility layout, showing their relation with the expected performance of the Admission Lounge and the Clinical Ward.

As mentioned in Section 1.1, hospitals register a vast amount of data that can be utilised for the implementation of methods from the field of operations research and logistics. *Decision support systems* (*DSS*) are common tools for complex and non-routine decisions, such as the establishment and configuration of an AL. Historical hospital data can serve as an input for future expectations given management decisions. We must represent the expected performances of the AL and CW with objective *Key Performance Indicators* (*KPIs*), from which hospital managers can derive conclusions that support their strategic decision-making process towards desired goals. While some hospitals may decide to stick with an economic line of reasoning, others prefer decisions that are entirely patient oriented. We want to provide insights to support decisions for both strategies. In addition to strategic decision support, the system should be able to support tactical decisions to some extent, making it a sustainable solution.

1.4. Scope

This research concerns *strategic* and *tactical resource capacity planning* (Figure 5), as stated by Hans, Houdenhoven, & Hulshof (2011). The decisions for the establishment of an AL are strategic, but to maintain the desired performance, management requires tactical decision support over time. Furthermore, the research solely focuses on elective patient admissions.

The strategic resource planning in Figure 5 shows the aspects we elaborated on in previous sections, namely the case mix selection and capacity dimensioning. Strategic planning decisions span a time period of 1 to 3 years and concern structural decision making. Tactical planning addresses the organization of the operations as a result of the strategic decisions. Tactical planning distinguishes itself from operational planning by the planning horizon. The planning horizon for tactical planning is between the operational and strategic level, which in the case of the AL and CW, would be several months. Tactical planning enables decisions such as temporary capacity expansions or reductions due to seasonality effects of patient arrivals (Hans et al., 2011). This is not possible in operational planning, as the workforce scheduling is already decided upon, and not up for adjustment.

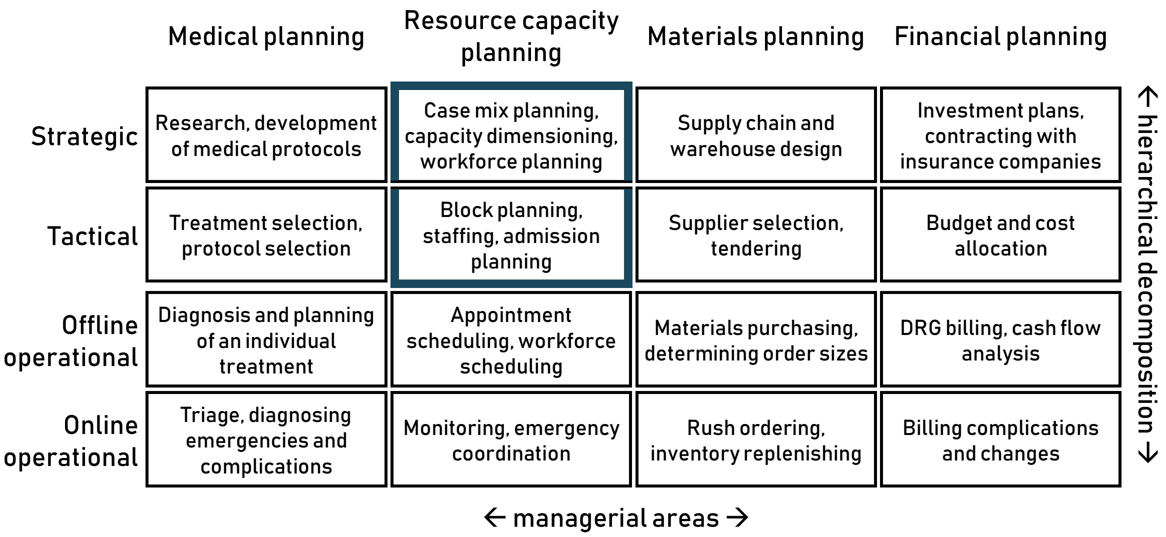

Figure 5 – Scope within the framework for healthcare planning and control (Hans et al., 2011).

Elective patient admissions are planned admissions for patients that require surgery, as we established earlier. Patients who are already admitted to the hospital and require surgery that was not planned or scheduled in advance, sometimes termed as semi-elective, are outside of the scope for the AL. The same counts for emergency patients. However, our model has to account for the effect that non-elective and non-surgical patients have on the occupancy of the CW.

1.5. Research questions

This first chapter answers the sub-questions 'What is the core problem?' and 'What is the research objective?'. The following chapters are structured towards attaining the research objective and thereby solving the core problem, by answering the main question:

How should a decision support system that presents the relations between case mix decisions and capacity dimensioning of the Admission Lounge and Clinical Ward be designed?

We emphasise on the relations between case mix and capacity dimensioning decisions and leave the concepts care unit partitioning and facility layout out of the main question. The former two concern decisions that are mostly quantitative and inside the scope; the latter mainly concern supporting qualitative decisions. Each chapter answers sub-questions that will lead to the answer to the main research question. The reading guide below lists the sub-questions per chapter and briefly describes the methodologies used per chapter.

Chapter 2: Strategic and tactical planning decisions

1. How are the admission processes regulated before and after the establishment of the AL?
2. What are the patient flows in the AL and the CW?
3. What capacity strategies are currently used for the AL and the CW?
4. What performance measures should be considered for the AL and CW?
5. What are the concrete decisions concerned with the establishment of the AL and which of them need quantitative support?
6. What are the key trade-offs in establishing the AL?

Chapter 2 identifies what changes are required to establish an AL and makes the reader familiar with concepts used throughout this thesis. The relevant stakeholders, processes, and patient flows throughout the perioperative process are identified. Followed by a description of the concrete decisions, key trade-offs, and desired performance measures for the establishment of the AL. The chapter concludes with a structured approach for the design of an AL.

Chapter 3: Analytical models for AL and CW performance

7. What logistical system matches with the patient flows in the AL and CW?
8. What analytical models are often used in the literature to measure performance for the identified logistical system?
9. What algorithms are appropriate to model the required capacities for the AL and the CW?

In Chapter 3, we perform literature research to describe both the underlying logistical system of the perioperative process and the analytical models to measure the performance of the logistical system. The chapter determines what models are most suitable for making the quantitative decisions described in Chapter 2.

Chapter 4: Decision support solution design

10. How should the algorithms for capacity dimensioning be integrated into a DSS?
11. How can we model the case mix decision in relation to capacity dimensioning and the performance for the AL and CW?
12. How can the DSS algorithm be verified and validated?

In Chapter 4, we apply the algorithms from Chapter 3 to hospital data from the development database of ChipSoft. We validate the algorithms and discuss their performance. After Chapter 4 we have all the building blocks to create a mock up for the DSS in Chapter 5.

Chapter 5: Implementation of a DSS

13. How can the DSS be integrated into HiX?
14. How can hospital managers and end-users use and interpret the DSS in practice?
15. How can the DSS be used at the strategic and tactical planning level?

Chapter 5 describes what the DSS looks like in the environment of HiX and how the DSS is used. We also provide insights about the use of the DSS for strategic and tactical decision making after the AL is implemented.

Chapter 6: Case study for solution tests

16. What is the performance of the DSS at the strategic level?

Chapter 6 tests the models and DSS architecture that follow from Chapter 3, 4, and 5 for a medium sized general hospital. We assess the performance of our models in order to give an indication of the decision support capabilities of the systematic decision making approach and DSS.

Chapter 7: Conclusions and recommendations

Chapter 7 summarises the findings of its preceding chapters and answers the main research question. Furthermore, we give recommendations for further research and reflect on the research process.

CHAPTER 2
DECISIONS AND TRADE-OFFS FOR THE ADMISSION LOUNGE AND CLINICAL WARD

This chapter describes the concrete decisions and trade-offs concerning the implementation of an AL and works towards a structured approach for the implementation of an AL. To understand the effects of the AL, it is necessary to know the patient flows in the perioperative process without the AL and how those flows change when the AL is introduced. Various strategic decisions define how the new patient flows can be supported. We provide an overview of the concrete decisions and trade-offs that are relevant for a hospital in order to follow their strategy and achieve their goals. Section 2.1 identifies the relevant stakeholders, describes the perioperative process in detail, and introduces concepts used in bed capacity management. Section 2.2 provides an overview of strategic decisions concerning the establishment of an AL and Section 2.3 discusses planning tactics for the AL. In Section 2.4, we give our conclusions and define a stepwise approach to determine the design and feasibility of the AL.

2.1. System description

This section describes the systematics surrounding the admission and discharge processes to make the reader familiar with the majority of the concepts used throughout this thesis. First, we introduce the relevant stakeholders. Second, we look at the perioperative process without the AL. Third, we give the perioperative process after introducing the AL. And fourth, we introduce concepts used in bed capacity management.

2.1.1. Stakeholders

Many stakeholders participate or have interest in the perioperative process. Below we describe the most relevant stakeholders: patients, secretaries, clinicians, planners, the *logistics team* (*LT*), and the hospital management.

Patients The patients within the perioperative process require surgery and want fast recovery. Surgery can be an intimidating concept to patients, therefore the patient needs to be informed, comforted, and treated with attention. We distinguish three types of patients: CW patients, AL patients, and non-elective patients. CW (AL) patients are elective patients with admission at the CW (AL). Non-elective patients are patients without an appointment. They can be divided into emergency patients and urgent patients. Emergency patients require surgery as soon as possible; urgent patients can wait up to a day until surgery.

Secretaries The first contact that patients have in a hospital is usually with the secretaries of the patient's designated department. Secretaries welcome the patient to the department and register the patient's arrival.

Clinicians There is a wide variety of clinicians that take part in the perioperative process. The most relevant clinicians are specialists, nurses, anaesthesiologist, and surgeons.

Specialist – When a patient goes to an outpatient clinic they are consulted by a specialist. The specialist indicates whether a patient requires surgery or not. If the patient requires surgery, the specialist requests an appointment for surgery.

Nurses – There is a wide variety of nurses, with various degrees of competencies and responsibilities. We distinguish three types of nurses in the order lowest degree to highest degree: the *licensed practical nurse (LPN)*, *nurse practitioner (NP),* and *specialised nurse (SN)* (Patiëntenfederatie Nederland, 2019). The more skills and responsibilities a nurse has, the higher the staffing costs are for that nurse. Compared to the SN, the LPN has a limited set of skills. This makes the LPN the cheapest nurse to employ.

Anaesthesiologist – The anaesthesiologist determines what type of anaesthesia the patient requires for surgery before surgery can take place. The anaesthesiologist is responsible for sedating the patient.

Surgeon – The surgeon is the most expensive human resource involved in the perioperative process. Surgeons are also specialists. They can be bottleneck resources due to their limited availability, which can be a limiting factor for surgical scheduling.

Planners The patient appointment planning, scheduling, and sequencing is determined by planners. Planners have the task to define an appointment schedule that is beneficial for the patient and clinicians and corresponds with available capacity.

Logistics team Hospitals are employing LT personnel to handle the transportation of patients, beds, goods, medicines, et cetera. The advantage of having an LT is that indirect care activities are executed by non-care-givers.

Management Hospital management makes decisions on strategies and tactics in order to achieve the hospital's goal. Board and management practices are both strongly related to a hospital's performance on quality of care and operational performance and efficiency (Huckman et al., 2015). In order to improve the performance of the perioperative process, it is important that hospital management gives clear direction during the introduction of a new department or process, such as the AL.

2.1.2. Perioperative process without the AL

The perioperative period is the period that starts with contemplation about the need for surgery and ends with patient discharge. Figure 6 gives an overview of the perioperative process phases and where each phase takes. The process overview identifies the relevant patient flows and how the patient flows affect care unit occupancies.

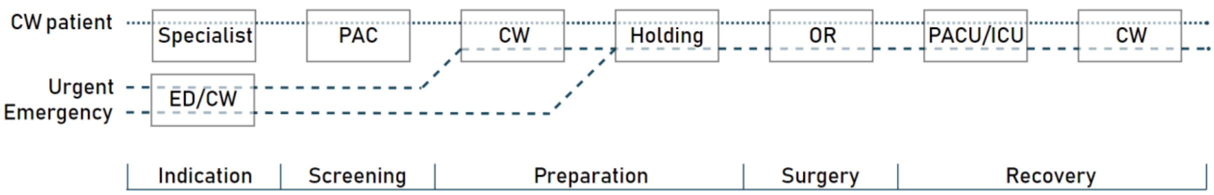

Figure 6 – Perioperative process with patient flows for CW patients and non-elective patients.

The perioperative process (Figure 6) consists of five phases: indication, preoperative screening, preparation, surgery, and recovery. These phases take place at dedicated care units. What care unit is appropriate, depends on the patient's urgency, and whether the patient is elective.

Indication During the indication phase, the specialist determines whether the patient requires surgery. For CW patients, this indication is given during, for example, an outpatient clinic appointment. The patient knows about the indication at least two weeks prior to surgery. These two weeks are also a requirement for hospital planners in order to schedule the patient at a fitting *time slot* in the *Master Surgery Schedule* (*MSS)*. The MSS serves as a blueprint for the OT planning and scheduling. The blueprint dictates what types of surgeries can take place in which OR and at what moment. The blueprint can be divided into dedicated time slots that reserve time for particular surgery specialties. Planners can assign patients to a time slot, and thereby schedule an appointment. After the time slots are filled, planners can adjust the sequence of surgeries to attain a preferred order. Sequencing rules have multiple effects on the operational efficiency of the OR (Leeftink, 2017). Because the OR is an expensive resource, the MSS is often a leading factor for elective patient planning. For non-elective patients, the indication is known shortly before the day or time of surgery at either the CW or the *Emergency Department (ED)*. Most hospital's OT schedules reserve time for non-elective surgeries for scheduling the non-elective patients on short notice. Many hospitals have one or more emergency ORs to reduce the impact on the OR schedule caused by the arrivals of non-elective patients (Borgman, 2017).

Screening In addition to the appointment for surgery, the CW patient receives an appointment for *preoperative screening* (*POS*). Screening takes place at the *pre assessment clinic* (*PAC*), where the patient receives in-depth preoperative teaching, and medical and anaesthesia consultations. The purpose of the POS is to ensure patients are well prepared and fit for surgery and to identify the patient's *ASA classification*. The *American Society of Anaesthesiologists classification system* (*ASA classification)* is a measure to indicate the health status of a patient. ASA classification distinguishes six levels of the physical status of a patient:

I) healthy patient;
II) mild systematic disease without functional limitation;
III) severe systematic disease with definite functional limitation;
IV) a severe systematic disease that is a constant threat to life;
V) moribund patient unlikely to survive 24 hours with or without operation
VI) declared brain-dead patient whose organs are being removed for transplantation (Deyo, Cherkin, Ciol, & ASA, 2014).

The decisions for the ASA classification are based on several indicators. Doyle & Garmon (2018) explain that anaesthesiologists sometime vary significantly in ASA classification assigned to patients, on the influence of factors such as age, anaemia, and obesity. They also note that the ASA classification implicitly assumes that age is unrelated to physiological fitness. This is not true since, e.g., neonatal and elderly are far more fragile in their tolerance of anaesthetics compared to young adults. The ASA classification, and other information on health status, can help with giving an estimate of the duration of the patient preparations before surgery; what type of nurse is required to perform the preparations; whether complications could be expected during surgery; how long the expected recovery period – in capacity management terms, the patient's *Length of Stay (LOS)* – will be; and what the required after care might be (Doyle & Garmon, 2018).

After the preoperative screening, the patient goes home. A few days before the day of surgery, the patient receives the details of the appointment, regarding the starting time and location of the admission.

Preparation The preparation phase generally starts on the day of surgery. A few days before the day of surgery, the schedule of the OT is ready and the time of surgery is known. Our reference hospitals explained if the surgery is at the start of an *OR day*, it is the first surgery that takes place in the scheduled OR. In that case the CW patient is expected to arrive at the hospital 1.5 hours before surgery. At other times, the CW patient is asked to arrive 2 hours before the scheduled time, to ensure that the patient is ready for surgery in time. Urgent patients are located at the CW before surgery and emergency patients go to the holding directly to start surgery as quickly as possible.

The CW patient takes place in the waiting room of the CW before the intake. When a bed is available at the CW, the intake of the patient takes place at the CW. The patient is then placed in bed and the CW nurse prepares the patient for surgery. Part of the preparations is a final briefing about the surgery to inform the patient and to assess whether the patient is fit for surgery. Some surgical procedures require additional preparations, such as injection of medication. When the OT is ready, the patient is transferred to the holding by either a nurse or a member of the LT, depending on the hospital's policy. The holding serves as a sterile environment and a buffer before the OR.

Surgery During surgery, the OR team is challenged to perform surgery with maximum efficiency and efficacy. There is a risk at the occurrence of complications that lead to a longer recovery period, the requirement for extra surgery, or death. The outcome of surgery determines the patients LOS; the OR team aims to maximise the patient's health and thereby implicitly minimise the patient's LOS (Collins, Daley, Henderson, & Khuri, 1999).

Recovery After surgery, the patient's recovery starts. If the patient is in a bad condition it might be necessary to transfer the patient to the *Intensive Care Unit* (*ICU*), which is done by a group of clinicians. Otherwise, the patient wakes up at the *Post Anaesthesia Care Unit* (*PACU*). After waking up, nurses or the logistics team brings the patient to the CW to recover from surgery. The CW staff aims to comfort and treat the patient and to ensure that the patient can leave the hospital as soon as possible, minimising the patient's LOS. Collins et al. (1999) give five indicators for prolonged LOS, summarising the indicators mentioned earlier in this subsection:

1. poor preoperative patient condition or health status;
2. high-complex surgery;
3. long surgery duration;
4. the occurrence of complications during surgery;
5. postoperative complications, as a result of prolonged LOS.

2.1.3. Perioperative process with the AL

The introduction of the AL goes along with the introduction of a new patient flow for the AL patients, represented by the updated perioperative process in Figure 7. With the AL, a selection of suitable patients, elective patients with characteristics defined by the hospital, is admitted at the AL. The patient flows for CW and non-elective patients remain the same.

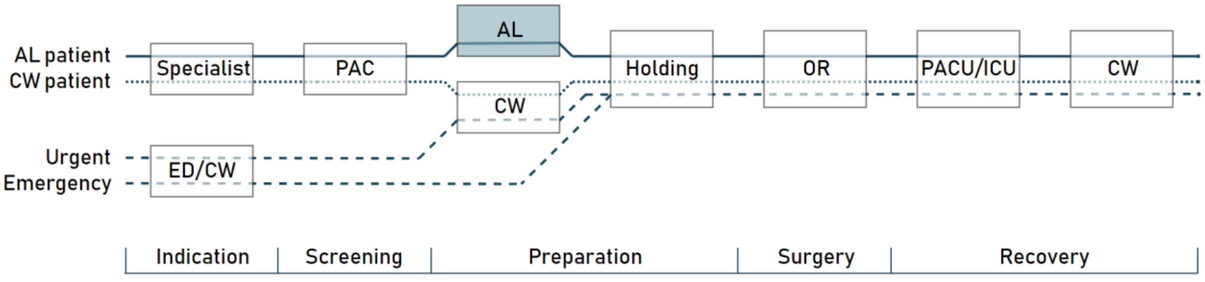

Figure 7 – The perioperative process and patient flows after the introduction of the AL.

Patients have to be selected for AL admission. During the POS, the anaesthesiologist can indicate, in conjunction with the ASA classification, whether the patient is suitable for AL admission. The suitability is based on the capabilities of the AL. The capabilities of the AL relate to the extent of the preparations that can be done at the AL, based on the staff mix. An AL with relatively low skilled staff can host low-complex patients, while a higher skilled staff could host higher-complex patients.

Planners are able to adjust the sequence of surgeries in order to match the inflow and outflow of the AL, OT, and CW (Steiner et al., 2016). Between the screening and the preparation phase, planners decide whether all patients selected for AL admission can be admitted to the AL, or whether they should be admitted to the CW due to capacity constraints. If on a given day there are too many potential AL patients, then some of those preselected patients are appointed for CW admission instead of AL admission, in compliance with *overflow rules* that management agrees upon (Hulshof et al., 2012). Similarly to the process without the AL, patients receive an appointment time, now along with a location that is either the AL or CW, a few days before surgery.

The admission procedure of the AL is similar to admission for the CW, except that the patient is not placed in bed until shortly before transfer to the holding. Instead of staying in bed, the patient can take place in an area that has a relaxing effect on the patient, except when the patient requires preparations that need to be done at the AL. For the AL nursing staff, there is a considerable difference compared to the CW, because there are no postoperative patients at the department. The AL staff only has to take care of new elective admissions and therefore has no work interventions caused by postoperative patients or non-elective admission.

The bed that the patient is placed in remains assigned to the patient during the perioperative process. This means that when the patient is transferred to the holding, by the AL staff or the LT, a new bed for a new admission must be available at the AL. The supply of beds has been a challenge for the hospitals in our preliminary research because the supply of beds was the responsibility of the AL staff, and the AL and CW were located relatively far away from each other. In one case, the AL and CW were not even on the same floor level, meaning that beds – with and without patients – had to be transported with an elevator. Giving the responsibility for bed transport to the LT solves the problem partially because AL and CW staff are not participating in the indirect care activity of bed transport, but still requires long transportation times and distances between the units. The proximity of the AL with respect to the CW and OT is a requirement for efficient intra-hospital transport.

After surgery, the patient does not return to the AL but is transferred to the CW. From then on, the AL patients follow the same steps as the CW patients.

2.1.4. Concepts used in bed capacity management

Before presenting the strategic and tactical decisions for the AL and CW in the following sections, we need to introduce some concepts used in (bed) capacity management. For capacity management in general, the objective is to minimise costs or maximise productivity while attaining a specified *service level*. In bed capacity management, the productivity is represented by *bed occupancy rate* and the service level by the *rejection rate* (Hulshof et al., 2012). The bed occupancy rate is the fraction of the time that a staffed bed is occupied by a patient. The rejection rate is the fraction of patient admissions that have to be rejected due to overutilisation. When all staffed beds are occupied, there is no room for new patient admissions and the patient must be rejected. The probability that such a rejection occurs is called the *blocking probability* (De Bruin, Van Rossum, Visser, & Koole, 2007).

2.2. Strategic planning decisions

Strategic planning decisions involve the hospital's mission to translate the decisions into the design, dimensioning and the development of healthcare delivery process. Strategic planning has a long planning horizon and is based on highly aggregated information and forecasts. The decisions on case mix, care unit partitioning, capacity dimensioning, and facility layout, set a baseline for the hospital's vision and potential performance. It answers the hospital's questions such as: "What kind of hospital are we?", and "What is our mission?". The answers to these questions can be operationalised through goals like *best accessible hospital* or *most cost-efficient hospital*. The strategic decisions also set a scope for the downstream tactical and operational planning decisions (Hulshof et al., 2012).

We use the iterative decision order in Figure 4 to create a systematic stepwise approach for strategic decision making. The stepwise approach addresses the concrete decisions and trade-offs that are relevant to the establishment of an AL. For each subsection we identify the KPIs to measure performance and *input parameters* (IPs) that management must decide upon.

2.2.1. Case mix

Case mix selection refers to the types and volumes of patients that the AL serves (and the types of volumes of patients that are admitted via the CW accordingly).

