MASTER THESIS

IMPROVING THE ALIGNMENT OF SUPPLY WITH DEMAND FOR THE INTENSIVE CARE UNIT OF ZIEKENHUISGROEP TWENTE

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Improving the alignment of supply with demand for the intensive care unit of Ziekenhuisgroep Twente

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Management summary

In organizing care processes, a balance needs to be found between available and required resources. In an Intensive Care Unit (ICU), the demand for beds is a difficult to estimate factor, which makes it hard to estimate required nursing staff.

Ziekenhuisgroep Twente (ZGT) is currently facing three changes that influence the required resources on the ICU. First, a new larger ICU is being built, for which new staffing levels need to be determined. Second, new guidelines for ICUs are recommending to shift the focus from the number of beds in an ICU to the actual patients in the ICU for determining staffing levels. Third, ZGT is interested in the effect of introducing a level of care intermediate between regular wards and the ICU (Medium Care Unit (MCU)), as patients who only need to be monitored more often than possible on a regular ward now often receive the highest possible care. The objective of this research is therefore:

> *Improve the alignment of supply with demand for intensive care, by considering the actual patients in the ICU and their complexity of care, where the objective is to find optimal nurse staffing levels to reduce costs, while maintaining a desired level of quality of care.*

The ICU-nurses work in shifts, a day, late and night shift, and in the current situation a fixed number of nurses is scheduled for the different types of shifts. From performance measurement we see that the coverage compliance, the percentage of time the ICU-staffing levels satisfy the recommended Nurse-To-Patient (NTP)-ratios, was almost 100% for all shifts. This also leads to a high overstaffing rate and because costs for nursing staff are over 50% of the total costs incurred by the ICU, ZGT can benefit from aligning staffing levels with patient supply.

Approach
To find optimal staffing levels, we modeled the patients in the ICU with the hourly bed census model (Kortbeek et al., 2014) and the required staffing levels with the flexible nurse staffing model (Kortbeek et al., 2015). In using these models, the quality of care is guaranteed because two different nurse-to-patient ratios are used, one which always needs to be satisfied and one which needs to be satisfied a certain percentage of time. We defined three scenarios for dividing patients over the two equal ICUs, the first was to not divide patients but merge units, the second to divide patients equally and the third to assign patients randomly to one of the units by means of halved arrivals. We examined four scenarios for nurse staffing. The first is introducing no extra flexibility. The second is using float nurses in a flex pool between two units, such that these nurses can be assigned to the unit where the nurses are needed most. The third is hiring agency nurses via an emergency agency. The last is separating MCU-patients for which different NTP-ratios hold.

For scenarios which could not be examined with the nurse staffing model, we created a simulation model.

Results

In Table 1 the results of this research are shown, by means of the yearly costs for nursing staff. The costs are lowered when less nurses need to be scheduled during a shift and the required amount of FTE is reduced. For the full staffing option, there will never occur any shortages in staff. For all other options, 75% of the ICU bed-capacity is always staffed and at least 95% of the time there are enough nurses scheduled compared to the number of patients present in the ICU. We see that separating MCU-patients leads to the biggest cost reduction, followed by including agency nurses. The option of merging units always gives the lowest costs and dividing patients equally over the two units is preferred over random assignments.

Table 1: Costs summary for nurse staffing for different scenarios.

	Costs (k€) per year		
	1 unit	2 units, equal division	2 units, random assignment
Full staffing	3,601	3,726	3,726
No flexibility	3,016	3,122	3,264
Float nurses	-	3,069	3,105
Agency nurses	2,784	2,842	-
ICU and MCU	2,590	2,768	-

We performed a sensitivity analysis to show how the optimal solutions react to changes in input and discussed implementation difficulties. When either arrivals or Length Of Stay (LOS) is increased, all optimal solutions found for the different staffing policies lead to shifts with a coverage below 95%. The most shortages occurred for the option with agency nurses, which also comes with some difficulties for implementation, as contracts need to be set up with employment agencies to make sure agency nurses are available on a short notice. Separating MCU-patients leads to the highest cost reduction, but challenges arise in implementation, as the nurses need to make sure they do not have a too high workload, while patients keep changing complexities. We do not see any difficulties for implementing the scenarios with no flexibility and float nurses, but the costs reductions for these scenarios are lower.

Conclusion and recommendation

We conclude that separating MCU-patients is beneficial for ZGT, as costs for nursing staff are reduced and the complexity of care of the patients is considered. We recommend for the implementation to determine on an individual level for the nurses how many patients they can care for at a time and finding a definition of MCU-patients such that the number of transitions between complexities does not get too large. We recommend on doing further research in combining float nurses with separating MCU-patients and the possibility of sharing float nurses with the Emergency Department (ED).

Management samenvatting

Bij het organiseren van processen in de zorg, moet een balans worden gevonden tussen beschikbaarheid van en vraag naar middelen. Voor een Intensive Care (IC) is de vraag naar bedden een moeilijk te schatten factor, dit maakt het moeilijk om benodigd personeel te bepalen.

Voor Ziekenhuisgroep Twente (ZGT) komen er drie veranderingen aan die het bepalen van benodigd personeel beïnvloeden. Ten eerste wordt er momenteel al een nieuwe grotere IC gebouwd waarvoor nieuwe personeelsbezettingen moeten worden bepaald. Ten tweede komen er nieuwe richtlijnen voor IC's, die aanraden de focus niet meer op aantal bedden te richten maar op de werkelijke patiënten op de IC bij het bepalen van personeelsbezetting. Ten derde is ZGT geïnteresseerd in de introductie van een zorgniveau dat tussen IC en gewone afdeling in ligt (Medium Care (MC)), omdat patiënten die alleen vaker gemonitord moeten worden dan mogelijk op een gewone afdeling nu vaak het hoogst mogelijke zorgniveau krijgen. Het doel van dit onderzoek is daarom:

> *Het verbeteren van de aansluiting van aanbod op de vraag naar intensive care, door rekening te houden met de werkelijke patiënten op de IC en hun zorgzwaarte, waar het doel is om optimale personeelsbezettingen te vinden om kosten te verminderen, met de restrictie dat een gewenst niveau van kwaliteit van zorg wordt behouden.*

De IC-verpleegkundigen werken in shifts, de dagdienst, late dienst en nachtdienst, waar momenteel een vast aantal verpleegkundigen werkt voor de drie shifts. Als we kijken naar de dekkingsgraad, het percentage tijd dat de personeelsbezetting voldoet aan aanbevolen verpleegkundige-tot-patiënt (NTP)-ratios, dan was deze bijna 100% voor alle shifts. Het percentage overbezetting was hierdoor ook hoog en omdat de kosten voor verpleegkundigen meer dan 50% van de totale kosten voor de IC zijn, is het gunstig voor ZGT om de personeelsbezetting beter te laten aansluiten op het aanbod patiënten.

Methode
Om optimale personeelsbezettingen te vinden, hebben we de patiënten op de IC gemodelleerd met het hourly bed census model (Kortbeek et al., 2014) en het benodigde personeel met het flexible nurse staffing model (Kortbeek et al., 2015). De kwaliteit van zorg wordt gegarandeerd in deze modellen, doordat er twee NTP-ratio's worden gebruikt, één waaraan altijd moet worden voldaan en één waar een percentage van de tijd aan moet worden voldaan. We hebben verschillende scenario's gedefiniëerd voor het verdelen van patiënten over de 2 units van de IC, de eerste is om ze niet te verdelen en de afdelingen samen te voegen, de tweede om patient gelijk te verdelen en de derde om patiënten willekeurig toe te wijzen aan 1 van de 2 units. Voor het bepalen van personeelsbezetting hebben we 4 scenario's onderzocht. De eerste is geen extra flexibiliteit introduceren. De tweede is gebruik maken van een flex pool tussen de 2 afdelingen, waardoor verpleegkundigen uit deze pool toegewezen kunnen worden aan de afdeling waar ze het hardst nodig zijn. De derde is het inhuren van uitzendkrachten via een uitzendbureau. De laatste optie is het scheiden van MC-patiënten van IC-patiënten, waarvoor andere NTP-ratio's worden

gebruikt. Voor de scenario's die niet onderzocht konden worden met het nurse staffing model, maken we gebruik van een simulatie model.

Resultaten
In Tabel 2 zijn de resultaten van dit onderzoek weergegeven, uitgedrukt in jaarlijkse kosten voor verpleegkundig personeel. De kosten zijn lager zodra er minder verpleegkundigen per shift geroosterd hoeven te worden en de benodigde Full Time Equivalent (FTE) dus wordt gereduceerd. Voor het scenario volle bezetting zal nooit een tekort voorkomen. Voor de andere scenario's is er altijd personeel voor 75% van de bed-capaciteit en tenminste een dekking van 95%. We zien dat het scheiden van MC-patiënten leidt tot de grootste kosten reductie, gevolgd door het inhuren van uitzendkrachten. Als de twee afdelingen samen worden gevoegd zullen de kosten het laagst zijn en gelijke verdeling is altijd beter dan willekeurige toewijzing.

Tabel 2: Kosten overzicht voor verpleegkundigen voor verschillende scenario's.

	Kosten (k€) per jaar		
	1 unit	2 units, gelijke verdeling	2 units, willekeurige verdeling
Volle bezetting	3.601	3.726	3.726
Zonder flexibiliteit	3.016	3.122	3.264
Flex pool	-	3.069	3.105
Uitzendkrachten	2.784	2.842	-
IC en MC	2.590	2.768	-

We hebben een gevoeligheidsanalyse uitgevoerd om te laten zien hoe de optimale oplossingen reageren op veranderingen in input en uitdagingen in implementatie besproken. Als of aankomsten vermeerderen of verblijfsduren stijgen, zijn er voor alle gevonden oplossingen voor de opties voor personeelsbezetting shifts met een dekking onder de 95%. De optie met uitzendkrachten laat echter de meeste tekorten zien en implementatie van dit scenario geeft ook moeilijkheden, omdat er contracten moeten worden opgesteld met uitzendbureau's, vanwege het feit dat veel uitzendkrachten worden ingehuurd en deze wel beschikbaar moeten zijn. Het scheiden van MC-patiënten geeft de grootste kosten reductie, het implementeren van dit scenario geeft moeilijkheden doordat verpleegkundigen constant moeten nagaan of ze niet teveel patiënten verzorgen en patiënten vaak van zorgniveau kunnen wisselen. Voor de opties zonder flexibiliteit en gebruik maken van een flex pool zien we geen moeilijkheden voor implementatie, de kosten reductie voor deze opties is lager.

Conclusie en aanbevelingen
We concluderen dat het scheiden van MC-patiënten winstgevend is voor ZGT, omdat kosten voor verpleegkundigen worden gereduceerd en er rekening wordt gehouden met de zorgzwaarte van de patiënt. We raden voor de implementatie aan om op individueel niveau te bepalen hoeveel patiënten van de verschillende niveau's verzorgd mogen worden en om MC-patiënten zo te definiëren dat het aantal overgangen tussen zorgniveau's niet te groot wordt. Tenslotte raden we aan om combinaties van scenario's voor het bepalen van personeelsbezetting, MC-patiënten en flex pool, te onderzoeken en de mogelijkheid te onderzoeken om een flex pool te delen met de spoed eisende hulp.

Glossary

1ICU Intensive care unit of ZGT on the first floor with ten beds.

5 Oost Intensive care unit of ZGT on the fifth floor with four beds.

agency nurse A temporary employee, hired via an employment agency.

ChipSoft Data system used in the entire hospital ZGT.

coverage compliance The percentage of time that there were no nurse shortages.

float nurse A cross-trained nurse, that is enabled to float between units within a specialization.

ICU-nurse Nurse with an extra diploma for providing critical care.

intensivist A board-certified physician who provides special care for critically ill patients.

Mediscore Data system used in the ICU of ZGT.

nurse-to-patient ratio Indication of the number of patients a nurse is allowed to care for simultaneously.

outreach activities Activities for which ICU-nurses are responsible that need to be performed outside of the ICU.

Acronyms

AAC Acute Admission Cycle.

CCU Corony Care Unit.

CIV Consulting ICU-nurse.

CPR Cardiopulmonary Resuscitation.

EA Employment Agency.

ED Emergency Department.

FTE Full Time Equivalent.

ICU Intensive Care Unit.

LOS Length Of Stay.

MCU Medium Care Unit.

MDO Multidisciplinary Consultation.

MSS Master Surgical Schedule.

NTP Nurse-To-Patient.

OR Operating Room.

PACU Post Anesthesia Care Unit.

PDMS Patient Data Management System.

SIT Emergency Intervention Team.

ZGT Ziekenhuisgroep Twente.

Preface

In September 2010 my time as a student at the University of Twente began, as I moved to Enschede to start the bachelor Applied Mathematics. I had always liked solving mathematical problems, which was why this bachelor suited me very well. In the last year of my bachelor, I followed courses for the minor Production and Logistics Management. I found that in this specific field of study mathematics was combined with even more practical problems, which made me decide to follow the master Industrial Engineering and Management after completing my bachelor. After 18 months of master courses, the time had come to find a graduation project.

Before I knew about this projects' existence, I replied to a project at ZGT which was no longer available. I received an answer of Saskia Busscher, who let me know that there was another project available at ZGT which might be interesting for me. After a meeting where head of the intensive care unit Marco Jong explained more on the changes that were going to come for the ICU of ZGT, we were all enthusiastic to start this research. At the start we were all still searching for the specific subjects of this study, but a couple of weeks later we all agreed on the project goals.

I would like to thank Marco Jong for his guidance on the ICU and making sure I was always in contact with the right people. I always felt really welcome at the ICU, which was also due to all other ICU-staff who always showed interest in my project. Also great thanks to Saskia Busscher and Renske Visser, especially Saskia for meeting with me every couple of weeks and reading my report.

I would also like to thank my supervisors from the University of Twente. Ingrid Vliegen, you helped me define the problems at the start and gave useful feedback on my thesis. Thanks to your guidance the results of the research have become as they are presented here. Also thanks to Derya Demirtas, your feedback on amongst others my English have improved my work.

Lastly, I would like to thank my family and friends for supporting me the past couple of years. Especially Albert, you have made the last six years as great as they were and really believed in me during this final project.

I hope you will enjoy reading this master thesis and appreciate the effort that has been put into it.

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Contents

Chapter 1

Introduction

Hospitals in the Netherlands increasingly reorganize care processes to improve efficiency, while maintaining desired service levels. A balance needs to be found between available and required resources, such as equipment and staff. To find this balance, information on bed capacity and staff capacity should be used, together with information on bed demand. This demand for beds is an important but difficult to estimate factor in intensive care units.

This research takes place in Ziekenhuisgroep Twente in Almelo. We first introduce this hospital (1.1) and describe characteristics of an intensive care unit (1.2). Then we state the problem the hospital faces (1.3), the research objective and scope (1.4) and lastly the research questions (1.5).

1.1 Ziekenhuisgroep Twente

Ziekenhuisgroep Twente (ZGT) was established in 1998 following a merger of Twenteborg Ziekenhuis in Almelo and Streekziekenhuis Midden-Twente in Hengelo. ZGT still consists of two hospitals, in Hengelo and Almelo, and it has field clinics in Geesteren, Goor, Nijverdal, Ootmarsum, Rijssen and Westerhaar.

ZGT has over 3,000 employees, 213 medical specialists and 742 beds. The hospital offers medical care to approximately 300,000 citizens. Every year there are over half a million visits at the outpatient clinic, 50,000 day cases and 36,000 admissions. In the year 2014, the turnover was approximately 276 million.

Nowadays, there is an increase in possibilities for specialized treatments in health care. Since it is impossible to offer all care at both hospitals, a clear distinctions between the care at the two locations is made. The hospital in Hengelo is developed to handle most of the planned, high-volume care. This means that the hospital in Almelo focuses on the highly complex and acute care, with a low volume.

1.2 Intensive care

An Intensive Care Unit (ICU) is a specialized department in a hospital. ICUs provide intensive care, treatment and monitoring, for people in a critically ill or unstable condition. The patients are cared for by specially trained staff.

There are several reasons for patients to be admitted to an ICU. An important reason is a problem with their lungs that requires respiratory support. The ICU is the only ward where ventilator support is possible. Some patients need close monitoring immediately after a major surgical operation or serious head injury. Another reason is that patients may have an imbalance in the level of chemicals, salts, or minerals in their bloodstream that requires close monitoring as these levels are corrected. Also, patients may have a serious infection in their bodies that requires specialized ICU care. The common factor is that patients in the ICU need to be monitored more often than the ones in a general ward.

1.3 Problem statement

Since patients in the ICU need to be monitored often and their complexity of care is high, an ICU-nurse can take care of less patients at a time than a nurse in a regular ward can. The ICU-nurses are highly qualified staff and therefore more expensive than regular nurses. ZGT needs to make sure that there is sufficient staff to take care of the patients who are critically ill. To find the right amount of staff is however not that easy.

The number of required nurses is difficult to estimate, because one day the ICU can be almost empty, the next day it can be fully occupied. A hospital wants to avoid paying nurses who do not have any patients to take care of. On the other hand, it is not desirable that critically ill patients can not be admitted because of a shortage in staff. This leads to overstaffing, which results in very high costs.

Another problem occurs when patients are healthy enough to not need intensive care, but they cannot be monitored enough in other wards. These patients stay in the ICU unnecessarily and are provided with the highest possible care by the expensive ICU-nurses. In these situations, some sort of intermediate care can be introduced.

In 2015 a first draft of new guidelines for intensive care units in the Netherlands were proposed (Nederlandse Vereniging voor Anesthesiologie, Nederlandse Vereniging voor Intensive Care en Nederlandse Internisten Vereniging, 2015). Where the focus used to be on the number of beds in the ICU and making sure that the full bed-capacity would be available, the focus is now shifting towards the actual patients in the ICU. The number of patients and their corresponding complexity of care could play an important role in determining the required number of ICU-nurses scheduled.

The new guidelines are not the only change for the ICU of ZGT. Currently, there are two units of intensive care on two different floors in Almelo and ZGT desires that the ICU will be in one location. The construction of the future ICU has already begun, the layout is shown in Figure 1.1.

Figure 1.1: 3D layout of new ICU

Because of this new intensive care unit, ZGT needs to determine optimal staffing levels for the new situation. In determining the staffing levels, the possibility for intermediate care can be taken into account, but more importantly, flexibility needs to be introduced. When shifting the focus from the number of beds in the ICU to the actual patients in the ICU, some sort of flexible nurse staffing is necessary. Because of all these changes, now is the right time to find staffing levels such that intensive care can be optimally provided to the patients. Therefore, ZGT is looking for the best options to better match the supply with the demand for intensive care.

1.4 Research objective and scope

The problem we described leads to the following objective:

> *Improve the alignment of supply with demand for intensive care, by considering the actual patients in the ICU and their complexity of care, where the objective is to find optimal nurse staffing levels to reduce costs, while maintaining a desired level of quality of care.*

This objective can be reached through multiple interventions, for example flexible nurse staffing. We discuss more options to better match the supply of intensive care with the demand in the following chapters.

The objective is to find optimal nurse staffing levels to reduce costs, because the deployment of adequate nurse staffing levels mostly accounts for the majority of hospital budgets (Wright et al., 2006). By finding the optimal nurse staffing levels for the actual supply of patients in need of intensive care we expect to reduce the costs for the ICU.

Maintaining a certain level of quality of care comes down to being able to admit the patients to the ICU who need to be admitted and provide them the care they need. It is not possible to admit all the patients, but a maximum percentage of rejected patients can be set. The quality of care can also be maintained by making sure one nurse does not care for too many patients.

The scope of this research is the ICU of ZGT, which is located in Almelo. The goal is to determine necessary resources, where we only focus on the required number of ICU-nurses. There are a variety of people working in an ICU, of which some are later shortly described, but only nurse staffing is a part of this research. We take other departments into consideration, regarding the patients that are referred to the ICU or the departments where ICU patients are referred to. Optimizing processes of other departments however, is not the purpose of this research.

The ICU is currently under construction, but changes to the layout of this new ICU are not contained in the scope of this research. Whether the capacity of this renewed ICU is appropriate might be discussed when questions concerning this subject arise during the study, but the goal is not to make any changes to the already existing plans as shown in Figure 1.1.

1.5 Research questions

In order to achieve the objective described in Section 1.4, we formulate the following research questions:

Chapter 2: Context analysis
What is the current situation with respect to processes, control and performance?

In this chapter we describe the context of this study, which includes the two different units, the guidelines, the staff and the admission and discharge process to the ICU. We also discuss some more detailed information on the process control of nurse staffing. The performance of the current ICU is looked at in this chapter, which is needed to find improvements later on. We present the preformance by indicators related to the nurse staffing process. In the context analysis we also discuss the planned changed for the ICU of ZGT.

Chapter 3: Literature study
What models on nurse staffing and matching supply with demand in health care are known from literature?

In this chapter, a literature study is performed in order to find out what methods and techniques are suggested in literature. We also look for possible interventions in the literature.

Chapter 4: Models
How can the ICU be modeled?

In this chapter we focus on applying theoretical models to the ICU of ZGT.

Chapter 5: Experimental design
How can we set up experiments to improve the alignment of supply with demand?

In order to perform different experiments, we define model input and validate and verify the models when this input is used. In this chapter we also describe the actual experiments we perform for finding the effect of different interventions.

Chapter 6: Results
What are the results from the performed experiments?

In this chapter we provide insight in the results from the experiments. We also analyze the effect of parameters on the output, by means of a sensitivity analysis.

Chapter 7: Conclusions and recommendations
What interventions should ZGT apply?

In this chapter we describe the overall conclusions of this research. We give recommendations to ZGT concerning the found interventions to improve the alignment of supply with demand for intensive care.

Chapter 2

Context analysis

In this chapter we describe the context of our research, where the goal is to gain more insight in current processes on the ICU of Ziekenhuisgroep Twente (ZGT). We start with general information on the ICU (2.1), we give a process description (2.2) and the process control (2.3), after which we determine the performance of the current ICU (2.4) and mention the planned changes for the new ICU (2.5). We end this chapter with a short conclusion (2.6).

It is important to note that data of the ICU of ZGT plays an important role in this chapter. The description of the data we selected from two data systems, ChipSoft and Mediscore, can be found in Appendix A.

2.1 General information

We start the context analysis with a description of the ICU of ZGT (2.1.1), we discuss the medical staff on an ICU (2.1.2) and the the new guidelines for an ICU (2.1.3).

2.1.1 ICU of Ziekenhuisgroep Twente

The Intensive Care Unit (ICU) of Ziekenhuisgroep Twente is an ICU especially for adults, children are given first acute care but will then be transfered to a pediatric ICU elsewhere. To give an indication of the characteristics of the ICU of ZGT Almelo, some descriptive statistics are presented in Table 2.1. The number of beds, the number of admissions, average inter-arrival time, average LOS and some quality indicators are shown (Van der Voort et al., 2004; De Vos et al., 2007; Braun et al., 2010; Brown et al., 2014).

The ICU consists of two units, on the first floor there is a unit with a total of ten beds (1ICU) and on the fifth floor there is a unit with a total of four beds (5 Oost). This adds up to a bed-capacity of fourteen, as shown in Table 2.1. This is only the case during the regular period, for a period of five weeks during the summer 5 Oost is closed and the bed-capacity of the ICU is only ten. The reason for this reduction is that there are generally less patients in the ICU during the summer, because there are less elective surgeries planned. This gives the opportunity to reduce the number of beds and nurses can go on holidays. This reduction in bed-capacity is shown in Figure 2.1.

Table 2.1: Descriptive statistics of the data from Mediscore, data from January 1 2014 - December 31 2015.

	Value
Number of beds	
regular period	14
reduction period (5 weeks per year)	10
Admissions	1497
Readmissions	154
Readmissions within 48 hours	27
ICU stay with ventilator support	630
Av. inter arrival time	0.49 days
Av. LOS	3.80 days
Av. duration ventilation	3.53 days
Av. occupancy rate	58.24%
100%-occupancy rate	1.42%
Rejection rate	3.23%
Mortality rate	11.91%

The reduction in bed-capacity by closing 5 Oost also happens in rare occasions when there are just a few patients in the ICU. In this situation, the nurses will have a stand-by shift and the protocol says that when the eighth patient is announced to be admitted, 5 Oost should be re-opened. Unfortunately, no data is available on how often this situation occurred.

Figure 2.1 not only shows the bed-capacity, but also the number of patients in the ICU over the years 2014 and 2015. The fluctuation in number of patients is clearly visible, as well as the fact that only in rare occasions the ICU is fully occupied. This is confirmed by the average occupancy rate and the 100%-occupied rate from Table 2.1. The fact that in rare occasions the ICU is full, is also reflected by the rejection rate which is only 3.23% as shown in Table 2.1.

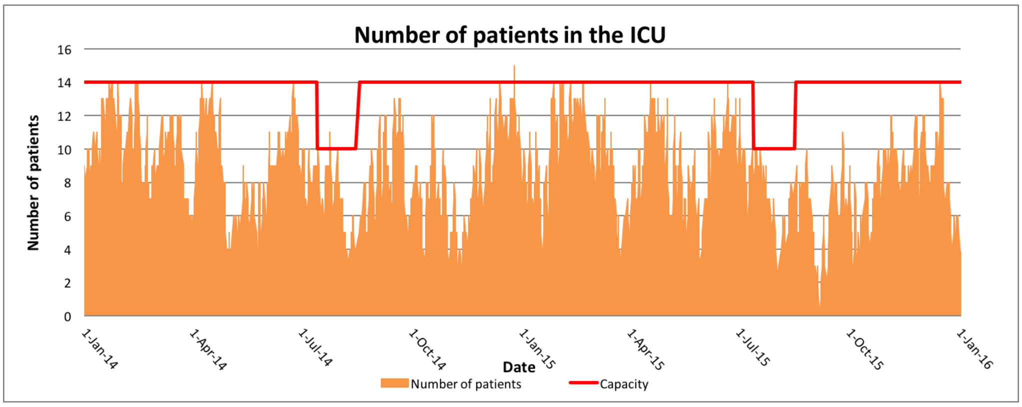


Figure 2.1: The number of patients in the ICU with the available bed-capacity. Data from January 1 2014 - December 31 2015 of 1497 admissions and discharges retrieved from Mediscore.

In Section 1.2 we stated that the ICU is the only ward where respiratory support is possible. From Table 2.1 we see that only 630 of the 1497 admissions to the ICU were admissions where the patient received respiratory support. It is possible that a patient is on ventilator support several times during its stay on the ICU. As the average duration of ventilation is 3.53 days, we can conclude that patients requiring ventilator support often have a longer stay in the ICU than the average as shown in Table 2.1.

The statistics in Table 2.1 describe the ICU of ZGT, this study does not focus on impoving these statistics. We focus on staffing levels that match the patient supply as shown in Table 2.1 and hence we describe the ICU medical staff in the next section.

2.1.2 Medical staff

To ensure 24 hour care, the ICU of ZGT Almelo has a lot of staff, each with their own responsibility. This staff includes intensivists, physician assistants and ICU-nurses. We give a short job description for these different staff members.

Intensivists

An intensivist is a board-certified physician who provides special care for critically ill patients. The intensivist has the primary responsibility for the ICU patients' care, he is in charge of deciding on treatments and medication. The intensivist consults other specialists, they visit the ICU when needed. Every day specialists concerning the patients currently at the ICU have a meeting with the intensivist and other ICU staff to discuss the patients treatments, which is called the Multidisciplinary Consultation (MDO). The intensivist makes the decision on whether a patient is admitted to the ICU and when a patient is discharged from the ICU. This process is described in Sections 2.2.1 and 2.2.2. Optimal staffing levels for intensivists is not part of this research.

Physician-assistants

Physician-assistants spend a period at the ICU to get more experience with critically ill patients and the different organ systems. They work one-on-one with the intensivist as they do the daily rounds to check on the patients every morning. The number of patients that can be treated in the ICU is partly determined by the size of the medical team, which consists of intensivists and physician-assistants. The physicians assistants are however not part of this research.

ICU-nurses

Since ICU-nurses are the main subject of this research, we give a more detailed description than for the other staff. To be an ICU-nurse in the Netherlands one must be in possession of a diploma for regular nursing before entering an 18-month program to attain another diploma for ICU-nursing. The specially trained nurses provide round-the-clock care and monitoring of the patients. The intensivist decides upon which and how much medication to give, but the nurses give the patient the drugs and fluids that the doctors have prescribed. They also take regular blood tests and record the patients blood pressure, heart rate and oxygen levels. They keep track of everything in the Patient Data Management System (PDMS), that includes the medication, food and drinks etc. The nurses are also responsible of changing the sheets, washing the patient in bed, cleaning the patients teeth and all other personal hygiene. The nurses may be called upon to assess patients quickly, particularly if they are not responding favorably to a certain treatment, and possibly adjust their treatment options themselves. Should the worst happen, they should also be skilled in a number of life saving techniques, such as cardiopulmonary resuscitation, and know how to use life saving equipment, such as defibrillators.

The ICU-nurses of ZGT do activities like work-groups or teaching outside of scheduled hours on the ICU, however, there are two side-activities that are performed by a nurse scheduled to work on the ICU:

- **Green spot: coordinator of work-floor**. One of the nurses is assigned the *green spot*, he is the contact person of the intensivist and the two of them need to make sure there is a proper distribution of the care intensity and he is also the contact person for people outside of the ICU. Being assigned the green spot is a side activity to being an ICU-nurse, the nurse can still be assigned a patient, but preferably only one.
- **Red spot: outreach activities**. One of the nurses is assigned the *red spot* and is responsible for all the outreach activities. This can be Consulting ICU-nurse (CIV) tasks, being called upon as part of the Emergency Intervention Team (SIT) or rushing to a patient in need of Cardiopulmonary Resuscitation (CPR).

More information on these outreach activities can be found in Appendix B.

Since there are guidelines for how much personnel should be employed on an ICU, we discuss these guidelines in Section 2.1.3.

2.1.3 Guidelines

The ICU is currently working according to the 2006 guidelines (Nederlandse Vereniging voor Anesthesiologie, 2006). A new concept of guidelines was published in 2015 (Nederlandse Vereniging voor Anesthesiologie, Nederlandse Vereniging voor Intensive Care en Nederlandse Internisten Vereniging, 2015), but it was rejected by Nederlandse Vereniging Intensive Care (NVIC). Zorginstituut Nederland (ZiN) is now working on an updated version of the renewed guidelines, which will mostly use the same principles as those of 2015, but the details will be less strict or better justified.

The 2006 guidelines focused on how many beds are located in the ICU and staff should be employed according to the number of beds with ventilation possibility. In case of the ICU of ZGT Almelo, there should be 3.5 Full Time Equivalent (FTE)

ICU-nurse available per ICU-bed with the capability of life support. This means that in the situation of ZGT Almelo, where fourteen beds are located in the ICU, a total of 49 FTE ICU-nurses should be employed. In the 2015 guidelines the organizations have chosen to shift the focus from number of beds and treatments days to the patients in the ICU. The requirements for staff formation have also focused on the actual patients in the ICU, instead of the number of beds. In the 2015 guidelines a distinction is made for the maximum number of patients an ICU-nurse can take care of per shift type (max. span of control). This is shown in Table 2.2.

In Table 2.2 the maximum span of control is shown for regular ICU-nurses as well as for nurses trained especially for an intermediate level of care provided to patients on a Medium Care Unit (MCU)), since ZGT Almelo is interested in introducing such a level on the ICU. The 2015 guidelines also state a recommended maximum span of control for other staff, but this is not part of this study.

Table 2.2: Span of control for nurses, according to concept guidelines of 2015.

Shift	Maximum number ICU patients per ICU-nurse	Maximum number MCU patients per ICU/MCU-nurse
Day	1.5	2.5
Late	1.75	2.75
Night	2	3

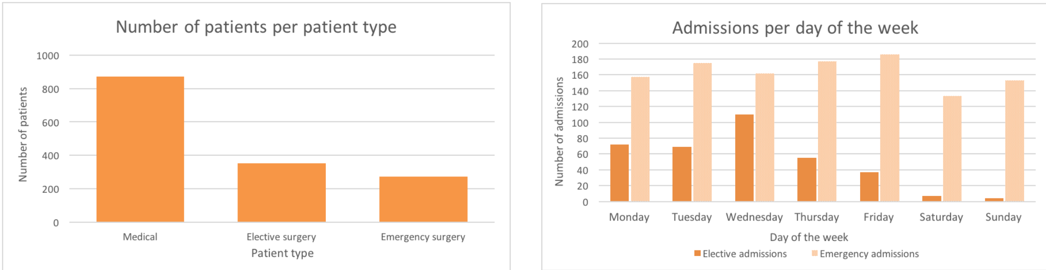
It is stated in the 2015 guidelines, that the number of patients that can be treated by a nursing team are based on full employability for patient care in the ICU (exclusive availability). The maximum number of patients is lower if simultaneous tasks need to be performed in the field of management, teaching or research or tasks outside of the ICU. That ICU-nurses need to perform simultaneous tasks was discussed in Section 2.1.2.

2.2 Process description

In this section we give a description of the patient admission process (2.2.1) and the patient discharge process (2.2.2). The process of the changing number of patients in the ICU greatly affects the number of nurses that need to be present on the ICU, which we discuss in the section Process control (2.3).

2.2.1 Patient admission

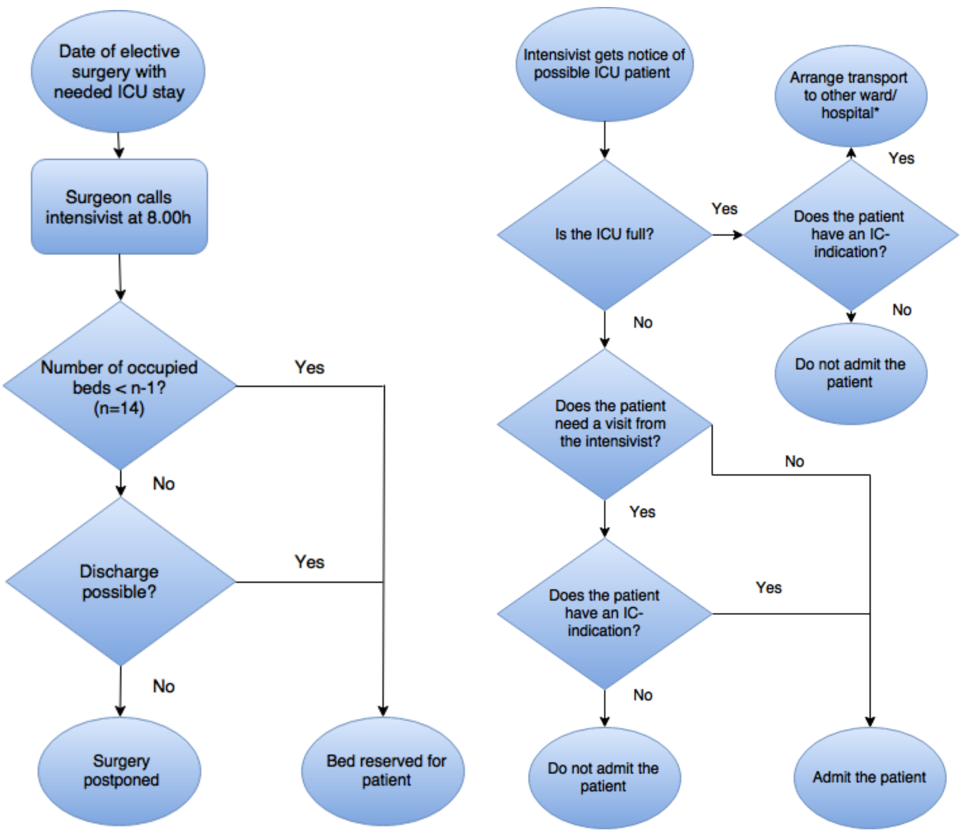
The intensivist is in charge of admitting the patients to the ICU. Admission can be through an elective surgery, or it can be an acute or emergency admission. The emergency admissions can be categorized as an emergency surgery or a medical admission. A medical admission is one where the patient did not undergo surgery. The number of patients in each category for the years 2014 and 2015 is shown in Figure 2.2a and the admissions per day of the week in Figure 2.2b. From Figure 2.2a we see that the category with the most patients is medical admissions. From Figure 2.2b we see the different arrivals of the patient types, because emergency admissions occur every day of the week, but elective surgeries are hardly performed during weekends.



