MATCHING CARE SUPPLY AND DEMAND IN THE WOMEN'S AND CHILDREN'S INPATIENT CLINIC

The value of flexible nurse staffing

Public version

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SUMMARY

BACKGROUND

As a result of the pressure on hospital budgets, the Academic Medical Center Amsterdam (AMC) is forced to reorganize the operations of inpatients' services during the upcoming years. In the Women's and Children's Inpatient Clinic (WCC) of the AMC, an area for improvement is matching patient demand and supply of care. Currently, the number of nurses staffed in a shift is not aligned with the number of patients on a ward. Performance measurement indicates that this frequently led to over- and understaffing of nurses in 2012. As a result of frequent understaffing, nursing coverage guidelines set by the AMC were not reached and quality of care was not guaranteed.

In the AMC, two mathematical models are developed to improve nurse staffing: the hourly bed census (HBC) model (Kortbeek et al. 2012a) and the nurse staffing (NS) model (Kortbeek et al. 2012b). The HBC model predicts the number of occupied beds (bed census) based on the surgical schedule and arrival patterns of acute patients. The NS model determines efficient nurse staffing levels while guaranteeing nurse coverage for two staffing policies: staffing on bed census predictions and staffing on bed census predictions with the deployment of flexible nurses. The models are developed for the surgical inpatient care units of the AMC. To get insight whether these models are widely applicable to other wards to minimize over- and understaffing, we research the application of these models to the wards of the WCC. Therefore, the research objective is:

Research the potential of applying the available mathematical models, which are developed for flexible nurse staffing for the surgical inpatient care units of the AMC, to minimize overstaffing and understaffing in the Women's and Children's Inpatient Clinic

APPROACH

To research the potential of the models, we required data of the WCC to use the methods of the HBC and NS model. The available data of our case study differed from the data of the surgical inpatient care units, which led to several limitations while applying the models. We encountered the limitation that the HBC model is not able to work with a surgical schedule from which patients of one surgery block can be admitted to various wards. This is the situation in the WCC and results in the inability to calculate bed census predictions based on an upcoming surgical schedule. Although the HBC model cannot be used to predict bed census in the future, we decided to manipulate historical surgical schedules in such way that the HBC model can be applied. The results of the application indicate which improvements are possible when the HBC model is usable for all surgical schedules.

RESULTS

This study resulted in insight in the limitations of the HBC and NS model. The main limitation is that the HBC model cannot be applied as a prediction tool for all surgical schedules. We were not able to overcome this limitation and use the HBC model as a prediction tool. Therefore, we decided to perform experiments with the HBC and NS model based on a historical surgical schedule and historical data. We used three wards of the WCC: Teenagers, Older Children, and Pediatric Surgery

and Infants. Results showed that the two staffing policies resulted in a consistent high coverage and that a reduction in the number of FTEs is possible.

Recommendations

We recommend to research the possibilities how to make the model usable for all surgical schedules. A method must be developed to use the HBC model in situations where patients from one surgery block can be admitted to various wards. If the model can be adapted to these situations, the HBC and NS models can be used as prediction tools in the WCC.

We were unable to predict the required nurse staffing levels for the future to minimize under- and overstaffing with the HBC and NS model. Therefore, we recommend the AMC's WCC to start with structurally analyzing the historical bed census of the wards. We analyzed the situation in 2012 where a fixed number of nurses is staffed from Monday to Friday while the week patterns in historical bed census show large fluctuations. Therefore, we recommend to analyze the week patterns of 2013 and determine what improvements are possible in adapting nurse staffing levels for 2014 based on these patterns. In this way, wards can improve the alignment of care supply and patient demand.

SAMENVATTING

ACHTERGROND

Door de hoge druk op ziekenhuisbudgetten is het Academisch Medisch Centrum Amsterdam (AMC) genoodzaakt om de processen in de kliniek te reorganiseren. In de divisie Vrouw/Kind van het AMC zijn verbeteringen mogelijk in de afstemming van vraag en aanbod. Op dit moment wordt het aanbod (het aantal verpleegkundigen) niet gebaseerd op het aantal patiënten op de verpleegafdelingen. De prestatiemeting over 2012 duidde op veel over- en onderbezetting van verpleegkundigen in de divisie. Door het vaak voorkomen van onderbezetting kon de kwaliteit van zorg niet gegarandeerd worden.

In het AMC zijn twee wiskundige modellen ontwikkeld om de inzet van verpleegkundig personeel te verbeteren: het hourly bed census (HBC) model (Kortbeek et al. 2012a) en het nurse staffing (NS) model (Kortbeek et al. 2012b). Het HBC model voorspelt het aantal bezette bedden op een verpleegafdeling gebaseerd op de operatieplanning en de aankomstpatronen van acute patiënten. Het NS model bepaalt voor twee methoden hoeveel verpleegkundigen moeten worden ingezet om kwaliteit van zorg te garanderen: inzet op basis van voorspellingen van de beddenbezetting en inzet op basis van voorspellingen van de beddenbezetting in combinatie met de inzet van flexibele verpleegkundigen. Deze modellen zijn ontwikkeld voor de chirurgische afdelingen van het AMC. Wij onderzoeken de toepassing van deze modellen op andere afdelingen om inzicht te krijgen in de brede toepassing van deze modellen op verschillende afdelingen. Dit resulteert in de volgende doelstelling:

Onderzoek de mogelijkheden van de beschikbare wiskundige modellen voor flexibele verpleegkundige inzet ontwikkeld voor de chirurgische verpleegafdelingen van het AMC om over- en onderbezetting te minimaliseren op de verpleegafdelingen van de divisie Vrouw & Kind

METHODE

Om te onderzoeken of de modellen bruikbaar zijn op andere afdelingen, is data nodig om de methoden van het HBC en NS model te gebruiken. De beschikbare data van de afdelingen in deze studie verschillen van de data van de chirurgische afdelingen in de studie van Kortbeek et al. (2012a). Dit leidde tot het inzicht van de beperkingen van de bruikbaarheid van de modellen. Een grote beperkingen van het HBC model is dat het niet de beddenbezetting kan voorspellen op basis van de operatieplanning waarbij patiënten uit een operatieblok kunnen worden opgenomen op meerdere afdelingen. Dit is de situatie in de divisie Vrouw/Kind en resulteert in de onmogelijkheid om op basis van de operatieplanning de beddenbezetting te voorspellen. Om inzicht te geven in de mogelijkheden van de modellen voor de divisie Vrouw/Kind, hebben wij de operatieplanning en de methode van het HBC model gemanipuleerd. Op deze manier hebben wij het HBC model toegepast op historische data en is inzicht verkregen in de mogelijkheden van de modellen als ze volledig toepasbaar zijn voor alle operatieplanningen.

RESULTATEN

Door deze studie is inzicht verkregen in de beperkingen van het HBC en NS model. De grootste beperking is dat het HBC model niet toegepast kan worden voor alle operatieplanningen. Wij

hebben deze beperking niet opgelost en kunnen het HBC model niet toepassen als voorspelmodel om over- en onderbezetting te voorkomen. Om inzicht te geven in de winst die er te behalen valt als het HBC model toegepast kan worden, hebben wij de historische data en de operatieplanning aangepast. Drie afdelingen van de divisie Vrouw/Kind zijn geanalyseerd: Tieners, Grote Kinderen en Kinderchirurgie en Zuigelingen. De resultaten tonen aan dat de toepassing van de modellen resulteren in voldoende dekking van verpleegkundigen en een besparing op het aantal FTE mogelijk is.

AANBEVELINGEN

Wij adviseren om onderzoek te doen naar de mogelijkheden om het HBC model bruikbaar te maken voor alle operatieplanningen. Er moet een methode bedacht worden hoe het HBC model gebruikt kan worden met operatieplanningen waarvan patiënten van hetzelfde operatiespecialisme opgenomen kunnen worden op verschillende afdelingen. Als het HBC model op deze wijze uitgebreid kan worden, kan het toepasbaar worden gemaakt tezamen met het NS model voor de divisie Vrouw/Kind.

Door de beperkingen van het HBC model hebben wij geen richtlijnen voor het aantal verpleegkundigen die nodig zijn om over- en onderbezetting te voorkomen. Wij hebben in deze studie bedbezettingspatronen in 2012 geanalyseerd. We zien grote variatie in beddenbezetting van maandag tot vrijdag, terwijl het aantal verpleegkundigen niet varieert. Wij adviseren het AMC om de bedbezettingspatronen ook in 2013 te analyseren. Op basis van deze patronen, kan beslist worden om niet meer een vast aantal verpleegkundigen in te plannen, maar het aantal ingeplande verpleegkundigen deze historische patronen te laten volgen.