During the case mix decision, hospital management determines what types and volumes of patients the hospital wants to serve with the AL and the CW. Traditionally, all elective patient admissions take place at the CW, and the variety of CW units have to be strategically filled with patients to exploit *pooling effects* through the patients' LOS and *service level requirements* (Hulshof et al., 2012). The AL can exploit the same effects through strategic case mix selection that ensures that most patients that go through the AL have similar characteristics. The AL's inclusion and exclusion criteria below are a combination of the criteria listed by the reference hospitals of our preliminary research. Note that the criteria can vary per type of hospital since hospitals have their own specific service mix. Some hospitals only serve children or focus on a specific specialty such as orthopaedics while other, general, hospitals have a broader service mix. We propose inclusion and exclusion criteria for patient characteristics that are applicable to general hospitals.

Priority Patients that use the AL are strictly elective patients. Elective patients undergo a preoperative screening one or two weeks prior to surgery. During the preoperative screening, relevant information about the patient is gathered, which is required to determine whether a patient is suitable for AL admission, i.e. admission in a facility where the preparation phase is carried out rapidly. Without an appointment, thus without preoperative screening, there are too many uncertainties about the patient, which makes the patient unfit for AL admission. The elective status of a patient is registered in HiX.

Age In our reference hospitals, patients that are 18 years or older are candidates for AL admission. Patients under the age of 18 are admitted to a children's ward. Relatively old patients are admitted to the CW. The selection of patients on the basis of age differs per hospital, based on a hospital's service mix, as we introduced in this subsection. Boundaries for the age selection can be set accordingly. The patient's age can be derived from the date of birth registered in HiX.

Health status During the preoperative screening, the anaesthesiologist can register the patient's ASA classification. Our reference hospitals use the ASA classification system as a patient selection method for the AL. All three hospitals agree that patients with classification I and II are fit for AL admission, one hospital also includes ASA III patients. The ASA classification is registered in HiX.

Specialty There are specialties that contain a majority of high-complex surgeries. A patient with a high-complex surgical procedure is likely to require a more extensive admission procedure and preparation phase (Heuven & Rene, 2018). Incorporating high-complex patients in the AL case mix may require staffing adjustments similar to the adjustments incurred by the health status. The specialty that a patient is assigned to is registered in HiX with an acronym.

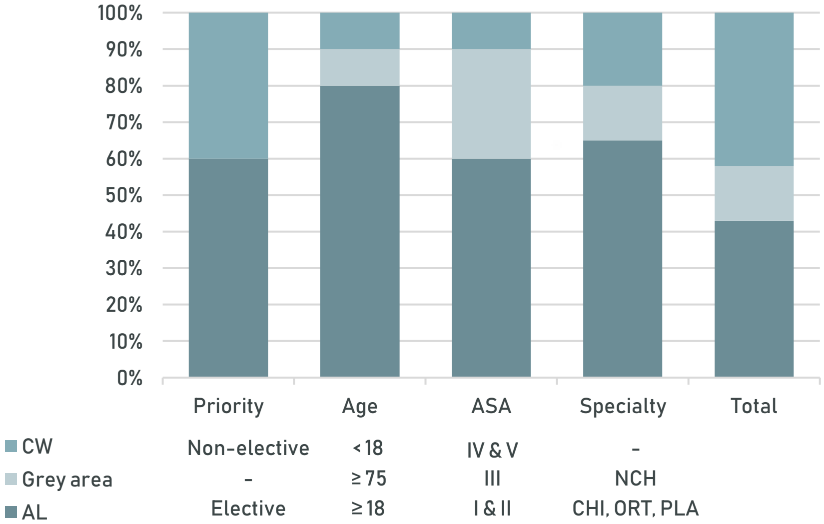

Figure 8 – Examples of patient selection criteria for the AL, CW, or the grey area in a "general" hospital, created with dummy data.

The patient selection criteria discussed in this subsection are summarised by Figure 8. It presents the decisions for inclusion and exclusion criteria for the AL and trade-offs (the grey area) per patient characteristic and gives insight into the relation between patient complexity and volume. The decisions in Figure 8 give bounds for the number of AL and CW patients; the lower bound (*LB*) is the fraction of patients directly suitable for AL admission; the upper bound (*UB*) is the *LB* combined with a fraction of patients that belong to the grey area. The range between the upper and lower bound shows the impact of the complexity within the case mix on the AL's patient volume. If that range is large, management can make stronger decisions for some characteristics and eliminate their grey area or our model could determine what patient groups within the grey area are interesting for AL assignment.

Case mix decisions and trade-offs

Patient selection for the AL ideally follows the hospital's mission, but is a trade-off between patient complexity and volume. Patients that require high-volume low-complex surgery are the most economical to select for AL admission, due to low staff skill requirements. Whether a hospital does low-complex surgeries in high volumes is dependent on the hospital's service mix. Management may require the inclusion of patients with higher-complex surgeries to attain higher patient volumes. The key trade-off in the patient selection is to weigh out the volume of patients that can profit from the AL against the costs of accompanying a higher-complex patient mix with higher-skilled staff. The LB and UB that arise from the selection criteria give an indication of the impact of the criteria for either AL or CW admission and the trade-offs that make patients fall within the grey area.

After the patient selection, the following KPIs are evaluated:

KPI 1 *Lower bound for the average number of admissions per facility*
KPI 2 *Upper bound for the average number of admissions per facility*

2.2.2. Care unit partitioning

Care unit partitioning refers to the decisions upon the medical care units in which the complete admission facility is divided.

The admission facility will be partitioned into the AL and the CW. Elective patients are admitted to the AL or to the CW, in compliance with the selection criteria. Although we refer to the CW as one unit, the CW is regularly divided into a set of specialty-specific wards. In Figure 9A this property is shown. Usually, these wards serve a selection of specialties. As our reference hospitals noted, a large part of the CW capacity is used for surgery-related admissions.

Figure 9B gives an exaggerated example of the distribution of capacities used for either admissions or recovery of patients for the entire CW and specialty-specific wards. Section 2.2.1 explained the classification of AL patients and CW patients. Figure 9C represents what portion of the capacity is required for AL (and CW) patient admission in our graphical example. When the AL is introduced, the physical partition shown in Figure 9D occurs.

With the care unit partitioning, management must determine how to facilitate the admissions for the derived patient profile. The goal of this subsection is to present the requirements for serving the patient mix and supporting the physical partitioning with appropriate types of staff, equipment, and additional processes at the AL and CW. Eventually, our systematic approach can be used for supporting the optimal subdivision for the variety of wards depicted in Figure 9A as well, but that is outside of the scope of this research. For the readers with interest in an approach for optimal department clustering, we refer to Van Essen, Van Houdenhoven, & Hurink (2015).

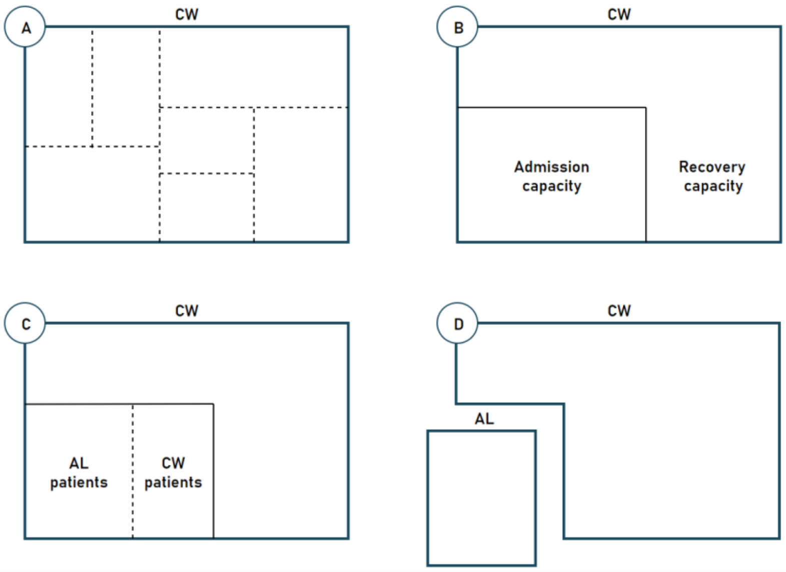

Figure 9 – Graphical representation of care unit partitioning.

Staff skill mix From the case mix decision health professionals can derive what types of staff members are required for the AL, based on the health status and the surgery complexity (Harper, Powell, & Williams, 2010). For example, ASA II patients require an LNP, while ASA III patients require an NP. The higher the complexity of the patient mix, the higher the staff skill requirements.

Internal transport The admission process contains several moments where transportation plays a role. We distinguish three types of transport: of patients, empty beds, and personal belongings. Management must decide what type of transport is executed by the staff of the dedicated care units or by LT staff.

Equipment It is possible to assess what patients require special equipment during the admission process. For example, patients that are not capable of walking on their own may require a lifting device. Whether the hospital wants to facilitate AL admission to patients that require special equipment, is up to the management. The required equipment can be derived from the patient mix, through assessment of the patient and surgery types covered by the patient inclusion and exclusion criteria, but that is outside of the scope of this research.

Care unit partitioning decisions and trade-offs

The staff skill mix requirements indicate what skills should be present within the entire staff; it does not set a minimum for one individual staff member. The staff can consist of a mix of lower and higher skilled nurses (LNPs, RNs, and SNs), as Section 2.1.1 states. The key trade-off in staffing is to provide good quality of care at an acceptable price; the higher the skill mix, the more expensive the staff becomes, as is the case when the staff size increases. Regarding internal transport, hospital management must decide whether the burden of indirect care activities is acceptable for the nursing personnel, or whether such activities must be carried out by a dedicated LT.

Hospital management decides upon the following IPs to quantify the staffing decisions related to care unit partitioning:

IP 1 *Staff skill division per facility*
IP 2 *Nurse-to-patient ratio per facility*

2.2.3. Capacity dimensioning

In conjunction with care unit partitioning, capacity dimensioning decisions consider the size of the AL and CW.

Care unit partitioning determines what type of resource is supposed to be allocated to the different care units. Capacity dimensioning expresses in what amount these resources are allocated to the units. The size of a care unit is generally expressed in staffed beds (Hulshof et al., 2012). A good estimation of the required capacity is essential to address congestion; a threat for the quality of care. Congestions could lead to the need for transfers to another hospital when all wards are completely full; temporarily misplacement of patients at departments that are not fully capable of treating them as required; a potential backlog at the emergency department (when a patient cannot be admitted) or the PACU (when the patient cannot recover at the CW); postponement of elective surgeries followed by an increased surgery waiting list because there is no room for additional admissions; or the need to pre-discharge patients to make room for new admissions (Dobson, Lee, & Pinker, 2010; Hulshof et al., 2012).

Beds and equipment The number of staffed beds is based on the volumes of patients the AL and CW have to situate on a daily basis, and the LOS characteristics of various patient types. In Chapter 3 we determine what analytical models are most suitable to determine the correct number of beds for the AL and CW given the desired blocking probability and occupancy rate set by management. The number of resources and amount of equipment to situate the volumes and types of patients can be related to the number of beds (Cochran & Bharti, 2006). If a care unit contains bottleneck resources other than staffed beds, it is relevant to estimate what amount of that resource is satisfactory. In our preliminary research, we asked about bottleneck resources during the admission process, but none of the hospitals could indicate any – beds aside. Equipment estimations are therefore outside of the scope of our research and up to hospital management to decide after the number of beds is estimated.

Waiting area The AL does not only consist of beds, but also of waiting places; the *lounge* aspect of the admission lounge. The waiting area should be sufficiently large to accommodate AL patients throughout the day and a certain level of comfort is desired. If the case mix includes patients that require guidance by, for example, a partner, the waiting area must also reserve capacity for them. Hospital management must decide on the size and comfort of the AL's waiting room in compliance with the determined number of beds.

Staff volume Virtually, the amount of staff required for the AL varies throughout the day, since the staff size can be derived from the number of staffed beds and the bed occupancy is generally not constant throughout the day. However, on a strategic level, we assume a constant staff size per day. Section 2.2.2 states that a department can staff LPNs, RNs, SN, or a mix of those. Staff size can be derived by multiplying the nurse-to-patient ratio set by management with the number of staffed beds (Harper et al., 2010). Determining the size of the LT staff, to support the indirect care activities, is outside of the scope of this research.

Capacity dimensioning decisions and trade-offs

In bed capacity management, the biggest trade-off is between bed occupancy and service level; the subsequent chapters will elaborate on this. Hospital management must decide what the size of the AL and the CW is going to be in terms of bed capacity. The staff volume will be derived from the number of staffed beds using a nurse-to-patient ratio. With a lower nurse-to-patient ratio, there are more nurses per patient, which may improve quality of care, but will increase cost, compared to a higher nurse-to-patient ratio.

We monitor the following KPIs for the capacity dimensioning decisions:

IP 3 *Desired service level per unit*
KPI 3 *Average rejection rate per unit*
KPI 4 *Average bed occupancy rate per unit*
KPI 5 *Average number of staffed beds per unit*

2.2.4. Facility layout

The facility layout concerns the positioning of the AL and the CW, based on which facilities should be close to each of the units.

In this subsection, we want to emphasise that some choices or restrictions within the facility layout can have a limiting effect on all preceding decisions. Long distances increase transportation and travel times between facilities, which lead to an increase in indirect care activities and limits certain decision:

- Between the AL and CW leads to increased empty bed transportation time;
- Between the AL and OT increases preoperative patient transportation time;
- Between the OT and CW increases pre- and postoperative patient transportation time;
- Between the lab and the AL and CW affects the decision whether, e.g., blood tests can be carried out during the admission process.

There is a wide range of methods to solve the facility layout problem of optimally locating all care units and facilities within the hospital. The literature contains models that solve the facility layout problem, in which the multitude of trips from and to facilities is minimised and penalised with the distance travelled. We refer to Hahn & Krarup (2001) and Özcan (2009) for examples of such models.

Besides the proximity to other units, it is necessary to assess whether the capacity requirements for the AL are feasible within the facility layout. The AL will experience a high rejection rate if there is not enough space to facilitate all AL admissions. However, this rejection rate does not result in a rejected patient, but admission to the CW. Hospital management must decide whether to accept this high rejection rate, or to reset the inclusion and exclusion criteria for the AL more strictly, limiting the AL patient volume. In the latter situation the rejection rate for the AL will drop, and the planner assigning patients to the AL or CW has to make less decisions about rejecting, or giving access to, a potential AL patient.

Facility layout decisions and trade-offs

The key trade-offs for the facility layout is to let the facility layout restrict the preceding decisions if needed or to rearrange existing facilities within the hospital to realise the strategy. If the preceding strategic decisions fail to fit within the facility layout and a redesign of the layout is unwanted, there is a need for readjustment of the decisions according to the ideal order in Figure 4. This means that the case mix should be reconsidered. The case mix can be adjusted manually, but it is also possible to optimise the case mix. In Chapter 3 we elaborate on the case mix optimisation algorithms.

Hospital management can set a goal for the capacity of the AL with the following IP:

IP 3 *Minimum or maximum bed capacity AL*

2.3. Tactical decisions

After the strategic decision in which the location and capacity of the AL are fixed, there is a need for tactical planning in order to account for variability. Strategic decisions cover averages, maximums and minimums over the course of multiple years, while tactical decisions account for the variability that occurs over the course of several months. More than strategic planning, tactical planning incorporates decisions on medium-term demand. We elaborate on the tactics temporary bed capacity changes, admission control, and staff shift scheduling, based on Hulshof et al. (2012).

2.3.1. Temporary bed capacity change

The bed capacity does not only have to be adjusted by physical reallocation of beds. It is also possible to temporarily close beds if staff levels are reduced. Incentives for such staff level reductions can be demand-driven due to seasonality or events, supply-driven through external staffing restrictions, or both demand and supply-drive in the case of a flu wave. If a bed is closed, admissions should not take place in that bed, meaning that there is a virtual capacity reduction.

2.3.2. Admission control

The MSS is an internal driver that causes variability in demand. In the MSS states what types of patients can receive surgery at a given moment. The arrivals that result from the scheduling within the MSS are highly variable for smaller sets of patients. Therefore, it is necessary to match demand and supply with different tactics for a variety of situations. This means that there may be a need for bed reservations. In bed reservations, admissions can be refused for certain patient types when the bed census exceeds a threshold. This ensures that patients from another type can also still use the AL if there is a sudden increase in arrivals for patients that belong to the type that exceeded the bed census. In such cases, there is a need for overflow rules that determine where a patient admission may take place if there is no place for them at either the AL or the CW.

2.3.3. Staff shift scheduling

By adjusting staff levels, hospitals can reduce care costs efficiently, as staff is an expensive bottleneck resource. Shift scheduling refers to the adjustment of staff levels in compliance with expected patient (type) inflow dictated by the MSS. Staff levels can be adjusted in either *full time equivalents (FTE),* skill mix, or both.

2.4. Conclusions

This chapter discusses the perioperative process its stakeholders and how to facilitate an effective and efficient admission and discharge process.

System analysis We distinguish patient flows of four groups of patients around the AL and CW: AL patients, CW patients, urgent patients and emergency patients. The AL is only affected by AL patients, while the CW can expect patients from all four patient flows. If we compare the admission processes of the AL and CW patients there is one main difference: the location of admission. The AL is ideally situated close to the holding such that the logistical advantages of the AL are exploited. We expect that the patients most suitable for AL admission are low-complex patients, because the staffing for the AL could be relatively cheap due to a lower staff skill mix.

Stepwise approach Throughout this chapter we listed KPIs for performance measurements and IPs for management interventions or decisions throughout the design process of the AL. We can reduce the critical decisions and trade-offs to a structured design process, consisting of five phases. The phases resonate with the proposed decision order in Chapter 1.

Phase 1 *Set up inclusion and exclusion criteria for the AL*

Inputs: Inclusion and exclusion criteria for the AL set up by a project group consisting of, e.g., hospital managers, clinicians, and planners. The criteria are preferably in line with the hospital strategy and depend on the hospital's service mix.

Outputs: Visualisation of the effects of the case mix selection criteria. Patients are categorised as AL patient, CW patient, or grey area patient.

Phase 2 *Determine the appropriate staff, equipment, and supporting processes for the AL and CW*

The project group determines the required staff skill mix, an appropriate nurse-to-patient ratio, and special equipment requirements for the AL and the CW. In this phase, the project group can also decide upon the need of a logistics team to handle the transport and reduce indirect care activities.

Phase 3 *Analysis of potential bed reductions for the CW and required capacity for the AL*

Inputs: Desired service levels for the AL and the CW.

Outputs: Chapter 3 introduces the algorithms for the performance analysis. The performance measures are: average rejection rate and occupancy rate per unit, and the corresponding required number of beds. Following, the inputs from Phase 2 can be used to derive the staff size for the AL and the CW.

Phase 4 *Analysis of feasibility within the facility layout*

After Phase 3 the required capacities to facilitate admissions for the AL patients are known. The project group determines whether the overall performance is acceptable and the required capacities are feasible within the facility layout. If the required capacity is not feasible because of limited space there are two options for the project group. The first option is to stick to the set patient selection criteria and accept a high rejection rate for the AL. The second option is to manually limit the inclusion criteria in Phase 1.

Phase 5 *Optimisation: assignment of the grey area patients to the AL or CW*

To research whether the assignment from patients within the grey area results in better performance of the AL and the CW, we give the option to optimise the grey area. Hospital management can decide upon final inclusion and exclusion criteria for the AL that are both effective and efficient, as well as in line with the hospital's strategy. Chapter 3 introduces the optimisation algorithm.

Inputs: All possible assignment combinations following from the inclusion and exclusion criteria for the attributes *age, ASA,* and *specialty*.

Outputs: Ranked outcomes with outputs also found in Phase 3.

CHAPTER 3
ANALYTICAL MODELS FOR THE AL AND CW

The AL is a new concept hardly described by the literature and to determine its dimensions and performance we need to research appropriate models for performance measurement. This chapter describes all algorithms used for the quantitative decision support. We first describe the logistical system of the admission and discharge processes in Section 3.1. Then we select appropriate analytical models from the literature (Section 3.2) to determine the capacity requirements and the performance for the CW (Section 3.3) and AL (Section 3.4). In Section 3.5 we discuss the case mix optimisation method, and we close the chapter with our conclusions in Section 3.6.

3.1. Job shops

The logistical system of the admission and discharge process can be related to a *job shop system* with strong precedence constraints. In manufacturing, a job shop system is typically designed for manufacturing a broad spectrum of products in relatively small quantities. The job shop is suitable for a wide variety of processes; typically for each process on or more universal machines are installed. Job shops are often largely process-oriented and are characterised by a functional layout. Job shops are typically found in make-to-order environments. In a job shop, many different jobs each have their own routing and jobs have to be sequenced on all individual work stations or a subset of those workstations, resulting in a complex problem with a large number of possible schedules. A primary goal, especially in make-to-order manufacturing systems, is often to meet due dates set on the higher production job planning and resource group loading level (Zijm, 2000).

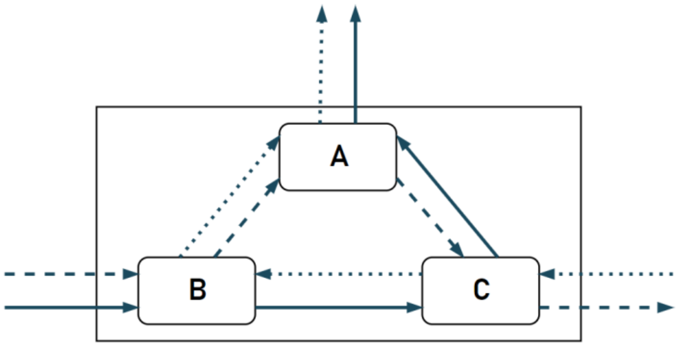

Figure 10 – A job shop system with three workstations and three products

Figure 10 gives a simplified graphical representation of a job shop consisting of three machines *A, B,* and *C*. Three different products each have to be processed by the three machines. The products have different process flows; the solid arrow follows the production order B-C-A; the striped arrow B-A-C; the dotted arrow C-B-A. The job shop allows the processing of various classes of products with capacity limitations inherent to the control and handling of the products and the preparation times of the machines. The machines of the system can perform operations on different classes of products which involve differing setup-times, lead-times, and levels of work in progress (Barreiros, 2013). This is similar to the system of the perioperative process and other hospital processes where each patient has to follow a given route and has to be treated at a number of different facilities while going through the system (Pinedo, 2009).

In the job shop system, patients can undergo the complete set of activities or a subset of the activities that are applicable to them (Leeftink, 2017). In the perioperative process, patients undergo roughly the same activities, but at different facilities. One facility can be used for multiple types of activities; the CW is a facility where patients can undergo multiple types of activities, namely admission and recovery. The characteristics of patients relate to the required preparation time (setup-times and lead times), and the patient's LOS at the CW (work in progress). The properties of the perioperative process correspond with the system descriptions by Barreiros (2018), Pinedo (2009) and Zijm (2000).