(a) Patient types. **(b)** Admissions per day of week.

Figure 2.2: Patient types and admissions per day of the week. Data from January 1 2014 - December 31 2015 of 1497 admissions/discharges retrieved from Mediscore.

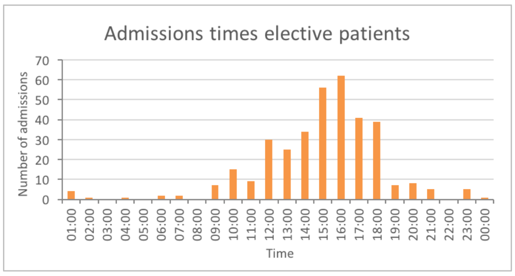
The flow charts of the admission process of the two types of patients, elective surgery and emergency, are shown in Figure 2.3.



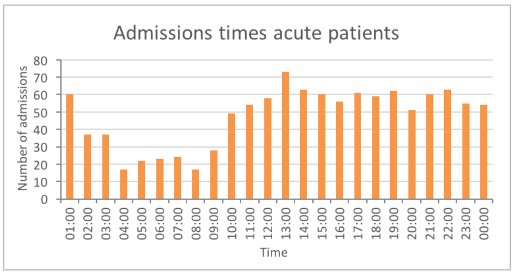
(a) Elective surgery **(b)** Emergency

Figure 2.3: Admission process
*Either the new patient or a patient from the ICU

In case of an elective surgery where ICU-stay is needed, the surgeons will contact the intensivist before the surgery and check whether there are enough beds available. Planned patients can be admitted as long as there are enough free beds, which in the current situation means that there is more than one bed available as the last bed is reserved for calamities. When there is only one bed free and a surgery is scheduled, this surgery will be postponed. When it is certain, however, that a patient is discharged of the ICU and there will be enough capacity later that day, the surgery will not be postponed to another day, but will be done as soon as possible that same day. Once it is certain that a surgery will be done that day, the bed is reserved for the elective surgery patient to make sure it is not used for an emergency patient. This admission process is shown in Figure 2.3a. In Figure 2.4a we see that most admissions of elective patients occur during office hours.



(a) Admissions elective patients.



(b) Admissions acute patients.

Figure 2.4: Admission times. Data from January 1 2014 - December 31 2015 of 1497 admissions/discharges retrieved from Mediscore.

In the current admission process only the number of free beds is checked upon, not the available ICU-nurses. The ICU is always staffed to full capacity, so there will always be a sufficient amount of staff available.

An emergency admission occurs when an intensivist gets a notion of a patient that might be in need of intensive care. This need for intensive care can arise from a surgery where complications arose, from an emergency surgery, from a patient who is brought in at the Emergency Department (ED) or a patient already admitted elsewhere in the hospital who is suffering deterioration of vital signs. In some cases, mostly when patients come from the operating room, patients are admitted without the intensivist seeing the patient beforehand. Otherwise, the Emergency Intervention Team (SIT) is called upon. The intensivist and an ICU-nurse visit the patient and determine whether the patient needs to be admitted to the ICU directly or whether they will come back after a short time period to check on the patient again. In Figure 2.4b we see that the admissions of acute patient occur each hour of the day.

When an acute admission is needed and there are 13 beds occupied, the patient is assigned the last bed in contrast to an elective patient. When the last bed is occupied, the goal is to transfer one of the patients in the ICU to another ward within 24 hours, which is not always possible. It might occur that another patient needs to be admitted to the ICU within the time the ICU is fully occupied. The intensivist needs to decide which patient needs to be transferred to another ward or another hospital (triage). Mostly, the new patient is transferred and is cared for as much as possible on the Corony Care Unit (CCU) or ED before being transferred to another hospital. Occasionally another patient that was already admitted to the ICU is transferred, because this patient is better capable of all the extra actions done in this process. The process of admitting the emergency patients is shown in Figure 2.3b.

It is important that the patient admitted to the ICU has an IC-indication, which means the patient can not be too sick or too healthy. When the patient is too sick, the care given will be disproportionate, it is required that the patient needs to benefit from his stay at the ICU. The IC-indication can be determined using the flow-chart from Figure 2.5, which was designed by Nederlandse Vereniging voor Anesthesiologie, Nederlandse Vereniging voor Intensive Care en Nederlandse Internisten Vereniging (2015) in the proposed guidelines of 2015.

In Figure 2.5 it can be seen that patients can be admitted to a variety of departments when their vital functions are deteriorating. Patients who are suffering solely from cardiac failure can be admitted to the CCU and patients who are expected to only need monitoring for a possible life threatening situation can be admitted to a Medium Care Unit (MCU). When a patient is undergoing surgery with threatened vital functions, but rapid improvement is possible, admission to a Post Anesthesia Care Unit (PACU) will be appropriate. When only CPAP, continuous positive airway pressure, is needed to improve the patients condition, this can be done in either the ICU, CCU, MCU or a separate Respiratory Care Unit. When patients do not fall into one of these categories, but they are suffering from a potentially life threatening condition where monitoring and/or intervention is needed, then the patient needs to be admitted to the ICU. In the case of ZGT, there is no MCU available, so these patients are admitted to the ICU as well. The care given to these patients that should be admitted to a MCU might be disproportionate, so ZGT can benefit from separating these patients. We look further into this possibility in Chapter 3.

2.2.2 Patient discharge

The intensivist determines whether a patient is ready to leave the ICU and be transferred to another ward. It might however not always be possible to transfer the patient. When other wards have limited capacity, they want to delay the transfer and keep the patient in the ICU although this is not needed.

Two times a day there is a control consultation (regie overleg) where representatives of all departments of the hospital meet. During this meeting it is discussed which patients need to be transferred and whether this is possible. This leads to the most discharges of patients on the ICU after the first meeting of 9.00h and the second

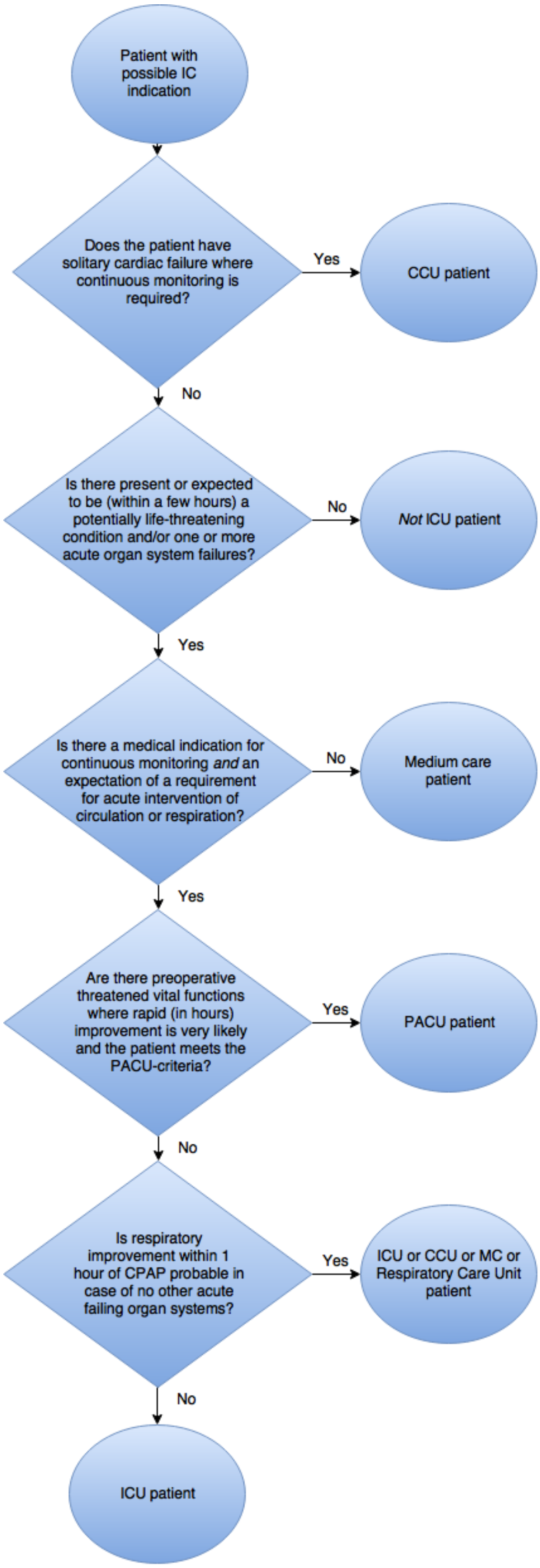
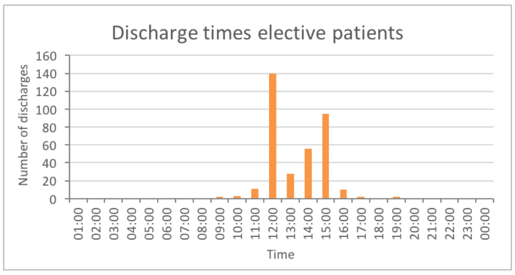
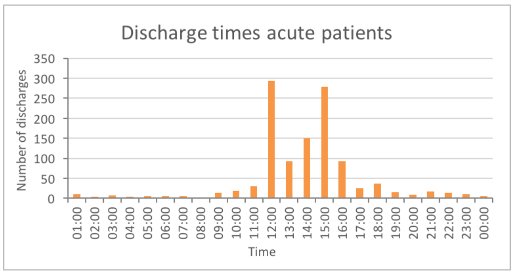


Figure 2.5: IC-indication according to Nederlandse Vereniging voor Anesthesiologie, Nederlandse Vereniging voor Intensive Care en Nederlandse Internisten Vereniging (2015)

of 14.00h, which can be seen in Figure 2.6. From Figure 2.6 we also see that, in contrast to the admissions times, the discharge times do not differ much between elective and acute patients.



(a) Discharges elective patients.



(b) Discharges acute patients.

Figure 2.6: Admission times. Data from January 1 2014 - December 31 2015 of 1497 admissions/discharges retrieved from Mediscore.

The ICU staff will emphasize the importance of a stay in the ICU as short as possible when others want to delay a transfer. In an ICU shocking situations might occur and being in this environment longer than needed is not desired for a patient, as the patient may experience negative psychological and social effects detrimental to its recovery (Jacobs et al., 1988). A delayed discharge is undesirable for the patients, as well as for the hospital. Since ICU services account for a significant proportion of hospital costs and resources, maximizing efficient and effective use of ICU is a prime concern to hospitals (Williams and Leslie, 2004). Therefore, patients should be discharged from an ICU when this specialized care is no longer needed. A level between intensive care and general wards can be desired to make sure patients are not receiving a too high level of care, or to make the transition from an ICU to a general ward easier.

2.3 Process control

In this section we describe how the nurse staffing process is currently controlled. We describe the shifts that are used to provide round the clock care (2.3.1) and staffing levels of ICU-nurses ZGT currently uses (2.3.2).

2.3.1 Shifts

The ICU-nurses have to take care of the patients 24 hours a day, for that reason they work in shifts. Some details about the different shifts are shown in Table 2.3.

Table 2.3: Shifts for nurses.

	Shift time		**Shift code**	
	Start time	End time	1ICU	5Oost
Day shift	7.15h	15.45h	11	61
Late shift	15.15h	23.30h	L1	L6
Night shift	23.00h	7.30h	N1	N6

For every shift change, there is an overlap in time to make sure the nurses can do a proper changeover. Since there are more obligations during the day shifts, only breaks are planned during this shift, not during the late and the night shift. Every nurse gets a 15 minute coffee break between 10.00h and 10.30h and a 30 minute lunch break between 12.00h and 13.00h. During the late shift, the nurses will have dinner when possible. The patients go to sleep and the nurses mostly need to do checkups. In between of these checkups they can find the time to have a break. The same goes for the night shift.

2.3.2 Staffing levels

The hospital currently schedules a fixed number of nurses during a shift. This number is shown in Table 2.4. There are more nurses during the day shift, because there are generally more tasks to be done during the day. For example, in the morning the beds need to be changed and the patients need to be washed. In the evening and during the night the nurses still need to check the vital signs regularly, but there are less obligations.

Table 2.4: Number of nurses per shift.

	1ICU		**5 Oost**	
	Code	Nurses	Code	Nurses
Day shift	11	7	61	3
Late shift	L1	5	L6	3
Night shift	N1	5	N6	2

Since 1ICU has a total of ten beds, the Nurse-To-Patient (NTP) ratio will be 1:1.43, 1:2 and 1:2 during the day, late and night shift respectively when the ICU is fully occupied. From Table 2.2 we see that this would be a violation during the late shift according to the 2015 guidelines, however ZGT currently uses a maximum number op patients per nurse of two for every shift. For 5 Oost where four beds are located, the Nurse-To-Patient (NTP) ratios are 1:1.33, 1:1.33 and 1:2 during the day, late and night shift respectively when 5 Oost would be fully occupied. This is correct according to the 2015 guidelines.

2.4 Current performance

In this section we discuss the current performance of the ICU of ZGT. We focus on the performance of nurse staffing, where the staffing levels are very important. It was already discussed in Section 2.3.2 that the ICU currently uses a fixed number of nurses per shift. In Appendix B we discuss the rare occasions where this number was not met, but for the calculation of the performance of the ICU we use the staffing levels as described in Table 2.4. We show the performance of the nurse staffing process by calculating the average Nurse-To-Patient (NTP) ratio used (2.4.1), the coverage compliance (2.4.2), the overstaffing rate (2.4.3) and the costs (2.4.4).

2.4.1 NTP ratio

The performance of nurse staffing can be determined by considering the used Nurse-To-Patient (NTP) ratio. We first look at the average NTP ratio that the ICU of ZGT faced in 2014 and 2015. To calculate the average NTP ratio we use the following formula:

$$\text{Average nurse-to-patient ratio} = \frac{\text{average number of nurses on the ICU}}{\text{average number of patients in the ICU}}$$

We calculate the average ratios by using data from 2014 and 2015 for the average number of patients in the ICU and by using the number of nurses as described in Table 2.4. We incorporate the reduction in operational beds during the reduction period and we determine the average ratios for the entire ICU and for 1ICU and 5 Oost separately. The result of this calculation is shown in Table 2.5.

Table 2.5: Average nurse-to-patient ratio, data from January 1 2014 - December 31 2015 of 1497 admissions retrieved from Mediscore.

Department	Day shift	Late shift	Night shift
ICU	1:0.83	1:0.99	1:1.19
1ICU	1:0.93	1:1.24	1:1.31
5 Oost	1:0.56	1:0.53	1:0.87
Guidelines	**1:1.5**	**1:1.75**	**1:2**

We see from Table 2.5 that the average NTP ratio is far below the NTP ratio as described in the 2015 guidelines. Especially for 5 Oost, the number of patients per nurse is significantly lower than the maximum. This is partly explained by the fact that 5 Oost closes during quiet periods, as discussed in Section 2.1 there is no data available on how often this occurred. To get a better idea on how often the guidelines are not met, we define the performance indicator coverage compliance.

2.4.2 Coverage compliance

The coverage compliance is the fraction of time where the ICU was covered by the correct number of nurses (Kortbeek et al., 2015). This can be calculated by the following formula:

$$\text{Coverage compliance} = \frac{\text{time NTP ratio below guidelines}}{\text{length of time horizon}} * 100\%$$

For the calculation of the values corresponding to this performance indicator, we add all the time from January 1 2014 to December 31 2015 where the ICU was staffed according to the 2015 guidelines and divide this by the total time. This gives the values as shown in Table 2.6.

Table 2.6: Coverage compliance, data from January 1 2014 - December 31 2015 of 1497 admissions retrieved from Mediscore.

Department	Day shift	Late shift	Night shift
ICU	100%	98.83%	100%
1ICU	99.82%	89.47%	99.77%
5 Oost	99.31%	100%	99.17%

From Table 2.6 we see that understaffing almost never happens during the day shift and night shift, but in more than 10% of the time on 1ICU during the late shift. This is explained by the fact that five nurses are scheduled during the late shift on 1ICU with ten beds. When there are nine or ten patients present in 1ICU, a shortage occurs. A remark should be made on the values of coverage compliance of the entire ICU. The number of beds are fourteen and the number of nurses of the two units are summed, and in using this combination a shortage can occur on a separate department, but not when the two units would be combined. The coverage compliance therefore becomes lower when looking at the separate departments.

2.4.3 Overstaffing rate

Since a balance needs to be found between not exceeding the recommended ratios too often and minimizing costs by avoiding overstaffing, we use the following performance indicator:

$$\text{Overstaffing rate} = \frac{\text{nurse capacity not used}}{\text{nurse capacity available}} * 100\%$$

For the calculation of the values corresponding to this indicator we add all the hours of nurse capacity scheduled but not used and divide this by the total amount of nurse capacity scheduled. We find the result which are shown in Table 2.7.

Table 2.7: Overstaffing rate, data from January 1 2014 - December 31 2015 of 1497 admissions retrieved from Mediscore.

Department	Day shift	Late shift	Night shift
ICU	45.11%	43.35%	40.45%
1ICU	38.08%	29.48%	34.37%
5 Oost	73.43%	80.07%	67.61%

We see that especially the nurse capacity scheduled on 5 Oost is not utilized much, for all shifts more than 65% of the staff capacity is not used.

2.4.4 Costs

The performance of the ICU is closely related to the costs. The costs made for the ICU of ZGT for the years 2014 and 2015 is shown in Table 2.8. We see that the costs for the salaries of the nurses is almost 50 percent of the total costs of the ICU. The other salary costs and social costs also include other staff besides the nurses, but when all the costs for the nurses are added, it easily exceeds the 50 percent of the total expenses of the ICU. When looking at the costs for patient related staff not employed, i.e. staff via an Employment Agency (EA), we see that in the year 2015 almost no temporary employees were hired. A more detailed overview of all the costs of the ICU together with the proposed budgets is shown in Appendix C.1.

Table 2.8: Costs for nurses 2014-2015

Cost type	**2014** Costs (k€)	Percentage of total (%)	**2015** Costs (k€)	Percentage of total (%)
Total	**5,559**		**5,154**	
Nurse salary	2,550	45.87	2,468	47.88
Other salary costs*	792	14.24	700	13.57
Overtime	27	0.49	18	0.36
Irregular shifts	359	6.45	355	6.88
Holiday pay	238	4.28	229	4.45
End of year bonus	229	4.12	216	4.20
Social costs*	990	17.81	860	16.69
Patient related staff not employed	245	4.41	6	0.11

* These costs are for all staff not just the nurses.

The contracted nurses receive their salary not only for the shift hours, also for extra activities such as schooling. To get a clear idea of the costs for the shifts worked by the ICU-nurses, we calculate the incurred expenses for the shift expenses only. In Appendix C.2 is described how ZGT determines the required amount of FTE and some assumptions used in their calculation. We use mostly the same numbers as in Appendix C.2: the shifts as described in Table 2.3, the staffing levels as described in Table 2.4 and the fact that each contracted nurse is available for 1540 hours per year. In Appendix C.3 an extended overview is given of the costs that need to be taken into account to determine the hourly costs for one nurse. This results in an amount of €42.50 per hour.

Using these available hours per contracted nurse and costs per hour, we know the exact costs for the shift hours for nurses per year. These costs are €3,105k each year when the reduction period is not used and €3,010k when a reduction period of 5 weeks is considered.

2.5 Planned changes

The future ICU is located on the first floor in the already existing building. The building is remodeled to fit the new department. The current ICU consist of two units, this will in fact be the case in the future ICU as well. The two units will both include eight beds, each in their own room. The new ICU leads to a new bed-capacity of 16, where both units have two isolation rooms. Each unit has its own nurses station and its own medical pantry.

The fact that each patient has its own room will be much more comfortable for the patients. They will not be bothered as much with the circumstances of the other patients. It does complicate the monitoring of the patients for the nurses, they can not see all the patients in one field of view. The beds are however located in such a way, that the patients are always directed towards the nurses workplace. These workplaces are little recesses in the rooms where a desk with computer is set up for the nurses. They can see the patients through the glass and work on the computer to see medication levels at the same time. Since the patients are well visible from the hall way, it should not be a big problem to take care of more than one patient at a time. It might be needed that all the nurses help each other out by keeping an eye on other patients apart from their own as well, but this will always be necessary when the ratio is smaller than 1:1.

As already mentioned, there will be two units both with eight beds. The two units are next to each other and the one unit is directly accessible from the other unit and vice versa. These two units are shown in Figure 2.7. It is important that the intensive care is not just one unit, because both units must be able to run separately in case of an outbreak of some sort. When there is a virus outbreak in one unit, it can be completely sealed off from the other.

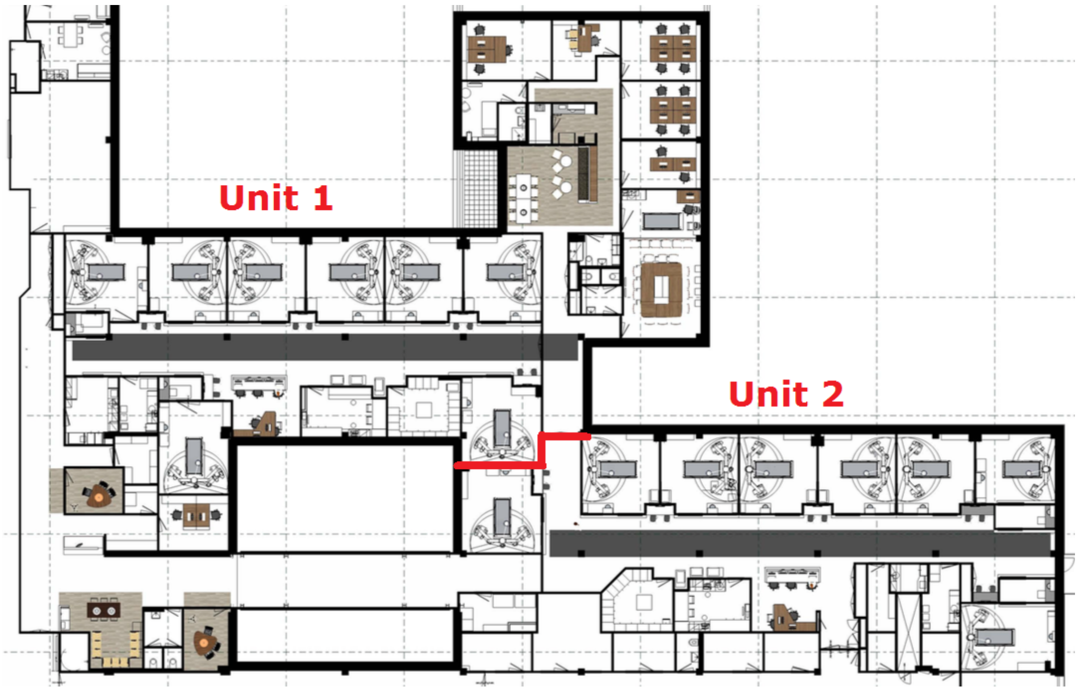


Figure 2.7: Layout of new ICU.

Since the new units both have eight beds, where it used to be ten and four, new staffing levels needs to be determined, which match the patients supply. The management of the ICU is also interested in the possibility to use some sort of a hybrid system where the number of operational beds of two different levels of care is determined according to the complexity of care of the patients present. When staffing levels need to match patients supply and a hybrid system of different levels of care is introduced, flexibility will be necessary in the staffing procedure. We focus more on these subjects in the literature study of the next chapter.

2.6 Conclusion

Intensivists have the main responsibility for the ICU patients, but ICU-nurses play an important role in the care provided to the patients. Patients admitted to the ICU can be elective patients or acute patients. An admission of an elective patient follows from a planned surgery, where an admission of an acute patient results from all patients needing ICU-stay when their stay was not planned.

ICU-nurses need to provide round the clock care for the patients in the ICU, which is why they work in shifts. In the 2015 guidelines ratios are defined such that there is a preferred maximum number of patients per nurse in each shift. ZGT currently assigns a fixed number of nurses to each shift.

The indicators we use to determine the performance of the nurse staffing process are:

- Average nurse-to-patient ratio
- Coverage compliance
- Overstaffing rate
- Costs

Currently, understaffing rarely happens and a lot of nurse capacity scheduled is not used. The salaries for nurses are more than 50% of the total costs of the ICU. When nurse staffing levels can be adjusted to match the patient supply it is probable that costs can be reduced.

Since ZGT is building a new ICU where more beds will be available, they want to find out optimal nurse staffing levels for the new situation and look into the possibility of introducing intermediate care. Not all patients are in need of the highest possible care.

With the new ICU and the new guidelines where the focus has shifted from beds in an ICU to actual patients, we are interested in designing a model for determining nurse staffing levels. In this model flexibility is needed to adjust staffing levels to the number of patients in the ICU and intermediate care should be included. These are the main subjects of which we need more information from already published literature. We therefore perform a literature study in Chapter 3.

Chapter 3

Literature study

In this chapter we perform a literature study in order to find research already done on the subjects concerning this study. We discuss literature on ICUs (3.1) and nurse staffing (3.2), followed by literature on intermediate care (3.3). We end this chapter with a short conclusion (3.4).

3.1 ICUs

To start our literature study, we are interested in research done where ICUs are the main subject. Most published articles focussing on ICUs concern the medical treatment in an ICU, for example comparing treatments such as the advantages of a tracheostomy versus intubation (Blot et al., 2008). In the field of operations research the main subjects concerning ICUs are finding the optimal bed-capacity for an ICU or problems concerning the size and skill mix of staff teams.

Some articles focussing on determining the needed number of beds in an ICU are by Ridge et al. (1998), Seung-Chul et al. (2000), Green (2002), McManus et al. (2004), Steins and Walther (2013) and Mallor and Azcárate (2014). Ridge et al., Seung-Chul et al., Steins and Walther and Mallor and Azcárate all use a simulation model for bed capacity planning in an ICU. Ridge et al. focus on the relationship between number of beds, mean occupancy level and the number of patients that have to be transferred through lack of bed space. Seung-Chul et al. evaluate various bed-reservation schemes to minimize the number of canceled surgeries. Steins and Walther built a credible simulation model by incorporating the dependency of the admission rate on the actual occupancy. Mallor and Azcárate greatly discuss the validity of the model, where they state that management decisions need to be included. Green and McManus et al. investigate the use of queueing theory to determine the requirement for beds in an ICU.

From these articles on bed capacity planning in an ICU we see that the number of beds and the occupancy level in an ICU play an important role in the possibility of admitting patients to the ICU. Since in our study the number of beds is already fixed, we focus on finding optimal staffing levels and are interested in articles that incorporate decisions on staffing levels. We found two articles that discuss staffing levels in particular on an ICU.

Kokangul et al. (2016) optimized the nurse capacity in a neonatal intensive care unit (NICU) with three levels of care. The objective was to maximize the number of admissions over a year under occupancy level constraints and satisfying demand rates. In this study a patient would be admitted when there would be a nurse unoccupied in the appropriate level. It is assumed that equipment such as incubators, respirators and beds are always sufficient. That there is always a sufficient number of beds in the ICU is also assumed in the article by Griffiths et al. (2005), where the requirement for supplementary nurses in an ICU is modeled. By means of a simulation model the optimal number of nurses that should be rostered each shift is determined.

We discuss more on the models of these articles for nurse staffing in the next section. We first explain the different levels that can be distinguished for the staffing process as part of resource capacity planning and then introduce other models for nurse staffing, not specifically for ICUs.

3.2 Capacity planning for nursing staff

In this section we first briefly discuss the four different hierarchical levels in capacity planning for nursing staff (3.2.1), we discuss possible interventions found from literature to introduce flexibility in the staffing levels (3.2.2) and we end this section with models presented in literature for nurse staffing (3.2.3).

3.2.1 Organizational control

The nurse staffing process consists of a set of hierarchical decisions over different time horizons that have different levels of precision. Hans et al. (2012) created a four-by-four framework, which spans four hierarchical levels of control and four managerial areas for health care planning and control. This research is part of the managerial area resource capacity planning, which is described as addressing the dimensioning, planning, scheduling, monitoring and control of renewable resources. These resources include equipment and facilities, as well as staff. We explain per hierarchical level what decisions on the nurse staffing process are made.

Strategic*: workforce planning.*
Strategic planning addresses structural decision making, it has a long planning horizon and is based on highly aggregated information and forecasts.

The strategic level of decision-making in the nurse staffing process is the workforce planning decision. Hulshof et al. (2012) describe this stage as determining the number of employees that must be employed, often expressed as the number of full time equivalents, and the mix in terms of skill categories. Articles that concern this stage are by Hancock et al. (1987), Lavieri and Puterman (2009) and Harper et al. (2010).

Tactical*: staffing.*
Hulshof et al. state that tactical planning translates strategic planning decisions to

guidelines that facilitate operational planning decisions. While strategic planning addresses structural decision making, tactical planning addresses the organization of the operations or the execution of the health care delivery process, meaning the what, where, how, when en who. This is similar to operational planning, however, decisions are made on a longer planning horizon (Hans et al., 2012).

The tactical level of the nurse staffing process is determining the staffing levels. Hulshof et al. describe this stage as staff-shift scheduling, where shift scheduling deals with the problem of selecting what shifts are to be worked and how many employees should be assigned to each shift to meet patient demand. Articles that concern this stage are by Griffiths et al. (2005), Oddoye et al. (2007), Véricourt and Jennings (2011), Yankovic and Green (2011), Davis et al. (2014), Kortbeek et al. (2015) and Kokangul et al. (2016).

Offline operational: *workforce scheduling.*
Operational planning involves short-term decision making, there is low flexibility on this planning level. Many decisions on higher levels have demarcated the scope for the operational level decision making (Hans et al., 2012). They state that the adjective offline reflects that this planning level concerns the in advance planning of operations.

According to Hulshof et al. the objective of workforce scheduling is to meet the required shift staffing levels set on the tactical level, while satisfying a complex set of restrictions involving work regulations and employee preferences. At this stage, the actual rosters for the nurses are made. This involves a complex set of restrictions on working hours per week, days off and other preferences. This subject is discussed a lot in literature as the nurse rostering problem or the nurse scheduling problem. Burke et al. (2004) and Ernst et al. (2004) who created an article classification, showed that literature has mainly focused on operational planning. Some of the articles that concern this stage are by Billionnet (1999), Wright et al. (2006) and Beliën and Demeulemeester (2008).

Online operational: *coordination*
According to Hans et al., online operational planning involves control mechanisms that deal with monitoring the process and reacting to unforeseen or unanticipated events. This can be staff rescheduling, where staff capacities might be adjusted to unpredicted demand fluctuations and staff absenteeism (Hulshof et al., 2012).

The online operational level of the nurse staffing process is concerned with hiring extra nurse capacity via an EA or contracted nurses working extra shifts or overtime in case of shortages. Articles concerning these kinds of flexibility are discussed in Section 3.2.2 and are amongst others by Wild and Schneewei (1993); Griffiths et al. (2005); Gnanlet and Gilland (2009); Harper et al. (2010); Dellaert et al. (2011); Davis et al. (2014).

The popular rostering methods generally take required staffing levels as prerequisite information, these levels should first be optimized on a tactical level. We focus mainly on the tactical level, where the determination of optimal staffing levels will also influence the strategic level of how many nurse-FTE should be hired. We discuss different kinds of flexibility from literature for the nurse staffing process, before discussing different models which we might use for nurse staffing on a tactical level.

3.2.2 Flexible nurse staffing

The introduction of flexibility in the nurse staffing process is discussed in several articles. Flexibility can be achieved by nurses working overtime, introducing bank hours, float nurses or hiring temporary employees. We discuss per subject what the kind of flexibility entails.

Overtime
Overtime is mentioned by Hancock et al. (1987); Wild and Schneewei (1993) and Griffiths et al. (2005). Wild and Schneewei state three disadvantages on using overtime for flexibility. First, only for a certain number of hours a day, a week, and/or a month, overtime is allowed. Second, overtime often is not an additional work time but has to be compensated later by free periods. Third, often the worker has to agree to the overtime order. These statements are supported by the collective labor agreements for Dutch hospitals (Nederlandse Vereniging van Ziekenhuizen, 2015). Also, overtime is especially useful for work that needs to be done within one shift, but could not be completed within that time and only a short amount of overtime is needed (Hancock et al.). It is not appropriate for nurses to work an 8-hour shift and work another 8-hour shift overtime when a nurse is short.

Agency nurses
Agency nurses are discussed amongst others by Wild and Schneewei (1993); Griffiths et al. (2005); Gnanlet and Gilland (2009); Harper et al. (2010); Dellaert et al. (2011); Davis et al. (2014). An agency nurse is a temporary employee that is hired via an employment agency. All articles discuss the fact that hiring a temporary nurse for one shift is a lot more expensive than having a contracted nurse work the shift, but the temporary nurses are a great tool for more flexibility in the number of nurses on a hospital ward.

Bank hours
Bank hours are mentioned by Griffiths et al. (2005). A bank nurse is one who does not work for a fixed number of hours per week. Instead they are assigned shifts as and when required, for which they often receive an increased hourly rate of pay (Griffiths et al., 2005). These bank hours are similar to hiring a temporary nurse, except that the bank nurse is contracted by the hospital and will be paid less than a temporary nurse.

Float nurses

Float nurses are discussed by Wild and Schneewei (1993); Gnanlet and Gilland (2009) and Kortbeek et al. (2015). A float nurse is cross-trained nurse, that is enabled to float between units within a specialization. These units within a specialization have different acuity levels and required treatments for patients, but are similar enough to cross-train nurses (Gnanlet and Gilland, 2009). Float nurses could for example be used to assign either to the ICU or to the ED. Since we only consider the ICU, we can only use the idea of float nurses as a flex pool between the two units of the ICU. The nurses in the flex pool are not assigned to one unit of the ICU before a shift starts, but float in between. At the beginning of a shift they can be assigned to one of the units where the need for an extra nurse is the highest.

We discuss more on models that use temporary nurses and float nurses in Section 3.2.3. Since both bank nurses and temporary nurses can be called upon at the last minute, we do not make a difference between the two. We conclude that overtime is not suited for nurse staffing in an ICU.

3.2.3 Staffing models

Models for determining the optimal staffing levels of a medical unit are proposed in several articles in literature. The models can be analytic or a simulation study. We first discuss some analytical models for nurse staffing found in literature, followed by the literature on simulation studies.

Analytical models

An analytic but deterministic model is proposed by Oddoye et al. (2007). The authors use goal programming to satisfy several goals simultaneously, where target values need to be set for each objective and priority levels to minimize the deviations from the target values in the correct proportions. Patients visit a medical assessment center and are triaged into one of five triage levels, the probabilities of the different levels are fixed. Then the recourse time per triage level is a fixed amount of time as well. This is not comparable to the situation of an ICU.

Stochastic models can be used as well for finding optimal staffing levels. Already in 1987, Hancock et al. (1987) made a model to determine staffing levels such that costs were low and productivity was high for departments with work to be done during the daytime. This is very different from the 24-hour service that needs to be provided on an ICU.

More recently, Véricourt and Jennings (2011) used a closed queueing model to determine efficient staffing policies. The authors find the minimum number of nurses that need to be present on a ward such that there is a certain bound on the excessive delay of patients in need of a nurse visiting. Another queueing model is proposed for nurse staffing by Yankovic and Green (2011). Just like Véricourt and Jennings the authors do not want to use the target nurse-to-patient ratios, so they use a queueing model to identify nurse staffing levels based on providing timely responses to patient needs. The authors use the inpatient demand for nursing care and the duration of nursing tasks as input to their model, which consists of two queueing systems. The first one is related to the beds in the unit and the second is related to the requests for nurses, then these two queues are related for the overall system. The objective is to have a low waiting time for a nurse. In a general ward a nurse is responsible for several patients. When several patients are in need of the nurse visiting at the same time, the delay of the visit can become quite large. In an ICU however, a nurse is mostly restricted to a maximum of two patients and will continuously switch between the patients he is assigned to. Therefore, restricting the excessive delay is not an objective of this study.