PREFACE

This research was performed in the Academic Medical Center Amsterdam at the department "Kwaliteit en Procesinnovatie". This research is the last phase of my study before obtaining my Master's degree in Industrial Engineering and Management with a specialization in Health Care Technology and Management at the University of Twente, Enschede.

In March 2013, I started my master's assignment at the AMC. During the first months, it was a challenge to grasp the existing complex mathematical models and the programming code I had to apply. Nikky Kortbeek and Aleida Braaksma were very helpful during this process. I want to thank them for the support they gave me during the entire process. Nikky, I very appreciated the constructive feedback you gave me in our weekly meetings. Aleida, although you were in the U.S. for a few months, you really gave me the feeling that I could contact you anytime. This was very helpful for me, especially in the last stage of my research.

Besides Nikky and Aleida, I am very thankful to Lieke Wiggers for her support and for introducing me to people working in the Women's and Children's Clinic. Furthermore, I would like to express my appreciation to Ronald Vollebregt and Ferry Smeenk for the pleasant atmosphere at the department and their help with Access and Excel.

Besides the people of the AMC, I thank my supervisor of the University of Twente, Erwin Hans for contacting Nikky about the opportunities to perform a master's assignment at the AMC. Erwin, you helped me a lot with the structure of my report and I could always contact you about problems with Delphi.

Last but not least, I want to thank Wendy, Rikke and Lieke for reading the chapters of my thesis. They really helped me with improving my thesis. And of course I want to thank all my friends and family who helped me by just being there for me when I needed distraction.

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1. INTRODUCTION

As a result of demographic developments and the improved access to health care, the demand for health care rises. Also due to technological developments and the improving medical knowledge, more health care can be provided. These factors lead to increasing health care costs. Many hospitals in the Netherlands are facing financial difficulties. To prevent losses, the Academic Medical Center Amsterdam (AMC) has to structurally save 65 million Euros until 2014 since insurance companies prohibit growth in output. However, some divisions of the AMC do have the possibility to grow due to an alliance with the VU University Medical Center Amsterdam (VUmc). This study focuses on one of these divisions: the Women's and Children's Clinic (WCC).

The AMC is forced to reorganize the operations of inpatients' services during the upcoming years. At the AMC an improvement program, called SLIM, has started in 2010 to improve quality of care and reduce costs. One part of the SLIM project is to improve the alignment between patient demand and the supply of care at the inpatient clinics.

Due to the alliance with the VUmc, it is important for the AMC to know how to utilize (and in the future use) their capacity (beds, nurses, etc.) in the most efficient and effective way. Currently, the WCC experiences variable workloads due to fluctuating demand for beds and varying lengths of stay. A balanced workload will (1) minimize the chance of medical errors, (2) maximize employee and patient satisfaction and (3) limit the employee costs (Carayon and Gurses 2008). In line with the SLIM project, the management of the WCC wants to improve the connection between patient demand and the supply of care.

Previous exploration by ATKearney (January 2013) indicates that the connection between patient demand and supply of care at the AMC's WCC can be improved. These improvements are possible in the patient admission planning and nurse staffing. Based on the research of ATKearney, the decision is made by the management of the WCC to centralize the patient admission planning and staffing in the WCC. Currently, the patient admission planning and staffing in the WCC is performed decentralized at different departments. To improve the connection between patient demand and supply of care, advice is needed to implement the centralized patient admission and nurse staffing office.

1.1. RESEARCH CONTEXT

1.1.1. ACADEMIC MEDICAL CENTER AMSTERDAM (AMC)

The AMC is one of the eight academic medical centers in the Netherlands. The AMC was founded in 1983, when two hospitals from the Amsterdam city center, the Wilhelmina Gasthuis and the Binnengasthuis, merged with the medical faculty of the University of Amsterdam. Five years later, the Emma Children's Hospital also became a part of the new academic hospital. The AMC has one of the eleven trauma centers in the Netherlands. The AMC has ten divisions, supported centrally by corporate staff and facility services.

In 2011, more than 380,000 patients visited the outpatient department, around 31,000 patients were treated in the day care unit and 30,000 admissions of more than one day took place. The AMC has an admission capacity of 1,000 beds and employs around 7,000 persons. In 2011, the number of nursing days was 202,000 with an average length of stay of 6.7 days (Academic Medical Center Amsterdam 2011).

1.1.2. Women's and Children's Clinic (WCC)

The WCC includes the Emma Children's Hospital and the Women's Clinic and consists of nine nursing wards. The WCC is one of the ten divisions of the AMC. A certain amount of procedures carried out concerns top-referral patient care. Top-referral patient care is associated with special and complex, diagnostic procedures and treatments. A lot of patients come from all parts of the Netherlands. Patient care is not limited to complex and unusual disorders: the hospital also serves as a general hospital for inhabitants of the region.

The Emma Children's Hospital consists of an outpatient department with a daycare unit and an inpatient department. The inpatient department has six nursing wards. There are three age-related wards: for children less than one year old ("Infants"), for children between one and nine years old ("Older Children"), and for children aged ten and older ("Teenagers). Furthermore, there are specialized wards: Pediatric Surgery, Pediatric Oncology, Pediatric Intensive Care Unit (PICU), and Neonatal Intensive Care Unit (NICU). The pediatric surgery ward is merged with the ward for infants less than one year old.

The Women's Clinic consists of four departments: Obstetrics, Gynecology, Center for Procreative Medicine, Sexology and Psychosomatic Gynecology. The inpatient department has three nursing wards: Gynecology, Obstetrics, and Maternity ward.

1.2. Problem statement

1.2.1. Problem description

In the WCC the patient demand and supply of care does not match. One of the problems is the variation in workload for nurses on the wards. The workload increases due to the number of patients on the wards, the number of admissions and discharges and the intensity of care of patients. In 2012, overstaffing and understaffing occurred in the wards. Understaffing occurs when too few nurses are staffed on a shift, whereby quality of care cannot be guaranteed as a result of the high workload. Overstaffing occurs when too many nurses are staffed on a shift. This can lead to low workloads and cost inefficiency. Furthermore, both situations can lead to job dissatisfaction among nurses.

The problem statement is as follows:

Overstaffing and understaffing of nurses in the wards of the Women's and Children's Clinic occurred in 2012. Therefore, the staffing was not efficient during times of overstaffing, and quality of care was not guaranteed during times of understaffing.

1.2.2. FRAMEWORK FOR PLANNING AND CONTROL

To give a more detailed description of the scope of this research, we use the framework of planning and control developed by Hans, van Houdenhoven, and Hulshof (2012). This framework provides four hierarchical levels of control and four managerial areas. The framework is shown in Figure 1. The managerial areas are medical planning, resource capacity planning, materials planning and financial planning. This research about nurse staffing falls in the managerial area of resource capacity planning. Resource capacity planning addresses the dimensioning, planning, scheduling, monitoring and control of renewable resources. The hierarchical decompositions are split into a strategic, tactical and operational level. On the operational level a further distinction can be made between the offline and online levels. The scope of this research is indicated in Figure 1.

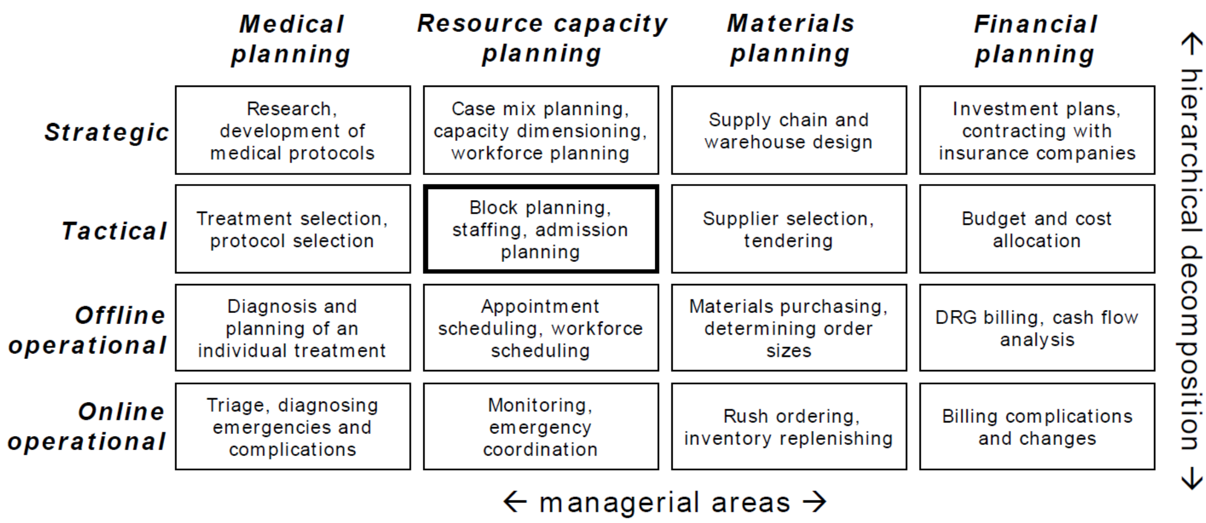

FIGURE 1: EXAMPLE APPLICATION OF THE FRAMEWORK FOR HEALTH CARE PLANNING AND CONTROL TO A GENERAL HOSPITAL (HANS ET AL. 2012)

Tactical resource capacity planning addresses the organization of the operations of the health care delivery process. This level is located between the strategic and operational level. Decisions on this level are made on an intermediate planning horizon. In this research, demand for beds has to be forecasted. The number of nurses to staff on each shift is based on these forecasts. This staffing decision is located on the tactical level. Rostering of nurses (allocation of individual nurses to a working shift) occurs on the operational level.