Most research on job shops considers detailed scheduling, where the performance of a prespecified set of sequencing rules on a particular job shop with a particular job mix is measured. This field of research relies heavily on simulation studies (Graves, 1986). Models that consider the broader issues of planning, at the strategic and tactical level, were first introduced by Jackson (1957, 1963). Barreiros (2013) also models a job shop plant with the use of queueing techniques; a technique that is often employed in hospitals for bed capacity dimensioning (Hulshof et al., 2012; Zijm, 2000). The use of queueing techniques allows the estimation of the impact of changes in demand, and the planning of the necessary steps to optimise the system response (Barreiros, 2013). These properties are relevant for modelling the perioperative process as patient demand also fluctuates over time, both on an hourly level as on a weekly, monthly, seasonal or a yearly level (Hulshof et al., 2012).

3.2. Models for bed capacity management

Both job shops and inpatient services are often dimensioned with queueing theory, simulation, or a combination of both, as a basis (Green, 2006; Hulshof et al., 2012). The taxonomic classification of Hulshof et al. (2012) gives an overview of the modelling techniques used for bed capacity management; the two most referred modelling techniques are computer simulation (29 references) and queueing techniques (18 references). Queueing and simulation models can be useful in identifying appropriate levels of staff, equipment, and beds.

Queueing models require little data and result in relatively simple expressions for predicting performance measures such as mean delay or probability of waiting more than a given amount of time before being served. They are easier and cheaper to use than simulation models, which require substantially more data and computation time (Green, 2006). Robinson (2014) confirms that simulation modelling is expensive because the software for simulation modelling is expensive, the modelling process is time-consuming and the models are data hungry. However, simulation models have the ability to cope with more variability and require fewer assumptions than queueing models (Robinson, 2014). Due to their adaptability, interpretability, and short computation time, queueing models are easier to implement into HiX.

We continue by researching the most suitable queueing model for our analysis. For the collection of literature for our study, we performed a backward and forward search on the article by Hulshof et al. (2012), looking further into queueing models. Appendix B contains the performed search method which resulted in 30 articles for our review.

3.3. Erlang loss model for the CW

In our selection of articles, 14 out of the 30 references mention the *Erlang loss model*. This model was first introduced for the assessment of queues in telecommunications and later applied to industries and healthcare (Barreiros, 2013; Green, 2006; Jackson, 1957, 1963). There is a variety of model formulations available; we follow the formulation of De Bruin, Bekker, van Zanten, & Koole (2010) because it is the most cited recent article in our selection.

3.3.1. Model assumptions

The Erlang loss model assumes that patient arrivals are Poisson distributed. Many authors have shown that arrival processes, especially unscheduled, can be approximated by a Poisson process (Cochran & Bharti, 2006; De Bruin et al., 2010, 2007; Green, 2006). For practical purposes, it is not required that the number of admissions follows the laws of a Poisson distribution exactly. The key point for practical modelling purposes is that the variability in the number of admissions is generally well captured by the Poisson distribution, making this a reasonable assumption for the arrival distributions that do not follow the Poisson distribution very well. Several studies have shown that unscheduled arrivals perform better under the Poisson distribution than scheduled arrivals (De Bruin et al., 2010; Green & Nguyen, 2001). However, scheduled arrivals can be modelled under the Poisson assumption as well (De Bruin et al., 2010; Gorunescu, Mcclean, & Millard, 2002; Li, Beullens, Jones, & Tamiz, 2007), especially if the results are solely required for strategic and tactical decision making (De Bruin et al., 2010). For decisions on the operational level, more accurate approximations may be required (Bai, Fügener, Schoenfelder, & Brunner, 2018; Bekker & De Bruin, 2010; Bhattacharjee & Ray, 2014). The model does not account for a time-dependent arrival pattern, mainly for a practical purpose: simplicity. A time-dependent model may be used for decisions on the operational level, e.g. to model weekly bed occupancy to determine the nurse rostering.

De Bruin et al. (2010) indicate that the *average length of stay* (*ALOS*) can be highly variable, across clinical wards. The indicator for variability used is the coefficient of variation, defined as the ratio of the standard deviation to the mean. For a perfectly Poisson-distributed LOS, the average and the mean are equal, so the coefficient of variation equals 1. De Bruin et al. (2010) and Green & Nguyen (2001) found that the coefficient of variation is greater than 1 for the vast majority of wards in their study, showing the high variability of the LOS at clinical wards. To cover this variable characteristic, the LOS distribution can be characterised by Lorenz curves and the related Gini coefficient. Lorenz curves are useful in identifying patients with prolonged stay and their disproportional resource consumption. Moreover, it illustrates the difference in LOS-characteristics between clinical wards. We note that in general, a model based on a fixed length of stay is not capable of describing complex and dynamic inpatient flow. This would give misleading results, termed the flaw of averages (De Bruin et al., 2010, 2007). For a more refined estimation, simulation modelling could be considered, because it is capable to incorporate more variability.

The occupancy determined with the Erlang loss model is defined as found in operations research and management science and differs from the definition of occupancy used in Dutch hospitals. The Dutch national definition of occupancy is based on *hospitalised days*, which is an administrative financial parameter (De Bruin et al., 2007). Under the latter definition, it is not uncommon that occupancy rates greater than 100% occur, because multiple patients may occupy a bed per day. The occupancy rate defined by the Erlang loss model gives better insight into the actual utilisation of the available capacity and is therefore used in our study (De Bruin et al., 2010).

3.3.2. Model description

We describe the Erlang loss $M/G/c/c$ model because it incorporates sufficient detail for strategic and tactical decision making. We use the model definition by De Bruin et al. (2010). In the $M/G/c/c$ model patients arrive according to a Poisson process (*Markovian* or *memoryless* arrivals, denoted by *M*) with parameter λ. The LOS of an arriving patient is independent and identically distributed with expectation μ. In the queueing model formulation the LOS distribution type is denoted by G, which stands for a general distribution. Often, the average service time is defined $1 / \mu^*$, where μ^*

is the service rate in the case of an exponential service time distribution (De Bruin et al., 2010). In the case of patients, the service time distribution is estimated using the LOS distribution. The number of operational (occupied) beds equals c. The model assumes that there is no waiting area, which means that an arriving patient who finds complete occupancy at the CW is blocked. The blocking probability is given by:

$$P_c = \frac{(\lambda\mu)^c/c!}{\sum_{k=0}^{c}(\lambda\mu)^k/k!} \tag{1}$$

This model is insensitive for the LOS-distribution and is valid for general service times. The occupancy rate is defined as:

$$Occupancy\ rate = \frac{(1-P_c)\lambda\cdot\mu}{c} \tag{2}$$

which is equivalent to:

$$Occupancy = \frac{Average\ number\ of\ occupied\ beds}{Number\ of\ operational\ beds}$$

The term $\lambda{\cdot}\mu$ is often referred to as the offered load to the system. A mistake that is often made is to set the capacity equal to the offered load, resulting in high rejection rates. With expression (1) we are able to assess the blocking probability for a set number of beds to avoid high rejection rates.

3.3.3. Arrivals approximation for the CW

De Bruin et al. (2010) note that we need to quantify the number of patient arrivals (λ) in order to apply the Erlang loss model and for purposed of validation later on. Hospital systems, such as HiX, only register the number of admissions; the number of refused admissions is generally unknown. De Bruin et al. (2010) state that it is necessary to make an educated guess about λ due to this probable administrative flaw. To do so, they use the historical average number of occupied beds and the number of beds that were present at a ward. ChipSoft, however, experiences that these figures are not trustworthy in HiX due to the many workarounds made in administration. The averages are unreliable because the registered number of opened beds in HiX is usually higher than its realisation. Therefore, one requires insights from capacity managers within the hospital for accurate interpretation of these figures. Moreover, the description of blocking by De Bruin et al. (2010) – meaning that a patient does not enter the system when all beds in a ward are occupied – does rarely occur in hospitals. Our reference hospitals confirm this. The blocking of patients usually results in patient allocation to other units within the hospital, increased access time for the surgery. Both are unwanted, as described in Chapter 1, but do not result in a loss of patient arrivals. Therefore we will use the average daily arrival rate as λ in our analysis.

3.3.4. Length of stay estimation

De Bruin et al. (2010) model the LOS with a hyper exponential distribution, using the Gini coefficient to represent the extent of variability in the LOS distribution. The $M/G/c/c$ model, however, only uses the ALOS as input for the LOS distribution. De Bruin et al. (2010) validated that the assumptions for modelling the LOS distribution with the hyper exponential distribution holds for most of the clinical wards in their case study, like the assumptions regarding the arrival process. Figure 11 shows how the LOS at the CW can be calculated for CW and AL patients. The LOS for CW patients (LOS_{CW}) is measured from the start of the admission to the CW until the discharge from the CW. The LOS for AL patients (LOS_{AL}) starts when the AL patient arrives at the CW for the first time.

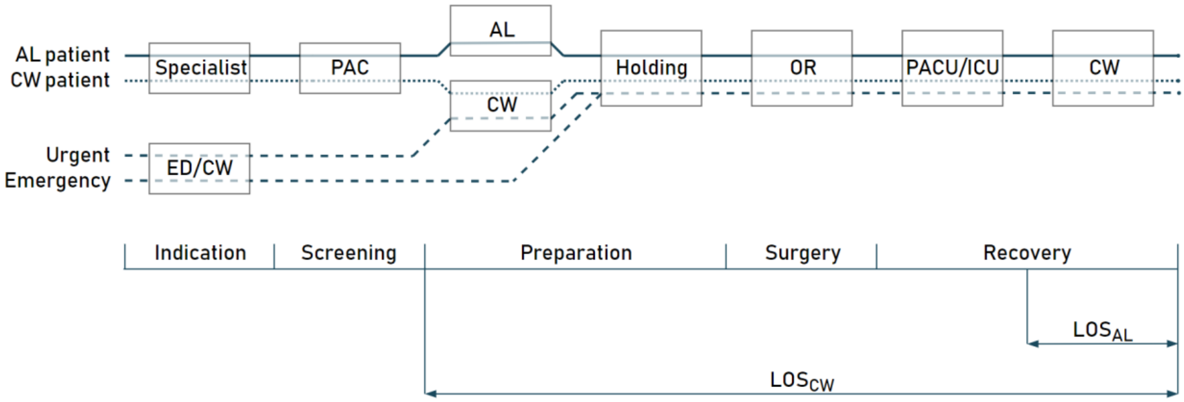

Figure 11 – Determining the LOS at the CW for AL and CW patients.

Given that a CW patient only has a $LOS_{CW,CW}$ and an AL patients only has a $LOS_{AL,CW}$ – meaning that for each patients there is one LOS estimation – the *ALOS* μ for a set of n_{AL} AL patients and n_{CW} CW patients is given by:

$$ALOS = \frac{1}{n_{AL}} \sum_{n_{AL}} LOS_{AL} + \frac{1}{n_{CW}} \sum_{n_{CW}} LOS_{CW}$$

3.4. The AL's dimensions and performance

Contrary to the CW, the AL most likely does not reach a steady state; the AL is filled with patients in the morning and is empty by the time it closes. Therefore the Erlang loss model cannot be applied to the dimensioning of the AL. Because we can treat the AL as a another type of workstation in the job shop system, it is possible to apply other analytical models to assess the performance of the AL. To dimension the AL we determine the load that the AL has to process daily and relate that offered load to a set number of beds, using basic techniques from the field of operations research and management sciences.

3.4.1. Arrivals approximation for the AL

AL arrivals will occur according to the appointment schedule and are therefore strongly related to the MSS. The MSS determines how much OR time is to be assigned to the variety of surgery groups – on the highest level represented by specialties – on each weekday (Hof, Fügener, Schoenfelder, & Brunner, 2017). Because capacity dimensioning decisions mainly focus on assigning OR time to disciplines, resulting in the MSS (Riet et al., 2016), the MSS is leading in the arrivals approximation for the AL.

As stated in Section 2.1.2, the MSS is often a cyclic timetable consisting of blocks assigned to specialties or sub-specialties. Hospitals have an incentive to utilise their ORs to a maximum because they are the most expensive components within the hospital. Accordingly, ORs experience little down time in times of high staff availability, and the MSS often plans to the maximum capacity of the OR.

We relate the arrivals of the AL patients to the daily total planned OR time for the specialties within the AL case mix. The daily total planned OR time for a specialty is the total duration of sessions within the MSS dedicated to the surgeries scheduled for a specialty. HiX registers the session, and its duration, an admission is linked to; sessions usually last from several hours up to eight hours. For one specialty, multiple sessions may take place on a day. To assess the arrivals on a given day, it is relevant to link the expected arrivals to the total session duration for a specialty.

Per specialty, the total planned time on days that allocate time to the specialty does not change often. So it is possible to estimate the expected arrival rate of patients from e.g., the specialty orthopaedics on days where the dedicated OR time amounts 8 hours, if that is a common session duration. We call days on which common amounts of OR time are allocated to a specialty *representative days* and use those days as a benchmark for the AL performance assessment.

3.4.2. The AL's required beds

Because there is no straightforward mathematical formulation to determine the patients' LOS at the AL, we have to use findings from our preliminary research to make assumptions on the LOS. Using basic techniques from the field of operations research we determine the offered load of the AL. The general consensus of our reference hospitals was to have the patient arrive at the AL two hours prior to the scheduled start of surgery. Based on the average hourly arrivals on representative days, we calculate the offered hourly load during working hours.

We define time buckets $t = (0,1,2,\dots,T)$ with duration d (in minutes) in which arrivals occur at the AL. The expected admission duration of D is a multiple of d and represents the time that patients spend at the AL. The opening time of the AL is at the beginning of $t = 0$, the opening time of the OT $start_{OT} \in T$ is in time bucket t and marks the moment that patients can leave the AL for transfer to the holding. Figure 12 gives a graphical representation of *t, d, D,* and $start_{OT}$ on a timeline.

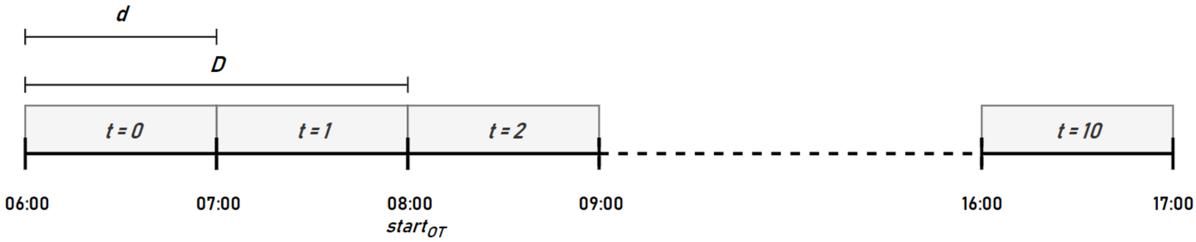

Figure 12 – Graphical example of time buckets t, the time bucket duration d (60 minutes), and the admission duration D (120 minutes) on a timeline. The AL is opened from 06:00 to 17:00.

Before $start_{OT}$, the arrivals λ_t during $t = (0,1,2,\dots,start_{OT})$ remain in the AL. If the patient has spent $\frac{D}{d}$ time buckets at the AL and the OT is open ($start_{OT} < t$), the patient leaves the AL. The offered load on the AL ρ_t during time bucket t on a given day is determined by:

$$\rho_t \begin{cases} \sum_{t=0}^{t} \lambda_t & ,0 \leq t \leq start_{OT} \\ \sum_{t=t-(\frac{D}{d})}^{t} \lambda_t & ,start_{OT} < t \leq T \end{cases}$$

The average load per time bucket $\overline{\rho_t}$ for a set of n representative days is obtained through:

$$\frac{\sum_n \rho_t}{n} \qquad ,\forall t$$

Meaning that the average number of required beds to accommodate all daily AL arrivals amounts $max\lceil \overline{\rho_t} \rceil$.

We assess the performance of the AL for a set number of beds, also for $max\lceil \overline{\rho_t} \rceil$, to determine how the AL would have performed on representative days. To do so, we compare the historical load on the AL by patients that would be assigned to the AL based their characteristics and the AL inclusion criteria. Whenever the load ρ_t exceeds the set number of beds, a patient must have been rejected. We term the percentage of the opening hours of the AL on which rejections took place, for all representative days, the *rejected hours rate*. We can also measure the fraction of days on which at least one rejection took place, termed the *rejected days rate*.

3.5. Case mix optimisation

Section 2.2.1 indicates how the inclusion and exclusion criteria for the AL and CW can result in a grey area of patient selection. We want to develop a method that helps choosing the most effective and efficient assignments for the AL and the CW. In our literature study we did not come across methods to optimise the case mix for the AL or comparable job shop elements.

We assign patients within the grey area to either the AL or CW by enumerating the assignment possibilities in the grey area. The AL and CW selection criteria serve as bounds for the optimisation method. The selection criteria for the dimensions *age*, *specialty*, and *ASA* can be up to discussion in the context of a general hospital. The case mix optimisation can have two objectives: optimal use of the AL and a maximal bed reduction for the CW.

We propose to divide the *age* category into subcategories, because enumerating for all ages within the grey area is too extensive and unlikely results in significant improvements. We expect that dividing age in categories of 5 years will suffice. The category ASA will consist of a small amount of assignment possibilities as well, since there are only three relevant ASA classifications (I, II, III) for the AL. If a hospital has a wide variety of specialties, or the model is refined towards sub-specialties, the solution space may increase rapidly, by a factor of 2^k, k being the number of specialties within the grey area. This can be a problem if the model has a long runtime for small solution spaces.

After the enumeration we compare the overall performance of the all assignment rule sets. Because there is a wide variety of available performance indicators we apply a scoring method to assess each configuration's performance. Hence, we can direct DSS users towards effective and efficient outcomes, and enable them to make comparisons relatively easy.

The scoring method weighs out efficiency and service level. Efficiency is represented by the occupancy ratios and the required numbers of beds for the AL and the CW. Service level is represented by the blocking probability for the CW and the hourly acceptance rate for the AL. For the analysis we are interested in configurations that may lead to a reduction in the total number of required beds; where the bed reduction for the CW exceeds the number of beds required for the AL. This is an economic point of view. We use the following objective function to weigh out effectiveness and efficiency of the solution:

$$Performance = (Bed\ reduction\ CW * Occupancy\ rate\ CW) - (Beds\ AL * \frac{(1 - rejected\ hours\ rate) + Occupancy\ rate\ AL}{2}).$$

The objective is a good overall performance. That is, effectiveness and efficiency are weighed for both the AL and the CW. Effectiveness of the CW is measured by the blocking probability, which indicates the service level. For the AL, effectiveness is measured by the accepted hours rate, (*1 – rejected hours rate*), which serves as an indicator for the service level of the unit.

There are many ways to put a formula like this together; there is not one right answer. To make this approach more robust we like to point out the possibility to assign weights to each component of the ranking equation. This way, the user can emphasize on a variety of performance measures: the effectiveness and efficiency of both units, or either for one unit.

3.6. Conclusions

We summarise the findings for this chapter below.

Logistical system The admission and discharge process for the AL and CW resemble a job shop. The AL and CW process patients coming from various flows. The processing time of the AL is the time that it takes for the admission and preparation of a patient before surgery. For the CW it is the LOS of the patients; the period starting when the patient arrives at the CW for the first time and ending when the patient is discharged from the hospital. We found that job shops are often analysed with queueing models or simulation modelling.

Capacity algorithms We first determined the most suitable model that determines the size and the potential bed reduction for the CW. We select the $M/G/c/c$ Erlang Loss model (see e.g. De Bruin et al., (2010)) for analysis of the CW. The Erlang loss model requires little data and computation time, and its results are easy to interpret. With the Erlang loss model we can derive the required number of beds and the occupancy ratio for a set blocking probability. Because the Erlang loss model assumes a Poisson arrival process we have to validate the goodness-of-fit of the model on the data in Chapter 4. Another assumption of the Erlang loss model is that the wards reach a steady state. The arrival and discharge moments at the CW, however, follow a clear pattern throughout the day. The capacity required for early patient admission probably exceeds the potential bed reduction that we will identify. Nevertheless, we expect that the model will effectively indicate the effects of a decreased length of stay at the CW for AL patients.

Because the AL most likely does not reach a steady state, we define a deterministic model that determines the load on the AL. The model assumes that patients stay at the AL for a fixed duration of, e.g., 1.5 or 2 hours. This complies with reality to a certain extent, because hospitals require patients to arrive 1.5 or 2 hours before surgery is set to start (see Chapter 1 and Appendix A). The algorithm determines the performance of the AL by comparing a set number of beds to the load on the AL on representative days. The KPIs for the AL's performance are the rejected hours rate and the rejected days rate. The former indicates the proportion of all hours on representative days on which one or more AL admissions had to be rejected because the load exceeded the number of beds. The latter indicates the proportion of days on which one or more AL admissions had to be rejected because the load exceeded the set number of beds on some hour of the day.

Case mix optimisation From the patient inclusion and exclusion criteria for the AL follows patient categorisation into AL patient, CW patients and grey area patients. The optimisation methods assigns patients from the grey area to the AL or the CW by resetting the inclusion and exclusion criteria for the AL. All possible combinations of attribute values within the grey area are enumerated. With a ranking function that balances efficacy and efficiency for the AL and CW we provide an overview of de top performing assignment combinations.

CHAPTER 4
DECISION SUPPORT SOLUTION DESIGN

For this chapter we use hospital data from ChipSoft's development database to test the algorithms of Chapter 3. We refer to this dataset as the ChipSoft development data. The development data represents a medium sized general hospital. The data is extracted from the ChipSoft database using an SQL query, after which it is loaded into RStudio for implementation of the algorithms. This is common practice for ChipSoft's R&D team for capacity management. This chapter shows how the algorithms are integrated into the DSS and how the available information will be presented. Section 4.1 shows the DSS methodology, which resembles stepwise approach introduced in Chapter 2 and relates it to the decision order introduced in Chapter 1. The sections following the five phases of the stepwise approach: patient selections (4.3), staffing decisions (4.4), capacity dimensioning (4.5), and – two phases in one section – a check for feasibility and case mix optimisation (0).

4.1. DSS methodology

The DSS requires data input to present relevant outputs. We summarised the DSS methodology drawing inspiration for the BPMN notation. Figure 13 presents this methodology, consisting of a sequence of calculations within the DSS, in correspondence with the sequence of the decision order in Figure 4 and the phases given in Section 2.4. The boxes with a script icon represent the steps within the DSS, the boxes with a person icon represent decisions or inputs by the DSS users.