Another stochastic approach is used by Kortbeek et al. (2015). A model for hourly bed census predictions was already established by Kortbeek et al. (2014) and the authors use this model to derive efficient nurse staffing policies. Their approach minimizes staffing levels while satisfying the nurse-to-patient ratios. For each working shift during a given planning horizon Kortbeek et al. determine how many employees should be assigned to each inpatient care unit and these numbers then provide a guideline for the decisions regarding the scale of the workforce at the strategic planning level. In this approach the authors use two nurse-to-patient ratio targets. The first ratio needs to be satisfied at all times, whereas the second more restrictive ratio must be satisfied for a certain fraction of time. The idea behind this second ratio is that there is slack in the time window during which certain indirect patient care tasks can be performed, without having direct negative consequences on patient safety or work stress. As a result, ratios may at times be violated, but not too often, nor too long. This idea is supported in our research as well, which was seen in the performance indicator from Section 2.4.1. Kortbeek et al. also propose a model with the use of float nurses, where float nurses are assigned to the unit they have to work at the beginning of the shift. This model is computationally too expensive, so an upper bound model and a lower bound model are created.

Two models that also focus on flexibility in nursing staff are by Gnanlet and Gilland (2009) and Dellaert et al. (2011). Gnanlet and Gilland create a model to find optimal staffing levels with the use of temporary nurses and float nurses, but combine it with the optimal number of beds. They focus on finding optimal resource levels required to meet stochastic demand at minimum cost, together with the difference in simultaneous and sequential decision making on the different kinds of resources. They use a two-stage stochastic programming and conclude that staffing flexibility reduces costs. Dellaert et al. develop a model of budget allocation for permanent and contingent workforce under stochastic demand. The focus is mainly on proposing a proper budget.

Some literature is focused on the problem of permanent nurse staffing estimation under demand uncertainty as newsvendor model. The classical newsvendor model is traditionally used to determine proper inventory levels of a known, perishable product during a short selling period of uncertain demand (Davis et al., 2014). The decision maker must weigh the consequences of not producing enough and missing out on possible sales and the changes of producing too much so as to determine the optimal amount of inventory for the selling period. Davis et al. reinterpret the stock-out price as daily per shift salary of a temporary nurse and the salvage value as the per shift benefit of having an extra permanent nurse on a shift. The authors find optimal staffing levels that minimize costs, while also maintaining a safe nurse-to-patient ratio for a high level of patient safety. Davis et al. conclude that the value of using the newsvendor model is dependent of the magnitude of the nurse-to-patient ratios. It has the greatest benefit in care units with small nurse-to-patient ratios, predominately ICU settings.

Other articles that use the newsvendor model are by He et al. (2012) and Green et al. (2013). He et al. use the newsvendor model to determine staffing levels for hospital operating rooms when there is uncertainty about daily workload. The authors conclude that staffing costs can be reduced significantly when staffing decisions are deferred until procedure type information is available. This method can not be used on an ICU as patients need constant care. Green et al. combined the newsvendor model with an investigation of factors influencing nurse absenteeism rates. The authors conclude that endogenous absenteeism, absenteeism as a function of the number of nurses scheduled, should be incorporated in determining staffing levels. This specific property is not part of this research.

Simulation models

Simulation is a widely used tool in operations research. The article by Griffiths et al. (2005) was already shortly discussed, as it concerns a simulation study for nurse staffing in an ICU. The authors find the optimal number of nurses rostered each shift to minimize costs, where supplementary nurses (bank or agency) are hired when there is a shortage. In this simulation model a NTP ratio of 1:1 is used and the study shows the hospital under consideration should increase its fixed number of nurses scheduled each shift. The authors also consider the effect of a shorter LOS and an increase in arrivals.

Harper et al. (2010) used an earlier built discrete event simulation model called PROMPT, which already allowed for predicting bed and operating theater use, to find the optimal number of nurses to employ and the appropriate skill-mix. Outputs of the simulation model are used as input for a stochastic programme, which seeks to minimize the cost of employing both permanent and temporary nurses, while satisfying the demand for each type of nurse in the output from the simulation. Although PROMPT captured shift-by-shift nursing needs, only nurses needed per day are considered in the stochastic programme (a percentage reduction in nursing needs during the late and night shift is applied). Then no fixed number of nurses per shift is determined, merely an optimal amount of FTE is determined.

Another article that uses simulation in combination with optimization was already mentioned in Section 3.1, and was written by Kokangul et al. (2016). The article concerns a NICU with three levels of care and the objective was to maximize the number of admissions, while satisfying constraints concerning occupancy level and meeting demand rates. The authors first collected statistical data, then identified important control parameters (occupancy level, satisfying demand rates, number of admissions) and used these parameters in their simulation model. From the output of the simulation model the authors find the mathematical relationship between the control parameters and the nurse capacity. Finally, they constructed a nonlinear mathematical model to find the optimal nurse capacity for each level.

3.3 Intermediate Care

The term Intermediate Care already indicates the kind of care it entails, namely a level of care that is intermediate between what is available in a ward bed and an intensive care bed. There are several other terms used for intermediate care in literature, amongst others step-down units (Prin and Wunsch, 2014; Mathews and Long, 2015), high dependency units (Ridley, 1998; Thompson and Singer, 1995) and Iapichino et al. (2007) make a distinction of care provided by an ICU in high level of care and low level of care. Medium Care is a term often used in the Netherlands for Intermediate Care.

Prin and Wunsch (2014) describe the intermediate care unit as a step-down unit (SDU). The authors make a distinction in SDU beds which are in a specific stand-alone unit, beds which are adjacent to but physical distinct from an ICU or general ward, or designated beds co-located within ICUs or general wards. Beds co-located within ICUs or wards can be separate beds reserved for only intermediate care or "flexible" beds that change designation based on patients needs. For clarity, these different kinds of units are shown in Figure 3.1. The co-location of SDU beds allows for beds use and nursing intensity to change with patient needs on a fluid basis, which requires flexible staffing. Large units will be better capable of handling sudden influxes of patients, where the separation of patients into smaller units reduces overall efficiency (Vincent and Burchardi, 1999; Solberg et al., 2008). The authors also mention that co-location may be associated with successful integration of new nurses into ICUs, because they care for intermediate-level patients while still gaining exposure to the critically ill.

Iapichino et al. (2007) investigated the use of high level of care (HLC) and low level of care (LLC) inside ICUs in Italy. The authors investigated whether the ICUs were able to provide HLC to the available beds according to international standards, using all available resources. For ICUs lacking staff or equipment for safe HLC in all declared beds, they calculated the best combination between HLC and LLC beds with less need for nurses and technology. The ICUs with shortages were in 97% percent of the cases lacking nurses. A combination of HLC and LLC could

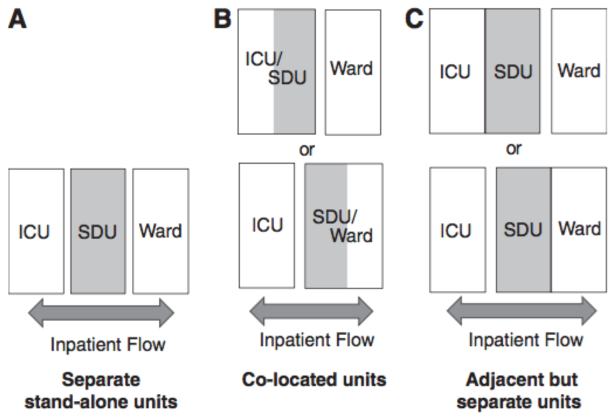


Figure 3.1: Potential SDU locations according to Prin and Wunsch (2014)

be provided with less nurses. These results show that not all patients in an ICU are in need of intensive care and some patients receive too much attention from the specialized ICU-nurses.

Thungjaroenkul and Kunaviktikul (2006) mention the possibility for cost containment when the number of intermediate beds is increased for patients who only require monitoring and intensive nursing, but not medical care. Approximately 40% of medical ICU and 30% of surgical ICU patients were admitted for monitoring purposes (Henneman et al., 2001). These patients filled the expensive ICU beds and consumed the precious resources, often to the exclusion of other patients who needed intensive care more (Daly et al., 1991). Increasing intermediate care beds can promote cost reduction, increase accessibility and not negatively impact patient outcomes. Ridley (1998) also mentions the cost reduction for intermediate care, where the costs per patient per day on an high dependency unit (HDU) are far smaller than on an ICU.

There are however quite some articles that question the cost reduction when introducing intermediate care (Prin and Wunsch, 2014). After establishing a SDU cost of care and ICU length of stay may increase, because the hospital is able to admit more patients with a high severity of illness to the ICU (Solberg et al., 2008). Reducing the number of SDU-level patients residing in ICUs may have little effect on overall critical care spending if the costs are then increased by an influx of higher-acuity patients. The SDU beds may also fail to contribute to costs savings for the ICU and SDU combined, if it results in an increase in admissions of low-acuity patients to the intermediate care unit. Introducing intermediate care can also be questioned when there is an overload of patients requiring significant interventions in terms of medical and nursing time in the first place. Then the opening of an intermediate care unit will of course not have any impact on the ICU workload (Ridley, 1998).

Mathews and Long (2015) created a simulation model to present an illustrative analysis on the impact of various bed allocation scenarios on outcomes, where the medical ICU and SDU at a single tertiary-care hospital was under consideration. The authors investigated several scenarios, namely varying the ICU/SDU sizes, reserved ICU beds as a triage strategy, lower targets for time to transfer out of the ICU and ICU expansion. Mathews and Long conclude that all SDU beds should be reallocated as ICU beds, as this will improve average waiting times for patients. Especially the acute patients had a reduced waiting time. The sub-acute patients however, had to wait longer for an available bed. It should be noted that the SDU under consideration is a separated SDU. As it is possible for an acute patient to wait for ICU admission during high census, while an SDU-bed is simultaneously occupied, waiting times are longer for acute patients when a SDU is separated. The authors did not consider the co-located model where medium care bed-capacity and intensive care bed-capacity change according to the needs of the patients. In concluding that all available beds should be ICU-beds the costs of covering these ICU-beds are not considered.

The question arises what is known about admission criteria for either Intermediate Care or Intensive Care. In Table 3.1 we summarized some statements made on the difference between patients that should be admitted to a SDU and patients that should be admitted to an ICU. A lot of the statements made in the literature on SDU patients coincide with the guidelines proposed in 2015 (Nederlandse Vereniging voor Anesthesiologie, Nederlandse Vereniging voor Intensive Care en Nederlandse Internisten Vereniging, 2015). In these guidelines reasons for admission to a SDU are described and are amongst others stabilization of vital functions, prevention of multi-organ failure, monitoring and providing care that is not possible on a general ward. In these guidelines a distinction is made between specific treatments that could be provided on a SDU and treatments that can only be provided on an ICU. This distinction also becomes obvious from the literature, namely that patients requiring invasive respiratory support or patients requiring Continuous Veno-Venous Hemofiltration (in case of acute reno failure) in combination with multi-organ failure should only be treated on an ICU. This is confirmed by intensivists from ZGT, where they did recommend that patients received noradrenaline should also stay in the ICU.

The recommended NTP ratios on a SDU differ a lot in literature, but are mostly somewhere between 1:2 and 1:4 (Prin and Wunsch, 2014). From the 2015 guidelines we find the ratios as shown in Table 2.2.

3.4 Conclusion

From the literature we have seen that two studies focus on optimal staffing levels for an ICU. Of the research already done, a lot of focus is on the operational level where weekly schedules need to be formed. Our focus lies in the tactical level, finding optimal staffing levels per shift.

Authors	Name for intermediate care	Intermediate care	Intensive care
Thompson and Singer (1995)	High-dependency unit (HDU)	”...who require more intensive observation, treatment and nursing care than can be provided on a general ward.”	”... requiring mechanical ventilation.”
Ridley (1998)	High-dependency unit (HDU)	”... monitors and supports patients with, or likely to develop, acute single organ failure.”	”...requiring multi organ support and patients requiring mechanical ventilation.”
Iapichino et al. (2007)	Low level of care (LLC)	”... non-invasive monitoring/observation with only one among supplementary functions: ventilatory care, minor circulatory support, or a dialytic support...”	”... monitoring coupled with active respiratory support and/or multiple vasoactive drugs.”
Nguyen et al. (2010)	Stepdown unit (SDU)	”...allow for the care of patients who do not require full intensive care but cannot be safely cared for on a normal ward. These patient requirements may include specific organ support, nursing needs, vital sign monitoring, or ventilator weaning.”	
Prin and Wunsch (2014)	Stepdown unit (SDU)	”...stepdown patients who still require frequent monitoring and/or nursing care and may also have some minimal organ support requirement...”, ”... step-up patients who generally include those with acute clinical changes...”, ”...postoperative patients requiring an increased level of care...”	”...respiratory support in the form of invasive mechanical ventilation...”

Table 3.1: Definitions patient suitable for Intermediate Care from literature.

In the literature four possibilities of introducing flexibility in the nurse staffing process are discussed. The first is overtime, which is not ideal for ICUs where the nurses work in shifts. The second is temporary nurses, which cost more than contracted nurses, but can be hired only when needed. The third are bank nurses, which are similar to temporary nurses and only work when needed but are contracted by the hospital and are not assigned a fixed number of hours per week. The last type of flexibility are float nurses. These nurses can be assigned to several wards, but in our situation, we can only use this type of flexibility as a flex pool of nurses who are not assigned to a particular ICU unit. These nurses float in between and work on the unit where more nurses are needed.

Several models are proposed in the literature for nurse staffing, these models can be analytic or simulation. The most promising analytical model is by Kortbeek et al. (2015), who use two NTP ratios, one that needs to be satisfied at all times and one that needs to be satisfied a fraction of time. Their model is a stochastic programme, which they also expand by introducing flexibility in the sense of float nurses.

There are several options for introducing intermediate care, but the option most related to ZGT its wishes is a system where the Step-Down-Unit (SDU) is co-located within the ICU and the SDU beds are flexible and change designation based on patients needs. The criteria for admitting a patient to a SDU instead of to an ICU differ somewhat, but most articles conclude that patients requiring invasive respiratory support or patients requiring Continuous Veno-Venous Hemofiltration (in case of acute reno failure) in combination with multi-organ failure should only be treated on an ICU.

In Chapter 4 we construct our model for nurse staffing, taking into account the several possibilities for flexibility and intermediate care.

Chapter 4

Models

In this chapter we present the models we use to obtain optimal staffing levels for the ICU of ZGT Almelo. In Chapter 3 we concluded that the analytic nurse staffing model by Kortbeek et al. (2015) looked promising for our problem. The nurse staffing model of Kortbeek et al. builds upon a previous built model for predicting hourly bed census (Kortbeek et al., 2014). We therefore first go into detail on the conceptual model of predicting hourly bed census, where we also mention the changes for our case study (4.1). We discuss the flexible nurse staffing model and how this model can be extended for situations of our interest (4.2). Lastly, we introduce our simulation model, which is used for the problems which could not be analytically solved (4.3). We end this chapter with a short conclusion (4.4).

4.1 Hourly bed census model

Kortbeek et al. (2014) presented a model for predicting the bed census on nursing wards by hour, which builds upon the model by Vanberkel et al. (2011). The model by Vanberkel et al. determines the impact of the surgery blocks on the wards daily census. We discuss the conceptual model (4.1.1) and the changes we make to use the model for our case study (4.1.2).

4.1.1 Conceptual model

The model by Kortbeek et al. is a generic analytic approach to predict the bed census on nursing wards by hour. In order to do so, a separation is made in elective and acute patients. For both patient groups an arrival pattern is used, which is repeated after a cycle. For elective patients this cycle is the Master Surgical Schedule, for acute patients the Acute Admissions Cycle. Within such a cycle, arrivals for both elective and acute patients are further divided to form different patient types within the elective and acute groups. Such a patient type can for example be distinguished by its surgical specialty or day of admission. To find the demand predictions for both the elective and acute groups, three steps are performed. First, the impact of a single patient type in a single cycle is determined, by which in the second step the impact of all patient types within a cycle can be calculated. Then the predictions from the second step are overlapped to find the overall steady-state impact of the repeating cycles. After the steady-state impact is determined for both patient groups, elective and acute, the workload predictions for the patient groups are combined. An additional step might be necessary to translate the demand distributions into census distributions, due to patients being rejected or misplaced. In the hourly bed census model several assumptions are made, of which a very important one is:

> **Assumption** Admissions of patients take place independently at the beginning of a time slot and discharges at the end of a time slot.

Because of this assumption, the number of patients in a ward will be overestimated with the hourly bed census model. Next, we show some of the formulas used in the bed census model. We start with the arrivals and discharges of both acute and elective patients, which are combined to determine census probabilities per patient type. These probabilities are used to determine the census probabilities per unit. For clarity, all symbols used in the bed census model are shown in Table 4.1.

Table 4.1: List of symbols for hourly bed census model.

Input	
Q	Number of days in a cycle
K	Number of wards
T	Number of time slots per day, i.e. hours
R	Number of days in a week (R=7)
I	Number of operating rooms
$\mathcal{J}$	Set of patient types
P	Set of specialties acute patients
Indices	
q	Day in a time cycle (0,...,Q-1)
k	Ward (1,...,K)
t	Time slot (0,...,T-1)
r	Day of the week (1,...,R)
s	Day of the Master Surgical Schedule (1,...,S)
i	Operating room (OR) (1,...,I)
j	Patient type ($j \in \mathcal{J}$)
p	Specialty of acute patient ($p \in P$)
n	Day in LOS of patient (-1,0,...,L^j)
Input parameters	
$b_{i,s}$	OR block at operating room i on day s to which a surgical specialty can be assigned
C^j	Maximum number surgeries performed during one block of specialty j
ϑ_j	Latest time where elective patient of type j is admitted on day $n = 0$
L^j	Maximum LOS of patient type j
λ^j	Arrival rate for Poisson arrival process of patient type j
Input probabilities	
$c_j(k)$	Probability of k surgeries performed in one OR block in case of specialty j, $k \in \{0, 1, .., C^j\}$
e^j_n	Probability that an elective patient of type j is admitted on day n, $n \in \{-1, 0\}$
$w^j_{n,t}$	Probability of admission on time t, given that a patient of type j is admitted on day n

$P^j(n)$	Probability that a type j patient stays n days after surgery, $n \in \{0, ..., L^j\}$
$m^j_{n,t}$	Probability of discharge during $[t, t+1]$, given that a patient of type j is discharged on day n
Calculated distributions	
$v^j_{n,t}$	P(type j patient admitted in time t, given that the patient is admitted on day n and is not yet before t
$a^j_{n,t}(x\|y)$	P(x patients of type j admitted until time t on day n, given that y admissions take place in total)
$a^j_{n,t}(x)$	P(x patients of type j admitted until time t on day n)
s^j_n	P(type j patient who is still present at the beginning of day n is discharged on day n)
$d^j_n(x)$	P(x patients of type j present at time $t = 0$ on day n for $n > 0$ and at time ϑ_j for $n = 0$)
$z^j_{n,t}$	P(type j patient to be discharged during $[t, t+1]$ on day n, given that the patient is still present at t)
$d^j_{n,t}(x)$	P(x patients of type j still in recovery at time t on day n)
$h^j_{n,t}(x)$	P(x elective patients of type j present on LOS-day n during time slot t)
$g^j_{n,t}(x)$	P(x acute patients of type j present on LOS-day n during time slot t)
Output	
$Z^k_{q,t}(x)$	P(x patients in ward k on day q at beginning of time slot t)

Acute patients

The basis for the flow of acute patients is a cyclic arrival process which is defined as Acute Admission Cycle (AAC), which has a length of R days. Each patient is characterized by patient group $p \in P$, arrival day r and arrival time θ, so $j = (p, r, \theta)$. Patients arrive according to a Poisson arrival process, where each patient type j has arrival rate λ^j. The arrival process is then described as follows:

$$\tilde{a}^j_t(x) = \frac{(\lambda^j)^x e^{-\lambda^j}}{x!}, \quad t = \theta.$$

The discharge process of acute patients is described by $\tilde{d}^j_{n,t}(x)$, where n counts the number of days after arrival of a patient and $n = 0, 1, ..., L^j$, with L^j the maximum LOS. This gives:

$$\tilde{d}^j_{n,t}(x) = \begin{cases} 0 & , n = 0, t \leq \theta, \\ \tilde{d}^j_n(x) & , n = 0, t = \theta + 1 \text{ and } n > 0, t = 0, \\ \displaystyle\sum_{k=x}^{\infty} \binom{k}{x} \left(\tilde{z}^j_{n,t-1}\right)^{k-x} \left(1 - \tilde{z}^j_{n,t-1}\right)^x \tilde{d}^j_{n,t-1}(x) & , n = 0, t > \theta + 1 \text{ and } n > 0, t > 0, \end{cases}$$

where $\tilde{d}_n^j(x)$ for day 0 is the probability that x patients are present at the start of the discharge process ($t = \theta + 1$) and for days $n > 0$ the probability that x patients are present at the start of the day. $\tilde{z}_{n,t}^j$ is the probability of a type j patient to be discharged during time interval $[t, t+1)$ on day n, given this patient is still present at time t.

With the admission and discharge processes known, the probability $g_{n,t}^j$ can be determined for a singe patient type j, which is the probability that on day n at time t, x patients are still in recovery. Next a single AAC is considered, where $g_{n,t}^j$ is translated into $Q_{w,t}$, the distributions for the total number of recovering patients at time t on day w ($w \in \{1, ..., R, R+1, R+2, ...\}$). Lastly, the complete impact of the repeating AAC is considered in the steady state. $Q_{w,t}^{SS}$ is determined by taking the convolution of the $Q_{w,t}$ distributions, which represents the steady-state distribution of the number of patients at time t on day r of the cycle.

Elective patients

Since elective patients are admitted after a planned surgery, the basis for arrivals of elective patients is the Master Surgical Schedule (MSS). A MSS is a cyclic schedule which displays what surgical specialty operates in which Operating Room (OR). Kortbeek et al. connect a surgical specialty of type j to block $b_{i,s}$, which represents a surgery of specialty j taking place in OR $i \in \{1, ..., I\}$ on MSS day s. The probability of k surgeries is then represented by $c^j(k)$ with $k \in \{0, 1, ..., C^j\}$. The arrival process of patients of surgical specialty j is represented by:

$$a_{n,t}^j(x) = \sum_{y=x}^{C^j} a_{n,t}^j(x|y) c^j(y).$$

where $a_{n,t}^j(x|y)$ is the probability that x patients are admitted until time t on day n, given that y admissions take place in total. This probability depends on $v_{n,t}^j$, the probability for a type j patient to be admitted in time t, given that he/she will be admitted at day n and is not yet admitted before t. $a_{n,t}^j(x|y)$ is calculated as follows:

$$a_{n,t}^j(x|y) = \begin{cases} \binom{y}{x} (v_{n,t}^j)^x (1 - v_{n,t}^j)^{y-x} & , n = -1, t = 0, \\ \displaystyle\sum_{g=0}^{x} \binom{y-g}{x-g} (v_{n,t}^j)^{x-g} & , n = 0, t = 0, \\ \quad (1 - v_{n,t}^j)^{y-x} a_{n-1,T-1}^j(g|y) & \\ \displaystyle\sum_{g=0}^{x} \binom{y-g}{x-g} (v_{n,t}^j)^{x-g} & , n = -1, t = 1, ..., T-1 \\ & , n = 0, t = 1, ..., \vartheta_j - 1, \\ \quad (1 - v_{n,t}^j)^{y-x} a_{n,t-1}^j(g|y) & \\ 0 & , t \geq \vartheta_j, \end{cases}$$

The discharge process is similar to that of acute patients and is described as:

$$d^j_{n,t}(x) = \begin{cases} 0 & , n = 0, t < \vartheta_j, \\ d^j_n(x) & , n = 0, t = \vartheta_j \text{ and } n > 0, t = 0, \\ \displaystyle\sum_{k=x}^{C^j} \binom{k}{x} \left(z^j_{n,t-1}\right)^{k-x} \left(1 - z^j_{n,t-1}\right)^x d^j_{n,t-1}(x) & , n = 0, t > \vartheta_j \text{ and } n > 0, t > 0, \end{cases}$$

where $d^j_n(x)$ for day 0 is the probability that x patients are present at the start of the discharge process ($t = \vartheta_j$) and for days $n > 0$ the probability that x patients are present at the start of the day. $z^j_{n,t}$ is the same as for the acute patients.

With the admission and discharge distributions known, the probability $h^j_{n,t}$ can be determined for a singe patient type j, which is the probability that on day n at time t, x patients are still in recovery. Next a single MSS is considered, where $h^j_{n,t}$ is translated into $H_{m,t}$, the distributions for the total number of recovering patients at time t on day m ($m \in \{0, 1, ..., S, S+1, S+2, ...\}$). Lastly, the complete impact of the repeating MSS is considered in the steady state. $H^{SS}_{m,t}$ is determined by taking the convolution of the $H_{m,t}$ distributions, which represents the steady-state distribution of the number of patients at time t on day s of the cycle.

Demand predictions per care unit

Kortbeek et al. determine $Z_{q,t}$, the probability distribution of the total number of patients recovering at time t on day q during a time cycle of length Q ($Q = LCM(S, R)$), by taking the convolution of $H^{SS}_{m,t}$ and $Q^{SS}_{w,t}$. The demand distribution of $Z^k_{q,t}$ can be determined by only considering the patients in W^k and V^k, where W^k and V^k represent the set of patients admitted to unit k for the elective and acute patients respectively.

Bed census predictions

The demand distribution $Z_{q,t}$ can be translated into a bed census distribution $\tilde{Z}_{q,t}$ by an allocation policy ϕ that uniquely specifies from a demand vector a bed census vector. Kortbeek et al. consider the situation where a patient can be misplaced on a unit when its preferred unit is full.

4.1.2 Case study ICU ZGT

In this section we describe the important changes to the model that need to be done for the special case of the ICU of ZGT Almelo. Because of these specific changes, the model as used in this research becomes a case study.

Patient types

In this section we describe the different patient types we define for the acute and the elective patients.

Acute patients
Patients in the ICU of ZGT come from a large variety of wards and also depart to a variety of wards. The origin and destination are not known for all patients and categorizing patients on treating specialty would give small data sets. It would hence not be possible to calculate reliable acute arrival distributions per treating specialty. To limit the patient types, we group all the patients from the different treating specialties. Since patients are still separated into groups by their admission day and admission time, this still leaves us with 168 patient types in the case of 7 days and 24 hours in a day.

Elective patients
ZGT Almelo uses a MSS with a cycle of one week. Since some specialties only very rarely perform surgeries where ICU-stay is needed and most surgical specialties perform surgeries on patients who go to various wards, we decide not to focus on the specialty of the surgery. Because of the variability in outflow from different surgical specialties to the ICU, it is hard to predict the inflow to the ICU from historical data. We group all the patients of the different specialties into one elective patient type, which causes that differences in LOS-distributions between surgical specialties are lost. We do differentiate between admissions on different days of the week. This is necessary because the number of planned surgeries performed depends on the day of the week, since for example almost no planned surgeries are performed in weekends. We therefore have 7 additional patient types.

Two dedicated wards

In case of the ICU of ZGT, all patients admitted to the ICU can be admitted to one of the two equal units. This means that each patient has two dedicated wards and an assignment procedure is required to assign the patients to one of the two units. After consultation with ZGT management it was established that it would be best that patients are assigned to both units and not first fill one of the units, to level the work load of the intensivists that are both assigned one of the units. We examine the option of assigning patients randomly to one of the units and the option of always making sure the patients are equally divided. For both options we explain how we model the division of the patients.

The first option for dividing patients is to randomly assign a patient to one of the units. In the long run, both units have the same occupancy level, but an equal division of patients is not guaranteed at any point in time. We achieve this division of patients in our model by taking half of the total admissions to the entire ICU, in case of equal unit sizes, and use the halved admission rates for both separate units.

The second option is dividing patients equally at any time point, which is achieved by first calculating the bed census probabilities for the two units merged and dividing the patients after the census calculation. In Algorithm 1 the procedure of dividing the patients over two units after the census calculation is shown. When the units are not of equal size, the patients are divided equally until two times the size of the smallest unit is reached, after that the patients need to be assigned to the biggest unit. When the number of patients is uneven, the last patients is assigned to the biggest unit. When both units have equal size, the last patient will simply be assigned to the first unit in case of an uneven number of patients.

Data: $minB$=number beds smaller unit, $maxB$=number beds larger unit;
for $x = 0$ **to** $(2 * minB)$ **do**
    if x *even* **then**
        divide patients equally;
    else
        divide x-1 patients equally;
        assign last patient to largest unit;
    end
end
for $x = ((2 * minB) + 1)$ **to** $(minB + maxB)$ **do**
    assign patients to largest unit;
end

Algorithm 1: Divide patients over two dedicated units.

The advantage of the procedure of Algorithm 1 is that the patients are actually equally divided. The disadvantage is that this division would be done each time period, which does not happen in practice. The procedure of using half the arrivals for both units can lead to an uneven load of patients in both units, but the advantage is that not only the data from the final census is known. For both units all other data on for example censuses per patient types are calculated as well, which might be needed for calculating flexible nurse staffing levels.

Admissions elective patients

In contrast to the model by Kortbeek et al. where admissions are possible on the day before and the day of surgery ($n = -1, 0$), in our model admissions can only take place at the day of the surgery ($n = 0$). These changes simplify the admission distribution. $w^j_{n,t}$ is the probability distribution of the time of admission, given a patient is admitted on day n. The probability for a type j patient to be admitted at time t, given that he/she will be admitted on day n and is not yet admitted before t ($v^j_{n,t}$) can be calculated as follows:

$$v^j_{0,t} = \frac{w^j_{0,t}}{\sum\limits_{k=t}^{T-1} w^j_{0,k}}.$$

With this distribution, the probability that x patients are admitted until time t on day n, given that y admissions take place in total ($a^j_{n,t}(x|y)$) can be calculated:

$$a^j_{0,t}(x|y) = \begin{cases} \binom{y}{x}(v^j_{0,t})^x(1-v^j_{0,t})^{y-x} & ,t=0, \\ \sum_{g=0}^{x} \binom{y-g}{x-g}(v^j_{0,t})^{x-g} & ,t=1,...,\vartheta_j-1 \\ \quad (1-v^j_{0,t})^{y-x}a^j_{0,t-1}(g|y) & \\ 0 & ,t \geq \vartheta_j, \end{cases}$$

Reject patients when ICU is full

As stated in Section 4.1.1 the demand distribution can be translated into a bed census distribution. Kortbeek et al. uses misplacements, where a patient is misplaced when the preferred ward is fully occupied, but the patient finishes its LOS in the preferred ward when a patient is discharged from the ward. Because of the severity of the illness of ICU-patients, they are often moved to another hospital when the ICU is fully occupied on time of arrival. Therefore, we need to change the translation into bed census distribution.

Kortbeek et al. adds all probabilities of patients above the maximum capacity to the probability of the maximum capacity. In our situation, we assume that it is never possible to have patients misplaced, they always leave the system and go to another hospital. We incorporate this rejection procedure, by cutting off the probability distribution for bed demand at the maximum capacity of the ICU. Such a truncated distribution is shown in Figure 4.1. To use these bed census probabilities as a distribution function, we need to rescale the graph, such that all probabilities still add up to 1.

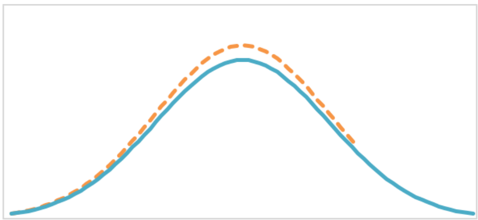
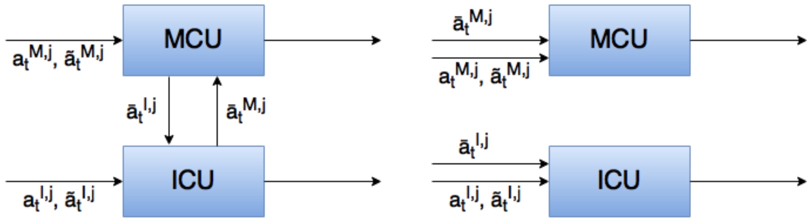


Figure 4.1: Example of a truncated distribution.

Separating ICU-patients and MCU-patients

To separate ICU-patients and MCU-patients, the patient categories need to be altered. There are twice as many categories, namely the categories as before but all for MCU-patients and ICU-patients. Patients can arrive to the ICU from an elective surgery and be categorized as ICU-patient as well as MCU-patient. The same goes for the acute patients, which means that arrivals $a^{M,j}_t$ and $\tilde{a}^{M,j}_t$ enter the MCU and $a^{I,j}_t$ and $\tilde{a}^{I,j}_t$ the ICU.

It is also possible that patients shift from the ICU to the MCU or vice versa. This means that $\bar{a}^{M,j}_t$ extra arrivals enter the MCU and $\bar{a}^{I,j}_t$ the ICU. All arrivals to the two different levels of care are shown in Figure 4.2a.



(a) Preferred dependent arrivals. **(b)** Independent arrivals.

Figure 4.2: Arrivals to MCU and ICU.

Although Figure 4.2a is preferred for separating the ICU and MCU-patients, independent arrivals of patients to either of the two levels of care are required for the bed census model. Each combination for census of different patient types makes use of convolutions, where independent arrivals are necessary when no joint distribution is known. By assuming independent arrivals the fact that one and the same patient shifts between the two levels is lost, as shown in Figure 4.2b. Since the transitions between the two levels of complexity make the arrivals to the MCU and ICU dependent, we model the situation where MCU-patients are included merely with a simulation model. This model is described in Section 4.3.

4.2 Nurse staffing model

Kortbeek et al. (2015) presented a model for finding optimal nurse staffing levels as discussed in Section 3.2.3. The model builds upon the hourly bed census model by Kortbeek et al. (2014). We shortly discuss the conceptual model (4.2.1) and then discuss the changes we need to make to use the model for the case of the ICU of ZGT (4.2.2).

4.2.1 Conceptual model

The model by Kortbeek et al. can be split up in a part where optimal staffing levels are found without a form of flexibility and a second part where float nurses are introduced. In both parts a planning horizon of Q days is used and each day is divided into T time intervals. The distribution for bed census from the hourly bed census model is used as input, additional symbols are shown in Table 4.2.

Table 4.2: List of additional symbols for the nurse staffing model.

Input	
$\mathcal{T}$	Set of shift types
Indices	
τ	Shift type ($\tau \in \mathcal{T}$)
Parameters	
b_τ	Start time slot of shift τ
y_τ	Length in time slot of shift τ
$r^k_{q,\tau}$	Patient-nurse ratio for shift (q, τ) on ward k
α^k	Desired overall service level per shift at unit k
β^k	Desired minimum service level per time slot at unit k

γ^k	Desired minimum fraction of dedicated nurses on ward k
w_d	Staffing costs for each dedicated nurse who is staffed for one shift
w_f	Staffing costs for each float nurse who is staffed for one shift
Service level	
$c^k_{q,\tau}(*)$	Expectation of the coverage compliance at unit k during shift (q,τ)
Assignment procedure	
π	Determines to which ward k float nurses are staffed at the start of shift (q,τ)
$g^{\pi}_{q,\tau}(\mathbf{d}, f, \mathbf{y})$	Vector denoting the number of float nurses assigned to each unit, given the number of dedicated nurses $\mathbf{d}$ on each ward k, the number of nurses in the flexpool f and the patients $\mathbf{y}$ present at the ward
Decision variables	
$s(q,\tau,k)$	Total number of nurses at shift (q,τ) in unit k
$d(q,\tau,k)$	Total number of dedicated nurses at shift (q,τ) in unit k
$f(q,\tau)$	Total number of nurses in flex pool at shift (q,τ)

As shown in Table 4.2 $r^k_{q,\tau}$ represents the NTP-ratio, this is the number of patients a nurse can be responsible for at any point in time. The coverage at any time is given by $r^k_{q,\tau} * s^k_{q,\tau}/x^k_t$, where $s^k_{q,\tau}$ represents the staffing level of day q, shift τ on unit k and x^k_t represents the number of patients at time t on unit k. A coverage of one or higher corresponds to a preferred situation.

In Section 3.2.3 we already described that the authors use two nurse-to-patient ratio targets. The first is β^k, the coverage minimum. The coverage at unit k may never drop below β^k. The second is α^k, the coverage compliance. The long-run fraction of time that the coverage at care unit k is one or higher is at least α^k. The expectation of the coverage compliance at unit k during shift (q,τ) is given by $c^k_{q,\tau}(*)$.