1.3. RESEARCH OBJECTIVE AND RESEARCH QUESTIONS

To minimize overstaffing and understaffing at the AMC, hospital management wants to improve the connection between patient demand and supply. The WCC management wants to install a centralized patient admission and nurse staffing office to achieve this connection.

With the start of the implementation of this centralized office, the hospital management wants to advise the planner on how many nurses should be staffed on each shift and each ward, based on the patient demand forecasts. Both flexible and non-flexible nurses can be staffed. Flexible nurses are staffed in a flex pool and can be allocated to the ward with the highest demand for care at the beginning of a working shift. Non-flexible nurses are staffed on a certain ward.

Based on the problem statement the research objective is as follows:

Research the potential of applying the available mathematical models, which are developed for flexible nurse staffing for the surgical inpatient care units of the AMC, to minimize overstaffing and understaffing in the Women's and Children's Inpatient Clinic.

The contribution of this research is to research the potential of flexible nurse staffing on nine wards. With the deployment of flexible nurses, the wards in the WCC can adequately respond to variability in patient demand. The mathematical models provide the planner with guidelines for nurse staffing (how many nurses should be staffed on each shift and size of the non-flexible nursing pools) based on the expected patient demand. In order to reach the objective, we will answer the following research questions:

Chapter 2: What is the current situation in the Women's and Children's Clinic?

i. What processes are involved in the admission of patients to the Women's and Children's Clinic?
ii. How is the nurse staffing executed for the Women's and Children's Clinic?

Chapter 3: How does the Women's and Children's clinic currently perform based on the guidelines set by the improvement program "SLIM in Women's and Children's Clinic"?

i. What is the variance in bed census on the wards of the WCC?
ii. What is the percentage of time that overstaffing and understaffing occurs in the WCC?

Chapter 4: Which models are currently known for nurse staffing on wards while minimizing overstaffing and understaffing?

i. Which models are known to determine the staffing levels of flexible and non-flexible nurses in line with the expected bed census?
ii. Which methods are known to reduce the over- and understaffing levels and how can they be used in the AMC?

Chapter 5: How can the existing mathematical models be extended and applied to the Women's and Children's Clinic?

Chapter 6: What is the advice for nurse staffing in the Women's and Children's Clinic?

Chapter 7: What can be concluded and recommended from this study?

i. What are the implications of the model for practice?
ii. How can these implications be successfully implemented in the AMC?

2. Context analysis

This chapter describes the current work and planning processes in the WCC. To develop a prototype decision support tool for nurse staffing in the WCC, information is needed about the current processes in the WCC. The information presented in this chapter is based on observations, interviews with nurses, OR planners and planners of the admission planning office and the nurse planning office. Section 2.1 is an introduction to the WCC and the improvement guidelines set by management. Section 2.2 provides insight in the patient process and Section 2.3 describes the nursing work process. Section 2.4 discusses the planning processes consisting of operating room planning, patient admission planning and nurse staffing and scheduling. This chapter closes with a conclusion (Section 2.5).

2.1. General information

2.1.1. Introduction WCC

The WCC consists of nine nursing wards, of which six wards in the Children's Clinic and three wards in the Women's Clinic. Table 1 shows the bed capacity of each ward. In the WCC, patients with different pathologies are admitted. Some patients come for surgery, others for a diagnostic procedure, drug therapy or observation. The patients can be elective or non-elective; elective patients are planned and non-elective patients are unplanned and announced just before arrival.

The Children's Clinic consists of three age-related wards: for children less than one year old ("Infants"), for children between one and nine years old ("Older Children"), and for children aged ten and older ("Teenagers). Furthermore, there are specialized wards: Pediatric Surgery, Pediatric Oncology, Pediatric Intensive Care Unit (PICU) and Neonatal Intensive Care Unit (NICU). The Pediatric Surgery ward is merged with the ward for Infants less than one year old. The most frequent diagnoses in the Children's Clinic are covered by the specialties Surgery, Oncology, General Pediatrics, ENT (ear, nose and throat) and Gastroenterology.

On the three age-related wards, children are admitted who do not need special care of one of the other pediatric wards and fit within the age group of the ward. Pediatric Surgery (and Infants) provides, besides the infants less than one year old, care for children who need extensive wound care after surgery. Children with oncological diseases are treated on the Pediatric Oncology ward. At the NICU medical care is given to newborn infants, especially the ill or premature newborn infants. On the PICU, children are admitted with life-threatening illnesses and injuries or immediately after surgery in case of invasive surgery and when the child is at high risk of complications. In 2011 and 2012 almost 7,250 children were admitted per year to the Children's Clinic, of which 20 percent was admitted for a planned surgery.

The Women's Clinic consists of three wards: Obstetrics, Maternity ward and Gynecology. Before the childbirth women are admitted to Obstetrics and after childbirth to the Maternity ward. At Gynecology, the majority of the patients are treated for diseases of the genital organs. The most frequent specialties in the Women's Clinic are gynecology and obstetrics. In 2011 and 2012 a total of 10.600 women were admitted to the Women's Clinic. Of these admissions 15 percent was admitted for a planned surgery. In the Women's Clinic the majority of the patients arrive unplanned, due to complications during pregnancy.

	Ward	Bed capacity
Children's Clinic	Pediatric Oncology	21 (15 beds, 6 daycare chairs)
	Teenagers	24
	IC Children (PICU)	11
	Older Children	24
	Surgery and Infants	24
	IC Neonatology (NICU)	20
Women's Clinic	Obstetrics	17
	Maternity ward	28 (14 beds, 14 cradles)
	Gynecology	30 (24 clinical beds, 6 daycare beds)

TABLE 1: CAPACITY OF THE WARDS

2.1.2. GUIDELINES AMC-WIDE IMPROVEMENT PROJECTS

As discussed in Chapter 1, the AMC is forced to reorganize the operations of services during the upcoming years. Due to this, AMC-wide improvement projects (SLIM) have been started to use available resources as efficiently as possible and improve the quality of care. These SLIM projects are started in the inpatient clinic, outpatient clinic, operating rooms, diagnostic departments, and overhead departments. The guidelines for SLIM in the inpatient clinic were set and communicated by the Board of Directors of the AMC in July 2012. The SLIM guidelines relevant for this research are focused on the optimal alignment between patient demand and care supply in the WCC. The relevant guidelines of SLIM to improve the current processes in the WCC are as follows:

1) Release the bed with (temporary) absence of the patient
2) Have flexibly deployable nurses
3) Allow for exchange of personnel between units
4) The number of nurses taking care of patients has to be in compliance with the nurse-to-patient ratios. The nurse-to-patient ratio indicates how many patients on average a nurse can take care of during a shift. Patient care is covered when nurses do not take care of more patients than set by the nurse-to-patient ratios. The AMC finds that in 90 percent of the time the coverage should be sufficient (enough nurses staffed to care for patients according to the nurse-to-patient ratios). Only in ten percent of the time the coverage can fall below these ratios. This is defined as a coverage compliance of 90 percent.
5) Do not allow to close beds on wards in case of understaffing (e.g. due to long term illness or maternity leave of personnel) (Wiggers et al. 2013).

In order to compare the current performance of the WCC to these guidelines, more insight is needed in the current processes. The upcoming sections describe the processes in the WCC. Chapter 3 presents the current performance in the WCC compared to the guidelines set above.

2.2. Patient process

In the WCC, both elective and non-elective patients are admitted. Elective patients are planned and non-elective patients are unplanned and announced just before arrival. This section describes the elective patient process in Section 2.2.1 and the non-elective patient process in Section 2.2.2.