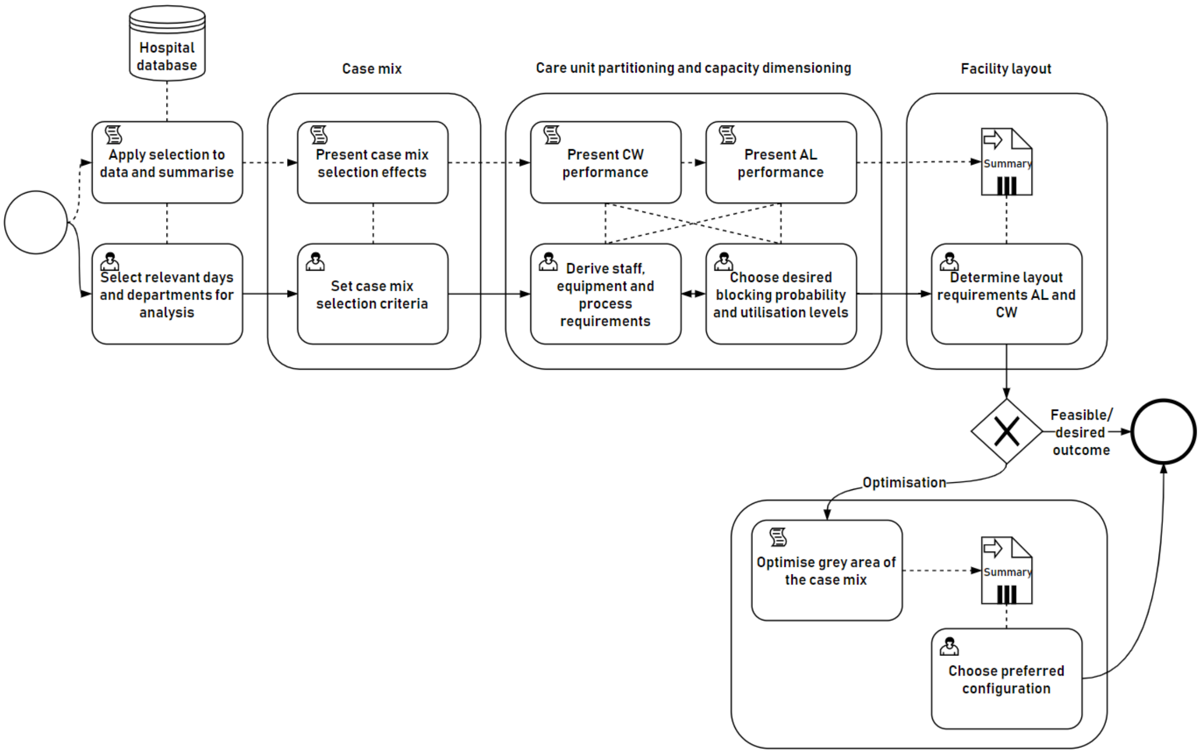

Figure 13 – DSS methodology overview.

4.2. Data preparation

Data preparation requires the users of the DSS to actively think about the relevant admissions within the scope of the project. For ChipSoft it is uncommon to actively show the data preparation step. We think that by presenting the results of the scoping decisions in the first phase, there is more understanding about the potential effects and impact of the project.

The data structure is defined by ChipSoft and it forms the backbone of HiX. Data extraction for our model will be similar for all hospitals that use HiX. However, different hospitals use different methods for data registration. This means that not all fields within the data structure are filled the same way for every hospital. Hence, the query must always be slightly tailored to the methods of the hospital that uses our DSS. Running the SQL query takes up 4 seconds and results in a dataset containing 85,060 patient admissions that took place during the years 2015, 2016 and 2017.

The data covers multiple departments. Four wards that mostly situate surgical specialties are selected, any admissions outside of these four departments are filtered out of the dataset (62,777 exclusions). We also solely select clinical patients, day care patients are hence filtered out (34,614 exclusions). Moreover, we only select admissions that took place during weekdays; any patient admissions that took place during the weekend, are filtered out (6,656 exclusions) as well as patients with a registered unfinished treatment (1,386 exclusions). Lastly, patients from specialisms that represent less than 1% of the admissions in the selected wards are not considered in the analysis (227 exclusions). Eventually, the dataset is reduced to 16,730 admissions, which sets the scope to a coverage of approximately 20% of all admissions in the virtual hospital. The specialties included in this analysis are:

- 25% General surgery (CHI);
- 4% Gynaecology (GYN);
- 16% Internal medicine (INT);
- 2% Ear nose throat medicine (KNO);
- 12% Lung medicine (LON);
- 6% Gastroenterology (MDL);
- 11% Neurology (NEU);
- 14% Orthopaedics (ORT);
- and 11% Urology (URO).

The data preparation step contributes to the hospital's understanding of the model's use because management must consider what the relevant wards are and it helps to understand the effects presented by the DSS later on. We show that the analysis in this chapter covers 20% of all patient admissions, which is useful for management because it addresses the scope of the project.

4.3. Phase 1: patient mix decision support

The patient mix decision support is presented in a way that resembles the example in Figure 8. The users of the tool decide on the patient profiles of the AL and CW patients. The model determines what proportion of patients belongs to the groups *CW, grey,* and *AL*. We supplied the model with the inputs in Table 1, which we assign using an educated guess. The resulting figure (Figure 14) gives an idea of the effects on the patient allocation. More information about the effects of the patient mix becomes available when users hoover over the figure in the DSS tool (Figure 15). With the current selection criteria, 22% of the admissions can take place in the AL, 67% have to take place at the CW, and 11% of the admissions fall within the grey area.

Table 1 – AL and CW selection criteria for the ChipSoft development dataset.

Variable	AL criteria	CW criteria
Priority	Elective	Non-elective
Adult	1	0
Age	18-75	0-17, 86-105
ASA	1,2	4, 5, 6
Specialties	CHI, URO, GYN, ORT	KNO, LON, NEU

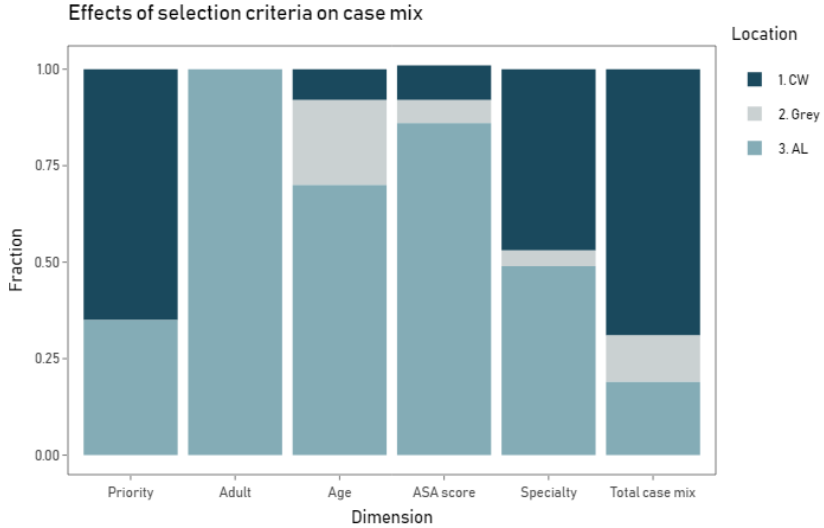

Figure 14 – Visualised effects of patient selection criteria in the DSS. (ChipSoft development data, 2015-2017, n = 16,730)

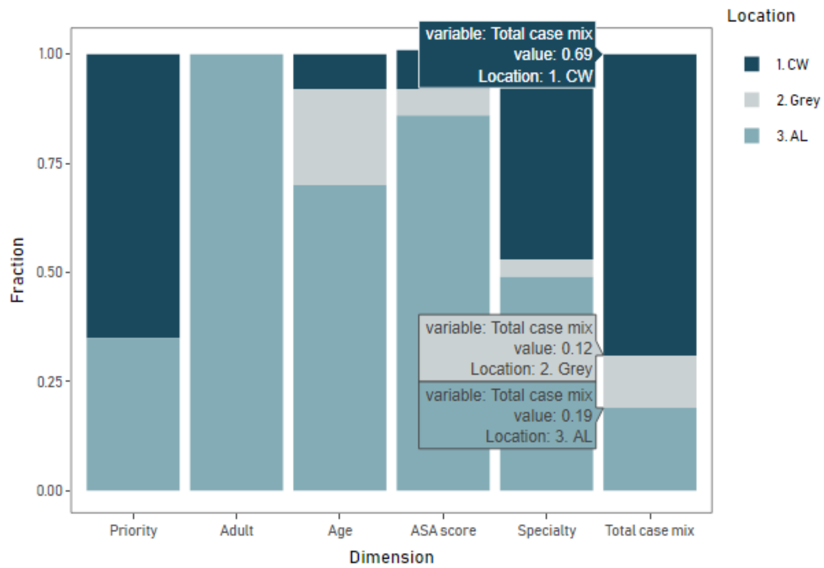

Figure 15 – Additional information about the effects of the patient selection criteria in the DSS. (ChipSoft development data, 2015-2017, n = 16,730)

From these results we can already tell that the size of the AL will be relatively small, since the lower bound for the AL population is 19% of 16,730 patients over the course of three years, which adds up to 3,180 patients. The upper bound of the AL population, with inclusion of the grey area, amounts 5,190 patients. The attribute *priority* has a significant influence on the size of the AL population, since roughly 65% of the patients is non-elective. This shows that the hospital has to process a lot of semi-urgent patients. The grey area is the largest for the attribute *age*, the attributes *specialty* and *ASA* have a relatively small grey area.

4.4. Phase 2: care unit partitioning decision support

As Chapter 1 mentions, the care unit partitioning step is carried out in conjunction with capacity dimensioning. The qualitative requirements for the equipment, staff and supporting processes are (re)considered based on the patient selection criteria. The case mix selection criteria indicate the care required by selected patient groups which help the users decide on the equipment and staff skills required for the care demanded. In addition to these qualitative aspects, the staff size can be quantified by setting a nurse-to-patient ratio for the AL and the wards of the CW. This quantification is in line with qualitative requirements for attaining a desired service level for the patient and a pleasant workload for the staff.

4.5. Phase 3: capacity dimensioning decision support

In Chapter 1 we established that one of the incentives of the AL was to release CW beds. In the capacity dimensioning step we first show the admission and discharge moments of patients with and without an AL. Second, we determine the expected bed reduction for the CW. Third, we determine the bed requirements for the AL.

When many admissions and discharges occur at the same time, the workload on CW staff can be very high. Figure 16 shows the admission and discharge moments at the CW in the situation without the AL (left) and a situation with the AL (right). With the AL, the moment that AL patients arrive at the CW is postponed on the day, resulting in a better distribution of the admissions over the course of the day, as the graph on the right shows. Moreover, the highest peak is slightly reduced. The following subsections show what the required beds are to facilitate this positive effect.

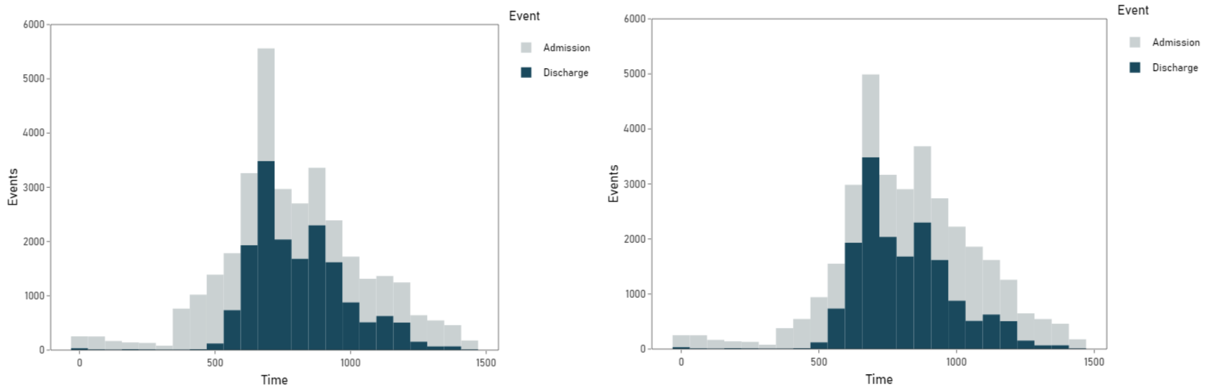

Figure 16 – Moments when admissions (light) and discharges (dark) take place at the CW of the fictive hospital. On the left without an AL and on the right with an AL (ChipSoft development data, 2015-2017, n=16730).

4.5.1. CW capacity

We apply the Erlang loss model described in Chapter 3. The Erlang loss model assumes that arrivals occur according to a Poisson process. To demonstrate that this assumption holds, we plot the arrivals of each specialty and perform a Chi-squared goodness-of-fit test in Appendix C. The Poisson assumption holds for 3 out of 10 specialties.

The Erlang loss model requires the inputs mean arrival rate λ (arrivals per day) and ALOS μ (days). The DSS determines the required number of beds, given a chosen blocking probability, for each speciality separately, as well as for the pooled specialties. In a hospital with multiple CW's the real bed requirements for the CW will lie between requirements per specialty and the pooled requirements. Table 2 gives an overview of the bed requirements for the CW given a blocking probability of 5% and 1% for the situation with and without the AL. Figure 17 illustrates the blocking probability and the occupancy rate as a function of the number of beds for the individual specialties. Figure 18 plots both lines in one plot for the pooled situation. These graphical representation can be consulted by the users of the DSS. In the functional design, more information becomes available when the user hoovers over the lines.

Table 2 – Required number of beds and occupancy (occ.) with a blocking probability (P_b) of 1% and 5% (ChipSoft development data 2015-2017).

		Current situation					With the admission lounge				
			$P_b = 0.05$		$P_b = 0.01$			$P_b = 0.05$		$P_b = 0.01$	
Specialty	λ	μ	Beds	Occ.	Beds	Occ.	μ	Beds	Occ.	Beds	Occ.
CHI	5.4	4.13	28	76%	32	68%	4.02	27	76%	32	67%
GYN	1.5	2.34	7	48%	9	39%	-	-	-	-	-
INT	3.5	6.09	27	77%	31	68%	-	-	-	-	-
KNO	1.5	1.30	5	37%	6	31%	-	-	-	-	-
LON	3.1	4.46	19	70%	23	62%	-	-	-	-	-
MDL	1.9	4.06	12	62%	15	52%	-	-	-	-	-
NEU	2.5	4.78	17	68%	20	60%	-	-	-	-	-
ORT	3.1	3.62	16	67%	19	59%	3.47	16	65%	19	57%
URO	2.9	3.27	14	66%	17	56%	3.19	14	64%	17	55%
Pooled	21.4	4.36	99	90%	110	84%	4.17	95	90%	106	84%

We can validate that the required number of beds for a blocking probability of 5% by counting the portion of historical days on which the peak load on the CW for the specialty CHI exceeded 28 beds (see Appendix D). Because the load on the CW exceeded 27 for less than 5% of the days, we conclude that 28 is a slight overestimation.

The required number of beds for the CW decreases by 4 in the pooled situation, from 99 to 95 when the blocking probability is 5% and from 110 to 106 when the blocking probability is 1%. When all specialties are assigned to their own wards, the required number of beds for the CW decreases by 1 ($P_b = 0.05$) and 0 ($P_b = 0.01$). We initially find this a surprisingly low result. This result can, however, be explained by looking at the ALOS and the arrival rate. The ALOS for each specialty reduces marginally, and since the arrival rate and ALOS are multiplied with each other in the Erlang loss formula, the change in $\lambda\mu$ is very slight. For the pooled situation, the ALOS also reduces slightly. But because the pooled arrival rate is quite large, the effect on $\lambda\mu$ is significantly greater – resulting in quite large reductions for the CW.

We also see that the number of beds strongly increases when the blocking probability is reduced from 5% to 1%, along with a decrease of the occupancy ratio. The decreasing occupancy ratio is easily explained by the increase in the number of beds. For the specialties, the occupancy ratio drops by 8% (for the larger specialties) or 10% (for the smaller specialties). In the pooled situation the decrease in occupancy is less extreme: the occupancy ratio decreases by 6% in the situation without and with the admission lounge.

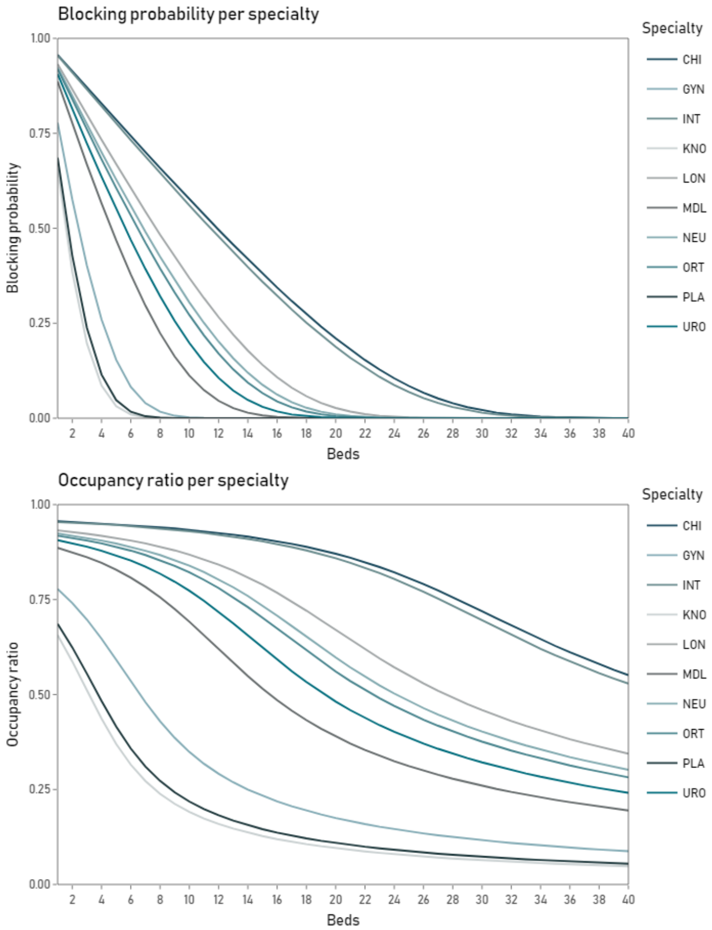

Figure 17 – Blocking probability (top) and occupancy ratio (bottom) for a set number of beds for the CW, without the AL. Calculated with the Erlang loss model.

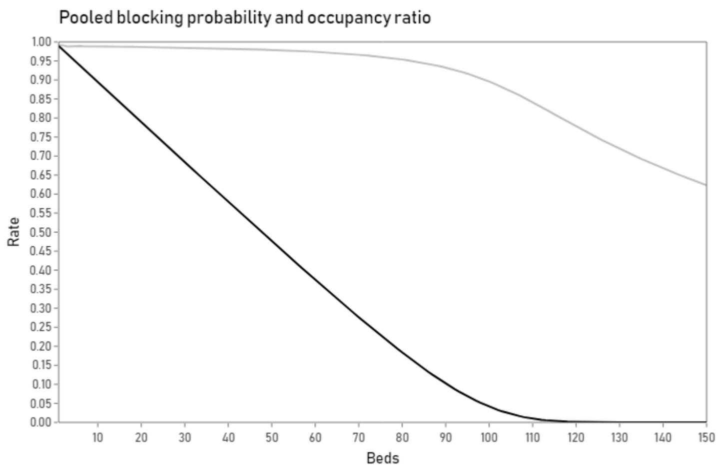

Figure 18 – Blocking probability (dark) and occupancy ratio (light) for a set number of beds in the pooled situation.

This analysis shows that there is an added benefit if patients from the same ward are assigned to the AL, because of the risk pooling effects. The first benefit we found is a larger bed reduction. The pooling effects also lead to a higher occupancy ratio that it is less sensitive for changes in the number of beds.

4.5.2. AL capacity

To decide on the number of beds for the AL, we first determine the representative days for arrivals for the AL, followed by calculating the load on the AL on those representative days. We assess the utilisation of the AL using two KPIs: the percentage of days and hours that all AL admissions can be fulfilled in the AL.

The load on the AL is only assessed for representative days. A representative day is a day on which the total OR time allocated to an AL specialty is a recurring amount of hours. We found that using a threshold of 15% as the fraction of days that a certain amount of hours of OR time is allocated to a specialty gives useful results for the development dataset. Table 3 shows the recurring time allocations per specialty. For CHI we assess days on which 8, 12 and 16 hours were allocated to CHI surgeries. The other specialties show more consistency in time allocation within the MSS; we assess days on which and 8 hours were allocated to ORT or URO.

Table 3 – Recurring OR times allocated to AL specialties. (ChipSoft development data, 2015-2017, n=16730).

Specialty	Allocated OR time (hours)	Days fraction	Cumulative days fraction
CHI	8	0.34	0.34
	12	0.30	0.64
	16	0.25	0.89
ORT	8	0.86	0.86
URO	8	0.64	0.64

Figure 19 shows the average hourly load on representative days with time buckets with duration d=60 minutes, the t=0 is at 6:00 and $start_{OT}$ occurs at 8:00, in t=2. D=120 minutes. Meaning the AL patients stay at the AL for 2 hours before they are transferred to the OT. The AL closes at 13:00 so T=7. We choose 13:00 as the closing time for the AL, since the mean arrivals strongly decline after 11:00. We used time buckets of 1 hour and an admission period of two hours because smaller ranges for both indicators results in higher variability in the load, while the results may not be more accurate. The figure shows that $max\lceil \overline{\rho_t} \rceil = 2$ and occurs around 11:00. The second busiest period is at 7:00. Between 7:00 and 11:00 the load on the AL is relatively low. The peak load at 11:00 suggests that most AL patients undergo surgery in the afternoon. The overall pattern of the load suggests that the hospital schedules most elective surgeries for around 9:00 and 13:00, at the beginning of a session. To balance the variability of the load on the AL, the hospital can consider spreading elective patient surgeries across the morning more.

We determine the rejected hours rate and the rejected days rate for the AL, as well as the occupancy rate of the AL with a set number of beds varying from 1 to 5 beds. This indicates whether the choice for the number of AL beds based on $max\lceil \overline{\rho_t} \rceil = 2$ is sensible. Table 4 gives an overview of the performance indicators. We see that with 2 beds, rejections would take place at 6.5% of all hours and 30.5% of all representative days. The occupancy rate would be 43.7%.

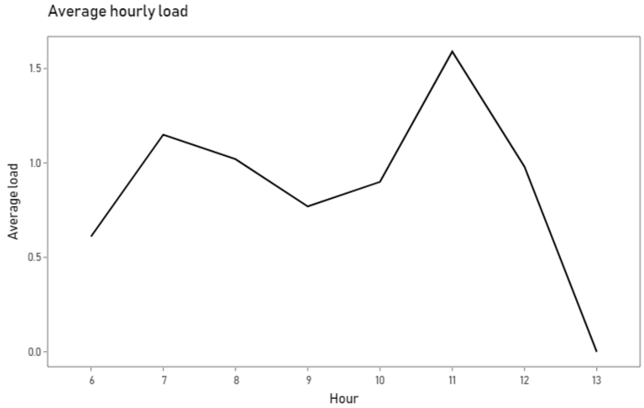

Figure 19 – Expected average hourly load on the AL (ChipSoft development data, 2015-2017, n=16730).

The rejected days rate is higher than the rejected hours rate, because a rejection on a day could have occurred at one hour, while the load at all other hours was lower than or equal to the set number of beds. The rejected days rate also decreases faster than the rejected hours rate as the number of beds increase. With 5 beds, there would not have been any rejections, as the load never exceeds 5. This would have resulted in an occupancy rate of 50%. A higher occupancy rate goes hand in hand with a lower acceptance rate (higher blocking probability), an effect also experienced by the CW. We think that an appropriate number of AL beds is 2 or 3. If the hospital values occupancy ratio greatly, the appropriate choice would be 2 beds. For a higher patient friendliness, 3 beds would be more appropriate.