Nurse staffing model without flexibility

The described requirements for coverage are used to determine the optimal staffing levels where no form of flexibility is used. There is no interaction between units, so the staffing levels need to meet the following decision problem:

$$\begin{array}{lll} min & z_F = w_d s^k_{q,\tau} & \forall(q,\tau),k \\ s.t. & s^k_{q,\tau} \geq S^k & \forall(q,\tau),k \\ & s^k_{q,\tau} \geq \lceil \beta^k M^k / r^k_{q,\tau} \rceil & \forall(q,\tau),k \\ & c^k_{q,\tau}\left(s^k_{q,\tau}, r^k_{q,\tau}\right) \geq \alpha^k & \forall(q,\tau),k \end{array}$$

The main objective is to minimize costs. These costs only contain the salaries for the nurses. When flexibility in the form of float nurses is introduced, the problem becomes more complex.

Nurse staffing model with flexibility

In introducing float nurses, another requirement is used, namely the flexibility ratio γ^k. At any time, the fraction of nurses at care unit k that are dedicated nurses has to be at least γ^k. The dedicated nurses are represented by $d^k_{q,\tau}$ and the float nurses by $d_{q,\tau}$. Furthermore, π represents the assignment procedure that allocates the float nurses to care units at the start of a shift (q,τ). The problem is then represented by the following program:

$$\begin{array}{lll}
min & z_E = w_f f_{q,\tau} + w_d \sum_k d^k_{q,\tau} & \forall(q,\tau) \\
s.t. & d^k_{q,\tau} \geq S^k & \forall(q,\tau),k \\
 & d^k_{q,\tau} \geq \lceil \beta^k M^k / r^k_{q,\tau} \rceil & \forall(q,\tau),k \\
 & c^k_{q,\tau}\big(\mathbf{d}_{q,t}, f_{q,\tau}, r^k_{q,\tau}\big) \geq \alpha^k & \forall(q,\tau),k \\
 & d^k_{q,\tau} \geq \gamma^k s^k_{q,\tau}(\mathbf{y}) & \forall(q,\tau),k,\mathbf{y} \\
 & s^k_{q,\tau}(\mathbf{y}) = d^k_{q,\tau} + g^{k,\pi^*}_{q,\tau}\big(\mathbf{d}_{q,t}, f_{q,\tau}, \mathbf{y}\big) & \forall(q,\tau),k,\mathbf{y}
\end{array}$$

Since finding the optimal solution to this problem is too computational extensive, a lower bound model and an upper bound model is created. The lower bound model assumes that it is allowed to reconsider the nurse-to-care-unit assignment at the start of every time interval. The upper bound model uses the distribution that represents the maximum census level that occurs on a care unit. For calculating the upper bound to the flexible nurse staffing model the distributions of the separate patient types are needed. Because of this reason it is *not* possible to use the division procedure as described in Algorithm 1 in combination with this optimization problem.

From the lower bound model and the upper bound model follow z_L and z_U respectively, which represent the number of nurses needed for each shift (q,τ). With these numbers the optimal allocation of nurses to a ward or flex pool can be determined in combination with z_F, which was determined in the model without flexibility. Six cases are specified:

1. $z_L = z_F = z_U$: optimal solution either upper bound solution or no flexibility solution, choose the one with the highest minimal coverage.
2. $z_L = z_U < z_F$: upper bound solution is optimal.
3. $z_L = z_F < z_U$: no flexibility solution is optimal.
4. $z_L < z_F = z_U$: uncertain if optimal solution is found, use either upper bound solution or no flexibility solution, choose the one with the highest minimal coverage.
5. $z_L < z_U < z_F$: uncertain if optimal solution is found, choose upper bound solution.
6. $z_L < z_F < z_U$: uncertain if optimal solution is found, choose no flexibility solution.

4.2.2 Case study ICU ZGT

In this section we describe the important changes to the model that need to be done for the special case of the ICU of ZGT Almelo.

Including float nurses in case of equal division

We already shortly mentioned in Section 4.2.1 that for calculating the upper bound to the flexible nurse staffing model the census distributions of the separate patient types are needed. Since these probabilities are not known when using Algorithm 1 for dividing the patients over the two units, it is not possible to calculate the upper bound for nurse staffing with float nurses. We also build a simulation model to represent the ICU of ZGT, so we have to find the optimum staffing levels with float nurses in case of equal division via the simulation model. This model is described in Section 4.3.

Including agency nurses

Agency nurses are nurses that are not part of the weekly planning. The agency nurses are only hired once in a couple of weeks time. When we want to optimize the number of nurses per shift in a week planning, we need to take into account the fraction of time we are able to hire an agency nurse, such that this is profitable. Ideally, we want to find the fraction of time where an agency nurse needs to be hired, such that:

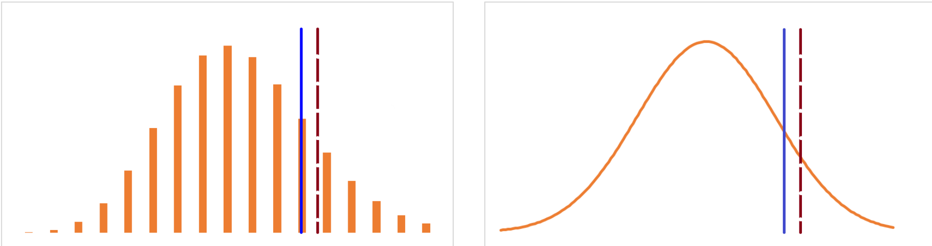
$$c^k_{q,\tau}\big(s^k_{q,\tau}, r^k_{q,\tau}\big) = \alpha^k.$$

For each time period, the coverage is calculated as follows:

$$\begin{aligned} c^k_{q,t}\big(s^k_{q,t}, r^k_{q,\tau}\big) &= P\Big(X^k_{q,t} \leq s^k_{q,t} \cdot r^k_{q,\tau}\Big) && (4.1)\\ &= \sum_{x=0}^{\lfloor s^k_{q,t} \cdot r^k_{q,\tau} \rfloor} Z^k_{q,t}(x) && (4.2)\end{aligned}$$

where $Z^k_{q,t}(x)$ has a discrete distribution. We can see by looking at Figure 4.3a where the dashed red line represents the α^k mark, that we will always end up with a coverage higher than α^k. We see that the dashed red line can lie in between of two values from the $Z^k_{q,t}$ distribution. From Equation 4.2 we see that the coverage is calculated by adding the probabilities of x patients, with a highest value of x equal to $\lfloor s^k_{q,t} \cdot r^k_{q,\tau} \rfloor$. Since this boundary needs to be rounded down because of the discrete distribution of the number of patients, we always find staffing levels to make sure that the coverage is higher than α^k, i.e. to the right of the red line. When $Z^k_{q,t}$ would be a continuous distribution as shown in Figure 4.3b, it would be possible to set the coverage equal to α^k.

We can still find the long term fraction of time where a temporary nurse needs to be hired by determining the coverage when a nurse less is hired than needed for a coverage level of α^k. This level is in Figure 4.3 as an example represented by the solid blue line. When we take the difference between this coverage with one nurse less and α^k, we know the long term fraction of time where an agency nurse needs to be hired where otherwise a shortage would occur.



(a) Discrete distribution. **(b)** Continuous distribution.

Figure 4.3: Difference between discrete distribution and continuous distribution for setting the coverage equal to α^k.

We can thus determine from the analytical model for which shifts it might be profitable to schedule one dedicated nurse less and hire an agency nurse during busy periods. We use the procedure as described in Algorithm 2.

Data: Optimal $s^k_{q,\tau}$ found from the nurse staffing model without flexibility, for each k and (q,τ);
for $k = 1$ **to** K **do**
  for $q = 1$ **to** Q **do**
    for $\tau = 1$ **to** T **do**
      if $s^k_{q,\tau} > max\left[S^k, \left\lceil \frac{\beta^k M^k}{r^k_{q,\tau}} \right\rceil\right]$ **then**
        $p^k_{q,\tau} = \alpha^k - c^k_{q,\tau}(s^k_{q,\tau} - 1, r^k_{q,\tau})$;
        if $w_d/(p^k_{q,\tau} w_t) \leq 1$ **then**
          $p^k_{q,\tau} = 0$;
        else
          $s^k_{q,\tau} = s^k_{q,\tau} - 1$;
        end
        $LB(t^k_{q,\tau}) = \lceil p^k_{q,\tau} W \rceil$;
        $UB(t^k_{q,\tau}) = \lfloor (w_d W)/w_t \rfloor$;
      end
    end
  end
end

Algorithm 2: Find shifts where temporary nurses are a possibility.

For each shift we check with β^k whether it is allowed to lower the number of nurses by one. When this is possible we calculate the difference in the new coverage compliance and the desired overall coverage α^k, which is represented by $p^k_{q,\tau}$. We then use the fact that when a dedicated nurse is used for a shift, the costs are w_d. When an agency nurse is used, this nurse needs to work *at least* the fraction $p^k_{q,\tau}$ of the time at costs w_t. When $w_d < p^k_{q,\tau} w_t$, we know that it is always less costly to hire a dedicated nurse more that shift, instead of using an agency nurse.

We already mentioned that the agency nurse has to work at least the fraction $p^k_{q,\tau}$ of the time. When considering a time period W, the number of weeks, the agency nurse has to work at least $\lceil p^k_{q,\tau} W \rceil$ shifts, represented by $t^k_{q,\tau}$, to get the coverage up to α^k as each shift occurs once each week. This is a lower bound, as this is only the real number of shifts if the entire time the agency nurse works a shortage would have occurred otherwise. In reality, a policy needs to be used for when an agency nurse needs to be hired, as it is not known in advance which hours or shifts lead to a shortage because of a large patient supply. When the costs for an agency nurse are known, the upper bound for the number of shifts during a period W is calculated by $\lfloor (w_d W)/w_t \rfloor$. When more shifts are worked by the agency nurse, this leads to higher costs than when a dedicated nurse was used.

Since we want to examine proper policies for when to hire an agency nurse, we also investigate the use of temporary employees via simulation. The simulation model is described in Section 4.3.

Including MCU-patients

As discussed in Section 4.1.2, it was not possible to use the hourly bed census model for separating MCU-patients, since the two complexities needed to be independent of each other. Instead, we use our simulation model (Section 4.3) to model the situation where both ICU-patients and MCU-patients are considered. We also refer to the simulation model for the staffing levels in case of including MCU-patients.

4.3 Simulation model

In literature simulation models have already proven to be a tool for optimizing processes on ICUs and especially investigating consequences of different staffing policies. A discrete-event simulation captures the fluctuating arrival rate of patients to the ICU, which represents reality. We give a short model description (4.3.1), discuss some important assumptions made for the simulation model (4.3.2), we introduce the actual model (4.3.3) and explain what bound are used for the staffing levels and how we find the optimal solution (4.3.4).

4.3.1 Model description

For this research, we prefer a simulation model that resembles the previous used bed census model to compare results from both the analytic nurse staffing model and the simulation model. We therefore choose to use the same input data as for the hourly bed census model and let events only occur every hour. By doing so, the outcome for the number of patients in the ICU is again an overestimate from reality.

Each hour we draw from the input distributions the number of elective and acute patients arriving. If a patient arrives, the event as shown in the flowchart in Figure 4.4 is triggered. Figure 4.4 shows that patients are rejected when the ICU is fully occupied, as well as that patients are divided equally over the two units. In contrast to the analytical model where patients are divided equally each time period, in the simulation model a patient is not moved after arrival to one of the units. When the end of the LOS of a patient is reached, the patient leaves the system.

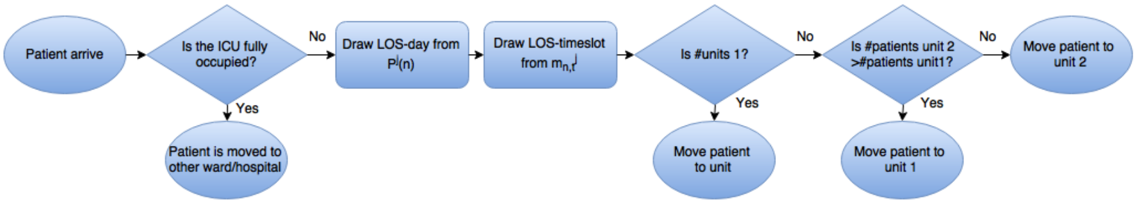


Figure 4.4: Arrival process in the simulation model.

The number of nurses per shift is input for the simulation model. We are interested in the performance of the system, given these staffing levels. For that reason, we measure the coverage compliance and the overstaffing rate every hour.

Including float nurses

The number of float nurses per shift are input to the model. The float nurses are assigned to a unit at the beginning of a shift. In alignment with the nurse staffing model, float nurses are assigned to the unit that has the lowest coverage at that moment in time. When there is more than one float nurse, the coverage is recalculated after the first assignment and then the next float nurse is again assigned to the unit with the lowest coverage.

Including agency nurses

When including agency nurses, the number of dedicated nurses for a shift are lowered. An agency nurse can then be hired when there are not enough nurses during a busy period. We need to determine the right policy for when an agency nurse needs to be hired. We consider the following two policies:

1. An agency nurse is hired when at the beginning of a shift there is a shortage in nurses for the current number of patients in the ICU.
2. An agency nurse is hired when at the beginning of a shift the maximum capacity of patients the nursing staff can take care of is reached or when there is a shortage in nurses for the current number of patients in the ICU.

When agency nurses are included, we measure at the beginning of a shift the number of agency nurses hired.

Including MCU-patients

When the difference between ICU and MCU-patients is included in the simulation model, we need to determine separate probability distributions of LOS for the ICU as well as for the MCU-patients. We also need some probabilities for transitions between the two levels of complexity. We decide not to use the separate input data on LOS for elective and acute patients, but we merge all patient groups to only make a distinction between ICU-LOS and MCU-LOS. This allows for more reliable LOS distributions. In order to do so, we first draw at the arrival of a patient its complexity at arrival and the number of transitions between the two levels. These probabilities are dependent on whether the patients is an elective patient or an acute patient.

When the complexity (either ICU or MCU) at arrival is known, the first LOS is drawn. When the LOS has ended, the simulation model checks whether the patient has already had its assigned number of transitions. When this is not the case, the patient changes complexity and is assigned a new LOS. This process is shown in Figure 4.5.

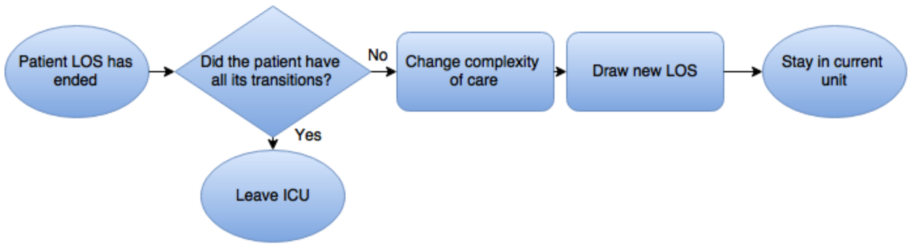


Figure 4.5: Transitions of MCU-patients and ICU-patients in the simulation model.

4.3.2 Assumptions

We discuss important assumptions made in building the simulation model. We divide the assumptions in the process assumptions concerning the patient flow through the ICU and the nursing staff assumptions, concerning the staffing levels. In using these assumptions, we desire to obtain a simulation model that gives similar results to the analytical models.

Process assumptions

- Arrivals take place at the beginning of an hour, departures at the end of an hour.
- When the maximum capacity of the ICU is reached, a new arrival will be declined. The patient does not enter a queue, but leaves the system.
- Patients are admitted to the unit with the lowest number of patients.
- The last bed is not reserved for acute patients, both acute and elective patients can be placed on the last bed.
- A patients can be assigned to any of the beds on its assigned unit, there is no difference in beds.

Nursing staff assumptions

- The scheduled nurses are fully employable, i.e. they do not have breaks or other activities than patient care.
- Nurses can share the care for one patient.
- The coverage at any time is determined for the entire nurses team, not on an individual level.

4.3.3 Introduction of the model

The simulation model of the ICU is shown in Figure 4.6. We briefly explain the components shown.

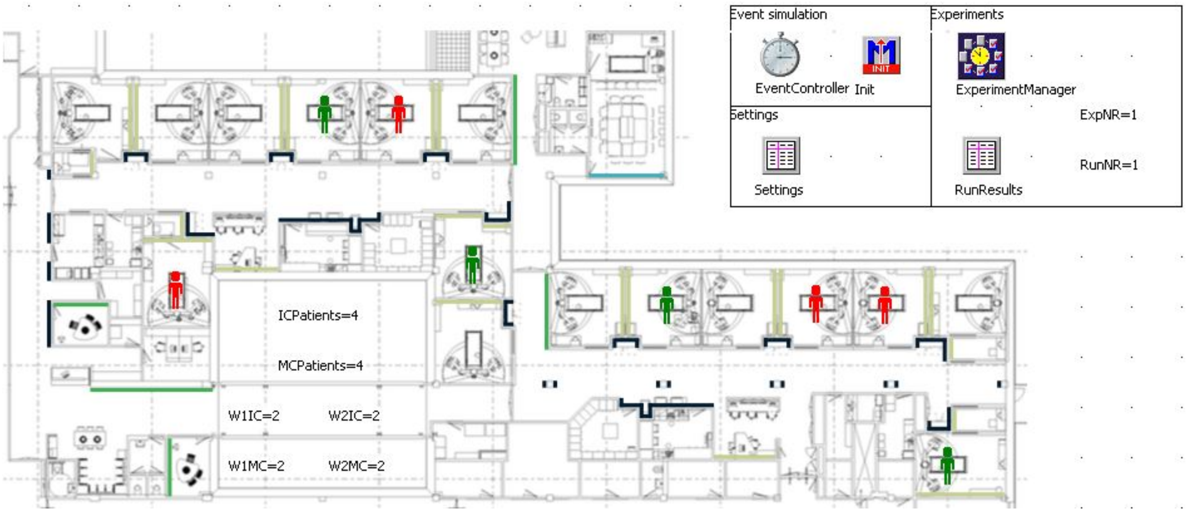


Figure 4.6: Screenshot of the simulation model.

Intensive care unit
In the ICU the patients arrive and are assigned to one of the 16 beds. The color of the patient shows its complexity of care, green means an MCU-patient and red an ICU-patient.

Event simulation
In the event simulation section the model is initialized at the start of a run. The Event Controller is also visible, this is the simulation clock, which keeps track of time. A generator is coupled to this simulation clock, to make sure that every hour patients can arrive and performance measurements are performed. In the simulation clock an end time is entered to mark the end of the simulation run.

Settings
In the settings section the number of nurses per shift can be altered. This includes the dedicated nurses, the float nurses as well as the possibility of hiring agency nurses during a shift. The nurse-to-patient ratio is also part of the settings of the simulation model.

Experiments
In the experiments section the Experiment Manager makes sure the right experiment is performed. The number of replications of an experiment can be entered to make conclusions on results more reliable. When an experiment is finished, the results of the measurements are stored in RunResults.

4.3.4 Selecting the optimal solution

The simulation model is created to find optimal staffing levels, where it was not possible to determine these optimal levels via the analytical models. In Section 4.3.1 we stated that the number of nurses is input to the simulation model. To find the optimal staffing levels, we need to vary the number of nurses per shift and select the best solution. In this section we explain per staffing scenario how the options for staffing levels are chosen by using the analytical models and what solution is selected as optimal.

Including no flexibility

For the staffing scenario where no extra kind of flexibility is introduced, optimal staffing levels can be found from the analytical models. In the situation where patients are divided equally over the two units, we also find optimal staffing levels via the simulation model. Since patients are divided equally over the two units at arrival in the simulation model and every time in the analytical model, we need to check whether the solution found from the analytical model is also feasible for the simulation model. We use the output on staffing levels from the analytical model as input for the simulation model and check whether shifts need more staff, or whether they can do with less.

Including float nurses

The staffing levels for the case of assigning patients randomly to one of the two units can be found from the analytical models, but as discussed in Section 4.2.2, the upper bound model cannot be solved in case of dividing the patients equally. For this situation we use the simulation model to find optimal staffing levels. We can use as a lower bound the lower bound found from the analytical model and as an upper bound the solution from the scenario with no flexibility. All solutions in between need to be examined. In finding the possibilities to examine with the simulation model, three cases can be defined:

1. $z_L = z_F$ *and the allocation to units/pool is the same for the no flex option and the lower bound.* In this situation, there is only one option, so no other possibilities need to be examined.
2. $z_L = z_F$ *and the allocation to units/pool is different for the no flex option and the lower bound.* We need to examine the options where the number of dedicated nurses are as in the lower bound up to the solution where the number of dedicated nurses are as in the no flex solution.

3. $z_L < z_F$. We need to examine all possibilities where the maximum total number of nurses is the number found from the model with no flexibility and the minimum is found from the lower bound model. Furthermore, all options with less dedicated nurses on a unit than the lower bound solution are excluded from consideration.

Staffing levels are chosen such that the number of nurses are the lowest, where the shift has a coverage above α^k on both units. When several options are possible with the same number of total nurses, the option is chosen with the highest minimum coverage compliance.

Including agency nurses

In case of finding the optimal staffing levels when agency nurses are included, we use the results from the analytical model as input for the simulation model. We lower the number of nurses for the shifts where it is allowed to use an agency nurse, for the other shifts we use the optimal number of nurses as found from the model with no flexibility. We examine the two policies for hiring an agency nurse as described in Section 4.3.1. We are provided with the coverage rates and the overstaffing rates, as well as the number of shifts that are worked by the agency nurse given one of the two policies. For options where the coverage compliance is below α^k, the number of nurses needs to be increased again and no agency nurses have to be hired for this shift. The same goes for shifts where the maximum number of shifts an agency nurse is allowed to work is exceeded. The results are which shifts can be worked by one less contracted nurse and the costs of both policies, we choose the policy with the lowest costs.

Including MCU-patients

For the scenario where MCU-patients are separated from ICU-patients, the optimal staffing levels are merely found from the simulation model, since it was not possible to model the transitions between the different complexities with the analytical model. As the upper bound for the number of nurses the optimal solution found with no flexibility is used. For the lower bound we use the minimum service level of β^k as described in the nurse staffing model, but we use the NTP-ratio of the MCU-complexity. We are provided with the coverage rate and the overstaffing rate for the different staffing possibilities and we choose optimal staffing levels such that the number of nurses is the minimum with a coverage above α^k.

4.4 Conclusion

In this chapter we discussed the conceptual models of the hourly bed census model (Kortbeek et al., 2014) and the nurse staffing model (Kortbeek et al., 2015). We also described the changes needed to use the models for the ICU of ZGT.

For using the bed census model we separated the patient types differently than Kortbeek et al. We have chosen two options for assigning patients to one of the two ICUs, random division by halved arrivals and equal division. In our situation elective patients can only be admitted on the day of surgery and we use a truncated distribution to translate the demand distribution to the bed census distribution. When separating MCU-patient from ICU-patients, the arrivals of patients need to be independent to use the bed census model, which is not the case in reality.

We can use the nurse staffing model to find optimal staffing levels when there is no flexibility, or when float nurses are introduced. The flexible model can however not give the optimal solution when using equal distribution of patients over the two units. We can use the analytical model to determine which shifts have the possibility of being profitable when an agency nurse is used during busy periods. For these shifts, the minimum fraction of time that an agency nurse needs to be hired can be calculated.

A simulation model is used to determine the optimal solution for using float nurses in case of equal division and to investigate the consequences of a policy for when to hire an agency nurse. We also use the simulation model for the situation where MCU-patients are included.

In Chapter 5 we explain in more detail the experiments we perform with the models described in this chapter.

Chapter 5

Experimental design

This chapter describes the different experiments we perform. We start with the model input we use for the experiments (5.1) and the verification and validation of the models from Chapter 4 with this input data (5.2). We discuss the experiments and their specifics (5.3), we end this chapter with a short conclusion (5.4).

5.1 Model input

In this section we describe the input we use for our different models. We start with the input for the hourly bed census model (5.1.1), we discuss the input for the nurse staffing model (5.1.2) and we end with the separate input for the inclusion of MCU-patients we need for the simulation model (5.1.3).

5.1.1 Hourly bed census model

For the input for the bed census model we used the data as described in Appendix A. Since we use a cycle of 7 days (S and R are 7 (Section 4.1.2), so Q equals 7), we only use data from January 1 2014 to December 29 2015 to make sure we have an equal number of observations per patient type. The number of admissions and average LOS of this period is shown in Table 5.1. For the arrival distribution we left out the 5 weeks per year where ZGT reduced the number of beds because of holidays, since the arrivals during this period significantly differ from the rest of the year. This leaves us with 104 observations for the LOS distributions for each patient type and 94 observations for the arrival distributions.

Table 5.1: Input data used.

	# admissions	Average LOS
Elective patiens	354	2.38 days
Acute patients	1143	4.24 days

The arrival, surgery, admission day, admission time, discharge day and discharge time distributions are estimated per patient type, as described in Section 4.1.2. We defined a total of 7 elective patient types and 168 acute patient types. We also mentioned in Section 4.1.2 that we do not differentiate between surgery specialties, so we do not need several ORs and only consider one OR. In Table 5.2 some of the input for the bed census model is shown.

Table 5.2: Input hourly bed census model.

Parameter	Description	Value
Q	Number of days in cycle	7
T	Number of timeslots in a day	24
I	Number of operating rooms	1
K	Number of units	2
M	Number of total beds	16
$\mathcal{J}$	Set of patient types	175

From the historical data, the maximum LOS equals 84 days. The maximum number of elective patients arriving during a day is 3 and the maximum number of acute patients arriving per hour is 2. The maximum time where an elective patient is admitted is 20.00h. In Appendix D the input for $b_{i,s}$ and the Poisson arrival rates for acute patients are shown. For the arrival distribution, we did not only want to take into account the realized admissions, but also the rejected patients. In Table 2.1 we saw that the rejection rate was 3.23% in the years 2014 and 2015, so we multiplied the arrivals for both elective and acute patients with 1.0323. Whether this method is valid for modeling the arrivals is shown in Section 5.2.

As discussed in Section 4.1.2, elective patients can not be admitted the day before surgery, only the day of surgery. The probabilities for $c_j(k)$, $w^j_{n,t}$, $P^j(n)$ and $m^j_{n,t}$ are shown in Appendix D. The discharge time, $m^j_{n,t}$, is determined separately for when a patient is discharged during its first or second day on the ICU, but after the second day, the discharge time distribution is the same for all days up to the maximum LOS.

5.1.2 Nurse staffing model

The input data to the nurse staffing model are shown in Table 5.3. The shifts start at 7.00h, 15.00h and 23.00h, to align the shifts with the hourly bed census model. The ratios $r^k_{q,\tau}$ are as described in Table 2.2. For the desired overall service level we choose 95% and for the desired minimum service level 75%. This means that in case of 1 unit of 16 beds, there will always be sufficient staff for 12 patients and in case of a unit of 8 beds, there will always be sufficient staff for 6 patients. Since we were not able of getting a good indication of the costs for a temporary nurse, we vary the costs from twice as much as a contracted nurse to four times as much.

Table 5.3: Input nurse staffing model.

Parameter	Description	Value
M^k	Bed-capacity unit k	[8,8]
$\mathcal{T}$	Set of shift types	3
b_τ	Start time slot of shift τ	[7,15,23]
y_τ	Length in time slot of shift τ	[8,8,8]
$r^{I,k}_{q,\tau}$	Patient-nurse ratio for shift (q,τ) on ward k in case of intenisve care	[1.5,1.75,2]

$r_{q,\tau}^{M,k}$	Patient-nurse ratio for shift (q, τ) on ward k in case of medium care	[2.5,2.75,3]
α^k	Desired overall service level per shift at unit k	95%
β^k	Desired minimum service level per time slot at unit k	75%
γ^k	Desired minimum fraction of dedicated nurses on ward k	2/3
w_d	Staffing costs for each dedicated nurse who is staffed for one shift	1
w_f	Staffing costs for each float nurse who is staffed for one shift	1
w_t	Staffing costs for each temporary nurse who is staffed for one shift	[2,3,4]

5.1.3 Simulation model

As described in Section 4.3.1, we use the input for the hourly bed census model as well for the simulation model. We only change the input, when differentiating MCU-patients from the ICU-patients. As discussed in Section 3.3, a patient is of the ICU-category when in need of respiratory support or dialysis. Otherwise, the patient is of the MCU-category. From historical data we used the start of ventilator support or dialysis from patients as the start of ICU-stay and the end of MCU-stay. Vice versa for the end of ventilator support or dialysis.

The LOS for the time until the next transition or until discharge for patients in the simulation model is only dependent of whether the LOS is a MCU-stay or a ICU-stay. In this distribution no more difference between the elective patients and acute patients is made, as described in Section 4.3.1 to obtain reliable LOS distributions. However, upon arrival the probability of arriving as a MCU-patient or a ICU-patient is dependent of the patient being an elective or acute patient. As described in Section 4.3.1 the number of transitions between complexities of care depends on whether the patients is elective or acute, and whether the patient belong to the ICU or MCU-category upon arrival.

Since the LOS-distribution for either MCU or ICU-stay is determined from historical data, all transitions that occurred in the years 2014 and 2015 are used. However, in the data a lot of LOSs were of a duration less than an hour, as a patient either arrives to the ICU not on respiratory support, but does require it half an hour later, or a transition between the two complexities is of a short duration. Since all these probabilities of a LOS less than an hour are not possible in the bed census model, as patients arrive at the start of an hour and can only be discharged at the end of the next hour, we merged these durations with the onces before or after. The input probabilities for the simulation model are shown in Appendix D.

5.2 Verification and validation

Law and Kelton (2000) define verification as determining whether the conceptual simulation model has been correctly translated into a computer program. Validation is described as the process of determining whether a simulation model is an accurate representation of the system, for the particular objectives of the study.

To check the correctness of the model implementation, we debugged the model while programming it. For this reason, we used the debugging options of Delphi for the bed census model and the nurse staffing model and the debugging option of PlantSimulation for the simulation model. For the purposes of the simulation model we observed animations. For both programs we did pilot runs to verificate the results of the models.

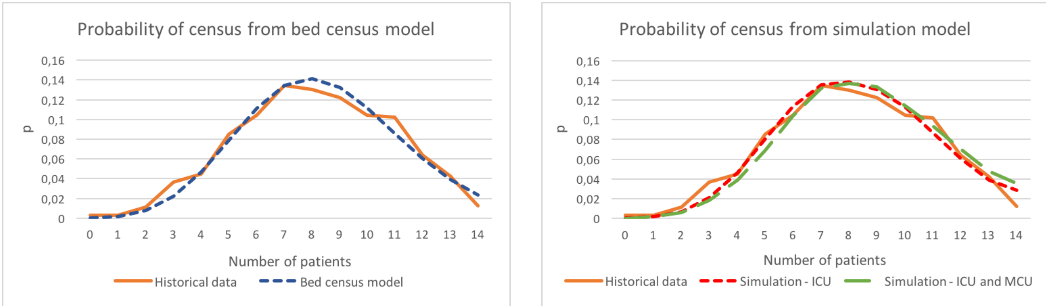
In validating our model, it is especially important that the probability distribution of the census model is correct in both models. To that end we compare the historical data on average number of patients, average admissions per week and average LOS of both elective and acute patients with the output of the bed census model and the simulation model. These figures are shown in Table 5.4. We also interacted with ICU management of ZGT on a regular basis, to make sure the right model was built and that the assumptions are valid.

For the results of the simulation model we did not use output from the first six months, because the system is empty at the start. Using this output would influence the results from the simulation model, where after six months the system is in a steady state. More on this warm-up period can be found in Appendix E.1 and Section 5.3.3.

Table 5.4: Validation of bed census data (#beds=14).

	Historical data	**Bed census model**	**Simulation model**	
			Only ICU	ICU and MCU
Average # patients	8.10	8.24	8.18	8.43
St. dev.	2.77	2.67	2.68	2.68
Average admissions per week	14.93	-	14.91	14.90
Average LOS elective patients (days)	2.38	-	2.43	-
Average LOS acute patients (days)	4.24	-	4.28	-

From Table 5.4 the conclusion can be drawn that output of the bed census model is in line with the historical data on average number of patients. That the average number of patients is a little bit higher for the bed census model is explained by the fact that patients are admitted at the beginning of a timeslot and discharged at the end of a timeslot. This leads to a longer LOS, while the arrivals stay the same. This gives a higher average number of patients in the ICU. In Figure 5.1a we also show the probabilities of 0 to 14 patients from the historical data and from the output of the bed census model. The graphs are very similar.



(a) Output from the bed census model. **(b)** Output from the simulation model.

Figure 5.1: Comparison of historical data from January 1 2014 - December 31 2015 of 1497 admissions/discharges retrieved from Mediscore with model output.

The average number of patients for the simulation model is slightly lower than that of the bed census model. This is explained by the fact that the simulation model makes use of random arrivals and patients are declined when the maximum bed-capacity is reached. Sending away a patient in the simulation model weighs more heavily on the average number of patients than using the truncated distribution function in the bed census model. When we look at the figures for LOS from the simulation model, we see that these are in line with the historical data, taking into account the overestimation.

When MCU-patients are included in the simulation model, we see that the average number of patients increases even further. Since after each transition from one complexity to the other a new LOS is determined, the influence of the overestimation of the LOS of the patients becomes even bigger. From Table 5.5 we see that the division of MCU and ICU-patients is similar to the historical data.

Table 5.5: Validation of #MCU- patients (#beds=14)

	Historical data	Simulation model
Av. # ICU-patients	4.00	4.19
Av. # MCU-patients	4.10	4.24

To see whether the model is valid we also check whether the average number of patients goes up for both the bed census model and the simulation model in case of 16 beds instead of 14. As already discussed, patient are declined ICU-stay when the maximum capacity is reached in the simulation model, so we expect the rejection rate to reduce when the number of beds in increased. From Table 5.6 we see that the average number of patients does indeed increase for the simulation model, as well for the bed census model.

Table 5.6: Validation of bed census data (#beds=16)

	Bed census model	Simulation model	
		Only ICU	ICU and MCU
Average # patients	8.38	8.33	8.61
St. dev.	2.82	2.83	2.86
Average admissions per week		15.16	15.14

5.3 Experiments

In this section we present the experiments we perform in order to find improvements in the nurse staffing process and which models are used to do these experiments (5.3.1). We also discuss the sensitivity analysis we perform (5.3.2) and the number of replications we use for our simulation model (5.3.3).

5.3.1 Design of experiments

In this research we have three scenarios for dividing patients over the two units. The first two are described in Section 4.1.2 and are dividing the patients equally or halving the arrivals such that patients are assigned randomly. We are also interested in the effect of merging the two units, such that only one nursing team is necessary. In Chapter 4 we already described the different staffing scenarios, namely introducing no extra kind of flexibility, using float nurses, hiring agency nurses or separating MCU-patients. An overview of the experiments where the patients division and staffing policy is combined, is shown in Figure 5.2.

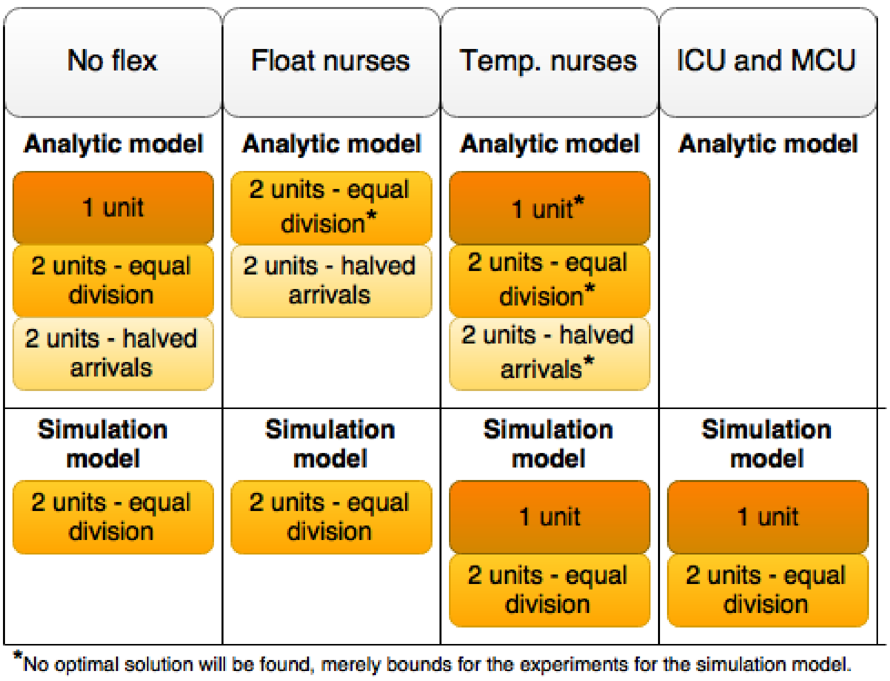


Figure 5.2: Scenarios examined in experiments.