2.2.1. Elective patient process

The elective patient process consists of several processes: pre-hospitalization process, pre-operative/pre-treatment process, surgical operation or treatment and the post-operative process (Burger and Smeenk 2011). Figure 2 visualizes the elective patient process. The figure shows the planned patient path which starts with a visit to the outpatient clinic.

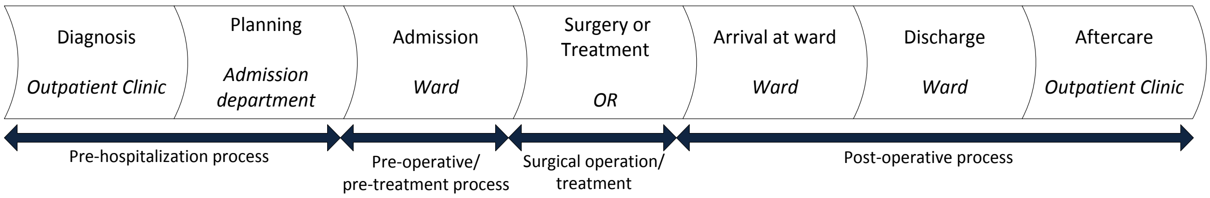

FIGURE 2: ELECTIVE PATIENT PROCESS

Pre-hospitalization process

The pre-hospitalization process is the process before a patient is admitted to the nursing ward. The hospital admission is registered during the outpatient clinic visit, where the physician decides to perform a surgical operation or treatment. The outpatient clinic contacts the admission planning to schedule the surgery or treatment. In case of surgery, the patient has to see the anesthesiologist for a preoperative assessment. This visit can take place in the month before surgery.

Pre-operative/pre-treatment process

The pre-operative/pre-treatment process is the process from the first visit of the patient to the nursing ward (the admission) until the start of the surgical procedure or treatment. In case patients are admitted to the hospital for a diagnostic procedure, observation or drug therapy, the majority of the patients are admitted on the same day and the patients are prepared for the procedure. In case of surgery, the patient is prepared for surgery and will wait for transport to the operating complex. Depending on the impact of the surgery, admission takes place on the day before surgery or on the day of surgery. Children are usually admitted the day before at 11 AM. Patients scheduled for surgery on Monday arrive at the hospital on Friday. After the anamnesis and the necessary observations (e.g., laboratory results), the patient can go home for the weekend. On Sunday evening, the patient returns.

Surgical operation or treatment

All surgical operations or treatments for elective patients are planned. The treatments can take place at various locations in the hospital, e.g. the radiology department, catheterization rooms. The surgery takes place in the operating room center (OR-center) by a surgeon of the specialty related to the diagnosis. The day of surgery depends on the OR-days assigned to the (sub)specialty. After surgery, the patient continues to either the Recovery Room (RR), the Intensive Care Unit (ICU) or the Pediatric Intensive Care Unit (PICU). In general, the patient continues to the RR, where the patient's recovery of the surgery and anesthetics is monitored. Most patients stay for a few hours in the RR before returning to the ward. When a patient enters the (P)ICU, this can be due to a planned admission or due to a complication occurred during surgery. The length of stay (LOS) in the (P)ICU depends on the patient's medical condition. In general, the patient will go back to the ward the day after surgery, but it can also take several days.

Post-operative/post-treatment process

The post-operative or post-treatment process is the process from arrival at the nursing ward from the RR, (P)ICU or other departments until discharge. After arrival on the ward, the nurse discusses the procedures that need to take place before discharge of the patient. Every morning the medical status of the patients is discussed during the physician's round and the decision is made whether or not to discharge the patient. The majority of the patients go home after discharge, some patients, however, continue their treatment in another hospital or rehabilitation center. In most cases, the patient has to see the medical specialist in the outpatient clinic a few days after discharge.

2.2.2. Non-elective patient process

Non-elective patients arrive unplanned and are announced just before arrival. These patients are admitted to the hospital from: the Emergency Department, the Emergency Department specialized for Women, (emergency) outpatient clinic, home (in case of complications), other hospitals or other wards within the AMC. After admission, these patients can go to the delivery rooms, OR, the (P)ICU or the ward. After admission, the patient process for non-elective patients is the same as discussed in Section 2.2.1.

2.3. Nursing work process

This section provides an overview of the nursing work process in the WCC. Section 2.3.1 addresses the nursing team, Section 2.3.2 the working times of the nurses and Section 2.3.3 the nurse-to-patient ratios.

2.3.1. Nursing team

Each ward has its own nursing team. In general, a team consists of one head nurse, a few senior nurses and general nurses. Furthermore, each team also has a few student nurses, nursing assistants and desk employees.

In the Women's Clinic the nursing team providing care for patients consists of (senior) nurses and maternity assistants. In the Children's Clinic all nurses are pediatric nurses, some nurses have additional qualifications for neonatal, intensive or oncological care. Nursing assistants, nurses in training for pediatric nursing and student nurses are also taking care of patients on some wards.

The total nursing capacity per ward is indicated in Full Time Equivalents (FTEs). Each nursing FTE of 1872 hours is deployable for 1525 hours after deduction of leave days, compensation for public holidays, education and average absence. The percentage of time a nurse can provide care for patients differs per nursing type. (1) The head nurse is responsible for the management of the nursing activities and ensuring high quality patient care on the wards. The head nurse does not provide care for patients, but is the manager of the ward. (2) Senior nurses work 25 percent of their shifts in the administrative office. During these shifts, the senior nurses do not take care of patients. These senior nurses have administrative tasks; such as to set up new protocols if necessary, manage quality improvement projects, etc. The other 75 percent the senior nurses are caring for patients and in the majority of these shifts they are the coordinator on the ward. (3) General nurses work for 100 percent on the wards where they provide care for patients. (4) Nursing or maternity assistants provide care for patients in 50 percent of the time (e.g. by assisting patients with personal hygiene). In the other 50 percent of the time they perform organizational tasks (e.g. replenishing stock). (5) Nurses in training also provide care for patients but they spend time on education as well. Student nurses also take care of patients but they are not fully qualified and need supervision of a (senior) nurse. Appendix A shows the number of FTE per nursing type and the percentage at the bedside (and caring for patients).

2.3.2. WORKING TIMES

A shift is a hospital duty that has a well-defined start and end time. On each ward there are three shift types: day, evening and night. The start and end time per shift differs per ward, see Appendix A. These shifts overlap due to the handover of patients from nurses of the current shift to nurses of the consecutive shift. In Appendix A, the time that nurses are responsible for patients is indicated. Nowadays, the day and evening shift have a length of eight hours, while the night shift has a length of nine hours. There is an ongoing discussion about changing the 8-8-9 schedules to 8-8-8 schedules, in which each shift has a length of eight hours.

2.3.3. NURSE-TO-PATIENT RATIOS

The nurse-to-patient ratio indicates how many patients on average a nurse can take care of during a shift. The nurse-to-patient ratios are set by hospital management and head nurses to make sure that every patient receives a sufficient amount of care. The nurse-to-patient ratio differs per shift, see Table 2. Due to safety reasons, the minimum number of nurses staffed per shift is two, irrespective of the number of patients on the ward.

	Nurse-to-patient ratio		
Ward	**Day**	**Evening**	**Night**
Pediatric Oncology	1:3	1:6	1:8
Teenagers	1:4	1:6	1:12
IC Children (PICU)	1:1½	1:2	1:2
Older Children	1:4	1:6	1:8
Pediatric Surgery and Infants	1:3	1:4½	1:6
IC Neonatology (NICU)	1:1½	1:2	1:2
Gynecology	1:6	1:7	1:12
Obstetrics	1:5	1:5	1:10
Maternity ward	1:5	1:5	1:10

TABLE 2: NURSE-TO-PATIENT RATIOS PER WARD PER SHIFT (WIGGERS ET AL. 2013)

At the beginning of a shift, all patients are discussed and nurses are assigned to a number of patients according to the nurse-to-patient ratio. Although the needed amount of care per specific patient can differ, the ratio is valid as an overall guideline for the corresponding ward. To equally distribute the workload for each nurse, the intensity of care of patients is included in the decision to assign nurses to patients.

2.4. Resource capacity planning

This section describes the operating room planning in Section 2.4.1 and the patient admission planning in Section 2.4.2. Section 0 describes the nurse staffing and rostering in the WCC.

2.4.1. Operating Room planning

The OR center consists of 26 operating rooms (ORs). It is divided in twenty clinical ORs, five ORs for daycare and one emergency OR. The clinical ORs are used for all patients admitted to the inpatient clinic (Academic Medical Center Amsterdam, 2013). To allocate the OR times to surgical specialties, different stages of OR planning occur leading to specified OR days for each (sub)specialty.