Table 4 – Daily and hourly acceptance rate, and occupancy for the AL on representative days (ChipSoft development data, 2015-2017, n=16730).

Beds	Rejected hours (%)	Rejected days (%)	Occupancy (%)
1	21.1	67.2	64.2
2	6.5	30.5	43.7
3	1.5	9.5	31.2
4	0.2	1.5	23.7
5	0	0	19.0

4.5.3. Decisions and trade-offs

There are several trade-offs in the capacity dimensioning decision. The main trade-off is between service level and occupancy rate; we see this for both the CW and the AL. The service level is represented by the blocking probability in the Erlang loss model for the CW and the rejection rates in the deterministic model for the AL. The occupancy rate is a measure used for both units. It is up to hospital management to decide what balance between service level and occupancy rate is desired. We like to point out the a low occupancy rate for the AL seems more acceptable than for the CW, since the AL starts and ends empty every day, while the CW is assumed to reach a steady state at a certain point.

4.6. Phase 4 and 5: feasibility and optimisation

Because the logistical aspects and the layout of the hospital are unknown, we cannot check whether the AL would fit in the current layout. We assume that there is no need to reset the patient selection criteria to create a smaller set of AL patients and reduce the load on the AL. On the contrary, we try to add patients to the AL patient mix by relaxing the selection criteria and adding criteria for the grey area to the inclusion criteria for the AL. We enumerate all possible allocations, resulting in twelve options, as Table 5 shows.

Option 7, the option for allocating no extra patients, is denoted by an asterisk, because it is concerns the inclusion and exclusion criteria used in the previous phases. We let the model reassess the bed reductions for the CW and the bed requirements for the AL, and the performance of both units. The results are compared using the goal function from Section 3.5:

$$Performance = (Bed\ reduction\ CW * Occupancy\ rate\ CW) - (Beds\ AL * \frac{(1 - rejected\ hours\ rate) + Occupancy\ rate\ AL}{2}).$$

The higher the performance score, the higher the option is ranked. For the required number of CW beds, we look at the first number of beds that results in a blocking probability of 5% or less. For the required number of AL beds, we look at the first number of beds that results in a rejected hours rate of 10% or less. We allow the rejected hours rate for the AL to be higher than the blocking probability for the CW because a rejection at the AL is less disruptive, for both the staff and the patient, than blocking at the CW. When a patient is blocked at the AL, it is known in advance of the admission, and the admission is scheduled at the CW. Blocking at the CW induces the need for ad hoc decision making.

Table 5 – Options for assignment from the grey area to the AL (ChipSoft development data, 2015-2017, n=16730).

Option	ASA	Age	Specialty
1	III	-	-
2	III	76-80	-
3	III	76-85	-
4	III	-	GYN
5	III	76-80	GYN
6	III	76-85	GYN
7*	-	-	-
8	-	76-80	-
9	-	76-85	-
10	-	-	GYN
11	-	76-80	GYN
12	-	76-85	GYN

Table 6 shows that the top ranked option is option 5, followed by option 6. Both options lead to the largest CW bed reduction (5) and the most beds required for the AL (3). They also lead to higher bed occupancy rates for the AL than the other configurations, while attaining the highest CW occupancy rates. Performance wise, the top two options are the best assignment rules for the AL. If the hospital is able to facilitate the admissions for the AL patients with the staffing decisions made in phase 2, and if three beds in the AL is feasible within the constraints of the facility layout, we would recommend to select AL patients according to the highest ranked option, option 5.

Table 6 – Top 5 ranked options for AL patient assignment (ChipSoft development data, 2015-2017, n=16730).

Rank	Option	Beds CW with AL	Reduction CW	Occupancy CW (%)	Beds AL	Rejected hours AL (%)	Occupancy AL (%)
1	5	94	5	90.1	3	6.2	52.6
2	6	94	5	90.0	3	7.8	56.1
3	7	95	4	90.0	2	6.5	43.7
4	1	95	4	89.9	2	8.0	47.8
5	8	95	4	89.9	2	8.6	48.8

4.7. Conclusions

In this section we reflect on the validation of the Erlang loss model's assumptions and the most important findings of each phase. The DSS methodology helped with structured performance assessment of the many results generated.

Erlang loss model The Erlang loss model assumes that patients arrive with according to a Poisson process. We showed that the Poisson assumption holds for 3 out of 10 specialties, which may appear too low to accept the Erlang loss model as an appropriate model for modelling the CW. The elective arrivals at the CW, however, occur according to a pattern that is dictated by the MSS. Moreover, supply and demand are tightly related in the context of a hospital, especially if the hospital has long waiting lists. As we mentioned in Chapter 3, the Erlang loss model gives quick insights about the CW's strategic requirements and is easy to implement, which we showed in this chapter.

Phase 1 The visualisation of the patient selection criteria helps to gain insights about the effects of inclusion and exclusion criteria for the AL. The size of the grey area also shows the potential of the optimisation in Phase 5.

Phase 2 For this chapter it was not possible to set up qualitative criteria for the staff, equipment and supporting processes, because these are decisions for the hospital to make.

Phase 3 We see an overestimation of the required number of pooled beds for the CW. It is unclear whether the calculated bed reduction is over- or underestimated. Because peak loads on the CW generally occur in the morning, when most admission take place, we suspect that the bed reduction is underestimated. We suspect a larger bed reduction because our formulation of the Erlang loss model is only able to take into account the reduced ALOS in the calculations for the bed reduction. Because the peak load can be reduced significantly by letting a majority of the admissions take place at the AL, we expect that the bed reduction may be higher than we quantified.

We set the opening hours of the AL between 6:00 and 13:00. The load on the AL peaks during the beginning of the morning and by the end of the morning, indicating that most AL patients arrive for the first surgeries of the morning shift and the first surgeries of the afternoon shift. The occupancy ratio for the AL is, with around 50%, relatively low compared to the CW. The low occupancy is caused by the peak loads. The peak loads also lead to a relatively high rejected hours rate. Because blocking at the AL is less disruptive, for both the staff and the patient, than for the CW, we accept a rejected hours rate that is higher than the blocking probability. From the development data we conclude that the hospital can reduce their CW beds by 4 in the pooled situation and that the AL requires 2 or 3 beds.

Phase 4 and 5 We compare the 12 assignment rules for the AL by enumeration of the possible assignments for patients within the grey area. To give an indication of the most effective and efficient configurations, we use a scoring function and present the results for the top 5 configurations. We conclude that the top 2 results are suitable for the hospital. The top 2 result in a bed reduction of 5 CW beds and require 3 AL beds to facilitate admissions with a rejected hours rate below 7% for the CW and a blocking probability below 5% for the CW. Both solutions are a good choice if it is feasible to allocate 3 beds to the AL within the limits of the facility layout.

CHAPTER 5
IMPLEMENTATION AND USE OF THE DSS

5.1. Implementation of the DSS

The implementation of the DSS is twofold: requirements for implementation into HiX and implementing the DSS into the hospital's planning methods. To give an idea of what the DSS will look like in HiX we present mock-ups for the DSS. In the mock-ups we show how the decision parameters can be selected and used to create the graphs and tables that can be seen in Chapter 4.

5.1.1. Mock-up design

We created a mock-up design of the DSS in HiX. The design encourages the use of the stepwise approach for decision making; the three main tabs concern case mix selection and visualisation, bed requirement calculations, and optimisation. Figure 20 shows the mock-up of the first tab *Case mix*. All figures are created with ChipSoft development data used in Chapter 4. For a larger image, see Appendix E.

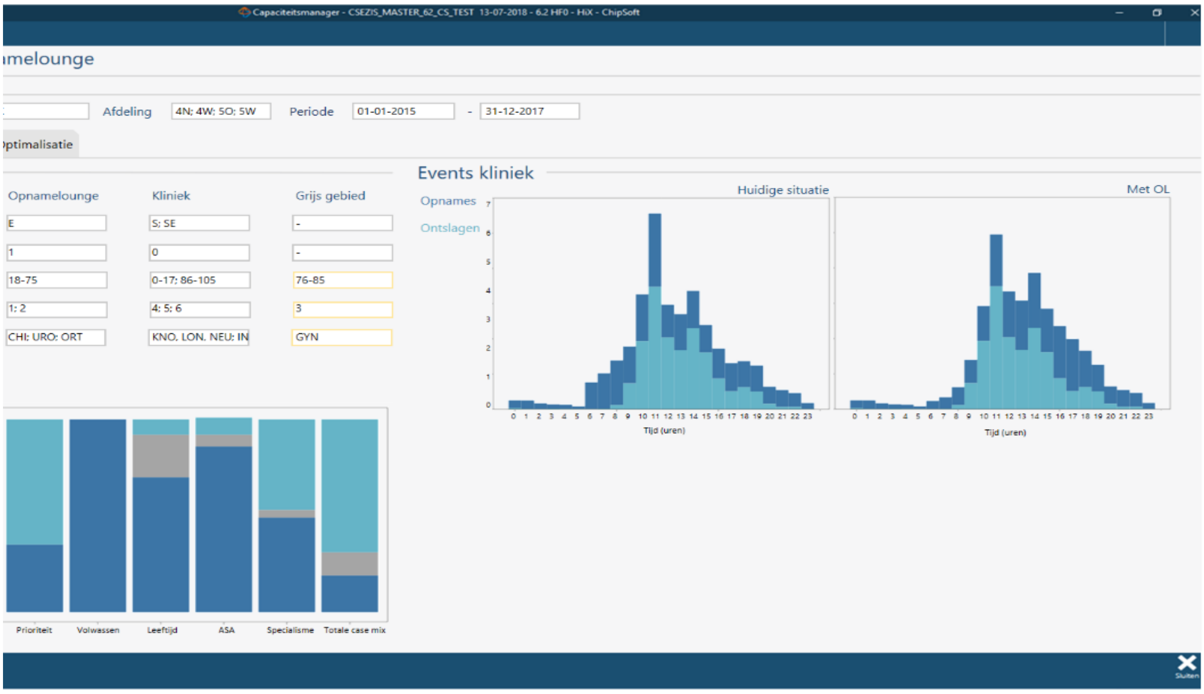

Figure 20 - Case mix tab of the DSS mock-up for HiX.

The input fields under the header *Input* are for the scope of the analysis. The user can enter the admission types (*type opname*), the wards (*afdeling*) and the start and end date of the analysis period (*periode*). In the case mix tab the user can insert the patient selection criteria for the AL (*opnamelounge*) and the CW (*kliniek*) on the attributes priority (*prioriteit*), adult (*volwassen*), age (*leeftijd*), ASA classification (*ASA*), and specialties (*specilismen*). The DSS derives what attribute values fall within the grey area (*grijs gebied*) and automatically fills the corresponding fields. Below the input fields the user sees the plot for the effects of the patient selection criteria. On the right side the DSS shows the plots for events at the CW (*events kliniek*) for the current situation (*huidige situatie*) and the new situation (*met OL*). When the patient selections are completed, the user can switch to the next tab *Bedden* (Figure 21).

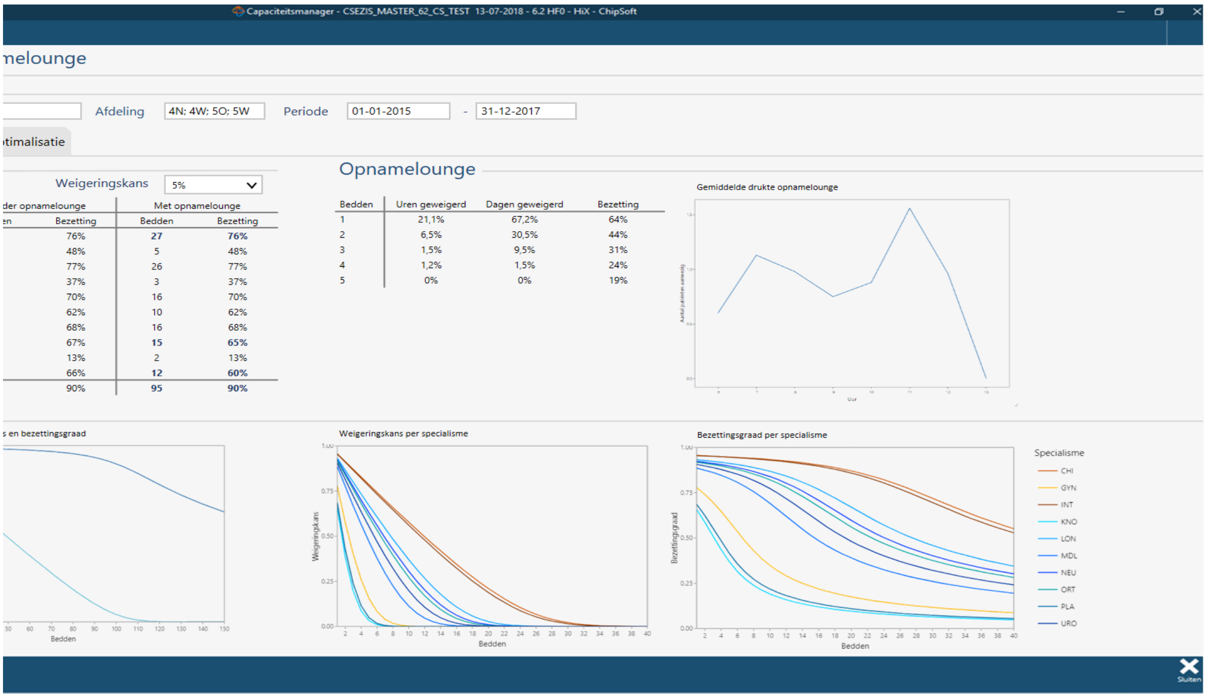

Figure 21 – Bedden tab of the DSS mock-up for HiX.

The most relevant information of the bed calculations are shown in the top of the tab *Bedden*: the required number of beds for the CW (below the header *kliniek*) and the AL (below the header *opnamelounge*). The user can select a desired blocking probability (*weigeringskans*) for the CW. The results for each specialty (*specialisme*) and the pooled situation (*gepoold*) are given for the situation without the AL (*zonder opnamelounge*) and with the AL (*met opnamelounge*). The results concern the required number of beds (*bedden*) and the expected occupancy ratio (*bezetting*). For the AL, the DSS shows the results reported in Table 4; the rejected hours rate (*uren geweigerd*), rejected days rate (*dagen geweigerd*) and the occupancy rate (*bezetting*) corresponding with a set number of beds (*bedden*).

Next to the results table of the AL, the DSS shows the plot of the average load for the AL on representative days (*gemiddelde drukte opnamelounge*). Beneath both results tables, the DSS shows the plots for the CW blocking probabilities and occupancy rates as a function of the number of beds. The graphical results are useful for visual inspection of the behaviour of the blocking probability and occupancy ratio. We choose to show the graphical results without the AL (*zonder OL*) and with the AL (*met OL*) in separate tabs, because an overview of all results would result in an overload of information. Moreover, comparisons of the results are also given in the results table above. If the users want to use our enumeration method, they can head to the tab *Optimalisatie* (Figure 22)

In the *Optimalisatie* tab, the user can give inputs for the service levels (*weigeringskans)* of the AL (*opnamelounge)* and CW (*kliniek*). For simplicity, we do not include the option to assign weights for the goal function. By clicking on the optimisation button (*optimaliseer)*, the user makes the DSS enumerate all the assignment rules, as is done in Phase 5 of our five phase stepwise approach. We present the top 5 ranked options of the enumeration in a results table. When the user selects one of the solutions in the top 5, the tabs *Case mix* and *Bedden* are filled accordingly, showing the results of the chosen assignment rule.

ChipSoft is working on a link between models developed in RStudio and the HiX environment. To implement the DSS in HiX, ChipSoft can use our DSS model developed in RStudio.

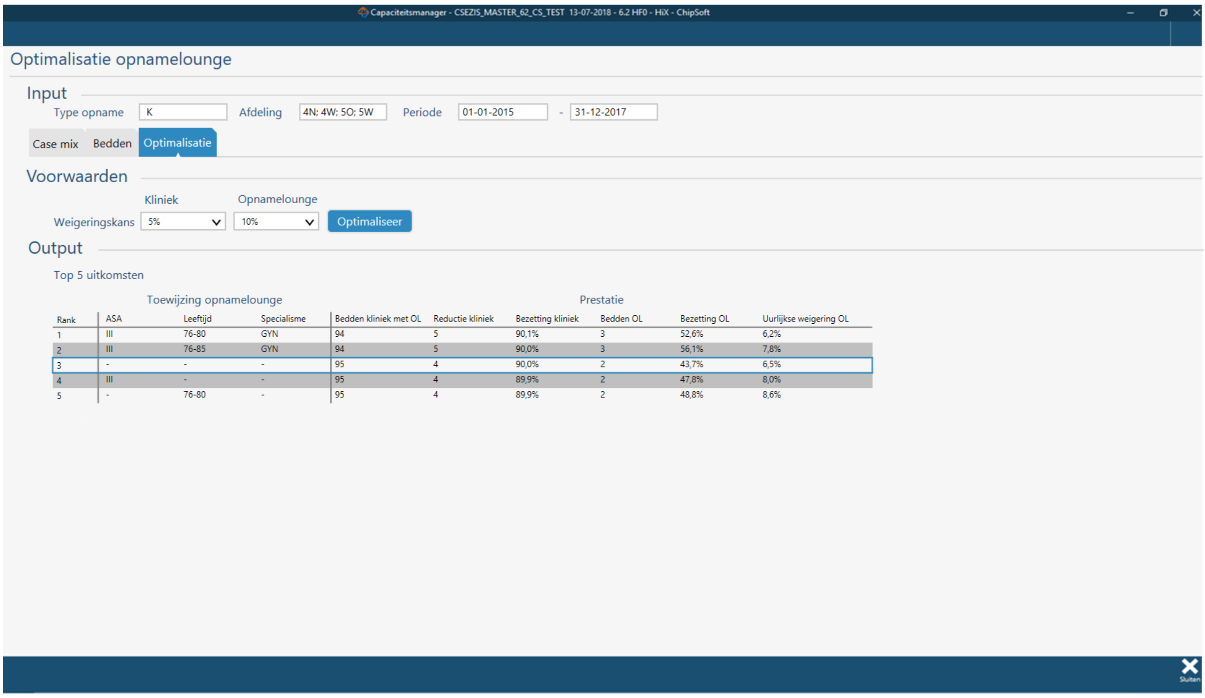

Figure 22 – Optimalisatie tab of the DSS mock-up for HiX.

5.1.2. Hospital implementation

The DSS is designed to be used by capacity managers or hospital managers with a general understanding of capacity management. To correctly use the DSS, the user should be able to interpret all indicators correctly. Our stepwise approach, however, does not only consider quantitative decisions; qualitative aspects regarding, e.g., essential staff skills and special equipment should also be considered during AL design process. Therefore, a clinician should also be part of the team that does the decision making. It is not up to ChipSoft to facilitate this multidisciplinary decision making, but we do recommend that hospital management is urged to set up a multidisciplinary team for the AL design process.

As goes for every ChipSoft implementation process, it is important that the data used in the DSS is retrieved from the correct data field within HiX. This check is always necessary because hospitals use different data fields to register the same type of information. Incorrect data retrieval leads to incorrect and misleading results, which must be avoided. For the planning and scheduling of patients, the planner should know if a to be scheduled patient has access to the AL. We recommend ChipSoft to consider creating a field in the preoperative assessment form that automatically fills in whether the patient must be admitted to the AL or the CW, based on the patient characteristics. The anaesthesiologist is not bothered with filling out extra information, because the field is filled automatically. Nevertheless, if the anaesthesiologist disagrees with the automatic assessment there should be a possibility to change the automatic indication. If the planner sees that the patient can be assigned to the AL, the planner can act upon that knowledge and assign the patient to the AL if it also fits the AL's capacity.

5.1.3. Coupling opportunities

ChipSoft is currently developing tools for capacity management for each planning level. There are three components that our DSS could be linked to: the tactical forecasting module, the strategic demand assessment tool, and the day-care planning module.

The tactical forecasting module forecasts the outflow of the OR to subsequent departments visited by patients. This outflow is a result of the configuration of the MSS and the forecasted demand. We suggest to forecast the inflow of the AL and the CW similarly to give a more accurate expectation of the load on the AL within a planning horizon of 12 to 15 weeks.

The strategic demand assessment tool (Knoben, 2019) translates hospital production budgets to required capacities. Significant changes in production could also affect the AL and its required capacity. Consequently, coupling of our developed DSS and the strategic demand assessment tool could lead to increased insights into the relations between production budgets and required capacities.

This thesis does not consider the effects of the AL on the day-care department. However, the day-care department is a hospital unit that experiences high demand from low complex high volume patient populations. Van Boekel (2018) researched the variability of resource utilisation of the day-care department and proposed the development of a tool for HiX. The proposed tool considers a variety of planning and scheduling heuristics to balance resource utilisation and is almost ready for implementation. By coupling the calculations for the load on the AL with the variability assessments of the day-care department there the opportunity arises to define an objective that addresses the utilisation variability of both units.

5.2. Sustainability of the DSS

We want to indicate that our models are also useful after the AL is introduced to the hospital. Therefore, we show how changing the input parameters can give additional insights. There are two main inputs that hospital management can adjust to get insights that are useful for strategic or tactical support. First we explain the use of adjusting the period for the data analysis. And then we make some notes on adjusting the inclusion and exclusion criteria manually.

By adjusting the period for the data analysis, the user can compare how AL performs during various periods. Hospital demand and supply is affected by seasonality, such as the reduction weeks during the summer period. During these weeks, the demand and supply are generally lower than during the rest of the year and therefore the occupancy ratio of the AL could be too low to keep all AL beds opened. If that is the case, the hospital can decide to close some beds, which we termed *temporary bed capacity change* (Section 2.3.1). We do note that the risk of selecting smaller time periods is that there is a higher variability in the data and that this could lead to less accurate results.

DSS users can assess the inflow of smaller patient groups, e.g. from one specialty, by only selecting that group for analysis in the model. In combination with selection of the periods, hospital can identify the inflow patterns of typical sets of patients during a chosen period or season. Generally, hospital management can foresee several patterns over the year, such as an increase in broken hips during the winter that leads to an increase of non-elective surgeries for the specialty orthopaedics. By adjusting the periods for analysis, and isolating particular specialties, users can assess whether the inflow of a certain patient group may become so high that the need for *admission control* (Section 2.3.2) arises.

5.3. Conclusions

This chapter shows the mock-up design of the DSS in the HiX environment of ChipSoft. In the top of the screen, the user gives inputs for the data preparation, regarding relevant wards for the analysis and the period of the data collection. Below those inputs, we placed the core of the DSS, which can be divided into three tabs. We describe DSS tabs, called *case mix, bedden,* and *optimalisatie*. Furthermore, we indicate the functionalities of the DSS after establishment of the AL.

Tab 1 The first tab is used for Phase 1 and 2 of our stepwise approach. The user can enter the inclusion criteria for the AL and the CW, and the model determines what patients belong to the grey area. The DSS shows the visualisation of the patient selection effects and the effects on the admission and discharge moments at the CW.