In Figure 5.2 we also indicate which models are used for the experiments. Ideally, the optimal staffing levels are found from the analytical model. In Section 4.2.2 we explained that this is not possible for all scenarios and hence experiments needs to be performed with the simulation model. How the optimal solution is found from the simulation model is described in Section 4.3.4.

5.3.2 Sensitivity analysis

Next to the regular experiments as described in Section 5.1, we also perform a sensitivity analysis. In doing so, we are interested in the changes in output when input to the models is altered.

In determining appropriate staffing levels for the ICU, we assumed values for amongst others the overall coverage α^k, the minimum coverage β^k, the ratio $r^k_{q,\tau}$ and the start times of the shifts b_τ. We investigate the changes in staffing levels when these parameters are altered, such that we know the effect of the chosen values.

We also assumed that data of 2014 and 2015 would be representative for the coming years and hence staffing levels based on historical data can be used. We are interested in the effect of changes in input data on required staffing levels. We investigate a change in patient mix where only acute patients come to the ICU. This situation where no more elective surgeries are planned for ICU-patients is similar to the current reduction period. We also examine a change in the number of arrivals to the ICU and a change in the LOS of the patients. When changing the arrivals and LOS of patients, we know the robustness of the found solutions. Lastly, we change the definition of a MCU-stay, to examine the effect on the staffing levels.

5.3.3 Number of replications

In Section 5.2 we already shortly mentioned the exclusion of output from the simulation model for the first six months. In Appendix E.1 we describe in detail how the warm-up period is determined. In short, we use the graphical method of Welch as described by Law and Kelton (2000), which can be used when a steady-state mean needs to be estimated for a non-terminating simulation. We calculate the moving average over a large window and choose the warm-up period as the time it takes for the moving average to converge.

Since we want reliable values for performance measures, we need to make sure that the confidence intervals for these measures do not get too wide. In our situation these measures are coverage compliance and overstaffing rate, as well as the number of shifts worked by an agency nurse.

Law and Kelton suggest two strategies for constructing point estimates and confidence intervals. The first is the fixed-sample-size procedure, where a single simulation run of an arbitrary fixed length is made, and then one of a number of available procedure is used to construct a confidence interval from available data. The second is the sequential procedure, where the length of a simulation run is sequentially increased until an acceptable confidence interval can be constructed.

We choose to use the fixed-sample-size procedure, in combination with the replication/deletion approach. In Appendix E.2 we show in more detail what the required number of replications are when using a confidence interval of 95% and a relative error of 5%, in Table 5.7 this information is summarized.

Table 5.7: Overview of number of replications per experiment.

Experiment	Required replications	Chosen replications
No flexibility	11	30
Float nurses	11	30
Agency nurses	61	100
ICU and MCU	11	30

5.4 Conclusion

In this chapter we presented the experimental design of our research. We have discussed the input we use for the different models that we use for our experiments. Using this input in these models, we verified and validated the models. The validation mainly focused on the number of patients in the ICU, since it is crucial that this is appropriately modeled to recommend on appropriate staffing levels. We concluded that the models all slightly overestimate the number of patients in the ICU, since patients can only arrive at the beginning of an hour and be discharged at the end of an hour. Still, the output from the bed census model and the simulation do not differ too much from the historical data.

In our research we perform four experiments, namely one where no flexibility is introduced, one where float nurses are used, one where it is possible to hire agency nurses and lastly one where MCU-patients are differentiated. We examine different policies for dividing patient over the two units, one where the patients are not divided because the units are merged, one where patients are divided equally and the third where patients are assigned to one of the units randomly is only applied in the analytical model. We either find optimal solutions from the analytic nurse staffing model, or when this is not possible, we use solutions from the analytical model as bounds for the experiments in the simulation model. Next to the regular experiments, we also perform a sensitivity analysis.

Since the simulation model is a non-terminating simulation, we use a warm-up period of 6 months and a run length of 20 years. For the experiment with agency nurses we do 100 replications in order to find reliable performance measures, for the other experiments 30 replications are done.

In Chapter 6 we discuss the results of the different experiments we performed.

Chapter 6

Results

In this chapter we describe the results of the different experiments we performed. Before we do so, we first show the staffing levels in case of the current policy of full staffing (6.1). Then we start with the results of the experiment with no form of flexibility (6.2), the results of including float nurses (6.3) and temporary nurses (6.4) and the results on separating MCU-patients from ICU-patients (6.5). We perform a sensitivity analysis (6.6), discuss the implementation of the different options (6.7) and we end this chapter with a short conclusion (6.8).

6.1 Current policy - Full staffing

We start our results chapter with the number of nurses that would be needed each shift if ZGT would use the policy of full staffing. Full staffing entails that there is always enough staff for the entire bed-capacity of the ICU, which is the current policy. We use the NTP-ratios as shown in Table 5.3 and the results are shown in Table 6.1.

Table 6.1: Staffing levels in case of full staffing for 16 beds.

	Nurses	Nurses 2 units		
Shift	1 unit	Unit 1	Unit 2	Total
Day	11	6	6	12
Late	10	5	5	10
Night	8	4	4	8
Total per week	**203**			**210**
FTE	**55.03**			**56.92**
Coverage	**1**			**1**

For the rest of this chapter, we determine the costs per year by multiplying the total number of shifts worked per week with the duration of a shift (8 hours), the number of weeks in a year (52.18 weeks) and the costs per hour for an ICU-nurse (€42.50). In case of 1 unit of 16 beds the yearly staffing costs would be €3,601k, in case of 2 units of 8 beds €3,726k.

6.2 Results - No flexibility

Since the hospital desires a change from the full staffing policy, the first experiment we performed finds optimal staffing levels where the coverage compliance needs to be above 95% each shift. We found that the solution from the analytical model gave a coverage below 95% in the simulation model in case of equal division for three shifts, namely the day shift on day 2, the night shift on day 4 and the day shift on day 6 (Table F.1). The results from the simulation model are used for the optimal solution. The optimal staffing levels in case of no flexibility and overall coverage levels above 95% are shown in Table 6.2.

Table 6.2: Staffing results nurse staffing model and simulation model, no flexibility (α^k=0.95, β^k=0.75).

		1 unit of 16 beds	**2 units of 8 beds**					
			Equal division			Halved arrivals		
Day	Shift	Total	Unit 1	Unit 2	Total	Unit1	Unit 2	Total
1	Day	9	5	4	9	5	5	10
	Late	8	4	4	8	4	4	8
	Night	7	4	3	7	4	4	8
2	Day	9	5	5	10	5	5	10
	Late	8	4	4	8	4	4	8
	Night	7	4	4	8	4	4	8
3	Day	10	5	5	10	5	5	10
	Late	8	4	4	8	4	4	8
	Night	7	4	4	8	4	4	8
4	Day	10	5	5	10	6	6	12
	Late	8	4	4	8	4	4	8
	Night	7	4	4	8	4	4	8
5	Day	10	5	5	10	5	5	10
	Late	8	4	4	8	4	4	8
	Night	7	4	3	7	4	4	8
6	Day	9	5	5	10	5	5	10
	Late	7	4	4	8	4	4	8
	Night	7	4	3	7	4	4	8
7	Day	9	5	4	9	5	5	10
	Late	8	4	4	8	4	4	8
	Night	7	4	3	7	4	4	8
	Total	**170**			**176**			**184**
	FTE	**46.08**			**47.71**			**49.88**
	Coverage	**0.976**			**0.984**			**0.977**

We see just like in the case of full staffing, that the amount of FTE required when the two units are merged is lower than when a nursing team is formed for two separate units. There is however a big difference between the required amount of FTE in case of equal division or halved arrivals. This is explained by the fact that there is more variability in the number of patients in the ICU in case of halved arrivals, which causes higher staffing levels to obtain a coverage compliance of 95%. To clarify, in case of halved arrivals, one of the two units can be fully occupied while the other unit can range from zero patients to the maximum capacity. In case of equal division, the only possibility of a fully occupied unit is when the other unit is also fully occupied. This means a lower probability of a fully occupied ICU, which means that less staff is needed to reach the 95% service level.

When looking at the overall coverage compliance in Table 6.2, we see that all values are between 0.95 and 1. In Figure 6.1 the coverage figures are shown for each shift and it can be seen that each shift has an overall coverage rate above 95%.

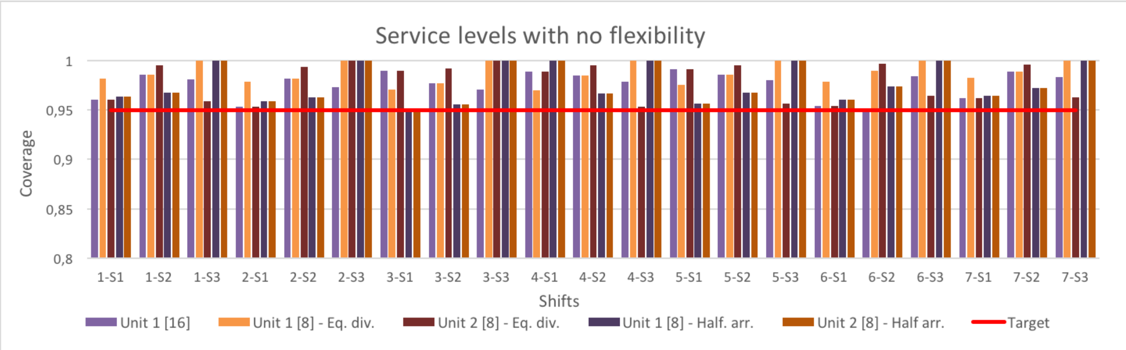


Figure 6.1: Service levels staffing levels with no flexibility (α^k=0.95, β^k=0.75).

The yearly costs for the case of 1 unit of 16 beds are €3,016k; which is a reduction of €585k compared to the full staffing policy. In case of 2 units with equal division, the yearly staffing costs are €3,122k; a reduction of €604k compared to the full staffing policy with 2 units. Lastly, the yearly costs in case of 2 units with random assignment via halved arrivals are €3,264k; which is a reduction of €462k each year compared to the full staffing policy.

6.3 Results - Float nurses

For the experiment where float nurses are included, we first discuss the case of 2 units and halved arrivals (6.3.1), where we base the optimal staffing levels merely on results from the analytical model. Then we discuss the results of the case with 2 units and equal division (6.3.2), where we base optimal staffing levels on a combination of the results from the analytical nurse staffing model and the simulation model.

6.3.1 2 units - Halved arrivals

The results on the staffing levels from the lower bound model and the upper bound model are shown in Table 6.3. For each shift, the total number of nurses from the lower and upper bound are z_L and z_U respectively. In combination with the solution from the model where no flexibility was used (z_F), we determine the optimal number of dedicated nurses per ward and the optimal number of nurses in the flex pool via the six cases defined by Kortbeek et al. (2015) and described in Section 4.2.1.

The selected allocation of dedicated nurses and float nurses is shown in Table 6.4. The use of float nurses in the case of halved arrivals leads to a FTE reduction of 2.44 compared to the optimal solution with no flexibility and at least a coverage of 95%. The yearly costs in case of incorporating float nurses with halved arrivals are €3,105k; this is a reduction of €621k compared to full staffing and €159k compared to the option with no flexibility.

Table 6.3: Results nurse staffing model with float nurses, lower and upper bound (α^k=0.95, β^k=0.75, γ^k=2/3).

		Lower bound				**Upper bound**			
Day	Shift	Unit 1	Unit 2	Pool	Total	Unit 1	Unit 2	Pool	Total
1	Day	4	4	1	9	4	4	2	10
	Late	4	4	0	8	4	4	1	9
	Night	3	3	1	7	3	3	1	7
2	Day	4	4	2	10	4	4	2	10
	Late	4	4	0	8	4	4	1	9
	Night	3	3	1	7	3	3	1	7
3	Day	4	4	2	10	4	4	2	10
	Late	4	4	0	8	4	4	1	9
	Night	3	3	1	7	3	3	1	7
4	Day	4	4	2	10	4	4	2	10
	Late	4	4	0	8	4	4	1	9
	Night	3	3	1	7	3	3	1	7
5	Day	4	4	2	10	4	4	2	10
	Late	4	4	0	8	4	4	1	9
	Night	3	3	1	7	3	3	1	7
6	Day	4	4	1	9	4	4	2	10
	Late	4	4	0	8	4	4	1	9
	Night	3	3	1	7	3	3	1	7
7	Day	4	4	1	9	4	4	2	10
	Late	4	4	0	8	4	4	1	9
	Night	3	3	1	7	3	3	1	7
	Total				**172**				**182**
	FTE				**46.62**				**49.33**
	Coverage				**0.979**				**0.985**

Table 6.4: Results nurse staffing model with float nurses, optimal solution (α^k=0.95, β^k=0.75, γ^k=2/3).

		Choose best				**Optimal solution**			
Day	Shift	z_F	z_L	z_U	Selection	Unit 1	Unit 2	Flex	Total
1	Day	10	9	10	z_U	4	4	2	10
	Late	8	8	9	z_F	4	4	0	8
	Night	8	7	7	z_U	3	3	1	7
2	Day	10	10	10	z_U	4	4	2	10
	Late	8	8	9	z_F	4	4	0	8
	Night	8	7	7	z_U	3	3	1	7
3	Day	10	10	10	z_U	4	4	2	10
	Late	8	8	9	z_F	4	4	0	8
	Night	8	7	7	z_U	3	3	1	7
4	Day	12	10	10	z_U	4	4	2	10
	Late	8	8	9	z_F	4	4	0	8
	Night	8	7	7	z_U	3	3	1	7
5	Day	10	10	10	z_U	4	4	2	10
	Late	8	8	9	z_F	4	4	0	8
	Night	8	7	7	z_U	3	3	1	7
6	Day	10	9	10	z_U	4	4	2	10
	Late	8	8	9	z_F	4	4	0	8
	Night	8	7	7	z_U	3	3	1	7
7	Day	10	9	10	z_U	4	4	2	10
	Late	8	8	9	z_F	4	4	0	8
	Night	8	7	7	z_U	3	3	1	7
	Total	**184**	**172**	**182**					**175**
	FTE	**49.88**	**46.62**	**49.33**					**47.44**
	Coverage	**0.977**	**0.979**	**0.985**					**0.975**

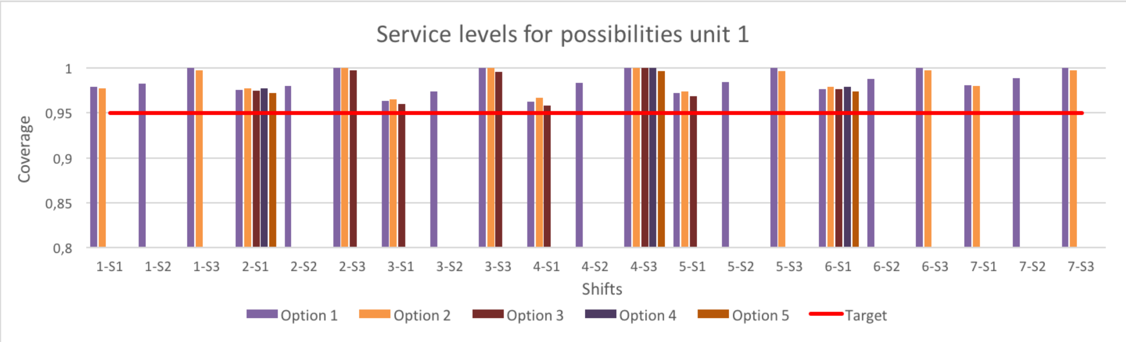
6.3.2 2 units - Equal division

As discussed in Section 4.3.4 for the case of 2 units with equal division, we first determine bounds for the number of nurses per shift via the analytical model. In Table 6.5 the optimal staffing levels are shown for the model with no flexibility and the lower bound model. From the no flexibility option and the lower bound we know all staffing possibilities that need to be examined, these possibilities are also shown in Table 6.5. It should be noted that in Table 6.5 the options that were already found to be insufficient in the previous section with no flexibility are not included.

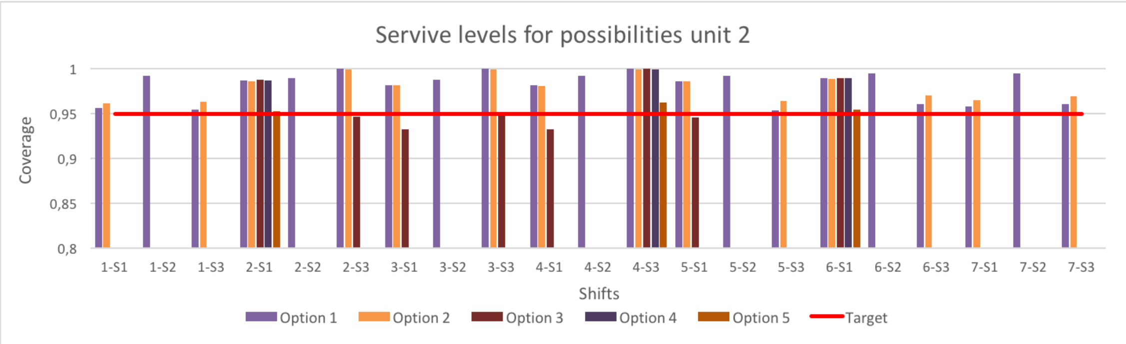
Table 6.5: Staffing results nurse staffing model with float nurses, lower bound and possibilities for optimal solution (α^k=0.95, β^k=0.75, γ^k=2/3).

		No Flex			**Lower bound**				**Possibilities**
Day	Shift	Unit 1	Unit 2	z_F	Unit 1	Unit 2	Pool	z_L	[unit1,unit2,pool]
1	Day	5	4	9	4	4	1	9	[5,4,0] [4,4,1]
	Late	4	4	8	4	4	0	8	[4,4,0]
	Night	4	3	7	3	3	1	7	[4,3,0] [3,3,1]
2	Day	5	5	10	4	4	1	9	[5,5,0] [5,4,1] [4,5,1] [4,4,2] [4,4,1]
	Late	4	4	8	4	4	0	8	[4,4,0]
	Night	4	4	8	3	3	1	7	[4,4,0] [3,3,2] [3,3,1]
3	Day	5	5	10	4	4	1	9	[5,5,0] [4,4,2] [4,4,1]
	Late	4	4	8	4	4	0	8	[4,4,0]
	Night	4	4	8	3	3	1	7	[4,4,0] [3,3,2] [3,3,1]
4	Day	5	5	10	4	4	1	9	[5,5,0] [4,4,2] [4,4,1]
	Late	4	4	8	4	4	0	8	[4,4,0]
	Night	4	4	7	3	3	1	7	[4,4,0] [4,3,1] [3,4,1] [3,3,2] [3,3,1]
5	Day	5	5	10	4	4	1	9	[5,5,0] [4,4,2] [4,4,1]
	Late	4	4	8	4	4	0	8	[4,4,0]
	Night	4	3	8	3	3	1	7	[4,3,0] [3,3,1]
6	Day	5	5	10	4	4	1	9	[5,5,0] [5,4,1] [4,5,1] [4,4,2] [4,4,1]
	Late	4	4	8	4	4	0	8	[4,4,0]
	Night	4	3	7	3	3	1	7	[4,3,0] [3,3,1]
7	Day	5	4	9	4	4	1	9	[5,4,0] [4,4,1]
	Late	4	4	8	4	4	0	8	[4,4,0]
	Night	4	3	7	3	3	1	7	[4,3,0] [3,3,1]
	Total			**176**				**168**	
	FTE			**47.71**				**45.54**	
	Coverage			**0.984**				**0.990**	
	Overstaffing			**0.412**					

We examined all options as described in Table 6.5 via the simulation model. As discussed in Section 4.3.4 the preferred setting is the one with the least number of total nurses and coverage compliance over 95%, where in case of a tie in number of total nurses the option is chosen with the highest minimum coverage compliance. The service levels for the different settings are shown in Figure 6.2.



(a) Unit1.



(b) Unit2

Figure 6.2: Service levels simulation model with 2 units, including float nurses (α^k=0.95).

From Figure 6.2 we see that the coverage rate for unit 1 is always sufficient, which is sometimes not the case for unit 2. This means that at the beginning of the shift a float nurse is often assigned to the first unit, since in case of equal census, a patient is assigned to the first unit. This in general leads to more patients in the first unit. The cases where the coverage is not high enough are the ones where both units are assigned one nurse less and one nurse is assigned to the flex pool. The second unit hardly benefits from this float nurse and is hence left with a shortage. In Table 6.6 the optimal assignment of nurses to the unit and to the flex pool is shown.

We see that the reduction in required amount of FTE compared to the solution with no flexibility is not that big. We conclude that the use of float nurses becomes more profitable when there is more variability in the bed census of the units that are supported by the float nurses. When the patients are already equally divided, which is only possible when a patient has two dedicated wards, the extra benefit from the float nurse becomes minimal. Although minimal, the yearly costs are reduced compared to the no flexibility option, €3,069k compared to €3,122k, which is a reduction of €53k. The solution with float nurses in case of equal division is also still better than the solution with float nurses in case of halved arrivals, namely a difference of €36k.

Table 6.6: Staffing results simulation model with float nurses (α^k=0.95).

		Optimal solution with float nurses			
Day	Shift	Unit 1	Unit 2	Pool	Total
1	Day	4	4	1	9
	Late	4	4	0	8
	Night	3	3	1	7
2	Day	4	4	1	9
	Late	4	4	0	8
	Night	4	4	0	8
3	Day	4	4	2	10
	Late	4	4	0	8
	Night	4	4	0	8
4	Day	4	4	2	10
	Late	4	4	0	8
	Night	3	3	1	7
5	Day	4	4	2	10
	Late	4	4	0	8
	Night	3	3	1	7
6	Day	4	4	1	9
	Late	4	4	0	8
	Night	3	3	1	7
7	Day	4	4	1	9
	Late	4	4	0	8
	Night	3	3	1	7
	Total				**173**
	FTE				**46.89**
	Coverage				**0.982**
	Overstaffing				**0.403**

6.4 Results - Temporary nurses

We start this experiment by using Algorithm 2 in the analytic nurse staffing model, so we know which shifts are excluded from the use of a temporary agency nurse, as well as the fraction of time an agency nurse at least has to work and the minimum number of shifts that need to be worked by the agency nurse in a period W. In Section 5.3.3 we determined that the simulation model has a run length of 20 years, so in these results W equals 20 years as well. The results from using Algorithm 2 are shown in Table 6.7. The results are for all values of w_t, as the results for the three different costs did not differ.

From Table 6.7 we see that most shifts have the possibility of using one nurse less and hiring an agency nurse instead. Notable is that the shifts from unit 2 of equal division have considerably less shifts where an agency nurse can be used. This is explained by the fact that the optimal nurse staffing levels found from the nurse staffing model for unit 2 with equal division are such that the coverage is just above 95%. Lowering the number of nurses with one will give a very low coverage and a too big fraction of time where an agency nurse needs to work.

In Algorithm 2 we stated that the upper bound to the number of shifts worked

Table 6.7: Staffing results nurse staffing model with agency nurses, the results are the same for all $w_t \in [2, 3, 4]$ (α^k=0.95).

		1 units		**2 units, equal div.**				**2 units, halved arr.**			
		16 beds		**unit 1**		**unit 2**		**unit 1**		**unit 2**	
Day	Shift	Time frac.	Sifts (in 20y)	Time frac.	Shifts (in 20y)	Time frac.	Sifts (in 20y)	Time frac.	Shifts (in 20y)	Time frac.	Shifts (in 20y)
1	Day	0.026	27	0.026	27			0.055	58	0.055	58
	Late	0.014	15								
	Night	0.029	31	0.029	31			0.061	64	0.061	64
2	Day	0.039	41	0.039	41			0.067	71	0.067	71
	Late	0.027	28								
	Night	0.054	57	0.054	57	0.007	7	0.079	82	0.079	82
3	Day	0.010	11	0.060	63	0.010	11	0.083	87	0.083	87
	Late	0.044	46								
	Night	0.063	66	0.063	66	0.012	13	0.088	92	0.088	92
4	Day	0.013	14	0.065	68	0.013	14	0.001	1	0.001	1
	Late	0.016	17								
	Night	0.037	39	0.037	39			0.066	69	0.066	69
5	Day	0.002	2	0.046	48	0.002	2	0.072	75	0.072	75
	Late	0.014	15								
	Night	0.032	34	0.032	34			0.061	64	0.061	64
6	Day	0.036	38	0.036	38			0.064	67	0.064	67
	Late										
	Night	0.019	20	0.019	20			0.049	52	0.049	52
7	Day	0.023	25	0.023	25			0.053	56	0.053	56
	Late	0.002	2								
	Night	0.022	23	0.022	23			0.052	54	0.052	54

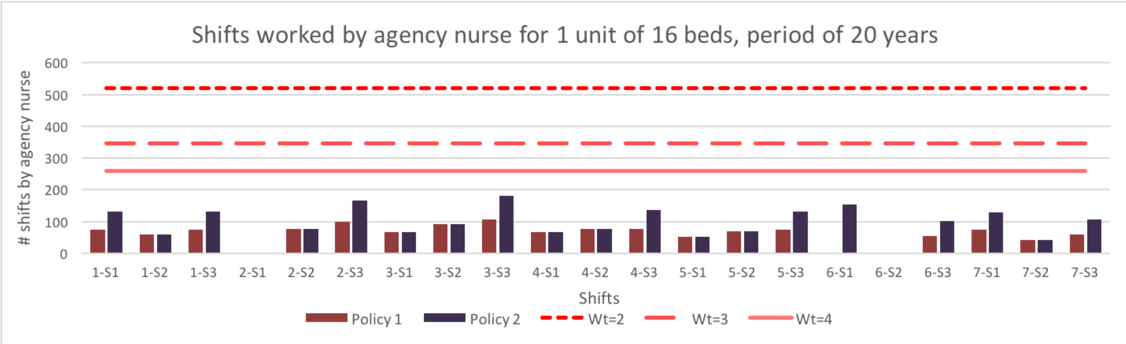
Time frac.=minimum proportion of time an agency nurse needs to work where otherwise a shortage occurs to maintain a service level of $\alpha = 0.95\%$.
Shifts=minimum number of shifts in 20 years an agency nurse needs to work where otherwise a shortage occurs to maintain a service level of $\alpha = 0.95\%$.

by an agency nurse is equal to $\lfloor (w_d W)/w_t \rfloor$. When more shifts are worked by an agency nurse than this upper bound, it would be beneficial to increase the number of dedicated nurses and not use an agency nurse. Using the values 2, 3 and 4 for w_t and a time horizon of 20 years, the maximum number of shifts worked by an agency nurse is shown in Table 6.8.

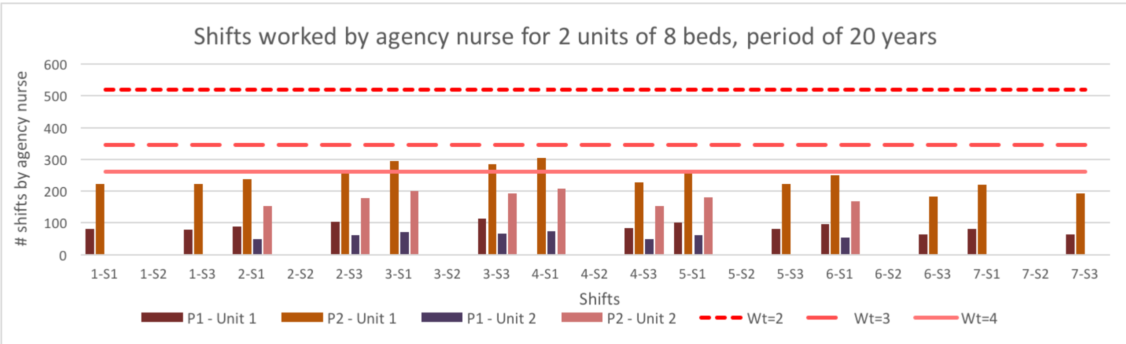
Table 6.8: Maximum number of shifts worked by an agency nurse in 20 years.

w_t	Maximum number of shifts in 20 years
2	540
3	346
4	260

Now that all shifts are known for which it might be profitable to use an agency nurse and the upper bound to the number of agency shifts is set, we can compare the two policies for hiring an agency nurse as described in Section 4.3.1. Recall that the first policy is to hire an agency nurse when at the start of a shift a shortage in nurses occurs, the second policy is to hire an agency nurse when at the start of a shift the maximum number of patients a nursing team can care for is reached or a shortage occurs. In Figure 6.3 for each shift type the number of shifts worked by an agency nurse is shown for the two different policies. We left out the values for which the coverage under the given policy did not reach the 95%, as the number of dedicated nurses needed to be increased again as described in Section 4.3.4. The three shifts for which the number of nurses had to be increased in case of no flexibility are also examined (Table F.1). A detailed overview of the results is shown in Tables F.2-F.4.



(a) Shifts by an agency nurse in case of 1 unit.



(b) Shifts by an agency nurse in case of 2 units.

Figure 6.3: Shifts worked by agency nurse under two different policies for a period of 20 years. Only shifts with a coverage higher than 95% are shown.

In Figure 6.3b we see 5 shifts from unit 1 with policy 2 where the maximum number of shifts by an agency nurse is exceeded in case of $w_t = 4$. The same goes for these shifts as those with a coverage lower than 95%, the number of dedicated nurses needs to be increased. All other options that we examined were profitable when a dedicated nurse less is scheduled and an agency nurse is hired during busy periods. To compare the two different policies, we summarized the service levels, overstaffing rate, required FTE and costs for all different options in Table 6.9.

In all situations policy 1, where an agency nurse is hired once a shortage occurs, leads to the lowest costs. It should also be noted that the overstaffing rate in considerably lower when the use of agency nurses is introduced, compared to all previous options. The optimal solution for the number of nurses for each shift and whether an agency nurse should be used, is for the case of 1 unit shown in Table F.5 of Appendix F, for the case of 2 units in Table F.6.

Table 6.9: Summary of results for both policies for hiring an agency nurse from simulation model (α^k=0.95).

		Policy 1				**Policy 2**			
	w_t	Service level	Overstaffing rate	FTE	Costs (k€)	Service level	Overstaffing rate	FTE	Costs (k€)
1 unit	2	0.967	0.331	41.20	2,741	0.970	0.331	40.93	2,746
	3	0.967	0.331	41.20	2,763	0.970	0.331	40.93	2,780
	4	0.967	0.331	41.20	2,785	0.970	0.331	40.93	2,813
2 units	2	0.979	0.347	42.26	2,805	0.983	0.355	41.74	2,897
Eq. div.	3	0.979	0.347	42.26	2,823	0.983	0.355	41.74	2,979
	4	0.979	0.347	42.26	2,842	0.983	0.367	43.10	3,053

For comparison with the other experiments, we use the worst case where w_t equals four. As seen in Table 6.9 the costs in case of 1 unit are then €2,785k, which is a reduction of €816k compared to full staffing and €213k compared to the no flexibility option. In case of 2 units the yearly costs are €2,842k, which is a reduction of €884k compared to full staffing, €280k compared to the no flexibility option and €227k compared to the option with float nurses in case of equal division.

6.5 Results - ICU and MCU

As shown in Figure 5.2, the experiment where MCU-patients are included is only performed with the simulation model. In Section 4.3.4 we explained that the upper bound for the number of nurses per unit is the outcome of the experiment with no flexibility. The lower bound is the minimum number of nurses that needs to be present in case of a minimum coverage of 75% and using the NTP-ratios for MCU-patients as described in Table 5.3. The ranges of nurses per shift are summarized in Table F.7 of Appendix F and are referred to as different options for staffing levels per shift in the rest of this section.

In Figure 6.4 the coverage compliance of each setting that we examined for the case where the two units are merged is shown. From Figure 6.4 we can see that for almost all shifts it is possible to schedule one nurse less than the no flexibility option, which is the upper bound, as still a higher coverage compliance than 95% in achieved.

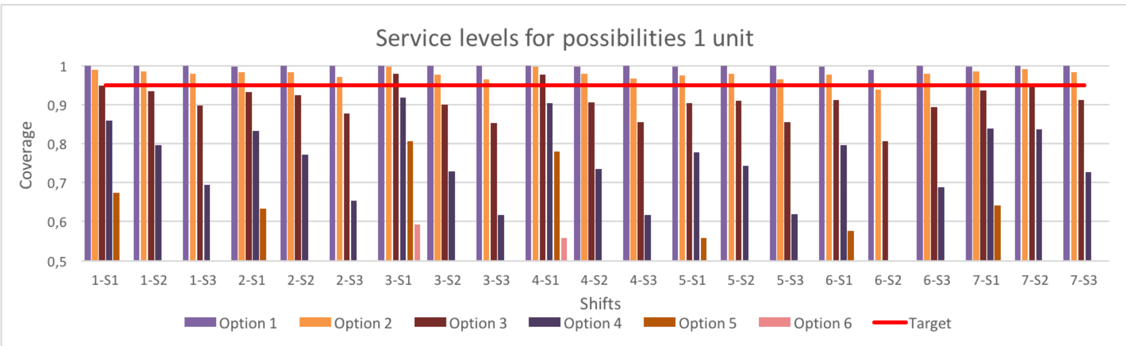
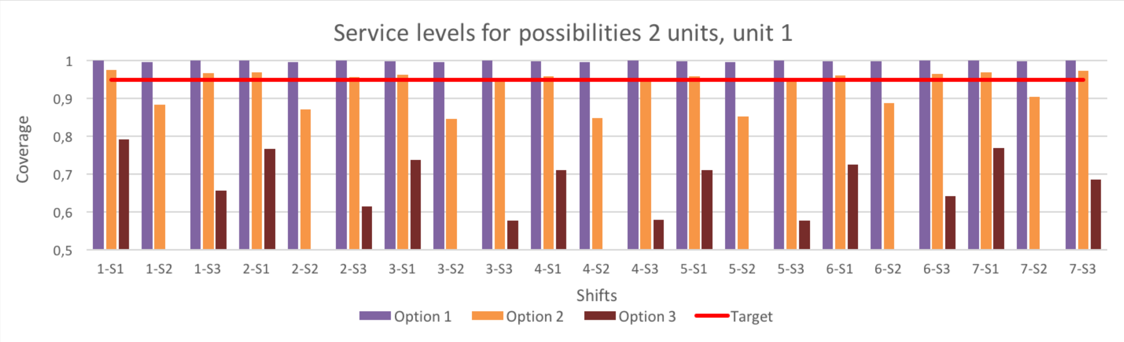
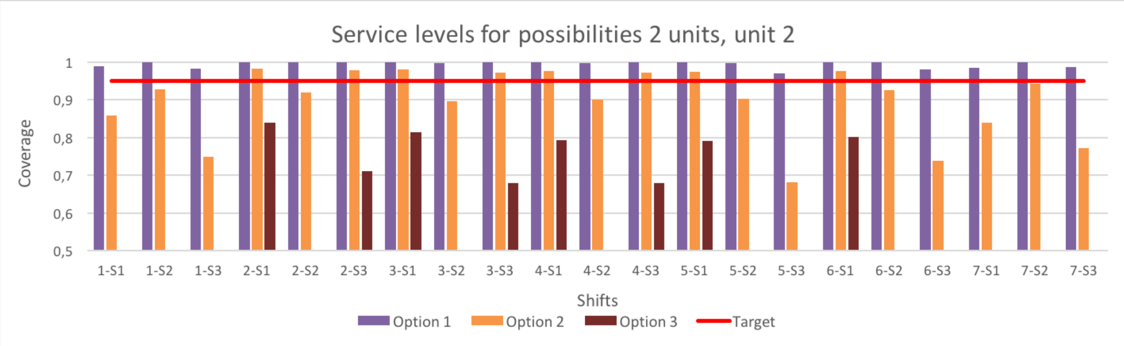


Figure 6.4: Service levels simulation model with 1 unit, including MCU-patients (α^k=0.95).

In Figure 6.5 the coverage compliance of each setting that we examined for the case where there are two units of 8 beds is shown. We again choose the minimum number of nurses per shift, given that the coverage compliance is more than 95%.



(a) Unit 1.



(b) Unit 2.

Figure 6.5: Service levels simulation model with 2 units, including MCU-patients (α^k=0.95).