2.4.1.1. Stages Operating Room planning

The planning and scheduling of operating room time is often described as a multiple stage process (Vanberkel et al. 2010). In the AMC, the operating room schedule is established in multiple stages. The multiple stage process in the AMC starts with the long term allocation of OR time to the surgical specialties, referred to as Stage 1 in Table 3. All stages are shown in Table 3 and described below.

Stages	**Planning horizon**	**Action**	**Performed by**	**Planning level**
Stage 1	Annual planning	Assign total number of OR hours to specialty	OR-center	Tactical
Stage 2	Quarter planning	Allocate OR days/hours to specialty (OR blocks)	OR-center	Tactical
		Start planning of patients	OR planner of specialty	Offline operational
	Dynamic	Reallocate cancelled blocks to other specialties	OR-center	Offline operational
Stage 3	Week planning	Definite OR schedule for semi-elective patients	OR-center and OR planner of specialty	Offline operational
		Adapt OR planning in case of cancellations and (semi-)urgent patients		
Stage 4	Day planning	Plan acute patients	OR-center	Online operational
		Monitor OR planning		

TABLE 3: STAGES OF OR PLANNING (ACADEMIC MEDICAL CENTER AMSTERDAM, 2013)

Annual planning

On the tactical level, the OR center receives requests for OR capacity from each specialty for the upcoming year. This request is based on the annual OR budget that is available to a specialty. The OR-center assigns surgery hours to specialties and these surgery hours are translated to a fixed number of operating room days per year per specialty.

Quarter planning

The OR planning is published monthly and has a dynamic time horizon of six months. The OR planning of OR days to specialty is definite for the upcoming three months. Dynamically, the OR hours can be reallocated to other specialties. Three months before the OR-day, the OR planner of the specialty can start with the allocation of OR hours to subspecialties. From that moment, the planning of patients can start. The planning of patients is based on historical OR-time per surgeon per surgery and the associated needed anesthesia.

Week planning

Every (sub)specialty is responsible for the planning of its available OR capacity. Each (sub)specialty has a planner responsible for the planning of patients in the OR planning. The week planning for the OR-center is determined on Thursday 11.00 am.

Day planning

One working day before the OR-day, once the definite planning of the (sub)specialties is known, the OR planning is determined by the OR-center at 10.30 am. During the OR day, the planned surgeries can still be cancelled. Possible reasons for cancellations include the absence of the necessary staff (OR-assistants or surgeon), delays in preceding surgeries or an occupied OR as a result of the surgery of an emergency patient. Non-elective patients at the OR-center are classified by four categories: acute, urgent, semi-urgent and semi-elective. The classification indicates whether a patients has to be operated directly or can wait for a maximum of 72 hours.

2.4.1.2. Operating Room days WCC

The OR planning consists of OR blocks for each sub specialty. The day of surgery for a specialty is not fixed for the whole year; the planning differs per week due to internal movements between specialties. Some OR blocks are specific for children's surgery, other OR blocks are both for adults and children's surgery. Elective patients are admitted to one (or more) nursing ward(s) in the WCC when they go for surgery. In 2011 and 2012 the elective patients of the WCC had surgery in twenty-three OR specialties, see Appendix A.

2.4.2. Patient admission planning and monitoring

2.4.2.1. Patient admission planning

Patient admission planning is the hospital admission of an elective patient to a ward in a hospital. The patient is provided with a bed and continuous nursing service. Besides the elective patients, non-elective patients arrive unplanned. The process of this hospital admission is shortly described in phase 2 of Section 2.4.2.2. The majority of the patients reside overnight, some patients do not stay overnight and only use a bed during the day shift. For all elective patients who need to be admitted to the hospital for a surgery, diagnostic procedure, drug therapy or observation, the date of admission needs to be planned. With the planning of the admission day, the planning of the surgery or treatment needs to be taken into account.

In the WCC, multiple persons are responsible for the patient admission planning. The patient admission office of the Children's Clinic performs the admission planning of all pediatric wards. IC Neonatology only has unplanned admissions. For Pediatric Oncology the individual treatment plans for the patients are made on the ward and are sent to the patient admission office to plan the admission days for the patient. The (adult) specialties (e.g. Otolaryngology, Ophthalmology) plan the surgeries of patients and inform the patient admission office about the surgery dates. The patient admission office plans on which ward the patient will be admitted. For patients admitted to a ward for e.g. a diagnostic procedure or drug therapy, physicians communicate with the patient admission office and discuss the admission dates of the patients.

In the Women's Clinic, the majority of the elective patients are admitted to the Gynecology ward. In the gynecology ward, patients are admitted for surgery, for an oncological treatment or arrive unplanned. The admission of (elective) surgical patients is planned by a medical specialist and a nurse. They are in contact with the OR-complex and the wards to check for capacity. Patients that need an oncological treatment are planned by the desk employees of gynecology, where five beds are available for these oncological patients. A lot of patients can be planned in advance, therefore every three weeks a planning is made.

Most of the patients admitted to obstetrics or the maternity ward arrive unplanned. Some patients are planned for a caesarean section. At the outpatient clinic the gynecologist decides to plan the patient for surgery. The assistant of the gynecologist communicates with the OR complex and informs the wards about the date of admission of the patient. These patients are only admitted on weekdays. In some cases more than one planned caesarean section is performed on a day, but normally the maximum is one.

2.4.2.2. Patient admission monitoring in the WCC

The monitoring of patient admissions consists of two planning phases. One week in advance, wards are informed about elective patients scheduled for surgery (phase 1). The head nurse decides whether these patients can be admitted to the ward and at what time. If the ward is expected to be fully occupied, the patient is assigned to another ward. On the admission day of the elective patient the head nurse evaluates the current bed occupancy and the planned admissions (phase 2). If the ward is fully occupied, the head nurses and the admission office can decide to reallocate a planned admission to another ward. The acceptance of non-elective patients depends on the current bed occupancy and the planned admissions for the upcoming days. The patient admission office checks the occupancy of each ward and decides to assign the non-elective patient to a ward. If all wards (where a patient can be assigned to) are full or in case there is not enough personnel to care for the patient, the patient is rejected. In this case, the patient is moved to another hospital.

2.4.3. Nurse staffing and rostering

Multiple stages need to be completed before nurse rosters can be created. These stages are described in Table 4. Stage 1 is a decision on strategic level, determining the appropriate number of FTE and the mix of skills that has to be employed. In nursing wards, the working times are divided in shifts. Before nurse rosters are created, the necessary number of nurses for each shift needs to be determined. The determination of the necessary number of nurses for each shift is defined as nurse staffing, see stage 2. Nurse rostering (stage 3) is based on these nurse staffing decisions and is the assignment of individual nurses to particular working shifts. Due to unexpected absence of nurses the nurse schedule needs to be reconsidered (stage 4). The focus of this research is on stage 2, the tactical decision about how many nurses to staff each shift.

Stages	Planning level	Planning horizon	Action
Stage 1	Strategic	Annual planning	Workforce capacity dimensioning decision: determine the number of FTE that has to be employed and the mix of skills
Stage 2	Tactical	Annual planning – Ten weeks in advance	Staff shift scheduling decision: determine the necessary number of nurses for each shift
Stage 3	Offline operational	Ten weeks in advance	Nurse rostering: allocation of nurses to shifts according to the staff shift scheduling decision
Stage 4	Online operational	Day planning	Staff rescheduling: reconsider the nurse rosters, on account of absence of personnel, etc.

TABLE 4: PHASES IN NURSE ROSTERING

In stage 2 in the AMC, the managements of the wards in the WCC have chosen to assign the same number of nurses to a shift for each week or weekend day, see Table 5. These numbers are based on the set nurse-to-patient ratios and expected bed census based on head nurses' experience. The different percentages of time a nursing type can take care of patients need to be taken into account, as described in Section 2.3.1. On some wards in the WCC the number of nurses staffed during weekdays differs from weekend days. In this case, the number of nurses staffed during weekend days is indicated between brackets in Table 5.

Ward	Number of nurses staffed to provide care		
	Day	Evening	Night
Pediatric Oncology	6 (5)	3	2
Teenagers	6 (4)	4 (3)	2
IC Children	8	6	6
Older Children	7 (5)	4	3 (2)
Pediatric Surgery and Infants	7	5	4
IC Neonatology	11	8	7
Gynecology	5 (4)	4 (3)	2
Obstetrics Maternity ward	8	8	5

TABLE 5: CURRENT NUMBER OF NURSES STAFFED PER SHIFT. IN CASE THE NUMBER OF NURSES STAFFED DURING WEEKEND DAYS DIFFERS FROM WEEK DAYS, THE NUMBER OF NURSES DURING WEEKEND DAYS IS INDICATED BETWEEN BRACKETS. (SOURCE: GUIDELINES WCC PLANNERS, APRIL 2013)

In stage 3, the WCC planners are responsible for the rosters of the nurses in all wards in the WCC. They aim to reach the required staffing levels in Table 5, while satisfying restrictions such as employee preferences and legal requirements (working and resting hours limit, skill levels). The offline operational rosters are created ten weeks in advance. These rosters indicate to which day and shift nurses are assigned, or whether nurses have a day off, are working in the office (for senior nurses) or have course days. Since the patient admission schedule is still uncertain, at the point nurse rosters are created it is unknown how many patients to care for.