Tab 2 In the second tab we give all the outputs required for the decision support in Phase 3. On the left side of the screen, the user can select a blocking probability to their liking in the assessment of bed reductions for the CW. Below the results table for the CW we show the relevant plots for the blocking probability and occupancy ratio as the result of the number of beds. The user can switch between tabs to show the plots for the situation without and with the AL. On the right side of the screen, we show the results table for the AL's service level and occupancy, together with the plot for the load on the AL.

Tab 3 The third tab can be used for the enumeration in Phase 5 of the five phase stepwise approach. The user can give inputs for the desired service levels of the AL and the CW. For simplicity, we do not include the option to assign weights for the goal function. The DSS presents the top 5 results of the enumeration in a table. After selecting a configuration of interest, the user can switch to tab 1 and tab 2 to see the detailed performance.

Sustainability The user selects periods for analysis in the input field at the top of the DSS. Selection of a typical period, for example during a period with a historically high demand, can give insights about the expected performance of the AL and CW during an expected increase in demand. Furthermore, the user can select a patient group of interest, to assess how that specific patient groups affects the performance of the AL and the CW.

CHAPTER 6
CASE STUDY FOR SOLUTION TESTS

In this chapter we conduct a case study with a regional hospital. What is different from Chapter 4 is that the case hospital can give inputs during the five phases, opposed to the educated guesses we made earlier. We can also assess whether the generated results for the DSS are interpretable and useful for making management decisions. This chapter is arranged as follows. Section 6.1 gives a short description of the case hospital. In Section 6.2, we explain the steps and effects of the data preparation. This is followed by use of the DSS methodology in Section 6.3. Section 6.4 gives some additional insights from the management of the case hospital. In Section 6.5 we draw conclusions from the case study and compare the results found in this chapter to the results in Chapter 4.

6.1. Context description

For the case study, we spoke with two health managers of the hospital, who are also involved with capacity management. The hospital uses one ward to situate all surgical specialties. This is a useful feature for validation of the outcomes, since the pooled bed capacities then reflect the capacity of the CW of interest.

The hospital is certain that there is a need for an AL, the main reason being the decrease of work interventions at the CW caused by new admissions during peak hours. The hospital already uses a separate room at the ward for the admissions in the morning, but this room can also be used as an overflow room for the CW. The CW is situated one floor beneath the OT. Management is unsure about the required number of AL beds, but expects that they will need three or four beds. Because the hospital is planning an expansion in the next year, there is not yet an indication for the potential location of the AL.

6.2. Preparation

We analyse the admissions that took place during the years 2015, 2016, and 2017 and apply the same data preparations as we did in Chapter 4. For the data preparation we select admissions of clinical patients, during weekdays, from one ward. This one ward is the destination for all adult, elective, surgical patients. Irregularities are removed from the dataset by applying a threshold of 0.5% of all admissions per specialty. This leaves us with seven surgical specialties in the dataset:

- Bariatric (BAR)
- General surgery (CHI)
- Jaw surgery (KAA)
- Neuro-surgery (NCH)
- Orthopaedics (ORT)
- Plastic surgery (PLA)
- Urology (URO)

From all 101900 admissions in the hospital, 7565 remain up for analysis. This makes the scope of the study relatively small (7.5% of all the hospital's admissions).

6.3. Five phase DSS approach

We apply the DSS methodology (Figure 13) to the case hospital. We recite the five phases as a reminder:

1. Set up inclusion and exclusion criteria for the AL
2. Determine the appropriate staff, equipment, and supporting processes for the AL and CW
3. Analysis of potential bed reductions for the CW and required capacity for the AL
4. Analysis of feasibility within the facility layout
5. Optimisation: assignment of the grey area patients

6.3.1. Phase 1

The case hospital indicates that patients that are allowed access to the AL are elective patients, aged between 18 and 75, with ASA classification I or II, and from every specialty of the surgical ward, except BAR patients. BAR patients are generally overweight and diabetic, meaning that special equipment is required during the admission process. Because the hospital is interested in the difference in performance of the AL with or without the BAR patients, the specialty is assigned to the grey area. Other inclusion and exclusion criteria can be seen in Table 7.

Table 7 – Patient inclusion and exclusion criteria for the AL, set up with the case hospital.

Category	Status	Age	ASA	Specialties
CW	Non-elective	≥ 86	IV, V	-
Grey	-	76-85	III	BAR
AL	Elective	18-75	I, II	CHI, KAA, NCH, ORT, PLA, URO

The patient mix decisions classifies the patients into 44% AL patients, 35% grey are patients, and 23% CW patients. Figure 23 shows that only adult patients are admitted to the ward, and that a small portion of the patients is non-elective. The attribute ASA has the largest grey area. With a large portion of patients in the grey area, there is a lot of room for optimisation in Phase 5. The lower bound for the number of AL patients is 44% and the upper bound is 77%.

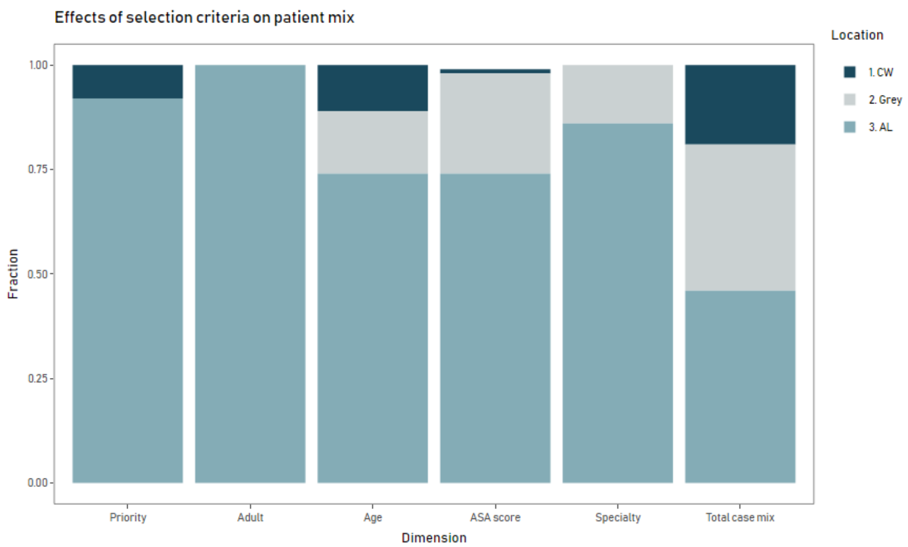

Figure 23 – Distribution of the patient mix as a result of the inclusion and exclusion criteria for the AL. (Case hospital data, 2015-2017, n=7565).

6.3.2. Phase 2

Phase 2 focusses on the selection of the appropriate staff, equipment and supporting processes for the AL. The hospital does not employ LPNs (the nurse type with the least qualifications), which indicates that practically all their available staff is qualified to admit higher-complex patients with, e.g., an ASA III classification. Clinicians indicated that an appropriate nurse-to-patient ratio for the admission process is 2 to 1 if the admissions have to take place over a short period of time. With a lower nurse-to-patient ratio the nurse has to hurry. In that case, the workload becomes too high, and the patient friendliness decreases.

The hospital has special equipment (larger beds and heavier mattresses) and facilities (wider doors and standing toilets) for the BAR patients. For the other patients, there is no indication of special requirements. We shortly discussed the transportation of patients from the AL to the holding. The current practice is that a nurse brings the patient to the holding. Because the CW is one floor level beneath the OT, the nurse has to use an elevator to transfer the patient to the holding. Sometimes the use of the elevator can be time consuming. The case hospital is not yet thinking about an logistics team for the transportation of patients. This might be reconsidered when the plans for the hospital's expansion are more concrete and the need for a logistics team arises.

6.3.3. Phase 3

In Phase 3, we first look at the plot of the admission and discharge moments at the CW, with and without the AL (Figure 24). The case hospital experiences a prominent peak load on the CW in the morning, caused by new patient admission. After the introduction of the AL, that peak load can be strongly reduced and the admission of patients are spread more evenly across the day.

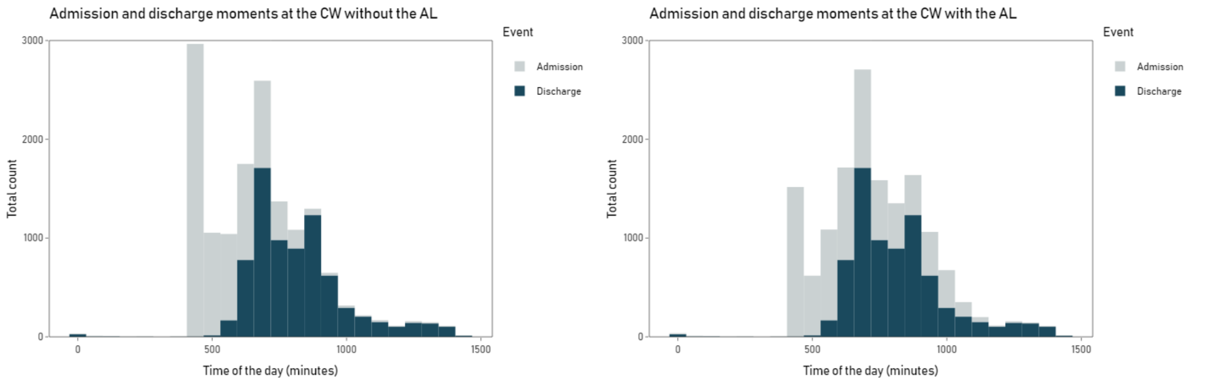

Figure 24 – Admission and discharge moments at the CW, with and without the AL. (Case hospital data, 2015-2017, n=7565).

Next we dimension the CW without and with the AL. Table 8 shows that the CW can reduce the required number of beds by 2 for a blocking probability of 5% and 1% in the pooled situation. The case hospital noted that a pooled capacity of 37 beds could be an accurate estimation for the assessed period. Because all surgical specialties are situated in one CW, it makes little sense to compare the results for the individual specialties. However, it is relevant to note that the individual specialties show the same behaviour as seen in Chapter 4: the occupancy rates are relatively low, and drop around 8% to 10% for the larger specialties when the lower blocking probability of 1% is selected instead of 5%.

Table 8 – Inputs for the Erlang loss models and the corresponding required beds and corresponding occupancy (occ.) ratios (Case hospital data, 2015-2017, n=7565).

		Current situation					With the admission lounge				
			$P_b = 0.05$		$P_b = 0.01$			$P_b = 0.05$		$P_b = 0.01$	
Specialty	λ	μ	Beds	Occ.	Beds	Occ.	μ	Beds	Occ.	Beds	Occ.
BAR	1.38	1.87	6	42%	8	32%	-	-	-	-	-
CHI	3.36	4.57	21	70%	25	61%	4.47	20	72%	24	62%
KAA	0.07	1.19	2	4%	2	4%	1.03	2	4%	2	4%
NCH	0.29	1.17	2	16%	3	11%	1.09	2	15%	3	10%
ORT	1.97	3.03	10	57%	13	46%	2.94	10	56%	12	48%
PLA	1.66	2.14	7	49%	9	39%	1.92	7	44%	9	35%
URO	1.12	2.21	6	40%	7	35%	2.14	6	39%	7	34%
Pooled	9.86	3.17	37	80%	43	72%	3.08	35	80%	41	71%

We also plot the blocking probability and occupancy ratio (Figure 25 an Figure 26) as a function of the number of CW beds. The plots are available for the situation without the AL (given in this thesis) and with the AL. The curves show the same behaviour for both situations, except with a quicker convergence for the situation without the AL. The case hospital states that the additional information given by hoovering over the lines is a helpful extension of the plots , because it increases the readability of the plots. This is possible in the functional mock-up.

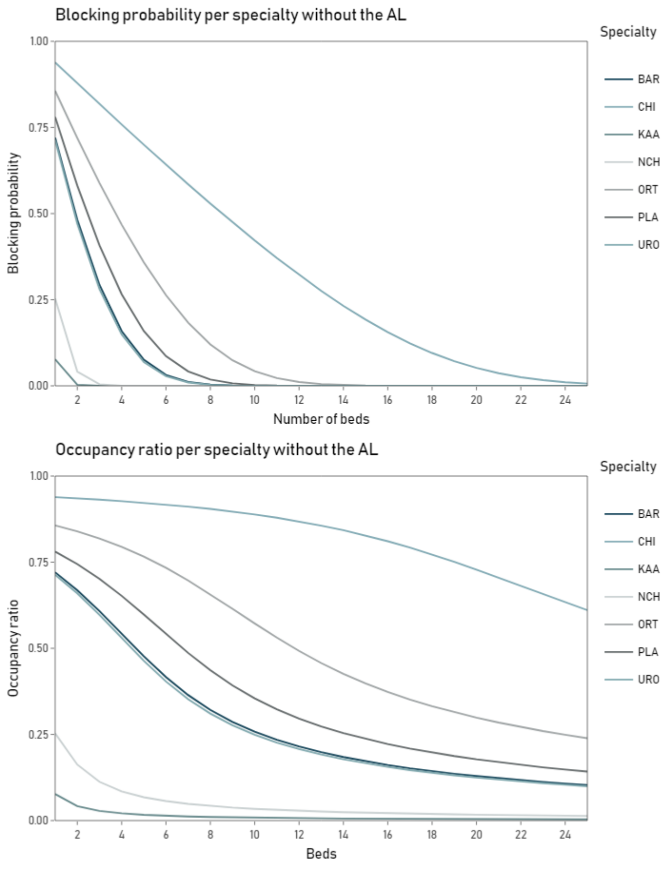

Figure 25 – Curves for the blocking probability (top) and occupancy ratio (bottom) as a function of the number of beds for the individual specialties, without the AL (Case hospital data, 2015-2017, n=7565).

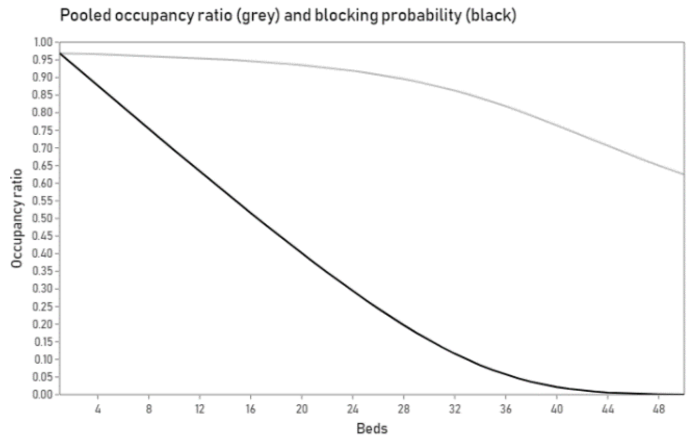

Figure 26 – Blocking probability (dark) and occupancy ratio (light) as a function of the number beds calculated with the Erlang loss model (Case hospital data, 2015-2017, n=7565).

With the current patient selection criteria, the performance of the AL will be as shown in Table 9 (on representative days), with opening hours from 6:30 to 11:00. With the current criteria we would recommend to open the AL with three or four beds. When the hospitals chooses to assign four beds to the AL, they may have to close beds during periods with lower demand, because the expected occupancy ratio of 41 percent is relatively low. With three beds, the occupancy ratio is over 10% higher (51.8%), and the rejected hours rate increases by only 2.2%.

Table 9 – Performance of the AL in the case hospital calculated with our deterministic model (Case hospital data, 2015-2017, n=7565).

Beds	Rejected hours (%)	Rejected days (%)	Occupancy (%)
1	25.1	71.4	82.9
2	12.3	41.9	65.5
3	5.1	20.4	51.8
4	2.9	8.1	41.4
5	0.4	2.1	33.9
6	0	0.2	28.4
7	0	0	24.3

Table 9 shows that the occupancy ratio is relatively low for a relatively high rejection rate, compared to the performance of the CW. This can be explained by the peak load on the AL early in the morning, seen in Figure 27. After 8:00, the load on the AL quickly decreases, which is a result of the planning and scheduling methods of the case hospital. AL patients are scheduled early in the morning and arrive accordingly.

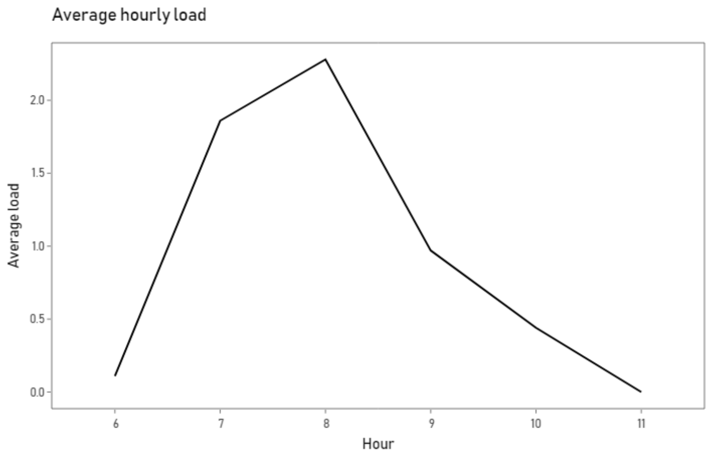

Figure 27 – Expected hourly load on the AL (Case hospital data, 2015-2017, n=7565).

6.3.4. Phase 4 and 5

The hospital is planning on an expansion in the next year, as we mentioned earlier in this chapter. It is still unclear where the AL will be situated, and therefore there are no limits to the maximal size of the AL for our analysis. We enumerate the patient selection criteria to find improvements on our current solution.

Together with the initial case mix selection there are 12 selection options to assess (Table 10), similar to the optimisation in Section 0. We use the goal function introduced in Section 3.5 to determine the top 5 performing configurations. We do not apply weights to the goal function to search for a more economical or patient friendly outcome. Due to time constraints we did not have time to assess these outcomes with our case hospital.

Table 10 – Patient assignment options for the AL, 7 being the assignment rules used in the previous phases.

Option	ASA	Age	Specialty
1	III	-	-
2	III	76-80	-
3	III	76-85	-
4	III	-	BAR
5	III	76-80	BAR
6	III	76-85	BAR
7*	-	-	-
8	-	76-80	-
9	-	76-85	-
10	-	-	BAR
11	-	76-80	BAR
12	-	76-85	BAR

The goal function (see section 3.5) highlights the top 5 performing assignment options: 1, 2, 4, 6, and 12 respectively. The number of CW beds is the number of beds that corresponds with a blocking probability of 5%. The number of AL beds is the number of beds that first leads to a rejected hours rate less than 10%. The option we examined in the previous phases, option 7, is not part of the top 5 performing assignment rules. The top 3 consists of similar results. Option 1, the best performing configuration, has the lowest patient complexity profile, lowest rejection rate, and the lowest occupancy rate for the AL. It is noteworthy that option 6, ranked fourth, causes the largest bed reduction for the CW, with a reduction of 3 beds. The CW bed reduction goes along with 4 required beds for the AL. The higher number of beds also comes at the price of the second lowest occupancy ratio for the AL. Given the nurse to patient ratio of 2:1 (see Section 6.3.2), we think that option 4 could have the most potential and impact in the hospital. If inclusion of BAR patients is not wanted, we recommend using option 1.

Table 11 – Top 5 performing assignment options for the AL's patient assignment enumeration (Case hospital data, 2015-2017, n=7565).

Rank	Option	Beds CW with AL	Reduction CW	Occupancy CW (%)	Beds AL	Rejected hours AL (%)	Occupancy AL (%)
1	1	35	2	79.6	3	6.9	56.0
2	2	35	2	79.3	3	9.1	59.8
3	4	35	2	79.3	3	9.7	60.1
4	6	34	3	80.1	4	7.5	56.2
5	12	35	2	79.8	3	7.9	57.0

6.4. Comments from the case hospital's representatives

The case hospital states that the findings from this study are useful and easy to interpret for a manager that is familiar with capacity management. Because the hospital is relatively small, and the surgical specialties are situated at a single CW, it is relatively easy to come to the same results of four beds by experience. More so, the number of AL beds that we come up with (3 or 4) is equal to the number of beds in the current dedicated admission room of the CW.

Besides the usefulness of the results, the case hospital indicates that there is more to managing projects like this besides offering the right set of tools. It is also important that the project is executed by a group with focus and clear direction. We also indicated this in Section 2.1.1.

6.5. Conclusions

We conducted a case study for a medium sized general hospital and requested their input during the use of the five phase DSS approach. The hospital locates all the surgical specialties at one ward, which makes the interpretation of the pooled capacity easier. The case hospital can reduce the pooled CW capacity by two beds, but needs at least three AL beds to facilitate admissions with an acceptable rejected hours rate (lower than 10%). Because the hospital is planning on an expansion in the next year, there are no limitations by the facility layout. We use the optimisation method to look for additional insights.

During the enumeration of 12 assignment options for the AL's patient mix we find a top 5 consisting of options different from the options discussed in the preceding phases. With a nurse to patient ratio of 2:1 the hospital is comfortable with using 4 AL beds, an outcome of the fourth ranked option. For this option, we see a decrease for the CW amounting 3 beds. The occupancy ratio for the CW is the highest of the top 5, and the rejected hours rate and occupancy ratio are acceptable.

In this case study and the case study in Chapter 4 we assessed the models for medium sized general hospitals. The main differences between this case study and the one in Chapter 4 is that the latter performed an analysis over multiple wards and that it used other opening hours of the AL. The AL's opening hours were from 6:00 to 13:00 in Chapter 4, because the AL experienced a peak load at the beginning and end of the morning. The AL's opening hours in this chapter were from 6:00 to 11:00 because the AL would not have substantial inflow after 11:00. In both case studies we find improved performance after enumeration of the grey area.

The managers of the case hospital were able to interpret the results of the analysis. They did remark that it is relatively easy to estimate the AL requirements for their hospital while it is more complex for a larger hospital with more departments and (sub)specialties.

CHAPTER 7
CONCLUSIONS AND RECOMMENDATIONS

In this last chapter we answer the main question (Section 7.1). We give our points of discussion and recommendations in Section 7.2. Further research suggestions close the chapter in Section 7.3.

7.1. Conclusion

The previous chapters have contributed to finding the answer to the main question introduced in Chapter 1: "How should a decision support system that presents the relations between case mix decisions and capacity dimensioning of the Admission Lounge and Clinical Ward be designed?". We start this section by giving an answer to the main question and we indicate the theoretical and practical value of our findings.

7.1.1. Findings

We identified that the AL can have an added benefit because of three reasons: reduced staffing costs, increased logistical efficiency, and increased patient friendliness. These benefits should be exploited as much as possible. We designed a stepwise approach for structured decision making, supported by a DSS. The DSS shows the potential performance of both the AL and the CW as a result of the inputs of the decision makers. The models use historical data to estimate the performance. Our approach covers five phases:

Phase 1 Set up inclusion and exclusion criteria for the AL

Phase 2 Determine appropriate staff, equipment, and supporting processes for the AL and CW

Phase 3 Analysis of potential bed reductions for the CW and required capacity for the AL

Phase 4 Analysis of feasibility within the facility layout

Phase 5 Optimisation: assignment of the grey area patients to the AL or CW

In Phase 1, we present the relation between the case mix selection criteria and the expected patient volumes for the AL. The case mix selection criteria are based on the attributes *elective status, age, ASA classification,* and *specialty*. Inclusion and exclusion criteria determine whether patients are assigned to the AL or the CW. Patients that can be assigned to both, fall within the grey area for patient selection. In Phase 2, management determines the qualitative requirements to facilitate admissions for the patients in the AL selection.