The optimal staffing levels when separating MCU-patients for both the case of 1 unit and 2 units is shown in Table 6.10. From Table 6.10 we see that the required amount of FTE is reduced significantly when separating MCU-patients compared to the solution when no flexibility was introduced, namely with 6.5 in case of merged units and 5.42 in case of separate units.

On average, there are definitely enough nurses per shift to assure a coverage of 95% or more, because the span of control for the entire nursing staff is used. It should be noted that using staff that takes care of MCU-patients and ICU-patients simultaneously leads to a situation where nurses continuously need to repeat the assessment of their workload to make sure their maximum workload is not exceeded. The assessment of their workload is complex when patients are shared with other nurses. It might be necessary that some nurses exceed the maximum workload a bit, while other stay below the maximum. We discuss more on the implementation in Section 6.7. Nevertheless, separating MCU-patients from ICU-patients will lead to a reduction in required FTE as on average more than half of the patients are of the MCU-complexity (Table 5.5).

Table 6.10: Staffing results simulation model with MCU patients (α^k=0.95).

		1 unit	**2 units, equal division**		
Day	Shift		Unit 1	Unit 2	Total
1	Day	8	4	4	8
	Late	7	4	4	8
	Night	6	3	3	6
2	Day	8	4	4	8
	Late	7	4	4	8
	Night	6	3	3	6
3	Day	8	4	4	8
	Late	7	4	4	8
	Night	6	4	3	7
4	Day	8	4	4	8
	Late	7	4	4	8
	Night	6	4	3	7
5	Day	8	4	4	8
	Late	7	4	4	8
	Night	6	3	3	6
6	Day	8	4	4	8
	Late	7	4	4	8
	Night	6	3	3	6
7	Day	8	4	4	8
	Late	6	4	4	8
	Night	6	3	3	6
	Total	**146**			**156**
	FTE	**39.58**			**42.29**
	Coverage	**0.977**			**0.982**
	Overstaffing	**0.404**			**0.439**

The yearly costs in case of merged units are €2,590k, which is a reduction of €195k to the solution with agency nurses, which was the best solution so far. The yearly costs in case of 2 units is €2,768k, a reduction of €74k compared to the previous best solution with agency nurses. In the conclusion of this chapter (Section 6.8) all costs are summarized.

6.6 Sensitivity analysis

In this section we examine changes in output when input to the models is altered. We investigate the changes in staffing values when the overall coverage α^k (6.6.1), the minimum coverage β^k (6.6.2), the ratio $r^k_{q,\tau}$ (6.6.3) or the start times of the shifts b_τ are altered (6.6.4). We investigate a change in patient mix where only acute patients come to the ICU (6.6.5), a change in the number of arrivals to the ICU (6.6.6) and a change in the LOS of the patients (6.6.7). Lastly, we change the definition of a MCU-stay (6.6.8).

6.6.1 Adapting α^k

To see the influence of the overall coverage α^k on the staffing levels, we differentiate α^k from 0.8 up to 0.975 in steps of 0.025 while keeping all other input parameters as described in the model input (Section 5.1) in case of the no flexibility option. We only show the effect of the changes on the no flexibility option, because the results of the other staffing scenarios will be similar. The required amount of FTE for the different values of α^k is shown in Figure 6.6.

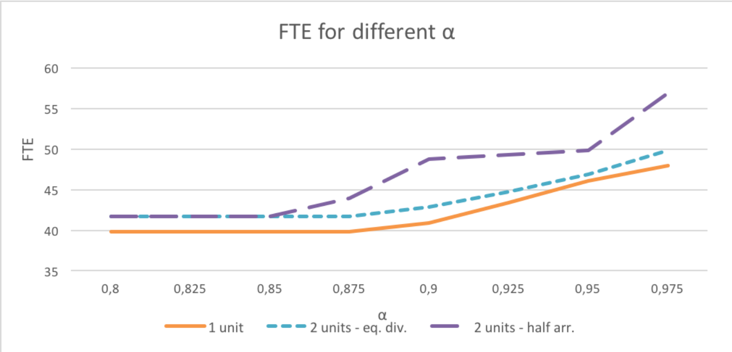
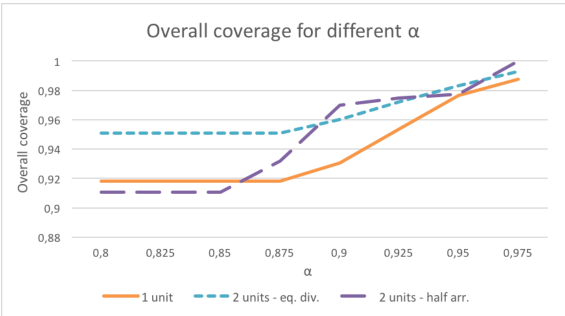


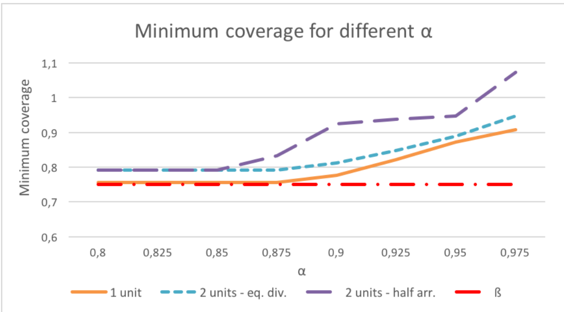
Figure 6.6: Sensitivity of α^k, results from nurse staffing model without flexibility for required amount of FTE (β^k=0.75).

From Figure 6.6 we see that the required amount of FTE increases when the boundary for overall coverage compliance increases. Lower values of α^k lead to less FTE required and hence a less costly solution, however, the quality of care will be lower as well.

The fact that the required amount of FTE for the first couple of values of α^k is constant can be explained by looking at the graphs for the realized overall coverage and minimum coverage in Figure 6.7. The overall coverage is constant for the first couple of values for α^k, as the minimum coverage is at its lower bound, represented by the red line in Figure 6.7b. We conclude that when the minimum coverage is at its lower limit, changing α^k does not influence the staffing levels anymore, otherwise staffing levels will increase as α^k increases.



(a) Overall coverage.



(b) Minimum coverage.

Figure 6.7: Sensitivity of α^k, results from nurse staffing model without flexibility (β^k=0.75).

6.6.2 Adapting β^k

To see the influence of the minimum coverage β^k on the staffing levels, we differentiate β^k from 0.5 up to 0.95 in steps of 0.05 while keeping all other input parameters as described in the model input (Section 5.1). We again only shown the case of no flexibility, as results will be similar for other staffing scenarios. The required amount of FTE for these different situations is shown in Figure 6.8.

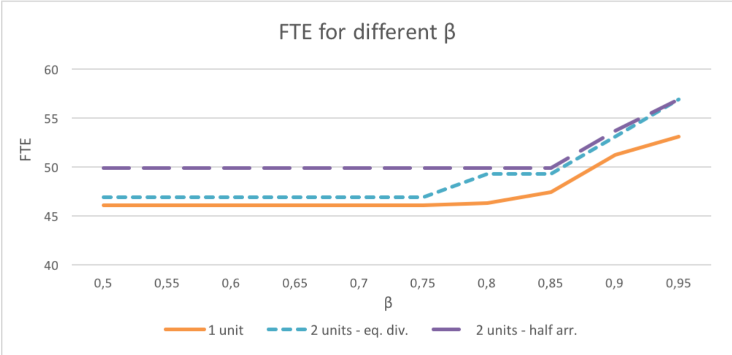
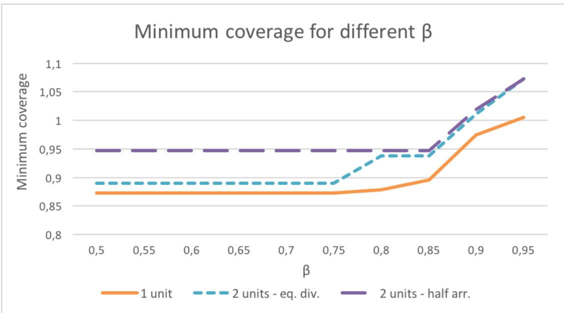


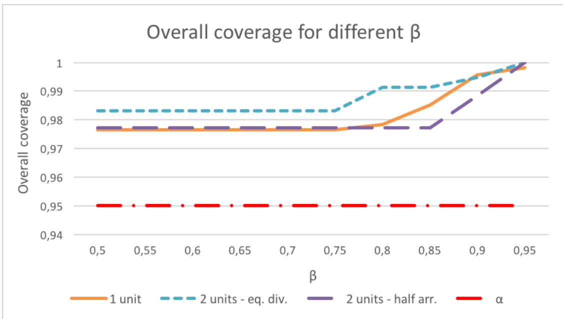
Figure 6.8: Sensitivity of β^k, results from nurse staffing model without flexibility for required amount of FTE (α^k=0.95).

We see in Figure 6.8 that the required amount of FTE stays constant for the low values of β^k, and increases for values of β^k of 0.8 or higher, similar to changing α^k.

When we again look at the realized minimum coverage and overall coverage in Figure 6.9, we see that in changing β^k the minimum coverage stays constant when it is not possible to lower the number of nurses per shift because of the target level for α^k. Hence the required FTE stays constant.



(a) Minimum coverage.



(b) Overall coverage.

Figure 6.9: Sensitivity of β^k, results from nurse staffing model without flexibility (α^k=0.95).

In Figure 6.9b the overall coverage level is shown, together with its limit of α^k of 0.95. The realized overall coverage might seem much higher than the lower bound, which is because the values shown are the averages over all shifts, where lowering the number of nurses for one of the shifts would lead to a coverage below 0.95 for that shift. We conclude that when the overall coverage compliance is at its lower limit, changing β^k does not influence the staffing levels. Otherwise staffing levels will increase as β^k increases.

6.6.3 Different ratio

In determining optimal staffing levels, we used for all experiments the Nurse-To-Patient (NTP) ratios as described in the 2015 concept guidelines (Nederlandse Vereniging voor Anesthesiologie, Nederlandse Vereniging voor Intensive Care en Nederlandse Internisten Vereniging, 2015). Since these guidelines were not accepted, we also determine optimal staffing levels for a situation where the ratio is changed.

In the current situation management of the ICU of ZGT desires not to exceed the ratio of 2 for every shift. With the current staffing levels it is only possible for the entire nursing team to reach this maximum during the late and night shift, as more nurses are scheduled during the day shift. Nevertheless, we examine the use of this ratio for all the shifts ($r^k_{q,\tau} = \{2, 2, 2\}$) in case of a total of 16 beds and the option with no flexibility, but with $\alpha^k = 0.95$ and $\beta^k = 0.75$. The results are shown in Table 6.11. The effect of the changed ratio will be similar for the other staffing scenarios.

Table 6.11: Staffing results nurse staffing model, no flexibility with ratios [2,2,2] (α^k=0.95, β^k=0.75).

		1 unit of 16 beds		**2 units of 8 beds**							
				Equal division				Halved arrivals			
Day	Shift	Total	Diff.	U1	U2	Total	Diff.	U1	U2	Total	Diff.
1	Day	7	-2	4	3	7	-2	4	4	8	-2
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	7		4	3	7		4	4	8	
2	Day	7	-2	4	3	7	-3	4	4	8	-2
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	7		4	4	8		4	4	8	
3	Day	7	-3	4	4	8	-2	4	4	8	-2
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	7		4	4	8		4	4	8	
4	Day	7	-3	4	4	8	-2	4	4	8	-4
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	7		4	3	7		4	4	8	
5	Day	7	-3	4	4	8	-2	4	4	8	-2
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	7		4	3	7		4	4	8	
6	Day	7	-2	4	3	7	-3	4	4	8	-2
	Late	6	-1	3	3	6	-2	4	4	8	
	Night	7		4	3	7		4	4	8	
7	Day	7	-2	4	3	7	-2	4	4	8	-2
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	7		4	3	7		4	4	8	
	Total	**146**	**-24**			**151**	**-25**			**168**	**-16**
	FTE	**39.58**				**40.93**				**45.54**	
	Coverage	**0.978**				**0.984**				**1**	

We see that since we increased the ratio for the day and late shift, i.e. a nurse is allowed to take care of more patients during these shifts, the required FTE is decreased. The difference in FTE is 6.5, 6.78 and 4.34 respectively for 1 unit, 2 units with equal division and 2 units with halved arrivals. A reduction in required FTE also means reduced costs. The yearly costs in case of 1 unit are €2,590k, a reduction of €426k compared to the solution with the original ratios. In case of two units, the costs are €2,679k and €2,981k respectively in case of equals division or halved arrivals, a reduction of €443k and €283k compared to the solution with the original ratios.

6.6.4 Different shift start times

In determining optimal staffing levels we used for all experiments the shifts start times $b_\tau = \{7, 15, 23\}$, which represented the start times of the shifts in the current situation. To examine the influence of these start times, we vary them from -3 hours to +3 hours in steps of one hour. The required amount of FTE for the different options is showed in Figure 6.10, for the case of not introducing extra flexibility.

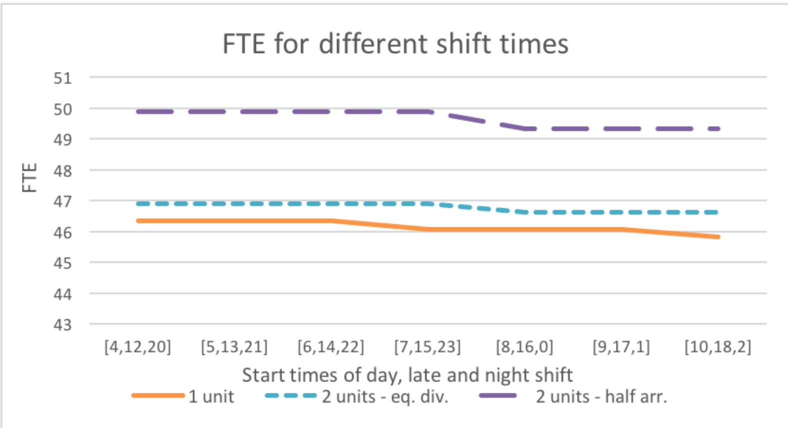


Figure 6.10: Sensitivity of shift start times, results from nurse staffing model without flexibility for required amount of FTE (α^k=0.95, β^k=0.75).

From Figure 6.10 we see that a small reduction in FTE for all division scenarios can be achieved when the start times of the shifts are changed to one hour later. The reduction is however very small, as for the situation of 1 unit and 2 units with equal division only one of the weekly shifts has a reduction of one nurse and for the situation of 2 units with halved arrivals, 2 shifts have a reduction of one nurse.

When considering the scenario of 2 units with equal division, the only change is during the day shift on Friday on unit 2, where five nurses used to be necessary, which is changed to four when the shift starts at 8.00h. The day shift has the most strict ratio, namely 1.5, hence four nurses can care for six patients during the day shift. We can conclude that from 7.00h to 8.00h there is a higher probability of more than six patients than during 15.00h to 16.00h. This is caused by the fact that discharges mostly occur before 15.00h and this explains why in this one situation one nurse less can be scheduled.

6.6.5 Only acute patients

In order to examine the effect of the change in patient mix, we determine optimal staffing levels in case of only acute patients. Leaving out all elective patients is chosen, because management of the ICU of ZGT can use the output in case of a reduction period during the summer. In Section 2.1 we stated that during a reduction period no elective surgeries are planned. Normally, every year there is a reduction period of 5 weeks during the summer.

We use the data as described in Section 5.1, except for β^k which we lower to 0.5, since it is probable that not all beds will be operational and the minimum staffing levels do not need to be for 75% of the total bed-capacity. The results are shown in Table 6.12, for the option of no flexibility as other scenarios will give similar results.

Table 6.12: Staffing results nurse staffing model, no flexibility, only acute patients (α^k=0.95, β^k=0.5).

		1 unit of 16 beds		**2 units of 8 beds**							
				Equal division				Halved arrivals			
Day	Shift	Total	Diff.	U1	U2	Total	Diff.	U1	U2	Total	Diff.
1	Day	8	-1	4	4	8	-1	5	5	10	
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	6	-1	3	3	6	-1	4	4	8	
2	Day	8	-1	4	4	8	-2	5	5	10	
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	6	-1	3	3	6	-2	4	4	8	
3	Day	8	-2	4	4	8	-2	5	5	10	
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	6	-1	3	3	6	-2	4	4	8	
4	Day	8	-2	4	4	8	-2	5	5	10	-2
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	6	-1	3	3	6	-2	4	4	8	
5	Day	8	-2	4	4	8	-2	5	5	10	
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	6	-1	3	3	6	-1	4	4	8	
6	Day	8	-1	4	4	8	-2	5	5	10	
	Late	7	-1	4	3	7	-1	4	4	8	
	Night	6		3	3	6	-1	4	4	8	
7	Day	8	-1	4	4	8	-1	5	5	10	
	Late	7	-1	4	4	8		4	4	8	
	Night	6	-1	3	3	6	-1	4	4	8	
	Total	**147**	**-23**			**148**	**-28**			**182**	**-2**
	FTE	**39.85**				**40.12**				**49.33**	
	Coverage	**0.969**				**0.976**				**0.987**	

In Table 6.12 we see that for all options the total number of shifts that need to be worked in a week are reduced, although with a minimal number in case of 2 units with halved arrivals. The variability is still very large with this option and hence there is almost no difference with the option where the elective patients were taken into account. When these staffing levels are used for a period of 5 weeks a year and the original staffing levels from Table 6.2 the rest of the year, the costs for the three options would be €2,977k, €3,075k and €3,261k respectively. When the staffing levels need to be reduced more because of nurses that take holidays, we recommend on closing some of the operational beds, which makes it more likely for patients to be rejected.

6.6.6 Change in number of arrivals

Since we used historical data to determine the number of arrivals to the ICU, we are interested in the consequences for staffing levels in case of a change in this arrival pattern. In Figure 6.11 the required FTE is shown for 85% of the arrivals up to 115% of the arrivals, in steps of 5%, determined with the nurse staffing model without flexibility. The other staffing scenarios will have similar results.

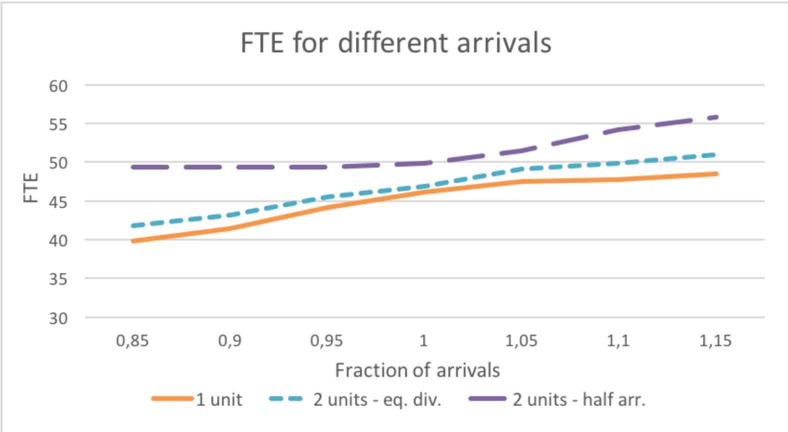
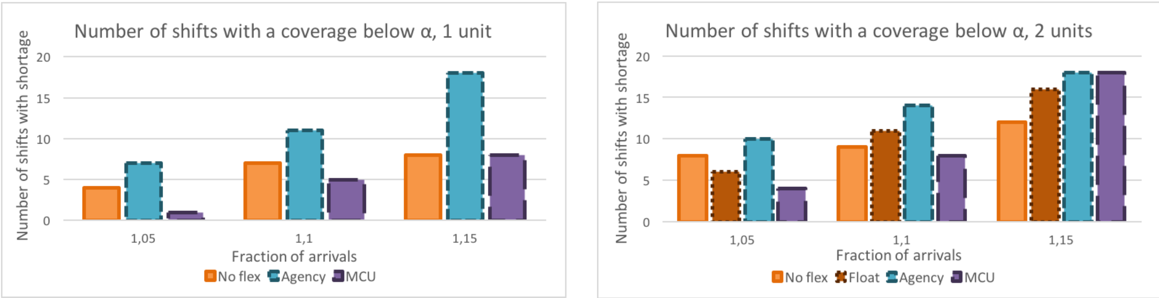


Figure 6.11: Sensitivity of arrivals, results from nurse staffing model without flexibility for required amount of FTE (α^k=0.95, β^k=0.75).

From Figure 6.11 we see that the required amount of FTE decreases when the arrivals decrease, which means the staffing levels decrease. In case of an increase in arrivals, the staffing levels have to be increased to meet the overall coverage level of 95%. Because of the change in required FTE when the arrivals change, we are also interested in the effect on the performance of the optimal solution found previously when the arrivals change.

To examine the performance of the optimal solution, we use the simulation model with the found optimal staffing levels as input and increase the arrivals. A decrease in arrivals is not examined as the optimal staffing levels will be sufficient to obtain the desired coverage level. The number of shifts with a coverage below α^k is shown for all staffing scenarios for increased arrivals in Figure 6.12.

From Figure 6.12 we see that the optimal solution where MCU-patients are separated is the most robust in case of a small increase in arrivals. The optimal solution with agency nurses using policy 1 gives in general the most shortages when the arrivals are increased. This is explained by the fact that for the agency nurse solution, the number of dedicated nurses is very small en the coverage of most shifts is such



(a) 1 unit (21 shifts). **(b)** 2 units (42 shifts).

Figure 6.12: Sensitivity of arrivals, shifts with a shortage from simulation model (α^k=0.95).

that it is just above 0.95. When arrivals are increased in case of agency nurses, either more dedicated nurses have to be scheduled or more agency nurses need to be hired.

When the use of agency nurses is not the preferred initial option for the optimal staffing levels, hiring agency nurses can be combined with the other options to make the solution more robust. When for example, we use the optimal solution for the no flexibility option but combine this with policy 1 for agency nurses, no shortages occur in any of the increased arrival cases. The average number of shifts worked by an agency nurse per year is shown in Table 6.13. For each shift the number of shifts by an agency nurse is far below the maximum number as described in Table 6.8. Since the shortages as shown in Figure 6.12 are very small (just below 95%), the coverage already reaches 95% when in rare occasions an agency nurse is hired.

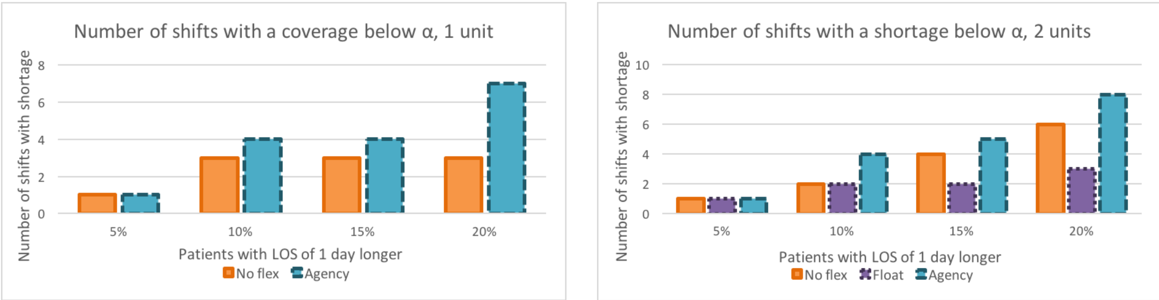
Table 6.13: On average the number of shifts worked by an agency nurse per year in case of increased arrivals and combining the optimal solution for no flexibility with policy 1 for agency nurses.

	Av. # shifts by agency nurse per year	
Arrival fraction	1 unit	2 units
1.05	33.54	47.49
1.10	43.69	61.94
1.15	55.90	79.12

6.6.7 Change in LOS

A change in the LOS of patients has a similar effect as a change in the arrivals of patients. When patients stay longer in the ICU, the average number of patients increase and more nurses will be needed. When patients stay shorter, less nurses will be needed. The effect of a change in LOS on required FTE is therefore similar to that of a change in arrivals, as it increases or decreases when LOS increases or decreases.

We are again interested in the effect of a changed LOS on the previous found optimal solutions for the different staffing scenarios. We used our simulation model to test the effect of a longer LOS, by adding one day to the LOS of 5%, 10%, 15% and 20% of the patients, while keeping the staffing levels constant. We excluded the experiment where MCU-patients are included, as the LOS is determined differently. Just as in Section 6.6.6, we determined the number of shifts per staffing option where the coverage was below 95%. The results are shown in Figure 6.13.



(a) 1 unit (21 shifts). **(b)** 2 units (42 shifts).

Figure 6.13: Sensitivity of LOS, shifts with a shortage from simulation model (α^k=0.95).

When we do the same as in Section 6.6.6, where we used the optimal staffing levels for the no flexibility option but combined this with policy 1 for agency nurses, we again see that there are no more shortages. We again see that the average number of shifts worked by an agency nurse is very low, which is shown in Table 6.14. The results are even lower than for the increased arrivals, which is because there are less shifts with shortages for the increased LOS options we examined than for the increased arrivals options.

Table 6.14: On average the number of shifts worked by an agency nurse per year in case of increased LOS and combining the optimal solution for no flexibility with policy 1 for agency nurses.

Patients with increased LOS	Av. # shifts by agency nurse per year 1 unit	2 units
10%	28.67	40.33
15%	30.69	43.21
20%	33.38	47.04

6.6.8 Change in definition of MCU-category

In the experiment where MCU-patients were included, we assumed that a patient is of the ICU-category if a patient is on respiratory support or dialysis, otherwise the patient is of the MCU-category. By doing so, a patient can shift multiple times between the two complexities of care, which we described in Section 4.3.1. To examine the influence of this decision, we determine optimal staffing levels in case of a different definition of MCU-patients.

For the purposes of the sensitivity analysis, we assume that a patient can only be of the MCU-category upon arrival to the ICU and as a last stage in the LOS. This means that the maximum number of transitions is two and all intermediate MCU-stays fall in the ICU-category. When a patient enters the ICU as an ICU-patient, only zero transitions or one transition is possible. When a patient enters the ICU in the MCU-category, it is possible to have zero, one or two transitions. In our simulation model we used the optimal staffing levels as found in Section 6.5 for including MCU-patients and calculated the coverage compliance for each shift with this new definition of the MCU-category. The shifts with a coverage below 0.95 are shown in Table 6.15.

Table 6.15: Sensitivity of definition MCU-category, shifts with a coverage below 0.95 from simulation model.

1 unit				**2 units**				
Day	Shift	Nurses	Coverage	Day	Shift	Unit	Nurses	Coverage
7	Late	6	0.945	4	Day	1	4	0.949
				5	Day	1	4	0.949
				5	Night	1	3	0.944

From Table 6.15 we see that in case of 1 unit there is only one very small shortage in the coverage level and in case of 2 units there are three small shortages. The shortages are however very small, so the fact that there are more ICU-patients than in our initial solution does not change to optimal solution too much. It is again a possibility to use agency nurses to make the solution for staffing levels more robust.

6.7 Implementation challenges

In this section we discuss some of the challenges of the different scenarios in terms of implementation. We start with the different options of merging the two units, using equal division or using halved arrivals.

Although we have shown in the previous sections that less nurses need to be scheduled when the two units are merged, this is not the most practical solution. The new ICU is designed such that each unit has its own nurses station and nurses supply and since both units are oblong, it will be hard to cover all beds with one team and keep a clear overview of all patients. The results for equal division can be used when each time a patient arrives, intensivists and nurses evaluate the number of patients in both units and assign the patient to the unit with the lowest census. It seems reasonable that this check is done each time a patient arrives, which leads to staffing levels lower than the situation where a patient has equal probability of being admitted to one of the units.

For the scenario where patients are divided equally over the two units, we examined four staffing scenarios, namely introducing no extra flexibility, using float nurses, hiring agency nurses and separating MCU-patients. To show the effort that is needed for these different staffing options compared to the impact, we have placed the options in an action priority matrix (Van Vliet, 2012) as shown in Figure 6.14. The action priority matrix consists of four quadrants, the quick wins which should always be executed, the thankless tasks which should be avoided and the fill ins and major projects which both need to be considered.

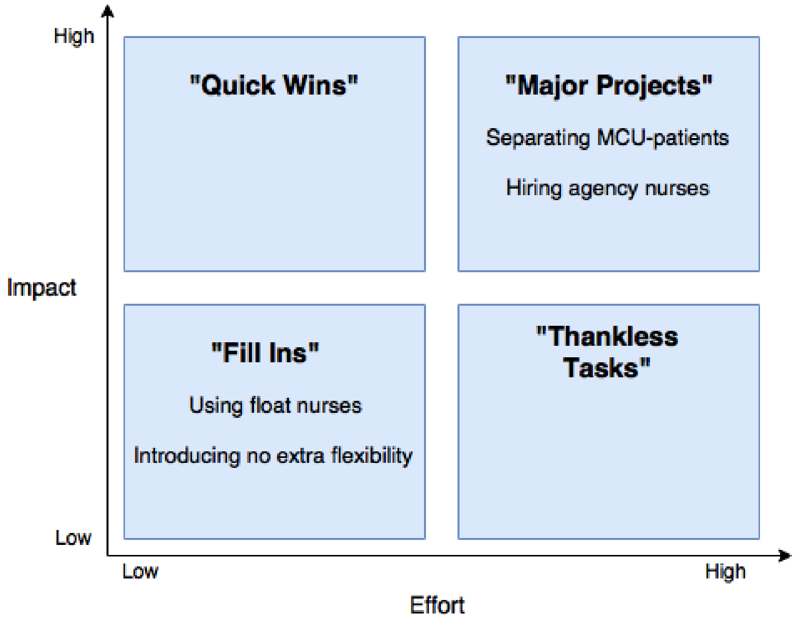


Figure 6.14: Action priority matrix (Van Vliet, 2012) for staffing scenarios in case of equal division of patients over the two units.

When comparing the four staffing scenarios, the most easy solution to implement is the option of no flexibility, followed by the option with float nurses. The float nurses are the same nurses as the regular nurses, but are assigned to the unit at the start of the shift, which is the only extra effort. Of the four options, these no flexibility and float nurse scenarios both have low impact on the cost savings in case of equal division. The low costs savings indicate that FTE does not need to be reduced much compared to the current situation with 14 beds, in fact the situation of no flexibility requires slightly more FTE as the costs are just above the current costs for shift hours. Combining these facts, leads to both scenarios being placed in the fill ins quadrant.

In the case of 2 units with equal division, we saw that separating MCU-patients led to the largest cost reduction. We already shortly mentioned the downside of this option, that dividing patients amongst nurses might be difficult and making sure each nurse is not taking care of too many patients is a constant process as patients keep switching between the two levels of care. Another issue is that the ICU-nurses need to be willing to take care of more patients at a time, as they are now used to taking care of at most two patients at a time. This option will take some time before it can be implemented, since the ICU management needs to find a way of dealing with the previous mentioned challenges. Another issue is that FTE needs to be reduced before the costs savings can be realized. To lower the effort of this option after implementation, it should be clear to the nurses how many patients of each complexity they can take care of at time on an individual level. When all options are known, it is easier for the nurses to asses their workload. ZGT management can also reconsider the definition of a MCU-patients, to assure less transitions between complexities. We conclude that this option requires high effort, but the impact will be high as well. For that reason, separating MCU-patients is placed in the Major Projects quadrant in Figure 6.14.

The second best option in case of 2 units with equal division was to make use of agency nurses. Before ZGT can use this option, contracts need to be closed with an employment agency, as ICU-nurses will be hired more often and these nurses need to be available. When ZGT desires to implement this scenario and make use of agency nurses, we have seen that the required FTE is the lowest, however just slightly lower than the MCU variant. The reduction in required FTE is one of the challenges of this scenario, as agency nurses are preferred over contracted nurses. It is however possible that ZGT changes contracts such that nurses work bank shifts, such that they can be called upon at the last moment, at a lower price than agency nurses. Another challenge of the agency nurse variant is dealing with an increase in arrivals or LOS. In Section 6.6.6 we saw that shortages occurred often when arrivals increase for some periods of time, as the coverage from the optimal solution is close to 95%, hence more agency nurses are needed than stated in the optimal solution. Combining the effort mentioned with the fact that the impact can be high when using agency nurses, we place this scenario in the Major Projects quadrant in Figure 6.14.

6.8 Conclusion

In this chapter we presented the results of the experiments as described in Section 5.3. The costs of the different scenarios we examined are shown in Table 6.16, which are based on the staffing levels required for each shifts in the week where an overall coverage of at least 95% is required. We also performed a sensitivity analysis to find the influence of some of the assumptions on these optimal solutions.

Table 6.16: Costs summary.

	Costs (k€) per year		
	1 unit	2 units, equal division	2 units, halved arrivals
Full staffing	3,601	3,726	3,726
No flexibility	3,016	3,122	3,264
Float nurses	-	3,069	3,105
Agency nurses	2,784	2,842	-
ICU and MCU	2,590	2,768	-

We concluded that staffing levels for both units will be best and equal division should be applied. The options with no flexibility and float nurses both do not give much problems for implementation, the scenario with float nurses only leads to a small reduction in costs for the case of equal division. We concluded that the scenarios with agency nurses and where MCU-patients are included both lead to a big costs reduction, but are a bigger challenge to implement. The option with agency nurses is not very robust when arrivals or LOS increase, and separating MCU-patients makes it harder for the nurses to assess their individual workload.

In Chapter 7 we give the final conclusions and recommendations on our research.

Chapter 7

Conclusions and recommendations

In this chapter, we present the conclusions of our research (7.1), recommendations for ZGT (7.2) and we end this chapter with suggestions for further research (7.3).

7.1 Conclusion

This research was initiated since ZGT is currently building a new larger ICU and new guidelines for ICUs are shifting focus to the actual patients in the ICU instead of number of beds. ZGT management was looking for more flexibility and hence the following objective was established:

> *Improve the alignment of supply with demand for intensive care, by considering the actual patients in the ICU and their complexity of care, where the objective is to find optimal nurse staffing levels to reduce costs, while maintaining a desired level of quality of care.*

We defined several research questions to realize this objective, of which we present the answers in short in this section.

The first question, *What is the current situation with respect to processes, control and performance?*, is answered in Chapter 2. We saw that on the ICU intensivists have the main responsibility of the patients, but ICU-nurses play an important role in the care provided. The staffing levels are currently fixed for the three shifts per day and Nurse-To-Patient (NTP) ratios are recommended in the guidelines for ICUs. Patients arriving can be categorized as acute or elective. For the performance measurement we looked at the realized NTP-ratios, coverage compliance, overstaffing rate and costs. We concluded that the staffing levels the ICU currently uses generally lead to overstaffing, as NTP-ratios were low, average coverage high as well as the overstaffing rate. Since more than 50% of ICU-costs are from nursing staff salaries, we concluded that it is probable that costs can be reduced when staffing levels better match patient supply. ZGT wanted to find optimal staffing levels for the new ICU and look into the possibility of intermediate care.

From literature we found previous research on these subjects to answer the question, *What models on nurse staffing and matching supply with demand in health care are known from literature?* We found several articles on nurse staffing that made use of either analytical models or simulation models. We chose the analytical nurse staffing model by Kortbeek et al. (2015), which focuses on finding optimal staffing levels with float nurses as a form of flexibility. The model makes use of two NTP-ratios, one that needs to be satisfied all the time and one that needs to be satisfied a certain percentage of the time. Another possibility of flexibility is hiring temporary agency nurses. From articles on intermediate care, we found that patients belonging on a Medium Care Unit (MCU) are patients not on ventilator support or dialysis.

To answer the question, *How can the ICU be modeled?*, we described the conceptual model for the nurse staffing model, as well as the conceptual model of the hourly bed census model (Kortbeek et al., 2014). The hourly bed census model is used as input for the nurse staffing model, as the output is a probability distribution for the number of patients in the ICU at any time point within the planning period. An important assumption is that patients only arrive at the start of an hour and leave at the and of an hour, which leads to results where the number of patients is overestimated. We needed to make some changes to the model to align it with our case study, of which one was the division of patients over the two equal ICUs. We defined two allocation policies, one where patients are equally divided and one where patients are assigned randomly to the units, by means of halved arrivals. For finding optimal staffing levels in case of including agency nurses and MCU-patients, we also built a simulation model.