To create satisfying rosters for nurses, the planner needs to consider the various nursing types and the days occupied by administrative tasks and courses. The nursing team consists of various nursing types (nurses, nursing assistants, senior nurses), which need to be effectively scheduled together to create a balanced nursing team for that shift (with the right competences to care for the patients). Besides the combination of nursing types, the planner has to schedule office-days and course-days. Senior nurses work for 25% of their shifts in the administrative office while they are not on duties on the wards. The planner schedules these office-days. Next to this, the planner also schedules course-days for the nurses to stay competent.

Besides holidays and maternity leave, nurses can indicate their personal roster preferences (e.g. preferences for a night shift, free time for sports activities) to the planner. If possible, the planner takes these preferences into account when creating the roster. The nurse roster is created ten weeks in advance by the planner of the ward and must be approved by the head nurse. During the ten weeks, nurses have the possibility to internally change shifts with each other, thereby changing the nurse roster.

On the online operational level (stage 4) nurses can become ill and replacement must be deployed. An option is to hire additional nurses. If no replacement can be found, the head nurse sometimes decides to close some operational beds on a ward. It is possible that one ward is overstaffed and the other ward is understaffed. In the WCC, a few steps are taken to deploy nurses flexibly and react to this situation. Every morning (during the "dagstart") the senior nurses and admission coordinator review the capacity of the Children's Clinic of that day. During this review, they discuss the nursing staff capacity and the demand for beds. In a reactive way the capacity can be shared with each other and patients or nurses can be moved to another ward. All pediatric nurses can be allocated to another ward to care for patients. In case of understaffing even nurses without additional qualifications can be helpful on specialized wards (e.g. PICU, NICU). These nurses are not able to completely care for a patient but can assist specialized nurses by the administration of medication and by helping patients with personal hygiene, etc.

In the Women's Clinic the capacity on the wards is not reviewed. For Obstetrics and the Maternity ward, capacity is already planned together. According to the management of the wards, Gynecology cannot exchange nurses with Obstetrics and the Maternity ward due to necessary qualifications concerning pregnancy and childbirths.

2.5. Conclusion

This chapter described the current work and planning processes in the WCC. The improvement guidelines important for this study are the minimum coverage compliance of 90 percent and the application of nurse-to-patient ratios. Nurse-to-patient ratios indicate the average number of patients a nurse can take care of during a shift. The nurse-to-patient ratios are set by hospital management and head nurses to make sure that every patient receives a sufficient amount of care. The nurse-to-patient ratios differ per ward, due to the different requirements of intensities of patient care. These ratios are a guideline applied in nurse staffing.

In the WCC, both elective as non-elective patients are treated. These patients follow a different patient path. The nursing teams differ per ward and the teams consist of various nursing types.

Some wards require nursing types with additional qualifications. The time a nursing type provides care for patients differs; some nursing types spend a certain amount of time on education or in the administrative office.

We described three resource capacity planning processes: OR planning, patient admission planning, and nurse staffing and rostering. The various planning horizons limit the possibilities to match care supply and patient demand. The OR planning in the WCC is an extensive planning due to the various surgical specialties of all patients in the WCC. In the nurse staffing and rostering process in the WCC, a fixed number of nurses is staffed in a shift, independent of the number of patients on a ward. The first step to flexible deployment of nurses is set in the Children's Clinic by reviewing the nursing capacity of all wards. In case of an understaffed and overstaffed ward, a nurse of the overstaffed ward will be moved to the understaffed ward.

To verify whether improvements are required in the current staffing process, we analyze the performance of the WCC. We are interested in the variation in the number of patients on a ward, because in the current staffing process a fixed number of nurses is staffed. Moreover we analyze the occurrence of overstaffing and understaffing in the wards. The next chapter presents the current performance.

3. CURRENT PERFORMANCE

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4. LITERATURE REVIEW

This chapter gives an overview of the currently available literature related to nurse staffing. Section 4.1 gives an introduction to operations research in healthcare. Section 4.2 gives an overview of the staffing literature. This research applies existing models for bed census prediction and nurse staffing. Section 4.3 describes the hourly bed census model of Kortbeek et al. (2012a) for predicting the bed census. Section 4.4 describes the nurse staffing model of Kortbeek et al. (2012b) extensively. These models are applied in this research to determine the staffing levels in the WCC. This chapter closes with the contribution of this study.

4.1. OPERATIONS RESEARCH IN HEALTHCARE

In resource capacity planning and control in manufacturing, Operations Research and Management Sciences (OR/MS) is widely used. Hulshof et al. (2012) state that "Resource capacity planning and control addresses the dimensioning, planning, scheduling, monitoring and control of renewable resources". Since the 1950s, efficiency gains are accomplished in health care delivery by the application of OR/MS to health care. Many different topics have been addressed, such as operating room planning, nurse staffing and appointment scheduling (Hulshof et al. 2012).

Hulshof et al. (2012) give an overview of the typical decisions to be made in resource capacity planning and control in healthcare. A taxonomy is presented to classify each planning and control decision. They structurally review the key OR/MS articles and the OR/MS methods and techniques that are applied in the literature to support decision making.

The subjects relevant to this research are demand forecasting (daily bed census prediction) and the nurse staffing decision. Demand forecasting is important in improving the efficiency of resource use in health care. Forecasting demand has two functions: the determination of the need for services (the demand side) and census planning (supply side). Analysis of demand on a daily basis drives hospital-wide decisions, including staffing, ancillary services, elective admission scheduling and support services (Pierskalla and Brailer 1994).

4.2. NURSE STAFFING

The main objective of staffing is to match personnel supply and patient demand. In hospitals, undesired staffing situations, such as understaffing and overstaffing, need to be avoided (Komarudin et al. 2013). Understaffing and work overload can have a direct effect on patient safety and can lead to poor nurse-physician and poor nurse-patient communication. Besides this, work overload can result in nurses' job dissatisfaction, burnouts and medical errors (Carayon and Gurses 2008). Overstaffing also needs to be avoided due to the fact that this can lead to unnecessary personnel costs (Komarudin et al. 2013).

Nurse staffing consists of four steps. Hulshof et al. (2012) discriminate between four hierarchical decision levels of staffing: (1) workforce capacity dimensioning, specifying the number of FTE; (2) staff-shift scheduling, specifying the required number of staff per day or shift; (3) staff-to-shift assignment, the allocation/rostering of staff members to shifts; and (4) staff rescheduling, the reassignment of staff members or the deployment of flexible employees.

Staff-to-shift assignment (also known as the nurse rostering problem) is extensively discussed in literature. Several literature reviews are available about the nurse rostering problem (Smith-Daniels et al. 1988, Pierskalla and Brailer 1994, Cheang et al. 2003, Burke et al. 2004, Ernst et al. 2004, Kellogg and Walczak 2007, Van den Bergh et al. 2013). The decision on a higher level, the staff-shift scheduling decision has only received little attention in literature. This decision is important to provide the right employees at the right time and at the right cost, while achieving a high level of employee job satisfaction (Ernst et al. 2004).

In the literature review of by Van den Bergh et al. (2013) is stated that current literature about the staff-shift scheduling decision is mainly focused on fixed inputs regarding the staffing of employees. This indicates the need to forecast the required staffing levels per shift in a hospital. Ernst et al. (2004) state that people involved in nurse staffing need decision support tools. The first step in the development of these tools is demand modeling. Historical data is used to forecast demand and convert the demand to staffing levels needed to satisfy service levels (Ernst et al. 2004).

The interdependence of decision levels of nurse staffing must be recognized to improve nurse staffing. Each level is constrained by available resources, by previous commitments made at higher levels and by the degrees of flexibility for later correction at lower levels. Therefore each level is strongly dependent on the other levels. For best performance, one level cannot be considered in isolation (Pierskalla and Brailer 1994). Also Van den Bergh et al. (2013) advise researchers to integrate multiple decisions in the personnel scheduling problem, such as demand forecasting, hiring and firing and considering multiple locations.