We assumed that the CW reaches a steady state and patients arrive according to a Poisson process. Therefore, the $M/G/c/c$ Erlang loss model was found appropriate for modelling the required number of beds for the CW. In Phase 3, patient admissions are evaluated during weekdays, because patient arrival intensity generally drops during the weekend. We compared the number of beds for a blocking probability of 5% to the peak load on weekdays to validate the outcome of the Erlang loss model. We concluded that the Erlang loss model overestimates the required number of CW beds by 1 bed for the specialty CHI and therefore assumed that the model gives an accurate estimation of the bed requirements.

In Phase 3 we also model the capacity for the AL as a function of the opening hours of the AL, the arrivals during those opening hours, and the expected admission duration. Arrivals for the AL were assessed for days on which the MSS allocates a common amount of OR time to specialties that have access to the AL, termed representative days. Using the rejected hours rate, we assessed the fraction of hours in which the load on the AL exceeded a set number of beds. We found a rejected hours rate of 10% as an appropriate service level for the AL. This rejection rate is found acceptable since the AL experiences peak loads that are a result of the morning and/or afternoon starting times of the OT. Slight decreases of the rejected hours rate lead to a disproportional drop of the occupancy rate for the AL. In both case studies (Chapter 4 and 6) we found that 50% is an acceptable occupancy rate for the AL, because the AL experiences peak loads and does not reach a steady state.

After management uses the model to determine the required capacities for their selection criteria, they determine whether the requirements for the AL and CW are feasible within their facility layout in Phase 4. In Phase 5, management can optimise the grey area for patient assignments to the AL. The DSS enumerates all possible combinations of assignments of patients in the grey area to the AL. The attributes *age*, *specialty*, and *ASA classification* each contained a grey area. In both case studies, we could assess 12 assignment combinations. With a goal function that weighs out the efficiency and efficacy of both the AL and the CW, we selected the top 5 assignment rules. In both cases we found assignment rules for the AL that outperformed the initial assignment rules determined in Phase 1. The new assignments lead to better utilisation of the AL and a significant bed reduction for the CW. In the first case study we find that the bed reduction for the CW exceeds the required number of AL beds. In the second case study, the hospital overall requires an additional bed to accommodate the AL admissions.

We made a mock-up of the DSS in the environment of HiX, ChipSoft's hospital information system. The mock-up can be seen in Figure 20, Figure 21, and Figure 22. Management of the case study hospital indicated that the tool is easily interpretable for a capacity manager.

7.1.2. Contribution to operations research

We developed a model to determine the load of an AL. The AL most likely does not reach a steady state. We also developed a case mix optimisation method, which we did not come across in the literature.

Mainly the use of the grey area with undecided patient allocations appears to be unique. The grey area sets bounds for the solution space, and enables hospitals to optimise within their strategic scope. The enumeration is mainly useful in situations where management is hesitant about the qualitative impacts of the assignment of a patient, and needs quantitative support to justify complex decisions.

Our modelling approach for the AL and CW can be applied other hospital units or job shop systems with similar characteristics. For example, the hospital's lab, can be modelled with the deterministic model. Clinicians at our case study hospital explained that the lab experiences peak load during the morning, short before elective surgeries take place. The peak load of the lab may be reduced by using other opening hours, which our model can assess.

7.1.3. Contribution to practice

ChipSoft can integrate the DSS with the models that are currently under development. We enable users of the DSS to systematically make decisions about the implementation of the AL. After the AL is implemented, the DSS can be used for tactical planning purposes by resetting inputs such as the wards for analysis, the analysis period, or the patient selection criteria.

7.2. Discussion and recommendations

We went into this analysis with the idea that the Erlang loss model would be applicable to analysis of the AL. However, the assumptions for a steady state Poisson arrivals make the Erlang loss model useless for the AL. We ended up using a deterministic approach with the assumption that patients stay at the AL during two time buckets of one hour each. In practice, this is less strict and there is more variability in the duration between the moment of a patient's arrival. We stand by this approach because we noticed that the use of smaller time buckets resulted in more variable arrival patterns. Although it is important to assess the variability in arrivals over the course of the opening hours of the AL, the decisions regarding dimensions of the AL is strategic. For the strategic decision we need a general indication of the (maximum) load on the AL. There are other methods such as simulation modelling that are better at capturing the variability patterns on an operational level.

The Erlang loss model leads to an overestimation of the required number of beds. It is unclear whether the calculated bed reductions were true to the real potential bed reductions. Nevertheless, we used the calculated bed reduction, a result from the shortened ALOS for selected patients, to quantify the potential advantages of the introduction of an AL. There is also a wide variety of qualitative aspects that influence the benefit of the AL. The main driver for hospitals will initially be the improved logistics and patient friendliness, while the bed reductions might be of marginal interest.

We visualised the admission and discharge events for the CW, but we did not incorporate the opening hours of the AL in this visualisation. Hence, AL patients that arrived outside opening hours of the AL were also modelled to arrive later at the CW, like patients arriving during opening hours. To make a more accurate visualisation of the events we recommend ChipSoft to incorporate the AL's opening hours in the visualisation of arrivals and discharges at the CW.

With the use of representative days one can wonder whether the flaw of averages is reduced or not. With representative days we automatically exclude outliers from the analysis of the AL. This means that we potentially over- or underestimate the number of days or hours on which patients are rejected. To gain more insights about the operational performance of the AL and the CW combined, a simulation study may be required. Another remark on the use of representative days for the analysis of the AL is that they might be non-existent when the MSS changes drastically. We recommend ChipSoft to link the calculations for the inflow of the AL to the models that are currently under development.

If a hospital wants to maximise the utilisation of the AL there are several options. Our first recommendation is to use the empty space as an overflow facility for e.g. the day care department of the CW. Our second recommendation would be to take in balancing the inflow of the AL into consideration when constructing the MSS. Our model for calculating the load of the AL could be used for assessment of the effects of the new inflow.

Enumeration of the case mix was done for a relatively small solution space. Let us assume that ASA classification 3 is the only classification up for debate, and that the age range for the grey area will be divided into a maximum of five categories. Then those combination already form 2 x 5 = 10 options to asses. The number of (sub)specialties within the grey area then has substantial influence on the size of the solution space. The number of combinations is then multiplied by 2^s, s being the number of specialties within the grey area. With 10 (sub)specialties within the grey area, there are then 2 x 5 x 2^{10} = 10,240 combinations to assess. Assuming that the runtime shows linear behaviour, we then require 10,240 / 12 * 3.8 seconds runtime = 54 minutes of runtime, which is acceptable for strategic decision making. However, when the number of (sub)specialties keeps adding up, the runtime quickly increases. With 15 (sub)specialties, the runtime of the model amounts 91 hours.

This numerical example shows the importance of setting boundaries in the patient inclusion and exclusion criteria.

We assumed all AL-classified patients are allowed to be admitted to the AL. By setting a limit to the maximal number of admissions from a certain patient type or group, it is possible to take admission control tactics into account. We recommend ChipSoft to integrate this into the model for extended tactical planning capabilities.

The model generates many outputs. This means that there is a wide variety of results that may not be interpretable for all users. We assessed the usability of the DSS with experienced developers from ChipSoft and one hospital in the case study and all respondents are people with a technical background. Someone with less technical knowledge may experience more difficulty with the interpretation of these results. However, hospitals that may consider using this tool from ChipSoft are already (slightly) experienced with the use of a DSS and hence we may have incorrectly assumed the usability and interpretability of the tool.

During preoperative screening it is already possible to determine the location of admission for the patient. We recommend ChipSoft to add a field to the preoperative screening document that indicates whether the admission can take place at the Al. This field can be filled automatically when the patient's characteristics comply with the AL selection criteria. This way there is no extra action for the screening anaesthesiologist, but there is more information about the patient available. When the AL is used for a longer period of time it is also easier to assess the performance of the AL, since it is know which patients used the AL at what times.

7.3. Further research

We used the Erlang loss model formulation by De Bruin et al. (2007) to determine the potential bed reduction for the CW. To account for the variability in arrivals at the CW, which is more useful for tactical planning, we recommend expanding the model with the time-dependent Erlang loss model (Bekker & De Bruin, 2010). The impact of the AL could also be quantified if the time dependent arrivals at the CW are based on the visualised admission patterns we incorporated in our DSS.

To further determine the extent of variability in the arrivals of AL patients, and the effects thereof, simulation modelling might be required. In simulation modelling it is possible to incorporate other details that we did not incorporate, such as the waiting room of the AL, the time that the patient spends at the holding, or the variability in admission duration. If the AL, CW and OT are modelled as one complex it is also possible to get more insights about the effects of changing the MSS.

One of the hot topics in operations management for health care is to balance the care burden across wards. The AL does this to a certain extent; the preoperative patients are no longer amongst the postoperative patients and therefore the care burden at both the AL and CW is more balanced than it would be without the AL. A way to exploit the effects of a balanced care burden would be to assign patients to the AL or CW on the basis of potential care burden.

We applied case studies to data of small general hospitals. Application to a larger of other type of hospital will result in more knowledge about the usability of the DSS. We expect that the DSS can be valuable for larger hospitals where the decisions for patient selection and ward selection are more complex than the contexts we studied. In a specialised hospital, the patient selection decisions might focus on other attributes than in our study. In that case, the attribute specialty may be replaced by, e.g., treatment type.

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APPENDIX A
INTERVIEW RESULTS

This appendix contains the interview questions used for our conversations with three hospitals. The questions are in Dutch, as is the summary of the findings. We let the hospitals review the summaries of their conversations, in Dutch. Due to possible translation errors we decide to maintain the questions and summary in Dutch.

Table 12 – Questions, and key words to pay attention to, used for conversation with hospitals.

Nummer	Vraag	Steekwoorden
1	Hoe kwam het idee voor de OOA tot stand?	
1a	Welke problemen heeft de OOA (niet) opgelost?	Verbeteringen; teleurstellingen; problemen; ziekenhuis; patiënt
1b	Hoe verliep de analyse/het ontwerptraject voor de OOA en met welke factoren is destijds rekening gehouden?	Berekeningen; aantal bedden; kosten/baten
1c	Hoe verliep de implementatie fase?	Tijdsduur; stappen; opbouw
1d	Wat is er veranderd op de kliniek?	Variatie; aantal patiënten
2	Hoe ziet een dag op de OOA eruit?	
2a	Perspectief personeel/management	Werkdruk; inzicht verloop
2b	Perspectief patiënt	Verloop; tijden; comfort
3	Wat zijn de karakteristieken van de OOA?	
3a	Welke type patiënt mag wel/niet gebruik maken van de OOA en waarom?	Klinische patiënt; poliklinische patiënt; spoed
3b	Hoeveel personeel is er dagelijks werkzaam op de OOA en hoe worden zij ingepland?	V:P ratio; dagvariatie; planningsmethodiek
3c	Wat is de capaciteit en benutting van de OOA en hoe maken jullie die inzichtelijk?	Aantal bedden; patiënten per dag; dashboard; benutting; KPIs; management; rapporten
3d	Wat zijn de wacht-/verblijf-/doorlooptijden op de OOA?	Samenvatting; sturing; verandering over tijd
3e	Wat beschouwen jullie als de resources van de OOA en welke daarvan zijn schaars/vormen een bottleneck?	Bedden; stoelen; loungeplekken; ruimtes
3f	Welke planningsmethodieken gebruiken jullie?	Heuristieken; software
4	Hoe worden onderstaande handelingen/uitdagingen ondervangen?	
4a	Beddenvervoer en -reserveringen	Van/naar OK
4b	Spreiding van de drukte	Variabele inzet personeel
4c	Tijdig oproepen van de patiënt	Software; WT
4d	Opbergen/vervoer van persoonlijke spullen	Kluisjes; doos; afdeling
4e	Begeleiding en bezoek voor patiënt	Min/max begeleiding
4f	Welke technische oplossingen zijn extra nodig voor het mogelijk maken van de OOA?	HiX; aanmeldzuil; entertainment

5	Als jullie het opnieuw zouden kunnen doen, wat zouden jullie dan anders doen in het opzetten van de OOA?	
Bonus 1	Wat waren onvoorziene barrières?	Tegenslagen; personeel
Bonus 2	Wat waren onvoorziene voordelen?	Financiële meevallers
Bonus 3	Wat is het takenpakket van het afdelingshoofd/capaciteitsmanager?	Monitoring; planning; coördinatie
Bonus 4	Wat voor manieren voor continue verbetering van de OOA passen jullie toe?	
Bonus 5	Maximale benutting van de ruimte (andere doeleinden?)	Andere programma's
Bonus 6	Privacy van patiënten	Andere kamers

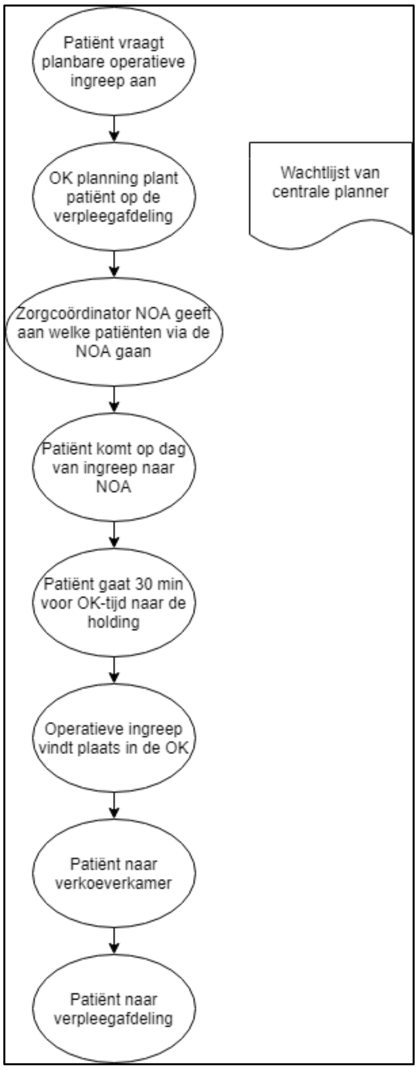
Summary of the findings

Aanleiding voor de OOA

- Er werd een hoge druk op de bedden in de ochtend waargenomen.
    - Veel patiënten komen vroeg in de ochtend.
    - Patiënten gaan ook weg in de ochtend.
- De OOA houdt preoperatieve patiënten bij de verpleegafdeling vandaan en daarmee wordt de ochtenddrukte verminderd op de verpleegafdeling.
- Veel van de capaciteit van de verpleging wordt gebruikt voor het faciliteren van opnames en kan dus efficiënter ingericht worden.
- Het probleem rondom de ontvangst van electieve patiënten met klinische opname kwam in eerste instantie uit een capaciteitsvraagstuk.
    - Er was meer verplegend personeel nodig wegens het reserveren van bedden voor patiënten. De patiënten worden in de oude situatie in een bed gelegd (grofweg) zodra ze het ziekenhuis binnenkomen en op de kliniek ontvangen worden. Dat vraagt om beddenreserveringen voor de preoperatieve fase. Als er bedden gereserveerd worden wordt daar ook personeel voor gereserveerd, wat soms tot een lage bedbezetting leidt. Er is dus veel variatie in bezetting van verpleging.
    - Personeel moet efficiënter ingezet worden wegens een beperkt aantal verpleegkundigen. Als alternatief moest worden gekeken hoe Verzorgenden Individuele Gezondheidszorg (VIG'ers) en Ziekenverzorgers (ZV'ers) hun taken deels over kunnen nemen.
- Daarnaast is er een financiële incentive.
- Het capaciteitsvraagstuk kan vertaald worden naar een vraag voor patiëntvriendelijkheid en vermindering van benodigde verpleegkundigen.
    - In de oude situatie worden patiënten ontvangen op de verpleegafdeling, waar zowel de pre- als postoperatieve patiënten liggen. Zodra de patiënt aankomt wordt diegene in een bed gelegd ter voorbereiding op de OK-sessie. De patiënt kan zodoende een aantal uur in bed liggen voordat de operatie uitgevoerd wordt, wat een negatieve werking heeft op de gezondheid van de patiënt. De preoperatieve ligduur is deels noodzakelijk wegens het voorbereiden van de patiënt, maar dit betreft vaak slechts 30 minuten.
    - Er ontstaat een duidelijk scheiding tussen twee verschillende processen: het preoperatieve en het postoperatieve. Een groot voordeel is dat preoperatieve verzorging minder specialistisch personeel vereist dan postoperatief. Daardoor is het mogelijk om het personeel in te zetten zoals het op de huidige manier gedaan wordt.
- **Sterktes OOA:**
    - Er komen meer bedden vrij op de verpleegafdelingen omdat bijna alle nuchtere opnames via de OOA gaan

- Personeel wordt efficiënter ingezet; de VIG'ers en ZV'ers nemen taken van verpleegkundigen over, waardoor verpleegkundigen op de klinische afdelingen beschikbaar zijn. (Niet bij ieder ziekenhuis het geval, want sommigen zetten liever "veilig" in met breed inzetbaar personeel).
- Er is een afname van de piek in de ochtend; een meer gestabiliseerde zorgvraag is ontstaan.
- Bedden worden dubbel benut op de OOA omdat patiënten daar kort verblijven.

- **Zwaktes OOA:**
  - De patiëntvriendelijkheid is nog niet merkbaar omdat de patiënt vaak niet goed geïnformeerd is over waar hij/zij op de dag van opname verwacht wordt. De patiënt loopt daardoor uit zichzelf naar de verpleegafdeling in plaats van de OOA en is later gefrustreerd als hij/zij dan toch op de verpleegafdeling komt te liggen.
  - Patiënt ervaart het achterlaten/overdragen van persoonlijke spullen als onvriendelijk en zou graag meer spullen mee willen nemen. De spullen worden in een plastic bak gestopt. Sommige patiënten nemen hele koffers mee, wat uiteraard niet in de box past. Het is de bedoeling dat patiënten slechts hun kleding in de doos stoppen en mee laten nemen door het personeel.
  - De OOA en de aansturende verpleegafdelingen zitten niet gelijkvloers; het scheelt 1 verdieping. Hierdoor is het personeel van de OOA soms moeilijk aan te sturen.
  - Lege bedden bij de OOA worden soms meegenomen terwijl ze korte tijd daarna nodig zijn. Daardoor is het personeel van de OOA vaak op zoek naar bedden.



Proces rondom de OOA

- Rechts wordt het proces rondom de OOA (aangeduid met NOA) weergegeven. Nadat de patiënt op de verpleegafdeling is gepland, wordt bepaald welke patiënten via de OOA gaan.

Patiënten die gebruik maken van de OOA

- Electieve opnames met de volgende exclusies:
  - Jonger dan 18 jaar
  - Hoog complexe patiënten
  - Patiënten die te veel voorbereidingen vergen
  - ASA score 4 en 5 (1 ziekenhuis ook score 3)
  - Niet ADL-zelfstandig zijn;
  - Een isolatie-indicatie hebben;
  - Niet nuchter opgenomen worden;
  - In het weekend opgenomen worden;
  - Geriatrisch/obees zijn;
  - Niet preoperatief gescreend zijn.
  - Patiënten met diabetes (1/3 ziekenhuizen)

- Uiteindelijk hopen ziekenhuizen dusdanig te kunnen plannen dat ze in weten te spelen op verwachte drukte bij verpleegafdeling, maar tijdens deze pilotfase is het nog moeilijk in te schatten in hoeverre dat gaat lukken

Logistiek en resources

- Het zal hoogstwaarschijnlijk zo zijn dat een aantal bedden die klaarstaan bij de NOA (als buffer) in de nacht weggepakt worden en de volgende dag verdwenen zijn. Het is lastig hier een oplossing voor te vinden.
- Er moeten voldoende (Computers on Wheels) COWs bij de NOA aanwezig zijn.
- De logistiek in het ziekenhuis wordt door een logistiek team geregeld in een van de ziekenhuizen. Dit team verzorgt zowel het vervoer van patiënten als van goederen. In andere ziekenhuizen wordt het patiëntenvervoer uitgevoerd door verpleegkundigen of ZV'ers.
    - In een van de ziekenhuizen wordt het logistiek team via een app aangestuurd. Deze houdt rekening met het toewijzen van taken aan de dichtstbijzijnde logistiek medewerker en bepaalt de optimale route voor het vervoer. De app zorgt ervoor dat het logistiek team productiever is dan voorheen en biedt echt uitkomst voor de oudere inefficiënte werkwijze.
    - Uiteindelijk is er een wens om vervoer naar de verkoeverkamer (vanaf de OK) ook door het logistiek team te laten doen, maar dat is lastig wegens het overdrachtsmoment dat normaalgesproken plaatsvindt
    - Dit overdrachtsmoment kan ook vervangen worden door goede documentatie in HiX, maar dit zal niet gauw geaccepteerd worden onder verpleegkundigen.

Wensen

- Een koppeling met de holding is gewenst, maar nu nog niet mogelijk omdat de holding en OOA niet direct aan elkaar gelinkt zitten. De koppeling met de holding zou moeten zorgen dat sommige patiënten van de OOA direct naar de OK kunnen (waar een sluis tussen OOA en OK gewenst is) en sommige patiënten van de OOA via de holding naar de OK gaan, wat vraagt om een sluis tussen de OOA en de holding. Dit vraagt om een uitgebreide verbouwing van de afdeling, wat er voorlopig nog niet aan zit te komen.
- De wachtkamer van de OOA kan worden uitgebreid en dichter bij de OOA geplaatst worden, maar om dat te realiseren moet de OOA naar een andere locatie verplaatst worden of er moeten een verbouwing plaatsvinden. Hiervan is bij alle ziekenhuizen nog geen sprake omdat het om een pilot gaat.

APPENDIX B
LITERATURE SEARCH

Table 13 – Search method for literature on queueing and bed capacity dimensioning, performed on March 26, 2019.