The answer to the question *How can we set up experiments to improve the alignment of supply with demand?*, is given in Chapter 5. To set up experiments, we defined model input and validated the outcome of the model. We defined scenarios where either the two ICUs are merged, patients are divided equally over the two units or patients are divided randomly over the two units. We also separated scenarios in staffing possibilities, where either no flexibility is introduced, float nurses are scheduled, agency nurses can be hired or MCU-patients are separated. Next to experiments concerning these scenarios, we also performed a sensitivity analysis.

To answer *What are the results from the performed experiments?*, we combined solutions from the analytical models and the simulation model, to define optimal staffing levels per scenario. We found that merging units always led to the lowest staffing levels and using halved arrivals for dividing patients led to the highest staffing levels, caused by higher variability. Separating MCU-patients gave the minimum costs for staffing, followed by including agency nurses, while using float nurses was for all scenarios better than not introducing any flexibility.

To answer the final question, *What interventions should ZGT apply?*, we analyzed the sensitivity of the optimal solutions for the different scenarios and discussed the implementation difficulties. When the number of arrivals or the LOS of patients increases, we have seen that all options have shifts where the target coverage is not met. However, the option with agency nurses has by far the most shifts with a shortage. We have shown that other options for staffing can be combined with agency nurses in case of such increases, to make the solution more robust. While the options with no flexibility or float nurses will not give any problems in the implementation, we recommend on separating MCU-patients as we have shown that this intervention leads to the lowest costs. We explained that some difficulties arise in implementing this change, as nurses need to take care of more patients at a time and dividing the patients amongst nurses is a difficult task when patients keep changing complexities. For all options dividing patients equally over the two units gave lower costs than halved arrivals. We concluded that merging units is not a practical solution, but dividing patients equally should be possible.

With the research questions answered, we have shown possibilities for improving the alignment of supply with demand on the ICU of ZGT. For all options the quality of care is guaranteed as the coverage could not fall below a target level and the coverage is determined by considering the actual patients in the ICU. When the option of including MCU-patients is used, the complexity of care of the patients is also considered. We have shown optimal staffing levels for the different possibilities, all such that costs were minimized.

7.2 Recommendations

In this section we provide the management of the ICU of ZGT with recommendations on the implementation of different scenarios (7.2.1) and on data gathering to gain more insight in the activities performed by ICU-nurses (7.2.2).

7.2.1 Implementation

As mentioned in Section 7.1, we recommend on separating MCU-patients from ICU-patients, although dividing patients among nurses becomes difficult. We recommend ICU management to determine on an individual level what combinations of patients one nurse is allowed to care for per shift type. When nurses are aware of what is allowed and what is not, it should be easier to divide patients over the nurses. To make this division easier, ICU management should also consider different options for categorizing the MCU-patients and ICU-patients. In our model we used the fact that an ICU-patient is a patient on respiratory support or dialysis, which allows for a short LOS of any of the two complexities. These short length-of-stays make it harder for nurses to determine their workload. We recommend on reconsidering the definition of a MCU-patient, such that less transitions are possible. Since the cost savings for separating MCU-patients can only be realized when FTE is reduced, we recommend on not contracting any new nurses. In the first phase of implementing this scenario it will be convenient to have some more nurses during the shifts to get used to the new system, so FTE should not directly be reduced.

For the time where it is not yet possible to separate MCU-patients we recommend on using the staffing levels with float nurses for equal division as shown in Table 6.6, as we expect that there will not be any implications for implementing this scenario. When arrivals or LOS of patients differ, we recommend on hiring agency nurses on rare occasions.

7.2.2 Data gathering for outreach activities

In Section 2.1 we discussed the outreach activities of ICU-nurses, of which in Appendix B.1 more details were shown. Of these activities not enough data was available to use it in this research. We recommend on gathering more data on the different outreach activities, to allow for reliable conclusions on the influence of these activities on staff availability. Ideally, data would also be gathered on all other activities by ICU-nurses, such as admitting a patient or cleaning a patient. When data is available on all activities performed by the nurses and the demand for all these activities, it would be possible to use models such as the queueing models by Yankovic and Green (2011) and Véricourt and Jennings (2011) as discussed in Section 3.2.3.

Since we have seen in our results that there are still nurses overstaffed in the optimal solution, we expect that most of the time there is a nurse available to perform an outreach activity for a short time period. During busy periods, it might be difficult to be away from the ICU even for a short period of time. The category with the most activities are the consultancy tasks, as shown in Appendix B.1. These tasks can be scheduled such that they do not need to be performed during busy periods. We recommend, as long as there is not enough data on the outreach activities, that not only ICU-nurses are responsible for the consultancy activities that are more urgent. When there are no ICU-nurses available, nurses from another ward should also be able to perform activities like inserting a peripheral infusion. The activities of ICU-nurses being part of the Emergency Intervention Team (SIT) and Cardiopulmonary Resuscitation (CPR)-team can not be done by other nurses, so data gathering on these tasks should give more clarity on how often this will lead to nurse shortages.

7.3 Further research

In this section we present three opportunities for determining staffing levels for the ICU, namely combining options for determining required nursing staff (7.3.1), sharing float nurses with the Emergency Department (ED) such that nurse capacity is used more efficiently (7.3.2), and designing a decision support tool such that staffing levels can be determined several times a year (7.3.3).

7.3.1 Combining options for nursing staffing

In this research we looked at four scenarios for determining optimal staffing levels separately. We only shortly looked at the option of combining the optimal solution for no flexibility with agency nurses in case on increased arrivals or increased LOS. We recommend on doing further research on combining the scenarios for determining optimal staffing levels. Options like float nurses and separating MCU-patients combined can further decrease the required amount of FTE, although implementation will be more difficult.

7.3.2 Share float nurses with the ED

In using float nurses, we found that equal division of patients led to lower costs, but the effect of the float nurses was minimal. For halved arrivals however, where the variability in bed census is bigger, the effect of float nurses was substantially higher. Because of this observation, we believe that float nurses that can be assigned to either the ICU or the Emergency Department (ED) will be beneficial for the staffing costs of both departments.

As discussed in Section 3.2.2, float nurses are cross-trained nurses, that are enabled to float between similar departments. An initial investment needs to be made to cross-train the nurses, but both department will need less dedicated nurses as they will benefit from the float nurses during busy periods. In order to find optimal staffing levels for both the ICU and ED, data should be gathered from both departments. This data can be used in the models described in this research.

7.3.3 Design a decision support tool

To develop the models of this research further, we recommend on developing a decision support tool. Such a tool should be able to handle raw data and calculate optimal staffing levels with the scenario chosen by ICU management. In doing so, it is no longer needed to prepare data every time the staffing models need to be applied. It also allows for determining optimal staffing levels several times a year, as patient characteristics may change over time.

We recommend on doing research on designing a user friendly interface, which can be used by the planners. Ideally, data can be retrieved directly from the Patient Data Management System (PDMS), to fasten the application of the models.

Bibliography

Beliën, J. and Demeulemeester, E. (2008). A branch-and-price approach for integrating nurse and surgery scheduling. *European journal of operational research*, 189(3):652–668.

Billionnet, A. (1999). Integer programming to schedule a hierarchical workforce with variable demands. *European Journal of Operational Research*, 114(1):105–114.

Blot, F., Similowski, T., Trouillet, J.-L., Chardon, P., Korach, J.-M., Costa, M.-A., Journois, D., Thiéry, G., Fartoukh, M., Pipien, I., et al. (2008). Early tracheotomy versus prolonged endotracheal intubation in unselected severely ill icu patients. *Intensive care medicine*, 34(10):1779–1787.

Braun, J.-P., Mende, H., Bause, H., Bloos, F., Geldner, G., Kastrup, M., Kuhlen, R., Markewitz, A., Martin, J., Quintel, M., et al. (2010). Quality indicators in intensive care medicine: why? use or burden for the intensivist.

Brown, S. E., Ratcliffe, S. J., and Halpern, S. D. (2014). An empirical comparison of key statistical attributes among potential icu quality indicators. *Critical care medicine*, 42(8):1821.

Burke, E. K., De Causmaecker, P., Berghe, G. V., and Van Landeghem, H. (2004). The state of the art of nurse rostering. *Journal of scheduling*, 7(6):441–499.

Daly, B., Rudy, E., Thompson, K., and Happ, M. (1991). Development of a special care unit for chronically critically ill patients. *Heart & lung: the journal of critical care*, 20(1):45–51.

Davis, A., Mehrotra, S., Holl, J., and Daskin, M. S. (2014). Nurse staffing under demand uncertainty to reduce costs and enhance patient safety. *Asia-Pacific Journal of Operational Research*, 31(01):1450005.

De Vos, M. L. G., Van der Voort, P. H. J., and Graafmans, W. C. (2007). Kwaliteitsindicatoren voor de intensive care. `http://www.rivm.nl/dsresource?objectid=rivmp:11798&type=org&disposition=inline&ns_nc=1`. Retrieved April 29, 2016, from Rijksinstituut voor Volksgezondheid en Milieu.

Dellaert, N., Jeunet, J., and Mincsovics, G. (2011). Budget allocation for permanent and contingent capacity under stochastic demand. *International Journal of Production Economics*, 131(1):128–138.

Ernst, A. T., Jiang, H., Krishnamoorthy, M., and Sier, D. (2004). Staff scheduling and rostering: A review of applications, methods and models. *European journal of operational research*, 153(1):3–27.

Gnanlet, A. and Gilland, W. G. (2009). Sequential and simultaneous decision making for optimizing health care resource flexibilities. *Decision Sciences*, 40(2):295–326.

Green, L. V. (2002). How many hospital beds? *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, 39(4):400–412.

Green, L. V., Savin, S., and Savva, N. (2013). ?nursevendor problem?: Personnel staffing in the presence of endogenous absenteeism. *Management Science*, 59(10):2237–2256.

Griffiths, J. D., Price-Lloyd, N., Smithies, M., and Williams, J. E. (2005). Modelling the requirement for supplementary nurses in an intensive care unit. *Journal of the Operational Research Society*, pages 126–133.

Hancock, W. M., Pollock, S. M., and Kim, M.-K. (1987). A model to determine staff levels, cost, and productivity of hospital units. *Journal of medical systems*, 11(5):319–330.

Hans, E. W., Van Houdenhoven, M., and Hulshof, P. J. (2012). A framework for healthcare planning and control. In *Handbook of healthcare system scheduling*, pages 303–320. Springer.

Harper, P. R., Powell, N., and Williams, J. E. (2010). Modelling the size and skill-mix of hospital nursing teams. *Journal of the Operational Research Society*, 61(5):768–779.

He, B., Dexter, F., Macario, A., and Zenios, S. (2012). The timing of staffing decisions in hospital operating rooms: incorporating workload heterogeneity into the newsvendor problem. *Manufacturing & Service Operations Management*, 14(1):99–114.

Henneman, E., Dracup, K., Ganz, T., Molayeme, O., and Cooper, C. (2001). Effect of a collaborative weaning plan on patient outcome in the critical care setting. *Critical care medicine*, 29(2):297–303.

Hulshof, P. J., Kortbeek, N., Boucherie, R. J., Hans, E. W., and Bakker, P. J. (2012). Taxonomic classification of planning decisions in health care: a structured review of the state of the art in or/ms. *Health systems*, 1(2):129–175.

Iapichino, G., Radrizzani, D., Rossi, C., Pezzi, A., Anghileri, A., Boffelli, S., Giardino, M., Mistraletti, G., and Bertolini, G. (2007). Proposal of a flexible structural-organizing model for the intensive care units. *Minerva anestesiologica*, 73(10):501.

Jacobs, C., Van der Vliet, J., Van Roozendaal, M., and Van der Linden, C. (1988). Mortality and quality of life after intensive care for critical illness. *Intensive care medicine*, 14(3):217–220.

Kokangul, A., Akcan, S., and Narli, M. (2016). Optimizing nurse capacity in a teaching hospital neonatal intensive care unit. *Health care management science*, pages 1–10.

Kortbeek, N., Braaksma, A., Burger, C., Bakker, P., and Boucherie, R. (2015). Flexible nurse staffing based on hourly bed census predictions. *International journal of production economics*, 161:167–180.

Kortbeek, N., Braaksma, A., Smeenk, F. H., Bakker, P. J., and Boucherie, R. J. (2014). Integral resource capacity planning for inpatient care services based on bed census predictions by hour. *Journal of the Operational Research Society*, 66(7):1061–1076.

Lavieri, M. S. and Puterman, M. L. (2009). Optimizing nursing human resource planning in british columbia. *Health care management science*, 12(2):119–128.

Law, A. M. and Kelton, W. D. (2000). *Simulation modeling and analysis*, volume 3. McGraw-Hill New York.

Mallor, F. and Azcárate, C. (2014). Combining optimization with simulation to obtain credible models for intensive care units. *Annals of Operations Research*, 221(1):255–271.

Mathews, K. S. and Long, E. F. (2015). A conceptual framework for improving critical care patient flow and bed use. *Annals of the American Thoracic Society*, 12(6):886–894.

McManus, M. L., Long, M. C., Cooper, A., and Litvak, E. (2004). Queuing theory accurately models the need for critical care resources. *The Journal of the American Society of Anesthesiologists*, 100(5):1271–1276.

Nederlandse Vereniging van Ziekenhuizen (2015). Cao ziekenhuizen 2014-2016. `https://www.nvz-ziekenhuizen.nl/_library/27608/Cao%20Ziekenhuizen%202014-2016%20boekje%202.pdf`. Retrieved April 5, 2016, from Nederlandse Vereniging van Ziekenhuizen.

Nederlandse Vereniging voor Anesthesiologie (2006). Richtlijn organisatie en werkwijze op intensive care-afdelingen voor volwassenen in nederland. `http://nvic.nl/sites/default/files/Richtlijnen%20aanmaken/Intensive%20Care%202006%2C%20CBO%20Richtlijn.pdf`. Retrieved March 1, 2016, from Nederlandse Vereniging voor Intensive Care.

Nederlandse Vereniging voor Anesthesiologie, Nederlandse Vereniging voor Intensive Care en Nederlandse Internisten Vereniging (2015). Richtlijn intensive care. `http://www.intensivistenopleiding.nl/downloads-8/files/Richtlijn%20IC%20definitief.pdf`. Retrieved March 1, 2016, from Regionale Intensive Care Opleiding Nijmegen.

Nguyen, Y.-L., Wunsch, H., and Angus, D. C. (2010). Critical care: the impact of organization and management on outcomes. *Current opinion in critical care*, 16(5):487–492.

Oddoye, J., Yaghoobi, M., Tamiz, M., Jones, D., and Schmidt, P. (2007). A multi-objective model to determine efficient resource levels in a medical assessment unit. *Journal of the Operational Research Society*, 58(12):1563–1573.

Prin, M. and Wunsch, H. (2014). The role of stepdown beds in hospital care. *American journal of respiratory and critical care medicine*, 190(11):1210–1216.

Ridge, J., Jones, S., Nielsen, M., and Shahani, A. (1998). Capacity planning for intensive care units. *European journal of operational research*, 105(2):346–355.

Ridley, S. (1998). Intermediate carepossibilities, requirements and solutions. *Anaesthesia*, 53(7):654–664.

Seung-Chul, K., Ira, H., et al. (2000). Flexible bed allocation and performance in the intensive care unit. *Journal of Operations Management*, 18(4):427–443.

Solberg, B., Dirksen, C. D., Nieman, F., van Merode, G., Poeze, M., and Ramsay, G. (2008). Changes in hospital costs after introducing an intermediate care unit: a comparative observational study. *Crit Care*, 12(3):R68.

Steins, K. and Walther, S. (2013). A generic simulation model for planning critical care resource requirements. *Anaesthesia*, 68(11):1148–1155.

Thompson, F.-J. and Singer, M. (1995). High dependency units in the uk: variable size, variable character, few in number. *Postgraduate medical journal*, 71(834):217–221.

Thungjaroenkul, P. and Kunaviktikul, W. (2006). Possibilities for cost containment in intensive care. *Nursing & health sciences*, 8(4):237–240.

Van der Voort, P., Keesman, E., Burger, D., Corsten, A., Van Dijk, F., De Jonge, E., Gielen, J., Polderman, K., De Graaf, W., and Van Zanten, A. (2004). Kwaliteitsindicatoren voor de intensive care en high care afdelingen. *Netherlands Journal of Critical Care*, 8(5).

Van Vliet, V. (2012). Action priority matrix. `http://www.toolshero.com/effectiveness/action-priority-matrix`. Retrieved September 1, 2016, from Toolshero.

Vanberkel, P. T., Boucherie, R. J., Hans, E. W., Hurink, J. L., Van Lent, W. A., and Van Harten, W. H. (2011). An exact approach for relating recovering surgical patient workload to the master surgical schedule. *Journal of the Operational Research Society*, 62(10):1851–1860.

Véricourt, F. d. and Jennings, O. B. (2011). Nurse staffing in medical units: A queueing perspective. *Operations Research*, 59(6):1320–1331.

Vincent, J. and Burchardi, H. (1999). Do we need intermediate care units? *Intensive care medicine*, 25(12):1345–1349.

Wild, B. and Schneewei, C. (1993). Manpower capacity planning?a hierarchical approach. *International Journal of Production Economics*, 30:95–106.

Williams, T. and Leslie, G. (2004). Delayed discharges from an adult intensive care unit. *Australian Health Review*, 28(1):87–96.

Wright, P. D., Bretthauer, K. M., and Côté, M. J. (2006). Reexamining the nurse scheduling problem: Staffing ratios and nursing shortages*. *Decision Sciences*, 37(1):39–70.

Yankovic, N. and Green, L. V. (2011). Identifying good nursing levels: a queuing approach. *Operations research*, 59(4):942–955.

Appendix A

Data selection

ZGT uses two data systems on the ICU, ChipSoft and Mediscore. ChipSoft is the Patient Data Management System (PDMS) used in the entire hospital. This means that in the ChipSoft system data is available on the ICU stay, but also on the arrival and departure from the hospital, other wards the patient has visited etc. Mediscore is a system only used on the ICU, it is a system where more information is available on the complexity of care of the patients and the medication the patient has received. Arrival and departure times are only available from the ICU. We received an anonymized list of all patients admitted to the ICU from both systems, a total of 1529 admissions were included in the Chipsoft data file and a total of 1506 admissions were included in the Mediscore data file. To make sure we used a list of the patients who had really been admitted to the ICU, we compared the two data files and excluded the admissions that were only stated in one of the lists. For some admissions a logical reason could be found for why the admissions was not included in the other list, but not for all. An overview of the characteristics of the excluded admissions is shown in Table A.1.

Table A.1: Admissions excluded from Chipsoft and Mediscore.

	Characteristics	ChipSoft	Mediscore
Total before exclusions		1529	1506
	Children	−13	
	Double admission		−3
	In system in both units		−4
	Test admission	−3	
	For no explainable reason not in other system	−16	−2
Total		1497	1497

We see that 13 admissions were excluded from the ChipSoft file, which were concerning children. Children are not supposed to be admitted to the ICU of ZGT, this only happens on rare occasions when the children stay very shortly to be stabilized such that they can be transferred to a pediatric ICU. For that reason these admissions can be left out of consideration without affecting the characteristics of the ICU. The other exclusions that can be explained are mainly mistakes in the data: test admissions which were no real patients, double admissions that were admissions twice in the system with slightly different times and patients that were admitted in the system in both units overlapped in time. This last error is caused by a transfer between units, where the patient was not discharged from the original unit in the PDMS. All these errors were excluded from the files. That leaves 16 admissions in the ChipSoft file that were not included in the Mediscore file and 2 vice versa. We excluded these admissions for our research, but no explanation could be found for the missing data.

Now that all admissions and patients in the two system match, only the admission times and discharge times differ slightly. We decide to use the data from the Mediscore file, because more information on the patients treatment can be found from this system and there were less admissions in this system that did not coincide with the other.

Appendix B

Extra information on nurses

In this appendix we show in more detail what outreach activities entail (B.1) and we discuss the rare occasions when there were less nurses than scheduled on the ICU (B.2).

B.1 Outreach activities

In Section 2.1.2 we discussed that an ICU-nurse can be assigned the red spot, which means he is responsible for all outreach activities. These activities consist of Consulting ICU-nurse (CIV), Emergency Intervention Team (SIT) and Cardiopulmonary Resuscitation (CPR). These outreach activities need some more explanation.

One of the CIV-tasks of the red spot nurse is after care for patients who have been recently discharged from the ICU and are transferred to a ward. When a patient has been in the ICU for more than 72 hours, a CIV needs to visit this patient every day on the ward for a minimum of two days. Other CIV-task are to be available on a consultancy basis for the ward nurses or support a ward nurse or advise on some of the more complex medical treatments. The most common CIV-activities are shown in Table B.1.

Table B.1: CIV-activities, data from January 1 2014 - December 31 2015 of 3370 activities retrieved from Chipsoft.

CIV-activity	Number of times	Avg. duration (min)
Insert a peripheral infusion	2138	12.02
After care	534	20.30
Tracheal suction on ward	237	14.25
Provide central line	82	13.01
Care for tracheostomy on ward	31	13.21
Other	348	14.16

The red spot nurse is also part of the already mentioned SIT team. This team consists of the resident of the ward, the intensivist and the red spot nurse of the ICU, they needs to visit patient rapidly when their vital signs are deteriorating. The SIT is separated from the other CIV activities, which are only on consultancy basis.

The red spot nurse is also part of the CPR team. When a patient goes into cardiac arrest, a team of different departments rushes to the patient. The red spot nurse needs to be present because it might happen that the patient is not able to breathe on its own and needs the help of a ventilator.

The CIV, SIT and CPR activities over the years 2014 and 2015 are shown in Table B.2. It becomes clear that the CIV-tasks needs to be performed more often than the SIT- and CPR-tasks.

Table B.2: Outreach activities, data from January 1 2014 - December 31 2015 of 3658 activities retrieved from Chipsoft.

	CIV	SIT	CPR
Total	3370	92	196
Avg. per day	4.62	0.13	0.27
Min. per day	0	0	0
Max. per day	20	5	4
Within office hours (9.00h-17.00h)	1370	23	69
Outside office hours	2000	65	86
Unknown time	0	4	41

B.2 Nurse shortages

In reality, the number of nurses working is not always according to the fixed number that are supposed to be working. Only some data is available on situations where a nurse declared in advance that he was not able to work the shift and where no replacement from the ICU-staff was found. Only in rare occasions, a nurse was hired via an EA. This is shown in Table B.3.

Table B.3: Shortages in nurses known in advance for the year 2015.

Shift	Total shortage nurses	Shifts by EA	Avg nurses per shift
11	30	0	6.92
L1	19	0	4.95
N1	27	3	4.93
61	2	1	2.99*
L6	3	0	2.99*
N6	5	2	1.98*
Total	**86**	**6**	

* Average taken over regular period only.

When looking closer at the nurse shortage, there are only 5 situations of the 86 that could lead to a (possible) exceeding of the max. span of control nurses. When one nurse was short, a problem might occur when there are 13 or 14 patients and when there are two nurses short, a problem might occur when there are more than

10 patients. It is important to note that we use 1:2 as the NTP ratio which ZGT currently uses.

Of these 5 situations, the only one that leads to a shortage in staff was during a late shift on February 21. During the entire shift there were 13 patients in the ICU, three nurses available on 5 Oost and four nurses on 1ICU. When there are four patients in 5 Oost, this gives a nurse-to-patient ratio of 1:1.33 and then there are 9 patients in 1ICU, which gives a nurse-to-patient assignment of 1:2.25. In this situation, the ratio 1:2 ZGT currently uses was exceeded. It would make sense that one nurse scheduled on 5 Oost would have worked on 1ICU, to make the ratios 1:2 and 1:1.8 respectively for 5 Oost and 1ICU.

Appendix C

ICU related costs

In this appendix we show the costs and budgets for the years 2012 until 2015 (C.1), the procedure of determining the required amount of FTE that ZGT uses (C.2) and lastly we determine the costs per hour for an ICU-nurse (C.3).

C.1 ZGT budget for ICU

Every year, a budget is established for the entire ICU. This budget consists of among others the costs for salaries, social costs, patient related costs and costs for building use. A large portion of the budget is spent on salaries, this is shown for the years 2012-2015 in Tables C.1.

Table C.1: Costs and budget for 2012-2015.

	2012		**2013**		**2014**		**2015**	
	Incurred expenses (k€)	Budget (k€)	Incurred expenses (k€)	Budget (k€)	Incurred expenses (k€)	Budget (k€)	Incurred expenses (k€)	Budget (k€)
Total	**5,089**	**4,742**	**5,307**	**4,677**	**5,559**	**4,989**	**5,154**	**4,903**
Salaries	3,485	2,964	3,804	3,349	4,202	3,522	3,989	3,427
General staff	62	53	53	54	52	57	56	57
Patient related staff	2,735	2,531	2,660	2,493	2,902	2,631	2,813	2,549
Nurses	2,466	2,246	2,517	2,339	2,550	2,487	2,468	2,403
Interns	24	–	0.7	–	2	–	–	–
Staff not employed	170	–	364	–	455	–	421	–
Patient related staff	170	–	282	–	245	–	6	–
Other salary costs	494	381	727	803	792	834	700	821
Overtime	11	11	13	11	27	11	18	11
Irr. work time	352	370	342	377	359	384	355	384
Maternity premium	-93	–	-72	–	-96	–	-119	–
Holiday pay	–	–	217	204	238	215	229	208
End of year bonus	224	–	227	212	229	224	216	217
Social costs	1,013	1,184	836	762	990	881	860	857

Some of the most important subcategories are shown for the different costs, but some additional explanation on costs categories is needed. The costs for general staff is for the department secretary, the ICU has its own secretaries. Patients related staff consists of a unit head, or team-leader, nurses, health-care assistants and medical specialists. The highest costs are for the nurse salaries, which are shown in the tables. Interns are not certified to perform real nurse activities, so they are not part of the nursing team. They only get a small fee for the time they spent in the ICU.

Staff not employed are the nurses or other staff that work via an emergency agency. These costs differ a lot over the last couple of years. The hospital has had some trouble with finding an appropriate team leader for the ICU and a medical specialist has suffered from a prolonged illness. This all led to occasional high costs, which are not included in the costs for patient related staff which are not employed. These costs can be attributed to shortages in nurse staffing, where a temporary employee was hired. Since the management of the ICU believed the costs for these employees was too high, a decision was made to try and avoid the situation of hiring temporary labor. This is clear from the costs made in 2015, as shown in Table C.1.

Lastly, the other salary costs consists of annual bonuses, holiday pay, maternity premiums and additional costs for overtime and irregular work times. According to the collective labor agreement for 2014-2016 (Nederlandse Vereniging van Ziekenhuizen, 2015), a compensation is given for irregular work times in the form of a financial reward or free time.

From Table C.1 we see that especially the costs for patient related staff is higher than its budget. This is explained by the fact that there is no budget available for medical specialists. This is due to the fact that these specialists are officially contracted by the intensive care department, but the ICU is paid a compensation for this staff. Because of this compensation no budget is available, but there are costs listed.

The budget for general staff and patient related staff is determined by necessary FTE. Often more FTE is used at the end of the year than the amount that was budgeted at the beginning of the year. This is caused by several reasons. One of them is nurses or other staff that go on maternity leave. These nurses are still employed, but are less available. The hospital receives a premium for maternity, which falls under other salary costs. An overview of the total amount of FTE of 2012-2015 for the ICU is given in Table C.2. Not only maternity leaves lead to a higher amount of contracted FTE, also the high sick leave rate amongst the ICU-nurses. In Table C.3 the absenteeism rates for the entire ZGT and the ICU are shown for the years 2012-2015. The rates for the ICU are substantially higher than for the overall hospital. These numbers can all be used to explain the increase in contracted FTE compared to the budget. How the required amount of FTE is currently calculated is shown in Appendix C.2.

C.2 Required amount of FTE

To give an idea on how the required amount of FTE is calculated to determine the budget, we explain the procedure for 2015.

Table C.2: FTE for 2012-2015.

	2012		2013		2014		2015	
	Actual FTE	Budget	Actual FTE	Budget	Actual FTE	Budget	Actual FTE	Budget
General staff	2.39	2.00	1.99	2.00	1.77	2.00	1.84	2.00
Patient related staff	70.49	65.13	67.61	64.55	69.24	67.34	64.62	64.80
Nurses	63.55	57.64	63.68	59.89	63.67	61.38	59.65	58.84
Other salary costs	-2.23		-1.59		-1.27		-2.44	
Maternity premium	-2.23		-1.59		-1.27		-2.44	
Total	71.76	67.13	68.00	66.55	69.74	69.34	64.02	66.80

Table C.3: Absenteeism figures for 2012-2015 for the entire hospital and the ICU.

	ZGT		**ICU ZGT**	
	Absenteeism (%)	Abs. excl. maternity (%)	Absenteeism (%)	Abs. excl. maternity (%)
2012	6.87	5.51	9.91*	7.83*
2013	6.36	5.06	10.85	8.58
2014	6.08	4.62	10.69	8.34
2015	6.69*	5.31*	13.14	9.34

*not all 12 months included

Calculation of required number of nurse-FTE for 2015

The assumptions made for the required number of nurses for 2015 are:

- The ICU in Almelo is still in two locations.
- The reduction-period is from June until August and during this period 5 Oost is closed.
- The ICU in Hengelo is still open with only 2 bed and requires just 1 nurse.
- The total amount of student nurses is 6.

We see that from January until May there are 14 beds available in Almelo and 2 in Hengelo (22 weeks), from June until August 10 beds are available in Almelo and 2 in Hengelo (14 weeks) and form September until December there are again 14 beds available in Almelo and 2 in Hengelo (16 weeks). In reality though, the reduction period is merely 5 weeks per year.

To make sure there is enough personnel for these beds, a fixed number of nurses is planned for each shift. From these fixed numbers the required FTE for nurses actually on the ICU are calculated. After these calculations are done, extra hours are determined for other direct hours and indirect hours. This is combined with available student nurses to come to a final figure on required FTE. In Table C.4 the total amount of hours required for the shifts per period is calculated, where the periods have the duration as just described.

With the amount of hours required, the required amount of FTE can be calculated. In order to do so, the amount of hours available from one FTE needs to be known.

Table C.4: Required nurse hours for shifts 2015.

	1ICU	5 Oost		Hengelo
Nurses	[7,5,5]	Regular	[3,3,2]	[1,1,1]
		Reduction	[0,0,0]	
Hours per pediod				
Jan.-May	21,329	10,010		3,773
June-Aug.	15,512	7,280		2,744
Sep.-Dec.	13,573	2,744		2,410

In Table C.5 we see that each contracted nurse is available for a total of 1540 hours per year. Using the required hours per year from Table C.4, we can calculate the required amount of FTE for 2015. The result for the required FTE for the shift hours is shown in Table C.6.

Table C.5: Gross hours and net hours per year per FTE.

Work hours per week	36 hours
Number of weeks per year	52.18 weeks
Gross hours per year	**1878.43 hours**
Reduction for public holidays, vacation days and sick leave	-338.43 hours
Net hours per year	**1540 hours**
Gross/net factor	**1.22**

Table C.6: Required FTE 2015 shift hours, excluding other direct hours, indirect hours and student nurses.

	1ICU FTE	5 Oost FTE	Hengelo FTE	**ZGT ICU FTE**
Jan.-May	13.85	6.5	2.45	22.80
June-Aug.	8.81	0	1.56	10.37
Sep.-Dec.	10.07	4.73	1.78	16.58
Total	**32.74**	**11.23**	**5.79**	**49.75**

This number of 49.75 FTE represents the required number of nurses to cover the shifts according to the predetermined fixed number of nurses that need to be present during a shift, we still need to add hours for other direct labor and indirect labor, such as CIV/SIT, and take student nurses into account. For direct and indirect labor extra hours are determined, which leads to an additional 5.37 FTE. It should be noted that extra hours for CIV/SIT are taken into account in making the budget for the amount of nurses employed in the corresponding year, but these tasks are performed by the nurses that work the shifts, for which the required nurses were already separately determined. So extra FTE is in the budget of the ICU for CIV/SIT tasks, but no separate extra personnel is scheduled for these tasks.

Lastly, the student nurses are taken into account in the required FTE calculated. 6 student nurses employed, who can take a workload of 38% (predetermined percentage), so 2.28 FTE. This amount is deducted, however, these 6 student nurses need to get paid as well, so a total of 6 is added again. This makes the final budget of

FTE for 2015 58.84, which is also shown in Table C.2. The numbers are summarized in Table C.7.

Table C.7: Required FTE 2015.

	FTE
Shift hours	49.75
Direct and indirect labor	5.57
6 student nurses 38% deployable	-2.28
6 student nurses	6
Total	**58.84**

C.3 Nurse associated costs

In this section we look at the salary of an ICU-nurse (C.3.1) and the costs for one hour of work by an ICU-nurse (C.3.2).

C.3.1 Salaries of ICU-nurses

In the collective labor agreements for hospitals (Nederlandse Vereniging van Ziekenhuizen, 2015) is described that an employee should have an employment contract with a current function description as part of the contract. The function is classified into one of the function classes 5-80, which is done according the FWG-system (FWG stands for job rating for health care (Functie Waardering Gezindheidszorg)).

The function class determines the salary scale, general nurses get a salary according to scale 45, while ICU-nurses get salaries according to scale 55. All different levels for salaries (for all scales) have an ip-number. The same ip-number can occur in different levels, however at different levels of experience. Within each salary scale one can earn more as the years of experience becomes bigger. For the average amount of salary for an ICU-nurse, ZGT uses the level 55-10, which means scale 55 with ten years of experience. In Table C.8 the salary scales 45-55 are shown

We see that an ICU-nurse earns on average €3,636.- per month, which is a total of €43,632.- per year. When we want to know how much we have to pay an ICU-nurse per hour, we need to use the net hours an ICU-nurse works per year and the extra social costs that need to be paid. We consider these subjects in the next section.

C.3.2 Costs for one hour work

To take all costs into account, we also look at holiday allowance and end of year bonus. On holiday allowance the following is stated in the collective labor agreements:

- The holiday allowance for the employee who has been employed for a full year on May 31 is 8% of the annual salary, where the annual salary is twelve times the prevailing wage on May 1.

Table C.8: Salaries for scales 45, 50 and 55.

Experience (years)	**Scale 45** ip-number	Salary (€)	**Scale 50** ip-number	Salary (€)	**Scale 55** ip-number	Salary (€)
0	14	2066	17	2251	22	2567
1	16	2195	19	2378	24	2695
2	18	2317	21	2505	26	2829
3	19	2378	23	2631	28	2960
4	20	2442	25	2760	30	3097
5	21	2505	27	2898	32	3227
6	22	2567	28	2960	34	3363
7	23	2631	29	3029	35	3425
8	24	2695	30	3097	36	3490
9	25	2760	31	3162	37	3562
10	26	2829	32	3227	38	3636
11	27	2898	33	3294	39	3709
12	28	2960	34	3363	40	3774

- If the employee has been employed only part of the period for which holiday allowance is calculated, or he worked part-time during that period, he is proportionately entitled to a holiday allowance.

For calculating the extra wage for one FTE for holiday allowance, we just add 8% of the annual amount of salary. In this case that is €3,490.56.

On the end of year bonus the following is stated in the collective labor agreements:

- The end of the year bonus for the employee who has been employed for a full year on December 31 is 8.33% of the annual salary, where the annual salary is twelve times the prevailing wage on December 1.
- If the employee has been employed only a part of the period for which the year-end bonus is calculated, or he worked part-time during, he is proportionately entitled to the annual bonus.

For calculating the extra wage for one FTE for the end of the year bonus, we just add 8.33% of the annual amount of salary. In this case that is €3,634.55.

When we add the numbers we get a total annual salary of €50,757.11. We still have to add the social costs to get the total amount ZGT needs to pay one ICU-nurse who works full-time. To come to this total amount, ZGT has advised to use a factor of 1.5 times the gross salary in a year, so 50% of costs are social costs, which include the holiday pay and the end of year bonus. When using the factor 1.5 we find the amount of €65,448.- per year.

When an ICU-nurse is available for 1540 hours each year (Table C.5) for a salary of €65,448.- per year, this means that the hourly pay for an ICU-nurse is €42.50.