Wright and Mahar (2013) and Maenhout and VanHoucke (2013) integrated different decision levels to improve nurse staffing. Wright and Mahar (2013) integrate staff-shift scheduling decision into the nurse rostering decision. Their methodology provides a contribution to the nurse scheduling literature due to the specification of the number of nurses required for each shift. They have studied how centrally scheduled cross-trained nurses across multiple wards in a hospital can reduce costs and improve nurse satisfaction. To determine the required number of nurses for each shift, a workload model is presented that accommodates nurse-to-patient ratios. This workload model calculates for different nurse staffing levels the probability that service levels are violated. To calculate whether these service levels are violated, nurse-to-patient ratios are used and the probability of a number of occupied beds during a shift is calculated using queuing methods (Wright et al. 2006).

Maenhout and Vanhoucke (2013) integrated the workforce decision in the nurse rostering decision. They state that the workforce decisions restrict staff-shift scheduling decision alternatives and the staff-shift scheduling decisions restrict the allocation alternatives. They show that staffing multiple nursing departments simultaneously increasingly leads to improvements in schedule quality in terms of cost, personnel job satisfaction and effectiveness in providing high-quality care. Although Maenhout and Vanhoucke (2013) integrated the strategic and operational level, the tactical level is not integrated. In their method, they make use of a fixed number of nurses for each skill category for each shift on each day in each ward.

Three main categories of uncertainty must be considered to determine the required staffing levels per shift. Van den Bergh et al. (2013) define three main categories of uncertainty: (1) uncertainty in demand – the unpredictable workload, (2) uncertainty in arrival – the unpredictable arrival pattern of workload, and (3) uncertainty of capacity – deviations between planned and the actual manpower. To respond to uncertainty in demand, nurses can be staffed in nursing float pools. Dzubia-Ellis (2005) defines a nursing float pool as a group of nurses who are staffed on a ward in response to the variability in patient demand. Float pools are considered as useful strategies for the management of unpredictable staffing needs. The major incentives for float pools are: the reduction of the need for reliance on costly agency or per diem staff, the lack of human resources and the fluctuations in patient census, acuity and volume. Little is known about the impact of nurse floating on patient outcomes (Dziuba-Ellis 2005).

Pronger (as cited in Dziuba-Ellis (2005)) states that one strategy to implement staffing of float nurses, is to set floating as a hospital policy. In this case, nurses are hired by the hospital and not by an individual unit and therefore nurses cannot refuse to float. According to the Joint Commission International nurses should be permanent employees hired directly into resource teams or should at least be limited to float into areas in which they have experience, are competent, and have access to adequate support and supervision (Dziuba-Ellis 2005).

From this section can be concluded that the nurse rostering problem is extensively discussed in literature. However, the staff-shift scheduling problem (the determination of staffing levels based on forecasts of patient demand) is not discussed. Kortbeek et al. (2012a, 2012b) developed two mathematical models for forecasting patient demand and determined staffing levels based on these patient demand forecasts. Section 4.3 describes the mathematical model of Kortbeek et al. (2012a) about demand forecasting and Section 4.4 discusses the nurse staffing model of Kortbeek et al. (2012b) to determine staffing levels based on demand forecasts.

4.3. HOURLY BED CENSUS MODEL

In order to describe the hourly bed census (HBC) model, we use citations of Kortbeek et al. (2012a) in this section. The hourly bed census (HBC) model developed by Kortbeek et al. (2012a) is a generic analytical approach to predict bed census on nursing wards per hour, as a function of the operating room block schedule (MSS) and a cyclical arrival pattern of emergency patients. The method builds upon the approach presented in a paper by VanBerkel et al. (2010). The approach of VanBerkel et al. (2010) determines the workload placed on hospital departments by describing demand for elective inpatient care beds on a daily level as a function of the MSS. The MSS is a cyclic OR-schedule which indicates which specialty operates in which OR on which day of the week. Kortbeek et al. (2012a) extend the approach of VanBerkel et al. (2010) to an hourly level and include the admission of non-elective patients.

The HBC model can assist decision-making on various planning levels. In the article of Kortbeek et al. (2012a), performance measures (e.g. rejection probability and misplacement probability) are formulated. With these performance measures the effectiveness of different logistical configurations can be assessed. In addition, what-if questions considering the impact of interventions (shortening the length of stay, changing the time of admission and discharges) are formulated. Insight can be gained on the impact of strategic (i.e. capacity dimensioning, case mix), tactical (i.e. allocation of operating room time, misplacement rules), and operational decisions (i.e. time of admission and discharge). For these decisions, rules-of-thumb can be established and explicit interventions can be formulated of which the effect can be predicted.

The bed census can be divided in two groups of patients: elective patients with a planned surgery and non-elective patients (all patients without a planned surgery). The model first determines the bed census per patient group separately and then combines the patient groups to determine the bed census on the wards.

The bed census resulting from elective patients is determined in three steps. First, the impact of a single surgery block on the bed census is determined and given by a discrete distribution. The distribution describes the number of elective patients from a single surgery block still recovering at a certain time slot and day. In the next step, the impact of a single cycle is determined by combining the distributions for single surgery blocks. Combining is done by the use of discrete convolutions. The last step is to obtain the steady state impact of the repeating MSS cycles. Since the recovery of patients of one MSS cycle may overlap with patients from the next MSS cycle, the distributions have to be overlapped in the correct manner. Again, convolutions are used to determine the distribution of the number of elective patients present in a ward during a certain time slot.

The bed census resulting from non-elective patients is also determined in three steps. The first step is to determine the bed census resulting from patient arrivals (for all non-elective patient types) during each day of the week. The process describing the number of non-elective patients admitted on a certain day still recovering at a certain time and day is based on the admission process and the discharge process. The admission process is a time-dependent nonhomogeneous Poisson process and the discharge distribution process is based on historical hospital discharge data. The next step is to calculate the result of patient arrivals during each day of the period. This is done by combining all individual bed census processes by taking convolutions. The last step is to obtain the steady state impact of the non-elective patients on the bed census. Again, convolutions are used to determine the distribution of the number of non-elective patients present in a ward during a certain time slot.

Finally, the demand distribution of the number of patients during a certain time slot and day is determined, by making use of convolutions to combine the demand distributions of the elective and non-elective patients. The obtained demand distributions are translated into bed census distributions, since demand and bed census can differ due to rejections and misplacements. A misplacement takes place when a patient should be admitted to a certain ward but due to lack of capacity, is placed on another ward.

4.4. NURSE STAFFING MODEL

In this section we use citations of Kortbeek et al. (2012b) to describe the nurse staffing (NS) model. The NS model developed by Kortbeek et al. (2012b) is a stochastic method that uses hourly census predictions (from the HBC model) to derive efficient nurse staffing policies. The generic analytical approach finds the number of nurses to be staffed each working shift that guarantees quality of care reflected by nurse-to-patient ratios in the most cost-effective matter. This model allows hospitals to dynamically respond to their fluctuating patient demand by employing flexible nurses besides the dedicated nurses. Dedicated nurses are nurses with a fixed assignment to a ward and flexible nurses are allocated to a flex pool. Flexible nurses are assigned to the ward with the lowest nursing coverage at the beginning of a shift.

The approach directly connects with the bed census prediction method of Kortbeek et al. (2012a). In this way, the alignment of staffing decisions with other interrelated inpatient planning decisions can be achieved (such as case mix, ward partitioning and size), as well as coordination with the operating room complex and the emergency department.

Although the inpatient population fluctuates, the fluctuation is to a certain extent predictable, due to its dependence on the operating room schedule and other predictable variability in patient arrivals (e.g. seasonality, day-of-week, and time-of-day effects). This predictable variation can be taken into account when setting the staffing levels for 'dedicated nurses', nurses with a fixed assignment to a ward. When two or more units cooperate by jointly appointing a flexible nurse pool, the variability of these random demand fluctuations balances out due to economies of scale, so that less buffer capacity is required.

The nurse staffing model consists of several steps. First, to match nursing capacity with demand predictions, optimal staffing levels are determined for only dedicated nurses. Next, the model with a flex pool with flexible nurses (besides the staffing of dedicated nurses) is executed. This model includes an assignment procedure that prescribes the rules according to which flexible nurses are assigned to specific wards at the start of each working shift. Due to the complexity an approximation model is presented which provides a lower and an upper bound on the staffing requirements.

4.5. Conclusion

This chapter provided an overview of the existing literature of nurse staffing and the application of flexible nurse pools. The staff-shift scheduling decision has received little attention in literature. Kortbeek et al. developed two models focused on the staff-shift scheduling decision: the HBC model to forecast bed census (2012a) and the NS model to determine staffing levels (2012b) based on forecasts of bed census. They make use of flexible nurses to react to variability in bed census.