Step 1:	Search for accessible articles on bed capacity dimensioning that use queueing theory, referenced by Hulshof et al. (2012). *(n=17)*
Step 2A:	Perform a forward search on Hulshof et al. (2012) with search criterion *bed queueing OR queue* on Google Scholar. *(n=72)*
Step 2B:	From the forward search, select accessible articles with 5 citations or more that are relevant for our review. *(n=11)*

Bekker, R., & De Bruin, · A M. (2010). Time-dependent analysis for refused admissions in clinical wards. Annals of Operations Research, 178(1), 45–65. https://doi.org/10.1007/s10479-009-0570-z

Bretthauer, K. M., Heese, H. S., Pun, H., & Coe, E. (2011). Blocking in Healthcare Operations: A New Heuristic and an Application. Production and Operations Management, 20(3), 375–391. https://doi.org/10.1111/j.1937-5956.2011.01230.x

Cochran, J. K., & Bharti, A. (2006). Stochastic bed balancing of an obstetrics hospital. Health Care Management Science, 9(1), 31–45. https://doi.org/10.1007/s10729-006-6278-6

Cochran, J. K., & Roche, K. (2008). A queuing-based decision support methodology to estimate hospital inpatient bed demand. Journal of the Operational Research Society, 59(11), 1471–1482. https://doi.org/10.1057/palgrave.jors.2602499

De Bruin, A. M., Van Rossum, A. C., Visser, M. C., & Koole, G. M. (2007). Modeling the emergency cardiac in-patient flow: an application of queuing theory. Health Care Management Science, 10(2), 125–137. https://doi.org/10.1007/s10729-007-9009-8

Dobson, G., Lee, H.-H., & Pinker, E. (2010). A Model of ICU Bumping. Operations Research, 58(6), 1564–1576. https://doi.org/10.1287/opre.1100.0861

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Gorunescu, F., Mcclean, S. I., & Millard, P. H. (2002). A queueing model for bed-occupancy management and planning of hospitals. Journal of the Operational Research Society, 53, 19–24. https://doi.org/10.1057=palgrave=jors=2601244

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Harper, P. R., Knight, V. A., & Marshall, A. H. (2012). Discrete Conditional Phase-type models utilising classification trees: Application to modelling health service capacities. European Journal of Operational Research, 219(3), 522–530. https://doi.org/10.1016/j.ejor.2011.10.035

Kim, S.-C., Horowitz, I., Young, K. K., & Buckley, T. A. (1999). Analysis of capacity management of the intensive care unit in a hospital. European Journal of Operational Research, 115(1), 36–46. Retrieved from https://ac-els-cdn-com.ezproxy2.utwente.nl/S0377221798001350/1-s2.0-S0377221798001350-main.pdf?_tid=00bb76f2-98f7-4a9e-ad51-5a49f08a3ba7&acdnat=1552385270_895f6ecbf4d722e6b4ca1c60979affd7

Li, X., Beullens, P., Jones, D., & Tamiz, M. (2007). An integrated queuing and multi-objective bed allocation model with application to a hospital in China. Journal of the Operational Research Society, 60(3), 330–338. https://doi.org/10.1057/palgrave.jors.2602565

Ridge, J. C., Jones, S. K., Nielsen, M. S., & Shahani, A. K. (1998). Capacity planning for intensive care units. European Journal of Operational Research, 105(2), 346–355. Retrieved from https://ac-els-cdn-com.ezproxy2.utwente.nl/S0377221797002403/1-s2.0-S0377221797002403-main.pdf?_tid=91cfefa9-f2c5-4d2e-8070-31adf342e756&acdnat=1552385375_b064093a22fefeb399d841de2d7765aa

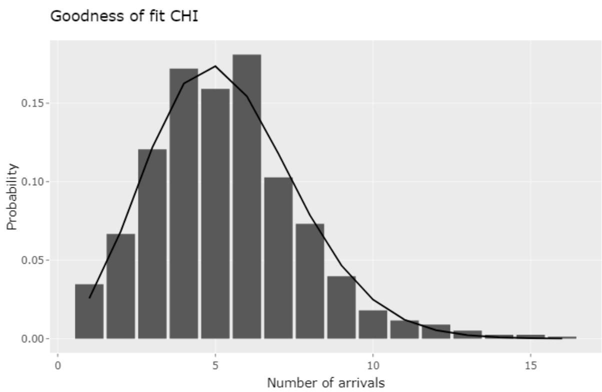
Thierry, A. ·, Chaussalet, J., & Robertson, N. J. (2010). A loss network model with overflow for capacity planning of a neonatal unit. Annals of Operations Research, 178(1), 67–76. https://doi.org/10.1007/s10479-009-0548-x

Utley, M., Gallivan, S., Davis, K., Daniel, P., Reeves, P., & Worrall, J. (2003). Estimating bed requirements for an intermediate care facility. European Journal of Operational Research, 150(1), 92–100. https://doi.org/10.1016/S0377-2217(02)00788-9

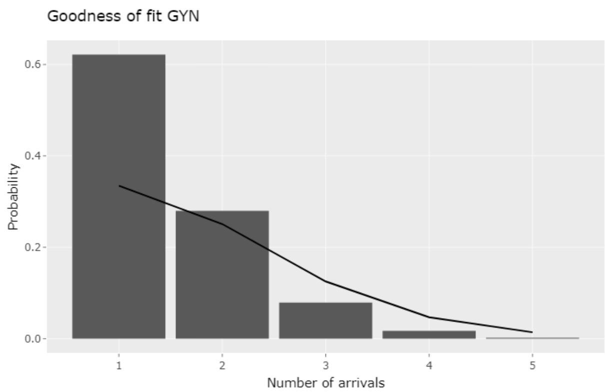
Van Dijk, N. M., & Kortbeek, · N. (2009). Erlang loss bounds for OT-ICU systems. Queueing Systems, 63(1), 253–280. https://doi.org/10.1007/s11134-009-9149-2

APPENDIX C
GOODNESS-OF-FIT TESTS

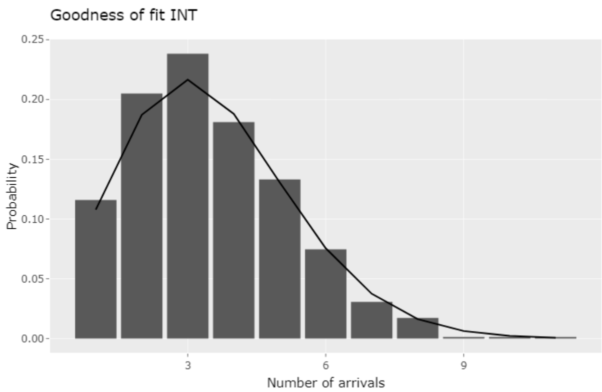
We use a Chi²-test to determine the goodness-of-fit of the Poisson distribution for the arrivals of each specialty of the ChipSoft development data. With a P-value of 0.1, the Poisson fit is accurate for 3 out of 10 specialties.



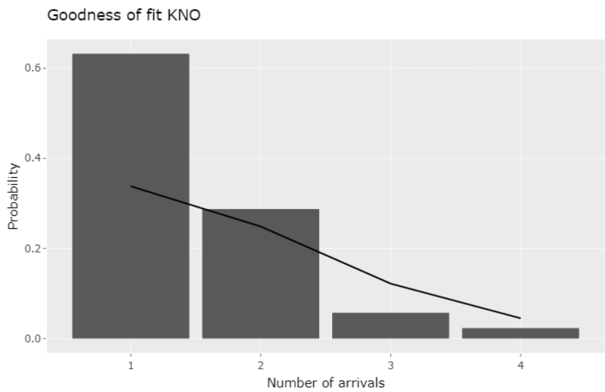
Poisson fit accepted for p-value ≤ 0.1



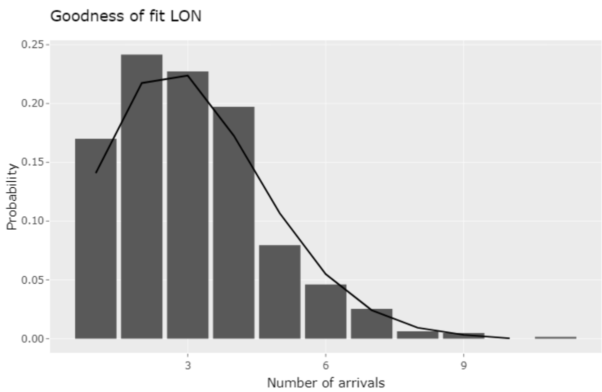
Poisson fit rejected.



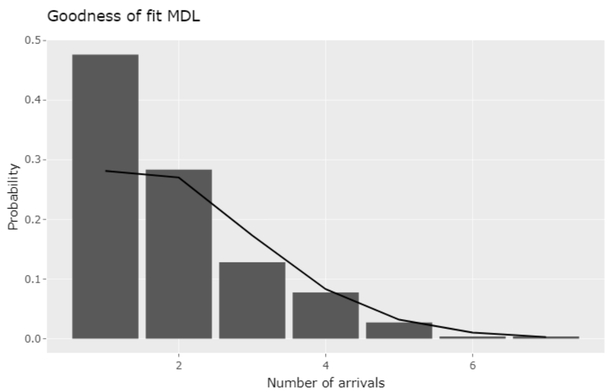
Poisson fit accepted for p-value ≤ 0.25



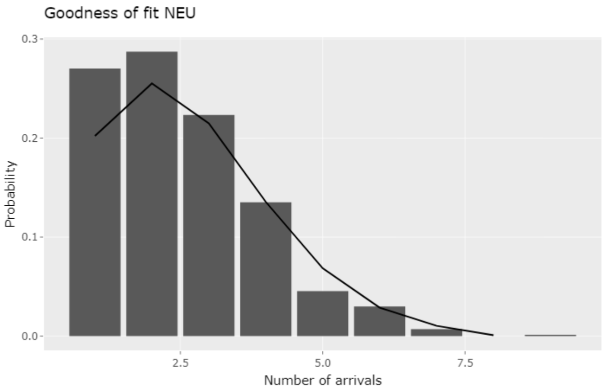
Poisson fit rejected.



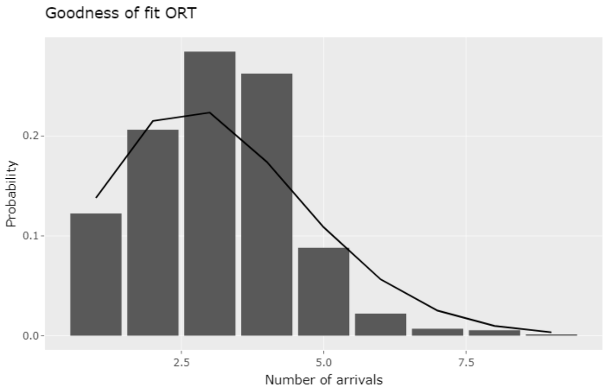
Poisson fit accepted for p-value ≤ 0.1



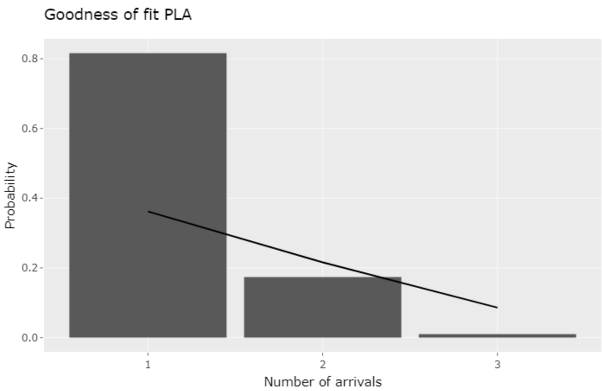
Poisson fit rejected.



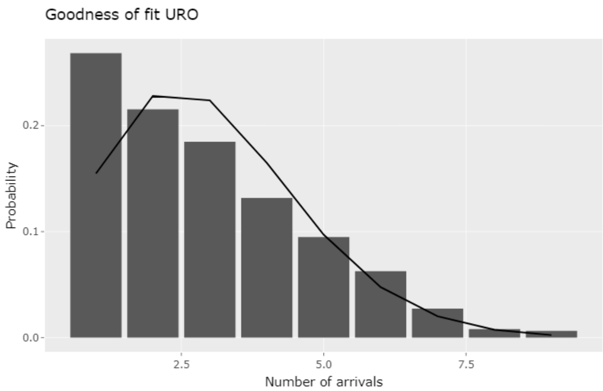
Poisson fit rejected.



Poisson fit rejected.



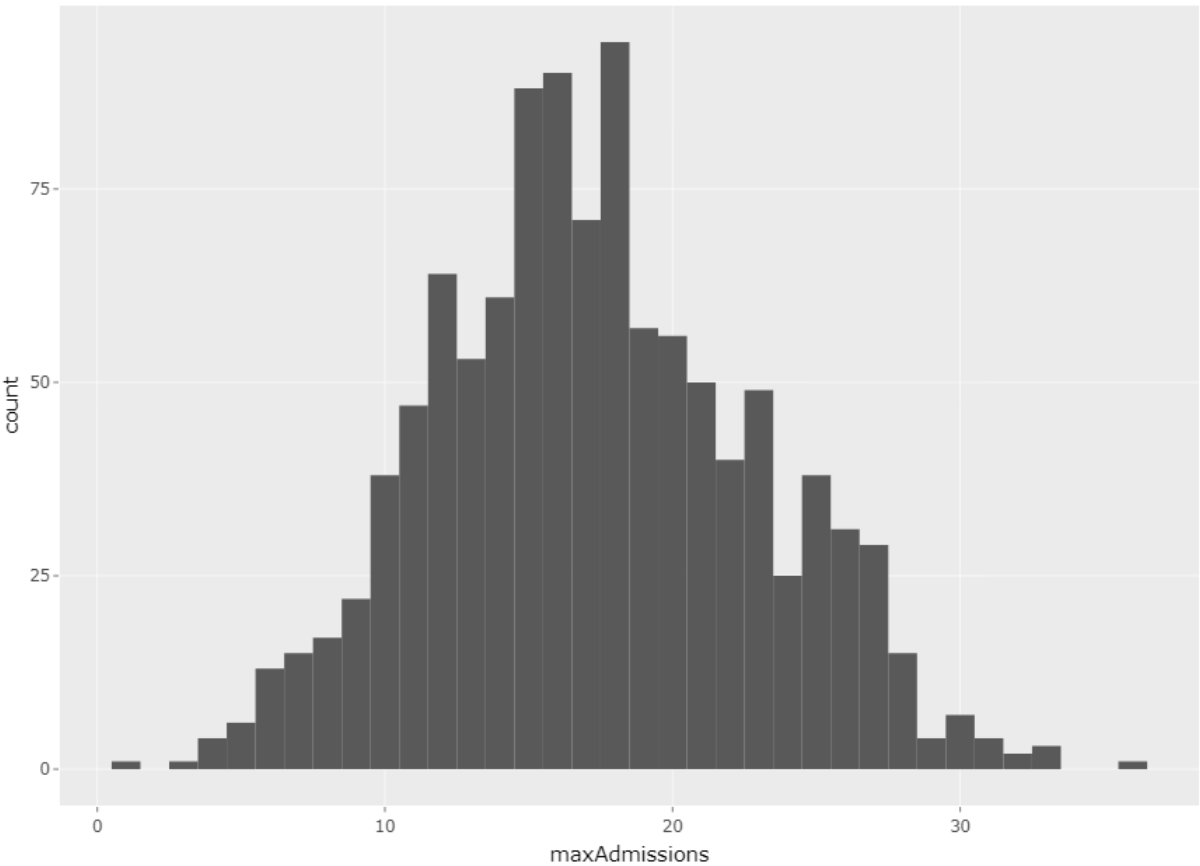
Poisson fit rejected.



Poisson fit rejected.

APPENDIX D
VALIDATION OF THE BLOCKING PROBABILITY

The figure below shows the peak load on the CHI beds for every weekday during the years 2015, 2016, and 2017 in the hospital of ChipSoft's development data. The load exceeds 27 beds for less than 5% of the days, which indicates that the blocking probability for the specialty CHI amounts approximately 5% for 27 beds. We make this conclusion under the assumption that blocking only occurs during moments that the peak load exceeds the strategically set number of beds.



Peak loads on the CHI beds. maxAdmissions = the peak load during the day, count = number of days.

APPENDIX E
LARGE MOCK-UPS HIX

Capaciteitsmanager - CSEZIS_MASTER_62_CS_TEST 13-07-2018 - 6.2 HF0 - HiX - ChipSoft

ıelounge

Afdeling 4N; 4W; 5O; 5W Periode 01-01-2015 - 31-12-2017

imalisatie

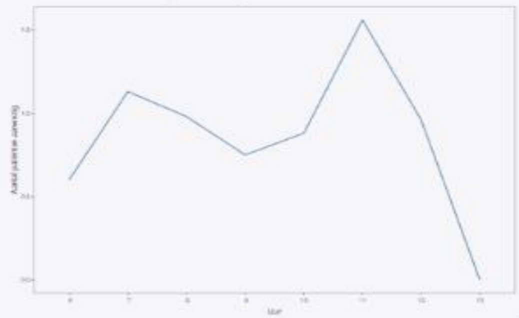
Weigeringskans 5%

er opnamelounge		Met opnamelounge	
ı	Bezetting	Bedden	Bezetting
	76%	**27**	**76%**
	48%	5	48%
	77%	26	77%
	37%	3	37%
	70%	16	70%
	62%	10	62%
	68%	16	68%
	67%	**15**	**65%**
	13%	2	13%
	66%	**12**	**60%**
	90%	**95**	**90%**

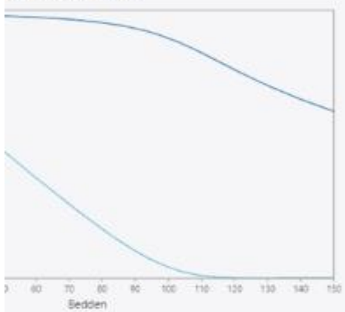
Opnamelounge

Bedden	Urenacceptatie	Dagenacceptatie	Bezetting
1	78,9%	32,8%	64%
2	93,5%	69,5%	44%
3	98,5%	90,5%	31%
4	99,8%	98,5%	24%
5	100%	100%	19%

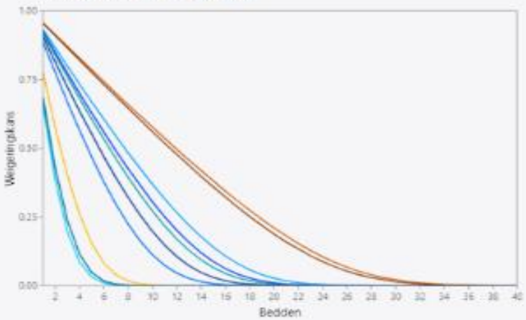
Gemiddelde drukte opnamelounge



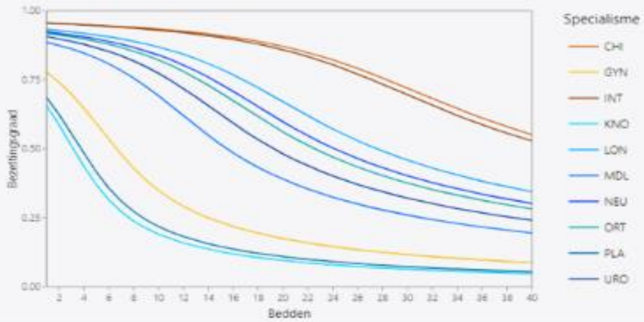
ıs en bezettingsgraad



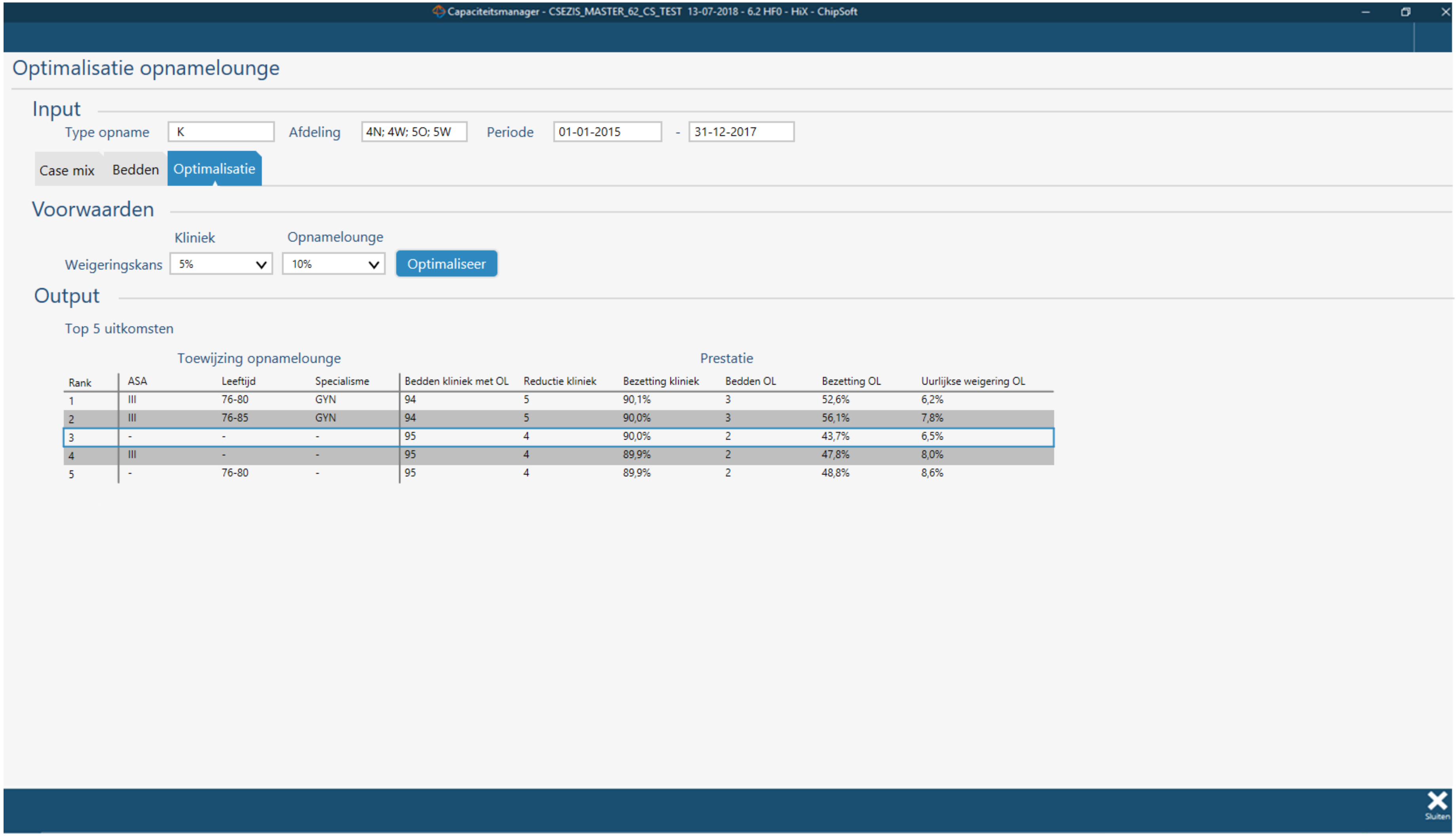
Weigeringskans per specialisme



Bezettingsgraad per specialisme



Sluiten


Capaciteitsmanager - CSEZIS_MASTER_62_CS_TEST 13-07-2018 - 6.2 HF0 - HiX - ChipSoft
Optimalisatie opnamelounge
Input
Type opname
K
Afdeling
4N; 4W; 5O; 5W
Periode
01-01-2015
-
31-12-2017
Case mix
Bedden
Optimalisatie
Voorwaarden
Kliniek
Opnamelounge
Weigeringskans
5%
10%
Optimaliseer
Output
Top 5 uitkomsten
Toewijzing opnamelounge
Prestatie
Rank ASA Leeftijd Specialisme Bedden kliniek met OL Reductie kliniek Bezetting kliniek Bedden OL Bezetting OL Uurlijkse weigering OL
1 III 76-80 GYN 94 5 90,1% 3 52,6% 6,2%
2 III 76-85 GYN 94 5 90,0% 3 56,1% 7,8%
3 - - - 95 4 90,0% 2 43,7% 6,5%
4 III - - 95 4 89,9% 2 47,8% 8,0%
5 - 76-80 - 95 4 89,9% 2 48,8% 8,6%
Sluiten