Appendix D

Input hourly bed census model

D.1 ICU-patients only

Table D.1: Input parameters $b_{i,s}$

$\boldsymbol{b_{i,s}}$	i	s	Patient type
	1	1	1
	1	2	2
	1	3	3
	1	4	4
	1	5	5
	1	6	6
	1	7	7

Table D.2: Input parameters λ_j

$\boldsymbol{\lambda_j}$	Arr.	Arrival time (θ)										
	Day	0.00	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	...
	Mo.	0.055	0.077	0.077	0.033	0.066	0.022	0.044	0	0.033	0.066	0.066	...
	Tu.	0.099	0.055	0.022	0.044	0.011	0	0.033	0.011	0.077	0.044	0.154	...
	We.	0.066	0.044	0.044	0.022	0.044	0.011	0.044	0.033	0.000	0.033	0.121	...
	Th.	0.044	0.055	0.077	0.011	0.011	0.022	0.011	0.044	0.044	0.066	0.077	...
	Fr.	0.066	0.044	0.066	0.011	0.033	0.044	0.033	0.033	0.044	0.121	0.099	...
	Sa.	0.088	0.044	0.033	0.011	0.022	0.044	0.055	0.044	0.044	0.066	0.044	...
	Su.	0.165	0.077	0.044	0.044	0.055	0.066	0.044	0.011	0.055	0	0.066	...

Table D.3: Input probabilities $c_j(k)$

$\boldsymbol{c_j(k)}$		Patient type j						
	k	1	2	3	4	5	6	7
	0	0.351	0.521	0.330	0.606	0.702	0.926	0.968
	1	0.574	0.298	0.309	0.266	0.234	0.074	0.032
	2	0.074	0.149	0.309	0.138	0.064	0	0
	3	0	0.032	0.064	0	0	0	0

Table D.4: Input probabilities e_n^j

$\boldsymbol{e_n^j}$	n	All patient types
	-1	0
	0	1

Table D.5: Input probabilities $w_{n,t}^{j}$

$\boldsymbol{w}_{n,t}^{j}$	t	Patient type j 1	2	3	4	5	6	7
	0.00	0	0	0.009	0	0.027	0.286	0
	1.00	0	0	0.009	0	0	0	0
	2.00	0	0	0	0	0	0	0
	3.00	0.014	0	0	0	0	0	0
	4.00	0	0	0	0	0	0	0
	5.00	0	0	0	0	0.054	0	0
	6.00	0	0	0	0.018	0.027	0	0
	7.00	0	0	0	0	0	0	0
	8.00	0	0	0.018	0.018	0.027	0.143	0.250
	9.00	0	0.072	0.009	0.073	0.108	0.143	0
	10.00	0.014	0.014	0.027	0.036	0.081	0	0
	11.00	0.014	0.058	0.155	0.073	0.081	0	0.250
	12.00	0.069	0.072	0.073	0.127	0	0	0
	13.00	0.028	0.188	0.082	0.127	0.081	0	0
	14.00	0.236	0.159	0.136	0.109	0.081	0.143	0.250
	15.00	0.292	0.145	0.173	0.091	0.189	0.143	0
	16.00	0.167	0.101	0.109	0.109	0.135	0	0
	17.00	0.111	0.116	0.118	0.091	0.054	0.143	0
	18.00	0.014	0.014	0.027	0.073	0	0	0
	19.00	0	0.014	0.036	0.018	0.027	0	0.250
	20.00	0.042	0.043	0.018	0.036	0.027	0	0
	21.00	0	0	0	0	0	0	0
	22.00	0	0	0	0	0	0	0
	23.00	0	0	0	0	0	0	0

Table D.6: Input probabilities $P^j(n)$

$\boldsymbol{P}^j(n)$		Patient type j										
	n	1	2	3	4	5	6	7	8	9	10	...
	0	0	0	0.009	0.018	0.135	0.143	0	0.200	0.375	0.571	
	1	0.569	0.696	0.691	0.618	0.514	0.143	0.250	0.600	0.375	0.143	...
	2	0.222	0.174	0.182	0.073	0.081	0.571	0.250	0	0.125	0.286	...
	3	0.069	0.029	0.045	0.073	0.054	0.143	0.250	0.200	0	0	...
	4	0.028	0.058	0	0.109	0	0	0	0	0	0	...
	5	0.028	0	0.018	0.036	0.054	0	0	0	0	0	...
	6	0.014	0	0	0	0	0	0.250	0	0	0	...
	7	0.014	0	0.009	0.018	0.054	0	0	0	0	0	...
	8	0.042	0	0.009	0.036	0	0	0	0	0	0	...
	9	0	0.029	0	0	0	0	0	0	0	0	...
	10	0	0.014	0	0	0.054	0	0	0	0	0	...
	11	0.014	0	0	0	0	0	0	0	0	0	...
	12	0	0	0.009	0	0	0	0	0	0	0	...
	13	0	0	0.009	0	0	0	0	0	0	0	...
	14	0	0	0	0	0	0	0	0	0.125	0	...
	15	0	0	0	0	0	0	0	0	0	0	...
	16	0	0	0	0	0	0	0	0	0	0	...
	17	0	0	0	0	0	0	0	0	0	0	...
	18	0	0	0	0	0	0	0	0	0	0	...
	19	0	0	0	0	0	0	0	0	0	0	...
	20	0	0	0	0	0	0	0	0	0	0	...
	21	0	0	0	0	0	0	0	0	0	0	...
	22	0	0	0	0.018	0	0	0	0	0	0	...
	23	0	0	0	0	0	0	0	0	0	0	...
	24	0	0	0	0	0	0	0	0	0	0	...
	25	0	0	0	0	0.027	0	0	0	0	0	...
	26	0	0	0.009	0	0	0	0	0	0	0	...
	27	0	0	0	0	0	0	0	0	0	0	...
	28	0	0	0	0	0	0	0	0	0	0	...
	29	0	0	0	0	0	0	0	0	0	0	...
	30	0	0	0	0	0	0	0	0	0	0	...
	...	...	...	...	...	...	...	...	...	...	...	...

Table D.7: Input probabilities $m^j_{n,t}$

$\boldsymbol{m}^j_{n,t}$			Patient type j									
	n	t	1	2	3	4	5	6	7	8	9	...
	0	0.00	0	0	0	0	0	0	0	0	0	...
	...	...	...	...	...	...	...	...	...	...	...	...
	0	11.00	0	0	0	0	0	0	0	1	0.333	...
	0	12.00	0	0	0	0	0	0	0	0	0	...
	0	13.00	0	0	0	0	0	0	0	0	0	...
	0	14.00	0	0	0	0	0	0	0	0	0	...
	0	15.00	0	0	0	0	0	0	0	0	0.667	...
	0	16.00	0	0	0	0	0	0	0	0	0	...
	0	17.00	0	0	0	0	0	0	0	0	0	...
	0	18.00	0	0	0	0	0	0	0	0	0	...
	...	...	...	...	...	...	...	...	...	...	...	...
	0	23.00	0	0	0	0	0	0	0	0	0	...
	1	0.00	0	0	0	0	0	0	0	0	0	...
	...	...	...	...	...	...	...	...	...	...	...	...
	1	9.00	0	0	0.026	0	0	0	0	0	0	...
	1	10.00	0	0.042	0.039	0.118	0	0	0	0	0	...
	1	11.00	0.317	0.583	0.395	0.441	0.421	1	1	0.333	0	...
	1	12.00	0.049	0.083	0.079	0.059	0.158	0	0	0.333	0	...
	1	13.00	0.220	0.125	0.132	0.235	0.158	0	0	0	0	...
	1	14.00	0.366	0.146	0.289	0.118	0.211	0	0	0	0.667	...
	1	15.00	0.024	0	0.039	0.029	0	0	0	0	0	...
	1	16.00	0	0.021	0	0	0	0	0	0	0.333	...
	1	17.00	0	0	0	0	0	0	0	0	0	...
	1	18.00	0	0	0	0	0.053	0	0	0	0	...
	...	...	...	...	...	...	...	...	...	...	...	...
	1	23.00	0	0	0	0	0	0	0	0	0	...
	≥ 2	0.00	0	0	0	0	0	0	0	0	0	...
	...	...	...	...	...	...	...	...	...	...	...	...
	≥ 2	9.00	0	0	0	0	0	0	0	0	0	...
	≥ 2	10.00	0.063	0	0	0.250	0	0	0	0	0	...
	≥ 2	11.00	0.313	0.333	0.450	0.250	0.333	0.250	1	0	0	...
	≥ 2	12.00	0	0.250	0.100	0	0	0.250	0	0	0	...
	≥ 2	13.00	0.250	0.167	0.150	0.250	0	0.250	0	1	0	...
	≥ 2	14.00	0.375	0.250	0.250	0.250	0.667	0.250	0	0	0.500	...
	≥ 2	15.00	0	0	0.050	0	0	0	0	0	0	...
	≥ 2	16.00	0	0	0	0	0	0	0	0	0	...
	≥ 2	17.00	0	0	0	0	0	0	0	0	0	...
	≥ 2	18.00	0	0	0	0	0	0	0	0	0	...
	...	...	...	...	...	...	...	...	...	...	...	...
	≥ 2	23.00	0	0	0	0	0	0	0	0	0	...

D.2 ICU-patients and MCU-patients

Table D.8: Input probabilities complexity upon arrival

	Patient category	
Complexity	Elective	Acute
MCU	0.844	0.690
ICU	0.156	0.310

Table D.9: Input probabilities number of transitions

	Patient category			
	Elective		Acute	
Transitions	MCU	ICU	MCU	ICU
0	0.947	0.096	0.756	0.255
1	0.011	0.750	0.063	0.626
2	0.036	0.019	0.134	0.009
3	0	0.115	0.014	0.077
4	0.007	0	0.021	0.003
5	0	0.019	0.003	0.025
6	0	0	0.008	0
7	0	0	0.001	0.006

Table D.10: Input probabilities $P^j(n)$ when MCU-patients included.

$\boldsymbol{P^j}(n)$	n	Patient type j **(complexity)** All MCU	All ICU
	0	0.165	0.252
	1	0.433	0.274
	2	0.204	0.120
	3	0.073	0.067
	4	0.044	0.040
	5	0.033	0.037
	6	0.015	0.031
	7	0.012	0.024
	8	0.006	0.024
	9	0.003	0.018
	10	0.001	0.019
	11	0.001	0.015
	12	0.003	0.012
	13	0.003	0.004
	14	0.001	0.001
	15	0	0.004
	16	0	0.001
	17	0.001	0.007
	18	0	0.007
	19	0	0.003
	20	0	0.001
	21	0	0.004
	22	0.001	0
	23	0.001	0
	24	0	0.007
	25	0	0.001
	26	0	0.001
	27	0	0.003
	28	0	0.001
	29	0	0.001
	30	0	0.001
	...	...	...

Table D.11: Input probabilities $m^j_{n,t}$ when MCU-patients included.

$\boldsymbol{m}^j_{n,t}$			Patient type j							
			MCU-patients				ICU-patients			
	n	t	0.00	1.00	...	23.00	0.00	1.00	...	23.00
	0	0	0	0	...	0	0	0	...	0
	0	1	0.071	0	...	0	0	0	...	0
	0	2	0.143	0	...	0	0.182	0	...	0
	0	3	0	0.50	...	0	0	0.071	...	0
	0	4	0.071	0	...	0	0.091	0	...	0
	0	5	0.071	0	...	0	0.091	0.071	...	0
	0	6	0	0	...	0	0	0	...	0
	0	7	0	0	...	0	0	0	...	0
	0	8	0	0	...	0	0.091	0.214	...	0
	0	9	0	0.250	...	0	0.182	0.143	...	0
	0	10	0	0	...	0	0.182	0.214	...	0
	0	11	0.214	0	...	0	0.182	0.071	...	0
	0	12	0.071	0	...	0	0	0.071	...	0
	0	13	0.143	0	...	0	0	0.071	...	0
	0	14	0.214	0	...	0	0	0	...	0
	0	15	0	0.250	...	0	0	0	...	0
	0	16	0	0	...	0	0	0	...	0
	0	17	0	0	...	0	0	0	...	0
	0	18	0	0	...	0	0	0	...	0
	...	...	...	...	...	...	...	...	...	...
	0	23	0	0	...	0	0	0	...	0
	≥ 1	0	0.071	0	...	0.056	0	0.063	...	0.063
	≥ 1	1	0	0	...	0.111	0	0	...	0.031
	≥ 1	2	0	0	...	0	0.04	0	...	0
	≥ 1	3	0	0	...	0.111	0	0	...	0.031
	≥ 1	4	0	0	...	0	0.04	0	...	0
	≥ 1	5	0	0	...	0	0	0	...	0
	≥ 1	6	0	0	...	0	0	0	...	0
	≥ 1	7	0.071	0	...	0	0	0	...	0.031
	≥ 1	8	0	0	...	0	0.040	0.063	...	0.031
	≥ 1	9	0	0	...	0	0.160	0.063	...	0.094
	≥ 1	10	0.143	0	...	0	0.080	0.188	...	0.063
	≥ 1	11	0.214	0	...	0.222	0.160	0.250	...	0.063
	≥ 1	12	0.143	0.222	...	0.167	0.040	0.125	...	0.063
	≥ 1	13	0.143	0.333	...	0.111	0.120	0	...	0.156
	≥ 1	14	0.143	0.222	...	0.111	0.080	0.063	...	0.125
	≥ 1	15	0	0.111	...	0.111	0.160	0	...	0.031
	≥ 1	16	0.071	0.111	...	0	0.040	0.063	...	0.063
	≥ 1	17	0	0	...	0	0	0	...	0
	≥ 1	18	0	0	...	0	0	0.063	...	0.031
	≥ 1	19	0	0	...	0	0.040	0.063	...	0.031
	≥ 1	20	0	0	...	0	0	0	...	0.094
	≥ 1	21	0	0	...	0	0	0	...	0
	≥ 1	22	0	0	...	0	0	0	...	0
	≥ 1	23	0	0	...	0	0	0	...	0

Appendix E

Reliable point estimates from our simulation model

In this appendix we determine a warm-up period for our simulation model (E.1) and we decide on how many replications to execute in order to obtain reliable point estimates (E.2). Law and Kelton (2000) describe procedures for determining the appropriate warm-up period and number of replications. It is important to note that we are dealing with a non-terminating simulation, which means that there is no natural event to specify the length of a run.

E.1 Warm-up period

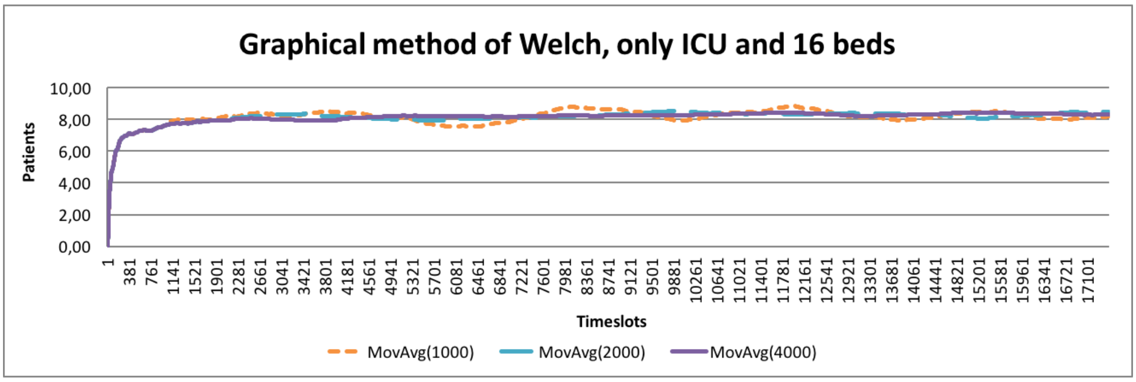
We have a non-terminating simulation model and are interested in the long-run system behavior. To obtain insight in this long-run behavior, we need to make sure the system actually acts like it should in a steady-state. Therefore, we need to remove initial outcomes from our performance calculation while the system is still in its warm-up period.

To determine the warm-up period, we use the graphical method of Welch. We take the following steps:

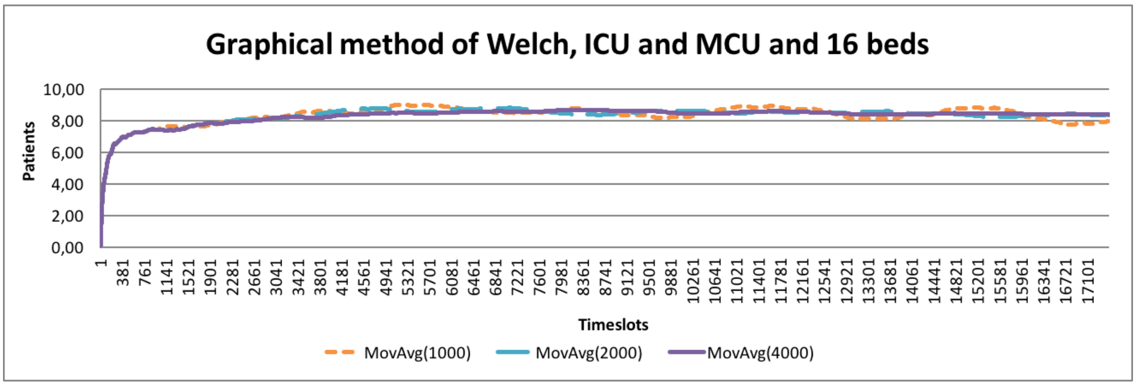
1. We make 10 independant replications of length 10 years.
2. We calculate the mean of the i^{th} observation over all 10 replications.
3. We calculate the moving average with a window of 1000, 2000 and 4000, to smooth out high-frequency oscillations.
4. Plot moving averages and choose observation h beyond which the output seems to be stable.

The results of the graphical method of Welch are shown in Figure E.1. Figure E.1a shows the moving averages when the data for only ICU-patients is used, Figure E.1b shows the moving averages when the data for the separated MCU-patients and ICU-patients is used.

From Table E.1a we see that when only ICU-patient data is used, the system is already in steady-state after 12 weeks (2,016 timeslots). However, from Figure E.1b we see that the average number of patients is still going up at this time point. We want to choose one warm-up period and use this for all the experiments, so



(a) ICU patients only.



(b) ICU and MCU patients.

Figure E.1: Welch method, 10 replications of 10 years, window 1000, 2000 and 4000, only the first two years (17472 timeslots) are shown.

we choose h=4,368 timeslots, which equals 26 weeks. From this point on, also the system with MCU-patients is in steady-state.

E.2 Number of replications

We need to make sure that the confidence intervals for the outcome measures of the simulation model do not get too wide. We use the fixed-sample-size procedure as suggested by Law and Kelton, in combination with the replication/deletion approach. We have to make n independent replications of length m observations, where each replication the warm-up period is removed. The length of m needs to be much larger than the warm-up period. We therefore choose a run length of 20 years.

To make sure the confidence interval of our outcomes is not too large, we have to determine the smallest number of replications n such that:

$$\frac{t_{n-1,1-\alpha/2}\sqrt{S_n^2/n}}{\bar{X}_n} \leq \gamma'.$$

We compute $\bar{X}_n$, the average of the n replications, and S_n^2, the variance in the n replications. $t_{n-1,1-\alpha/2}$ is the student t-value for $(n-1)$ degrees of freedom and a confidence interval of $(1-\alpha)$ and γ' is the corrected relative error.

We investigate the required number of replications for the performance measures coverage compliance and overstaffing rate. We also want a reliable indication of the number of shifts worked by an agency nurse, so we also determine the required number of replications separately for the temporary employees experiment. We use a 95% confidence interval and a relative error of 0.05 (γ'=0.048).

For all four experiment types we determined the number of replications needed for estimates for the coverage compliance and overstaffing rate such that the half width of the 95% confidence interval is not bigger than γ'. The highest number of replications needed for these two measures are shown in Figure E.2. For the coverage compliance at least 6 replications are needed, for the overstaffing rate 11 replications are needed. We choose to do 30 replications to give an even more precise estimate, since the simulation model only takes a very small amount of time to run.

2	0.0454	0.1536	0.0087	0.1434	0.0925	0.2244	0.1563	0.0951	0.0631	0.0935	0.178	0.2366	0.2109	0.1926	0.2247	0.2907	0.1067	0.1696	0.1433	0.0651	0.1554
3	0.0123	0.03	0.0093	0.0286	0.0211	0.047	0.0481	0.0253	0.0397	0.077	0.0503	0.0535	0.0532	0.0384	0.0819	0.0628	0.0218	0.0788	0.0287	0.0129	0.0381
4	0.029	0.0258	0.0324	0.0353	0.0256	0.0518	0.0436	0.0289	0.0533	0.062	0.0395	0.0714	0.0645	0.0289	0.0483	0.0397	0.0166	0.0521	0.0329	0.0191	0.0333
5	0.0208	0.0175	0.022	0.024	0.0173	0.0352	0.0301	0.0196	0.0361	0.0427	0.0275	0.0487	0.0436	0.0206	0.0327	0.0269	0.012	0.0361	0.0228	0.0141	0.0235
6	0.016	0.0136	0.0169	0.0184	0.0132	0.0267	0.0229	0.0154	0.0277	0.0334	0.0211	0.0368	0.0331	0.0156	0.0323	0.0224	0.0091	0.028	0.0172	0.0107	0.022
7	0.0134	0.0109	0.0155	0.0157	0.0112	0.0219	0.0188	0.0129	0.023	0.0269	0.0171	0.0314	0.0269	0.0134	0.0345	0.0216	0.0086	0.027	0.0163	0.0095	0.0206
8	0.014	0.0112	0.019	0.0164	0.0101	0.0191	0.0163	0.0122	0.0207	0.0232	0.0143	0.028	0.0231	0.0131	0.0298	0.0193	0.0094	0.0277	0.017	0.01	0.0182
9	0.0124	0.0097	0.0164	0.0141	0.0092	0.0169	0.0141	0.0106	0.0185	0.0203	0.0123	0.0241	0.02	0.0112	0.0267	0.0166	0.0082	0.0239	0.0146	0.0086	0.0166

(a) Replications needed for the coverage compliance.

4	0.0281	0.0302	0.0427	0.0502	0.0417	0.0342	0.0469	0.0611	0.0963	0.0821	0.0793	0.099	0.0878	0.0673	0.1087	0.0863	0.0484	0.0626	0.0423	0.0277	0.025
5	0.0226	0.021	0.0306	0.035	0.0284	0.0244	0.0318	0.042	0.0684	0.0561	0.0536	0.067	0.0595	0.0459	0.0748	0.0587	0.0337	0.0423	0.0293	0.0218	0.028
6	0.019	0.0174	0.028	0.0277	0.0217	0.0221	0.0252	0.0319	0.0541	0.0424	0.0411	0.0539	0.0455	0.0352	0.0582	0.0469	0.0274	0.0378	0.0249	0.018	0.026
7	0.0279	0.0216	0.039	0.0331	0.0277	0.0539	0.04	0.0344	0.0671	0.0452	0.0391	0.0585	0.046	0.0386	0.065	0.0481	0.0283	0.0444	0.0329	0.0248	0.0398
8	0.0234	0.0181	0.0347	0.0277	0.0232	0.0459	0.0336	0.0288	0.0564	0.0379	0.0328	0.0489	0.0387	0.0334	0.0548	0.0407	0.0241	0.0371	0.0276	0.0211	0.0333
9	0.0203	0.0157	0.0299	0.0239	0.0209	0.0421	0.0296	0.0248	0.0494	0.0327	0.0283	0.0422	0.0333	0.0288	0.0472	0.0351	0.0208	0.032	0.0237	0.0184	0.0289
10	0.0192	0.0148	0.0265	0.0216	0.0209	0.0411	0.0287	0.0232	0.0478	0.033	0.025	0.0371	0.0294	0.0259	0.0425	0.0317	0.0187	0.0288	0.0215	0.017	0.0268
11	0.0189	0.014	0.0243	0.0204	0.019	0.0368	0.0259	0.021	0.0429	0.03	0.023	0.0334	0.0273	0.0242	0.0388	0.0293	0.0175	0.0272	0.0216	0.0175	0.027

(b) Replications needed for the overstaffing rate.

Figure E.2: Number of replications needed for the coverage compliance and the overstaffing rate for a confidence interval of 95% and relative error of 0.05.

For the experiment with agency nurses we also need to determine the required number of replications to give a good estimate of the number of shifts worked by a temporary nurse. In Figure E.3 we see that the variability in the outcome of this measure is a lot larger, since the number of required replications is at least 61. We choose to do 100 replications in case of the experiment where agency nurses are included.

54	0.03418	0.03149	0.02721	0.02932	0.03172	0.03953	0.03531	0.03781	0.03616	0.04612	0.0365	0.04292	0.04984	0.04539	0.04141	0.04287	0.03825	0.04891	0.03762	0.05203
55	0.03405	0.03089	0.02671	0.02879	0.03115	0.0388	0.03464	0.03714	0.0355	0.04547	0.03592	0.04223	0.04898	0.04478	0.04074	0.04225	0.03776	0.04827	0.03705	0.05152
56	0.03348	0.03045	0.02643	0.02863	0.03078	0.0383	0.034	0.03649	0.03495	0.04467	0.03529	0.04145	0.04807	0.04417	0.04022	0.04152	0.03709	0.04738	0.03643	0.05086
57	0.03296	0.03017	0.02612	0.02813	0.03023	0.0376	0.0334	0.03585	0.03431	0.044	0.03466	0.04088	0.04719	0.04336	0.03962	0.04079	0.03657	0.04664	0.03595	0.04992
58	0.03242	0.02976	0.02571	0.02763	0.02969	0.03693	0.0328	0.03525	0.03373	0.04351	0.03473	0.04031	0.04713	0.04285	0.03903	0.04034	0.03601	0.04583	0.03531	0.04938
59	0.03226	0.02988	0.02577	0.02723	0.0292	0.03633	0.03229	0.03467	0.03314	0.04281	0.03413	0.03969	0.04764	0.04268	0.03856	0.03969	0.03544	0.0451	0.03468	0.04854
60	0.03182	0.02937	0.02538	0.02699	0.02898	0.0358	0.03216	0.03424	0.03261	0.04208	0.03357	0.03901	0.04684	0.042	0.03801	0.03921	0.03487	0.04476	0.03424	0.04773
61	0.03136	0.02894	0.02514	0.02721	0.02888	0.03529	0.03173	0.03366	0.03207	0.04138	0.033	0.03861	0.04645	0.0414	0.03737	0.03874	0.0345	0.04401	0.03367	0.04711

Figure E.3: Number of replications needed for the number of shifts worked by an agency nurse for a confidence interval of 95% and relative error of 0.05.

To summarize, the required number of replications and the number of chosen replications are shown in Table E.1.

Table E.1: Overview of number of replications needed and chosen per performance measure.

Experiment	Required replications	Chosen replications
Coverage compliance	6	30
Overstaffing rate	11	30
Shifts by agency nurse	61	100

Appendix F

Extra results

Table F.1: Changes is staffing levels from nurse staffing model to simulation model (α^k=0.95).

		Check coverage levels, staffing levels from nurse staffing model in simulation model					
		Unit 1			**Unit 2**		
Day	Shift	Nurses	Ser. level	Change	Nurses	Ser. level	Change
1	Day	5	0.980		4	0.956	
	Late	4	0.983		4	0.992	
	Night	4	1.000		3	0.954	
2	Day	5	0.975		4	0.946	+1
	Late	4	0.980		4	0.990	
	Night	4	1.000		4	1.000	
3	Day	5	0.963		5	0.982	
	Late	4	0.974		4	0.988	
	Night	4	1.000		4	1.000	
4	Day	5	0.963		5	0.982	
	Late	4	0.983		4	0.992	
	Night	4	1.000		3	0.948	+1
5	Day	5	0.972		5	0.987	
	Late	4	0.984		4	0.993	
	Night	4	1.000		3	0.954	
6	Day	5	0.976		4	0.948	+1
	Late	4	0.988		4	0.995	
	Night	4	1.000		3	0.961	
7	Day	5	0.981		4	0.958	
	Late	4	0.989		4	0.995	
	Night	4	1.000		3	0.961	

Table F.2: Results nurse staffing levels from simulation model with agency nurses in case of 1 unit, $w_t \in [2, 3, 4]$.

Day	Shift	Nurses	Policy 1 Ag. shifts	Policy 1 Coverage	Policy 2 Ag. shifts	Policy 2 Coverage
1	Day	8	74.54	0.955	132.08	0.961
	Late	7	58.8	0.968	58.8	0.968
	Night	6	73.46	0.973	131.84	0.981
2	Day	8	82.1	0.937	143.36	0.946
	Late	7	76.9	0.965	76.9	0.965
	Night	6	98.92	0.971	166.99	0.978
3	Day	9	65.87	0.973	65.87	0.973
	Late	7	91.01	0.957	91.01	0.957
	Night	6	107.5	0.961	180.87	0.970
4	Day	9	65.76	0.971	65.76	0.971
	Late	7	76.87	0.973	76.87	0.973
	Night	6	76.06	0.963	135.62	0.971
5	Day	9	52.1	0.978	52.1	0.978
	Late	7	69.3	0.974	69.3	0.974
	Night	6	74.53	0.971	131.35	0.979
6	Day	8	90.01	0.946	154.05	0.953
	Late	7	0	0.953	0	0.953
	Night	6	54.62	0.972	102.42	0.980
7	Day	8	73.86	0.960	130.19	0.965
	Late	7	42.56	0.982	42.56	0.982
	Night	6	58.56	0.973	107.66	0.982
	Total			**150**		**150**
	FTE			**40.66**		**40.66**
	Coverage			**0.966**		**0.970**
	Overstaffing			**0.324**		**0.328**

Table F.3: Results nurse staffing levels from simulation model with agency nurses in case of 2 units and policy 1, $w_t \in [2, 3, 4]$.

Day	Shift	Unit 1 Nurses	Unit 1 Ag. shifts	Unit 1 Coverage	Unit 1 Nurses	Unit 1 Ag. shifts	Unit 1 Coverage
1	Day	4	79.69	0.971	4	0	0.958
	Late	4	0	0.983	4	0	0.992
	Night	3	79.27	0.992	3	0	0.955
2	Day	4	87.43	0.956	4	49.02	0.976
	Late	4	0	0.980	4	0	0.990
	Night	3	103.87	0.990	3	60.72	0.994
3	Day	4	120.17	0.944	4	71.86	0.969
	Late	4	0	0.974	4	0	0.988
	Night	3	113.62	0.992	3	65.32	0.994
4	Day	4	124.88	0.941	4	72.8	0.966
	Late	4	0	0.983	4	0	0.992
	Night	3	82.67	0.991	3	48.07	0.994
5	Day	4	101.38	0.953	4	59.98	0.975
	Late	4	0	0.984	4	0	0.993
	Night	3	80.56	0.991	3	0	0.953
6	Day	4	95.12	0.967	4	54.07	0.983
	Late	4	0	0.989	4	0	0.995
	Night	3	62.49	0.988	3	0	0.962
7	Day	4	79.62	0.976	4	0	0.959
	Late	4	0	0.989	4	0	0.995
	Night	3	64.47	0.990	3	0	0.962
	Total			**77**			**77**
	FTE			**20.87**			**20.87**
	Coverage			**0.977**			**0.978**
	Overstaffing			**0.313**			**0.369**

Table F.4: Results nurse staffing levels from simulation model with agency nurses in case of 2 units and policy 2, $w_t \in [2, 3, 4]$.

Day	Shift	Unit 1 Nurses	Unit 1 Ag. shifts	Unit 1 Coverage	Unit 1 Nurses	Unit 1 Ag. shifts	Unit 1 Coverage
1	Day	4	223.01	0.980	4	0	0.958
	Late	4	0	0.983	4	0	0.992
	Night	3	222.12	1.000	3	0	0.955
2	Day	4	238	0.972	4	154.04	0.986
	Late	4	0	0.980	4	0	0.990
	Night	3	266.67	1.000	3	178.48	1.000
3	Day	4	294.61	0.961	4	200.49	0.980
	Late	4	0	0.974	4	0	0.988
	Night	3	285.38	1.000	3	193.81	1.000
4	Day	4	303.82	0.959	4	207.1	0.979
	Late	4	0	0.983	4	0	0.992
	Night	3	228.43	1.000	3	152.65	1.000
5	Day	4	263.34	0.970	4	178.98	0.985
	Late	4	0	0.984	4	0	0.993
	Night	3	221.86	1.000	3	0	0.953
6	Day	4	250.19	0.976	4	167.59	0.989
	Late	4	0	0.989	4	0	0.995
	Night	3	183.91	0.999	3	0	0.962
7	Day	4	220.13	0.982	4	0	0.959
	Late	4	0	0.989	4	0	0.995
	Night	3	191.95	0.999	3	0	0.962
	Total			**77**			**77**
	FTE			**20.87**			**20.87**
	Coverage			**0.985**			**0.982**
	Overstaffing			**0.333**			**0.378**

Table F.5: Optimal nurse staffing levels with agency nurses in case of 1 unit with the chosen policy, $w_t \in [2, 3, 4]$.

Day	Shift	Nurses	Policy	Coverage
1	Day	8	Policy 1	0.955
	Late	7	Policy 1	0.968
	Night	6	Policy 1	0.973
2	Day	9		0.952
	Late	7	Policy 1	0.965
	Night	6	Policy 1	0.971
3	Day	9	Policy 1	0.973
	Late	7	Policy 1	0.957
	Night	6	Policy 1	0.961
4	Day	9	Policy 1	0.971
	Late	7	Policy 1	0.973
	Night	6	Policy 1	0.963
5	Day	9	Policy 1	0.978
	Late	7	Policy 1	0.974
	Night	6	Policy 1	0.971
6	Day	9		0.954
	Late	7		0.953
	Night	6	Policy 1	0.972
7	Day	8	Policy 1	0.960
	Late	7	Policy 1	0.982
	Night	6	Policy 1	0.973
	Total			**152**
	FTE			**41.20**
	Coverage			**0.967**
	Overstaffing			**0.331**

Table F.6: Optimal nurse staffing levels with agency nurses in case of 2 units with the chosen policy, $w_t \in [2, 3, 4]$.

		Unit 1			**Unit 2**			
Day	Shift	Nurses	Policy	Coverage	Nurses	Policy	Coverage	Total
1	Day	4	Policy 1	0.971	4		0.958	8
	Late	4		0.983	4		0.992	8
	Night	3	Policy 1	0.992	3		0.955	6
2	Day	4	Policy 1	0.956	4	Policy 1	0.976	8
	Late	4		0.980	4		0.990	8
	Night	3	Policy 1	0.990	3	Policy 1	0.994	6
3	Day	5		0.963	4	Policy 1	0.969	9
	Late	4		0.974	4		0.988	8
	Night	3	Policy 1	0.992	3	Policy 1	0.994	6
4	Day	5		0.963	4	Policy 1	0.966	9
	Late	4		0.983	4		0.992	8
	Night	3	Policy 1	0.991	3	Policy 1	0.994	6
5	Day	4	Policy 1	0.953	4	Policy 1	0.975	8
	Late	4		0.984	4		0.993	8
	Night	3	Policy 1	0.991	3		0.953	6
6	Day	4	Policy 1	0.967	4	Policy 1	0.983	8
	Late	4		0.989	4		0.995	8
	Night	3	Policy 1	0.988	3		0.962	6
7	Day	4	Policy 1	0.976	4		0.959	8
	Late	4		0.989	4		0.995	8
	Night	3	Policy 1	0.990	3		0.962	6
	Total							**156**
	FTE							**42.26**
	Coverage							**0.979**
	Overstaffing							**0.347**

Table F.7: Ranges for staffing levels per shifts in case of including MCU-patients in the simulation model.

		1 unit		**2 units**			
				Unit 1		Unit 2	
Day	Shift	UB	LB	UB	LB	UB	LB
1	Day	9	5	5	3	4	3
	Late	8	5	4	3	4	3
	Night	7	4	4	2	3	2
2	Day	9	5	5	3	5	3
	Late	8	5	4	3	4	3
	Night	7	4	4	2	4	2
3	Day	10	5	5	3	5	3
	Late	8	5	4	3	4	3
	Night	7	4	4	2	4	2
4	Day	10	5	5	3	5	3
	Late	8	5	4	3	4	3
	Night	7	4	4	2	4	2
5	Day	9	5	5	3	5	3
	Late	8	5	4	3	4	3
	Night	7	4	4	2	3	2
6	Day	9	5	5	3	5	3
	Late	7	5	4	3	4	3
	Night	7	4	4	2	3	2
7	Day	9	5	5	3	4	3
	Late	8	5	4	3	4	3
	Night	7	4	4	2	3	2