In this study we want to research the potential of applying the HBC and NS model to a new case study. By using nurse-to-patient ratios and applying the HBC model to the WCC, the NS model of Kortbeek et al. (2012b) is used to determine the staffing levels in the WCC. The goal is to achieve the desired nurse coverage compliance of 90% in the WCC with a minimum amount of nurses.

The next chapter describes the working of the HBC and NS models, the application of both models and the limitations of these models. Due to differences of this case study compared to the case study used in the article of Kortbeek et al. (2012b), we encounter limitations in the application of the HBC and NS model.

5. APPLICATION OF THE HBC AND NS MODEL

We conclude from previous chapters that improvements are required in the staffing policy. In the current staffing policy a fixed number of nurses is staffed in a shift and bed census fluctuates during the week. Therefore staffing is not aligned with the fluctuating bed census. Kortbeek et al. (2012a, 2012b) developed two models in the AMC to optimize nurse staffing based on bed census predictions. Within this study we research the possibilities to apply these models to another case study. This chapter discusses how both models work, the information needed to use the models, the limitations of the models and how the models are applied to the WCC.

Section 5.1 gives an introduction of the HBC and NS model. Section 5.2 provides an overview of the limitations of the models. Section 5.3 describes the application of the HBC model and Section 5.4 describes the application of the NS model. In these sections a distinction is made between the conceptual model, the case study of Kortbeek et al. (2012b), and our case study. This chapter closes with a conclusion in Section 5.5.

5.1. INTRODUCTION OF THE HBC AND NS MODEL

Figure 3 shows the conceptual model of the HBC (Kortbeek et al. 2012a) and the NS model (Kortbeek et al. 2012b). The HBC model requires information of acute and elective patient arrivals, length of stay distributions and the bed capacity to calculate bed census distributions. To predict the arrival of elective patients on wards, the HBC model requires the upcoming Master Surgical Schedule (MSS), surgery distributions and admission day and time distributions. The MSS indicates on which day, in which OR-number, which surgical specialty operates. The surgery distributions and admission day and time distributions are based on historical data. Based on the MSS and the surgery distributions the probability can be calculated how many patients of a surgical specialty will be admitted to a ward. The admission day and time distributions are the probabilities that a patient is admitted the day before or at the day of surgery and the time of admission.

To predict the arrival of acute patients, an arrival rate is calculated based on the historical admissions of acute patients. Length of stay probabilities indicate how long an acute or elective patient will stay on a ward. This probability is divided in the discharge day and discharge time probability. These probabilities are also calculated based on historical patient admission data.

Based on the elective and acute arrival distributions, and the length of stay distributions, demand distributions can be calculated. The obtained demand distributions are translated into bed census distributions based on the bed capacities op the wards since demand and bed census can differ due to rejections and misplacements to other wards. Misplacements take place when a patient should be admitted to a certain ward but due to lack of capacity is placed on another ward. The bed census distributions provide the probability for each bed census (from zero to the maximum bed capacity) for each timeslot.

These bed census distributions, together with coverage requirements and the start and end times of working shifts are needed to calculate optimal staffing levels with the NS model. The NS model determines the number of nurses to staff each working shift in such way that quality of care is guaranteed in the most cost-effective matter. The NS model uses the coverage requirements to guarantee the quality of care. One of the coverage requirements is the guideline for the coverage compliance. All coverage requirements are described in Section 5.4.3.

The NS model calculates the number of nurses to be staffed each working shift and the required number of FTE while achieving the coverage requirements for two staffing policies:

(1) Staffing on bed census predictions. Based on the bed census predictions per shift and the nurse-to-patient ratios, the number of required nurses to reach the coverage compliance requirement is calculated. Flexible nurses are not staffed, only dedicated nurses are staffed.
(2) Flexible staffing – staffing based on bed census predictions with a flex pool. Wards interact due to the presence of a flex pool. Based on bed census predictions the required number of dedicated nurses per ward, supplemented by the calculated required number of nurses in a flex pool, is determined.

Appendix C and D shows a detailed description of the models. The conceptual HBC and NS model are programmed in Delphi Embarcadero RAD studio to automate the calculations. We define the programmed models as the technical design of the models. In the next section we will discuss the limitations of the conceptual models and the technical design of the models. Section 5.3 and Section 5.4 describe the application of the models to our case study. This chapter closes with a conclusion.

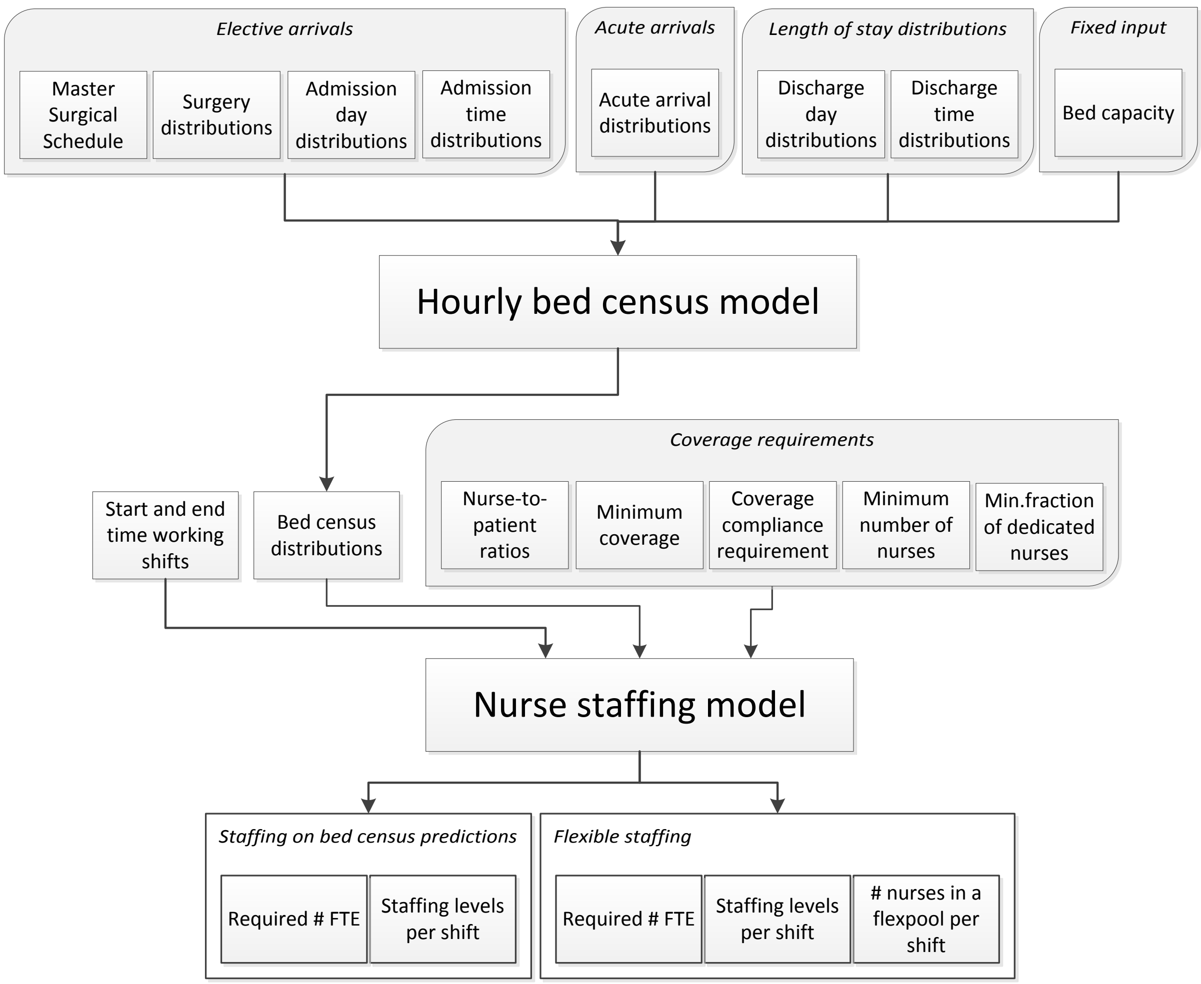

FIGURE 3: OVERVIEW OF CONCEPTUAL HBC AND NS MODEL

5.2. LIMITATIONS OF THE MODELS

The HBC and NS model have several limitations. These limitations can be divided in limitations of the conceptual model and limitations of the technical design.

5.2.1. LIMITATIONS OF THE CONCEPTUAL HBC MODEL

1) In reality, wards interact with each other when misplacements take place (in case of exceeding the capacity of a ward) and when patients are moved to another ward for medical reasons. The HBC model cannot completely mimic the exact interaction of wards. In this model, wards only interact with each other in case one of the wards exceeds the capacity of the ward and misplacements need to take place. Movements between wards due to medical reasons and the temporary absence of a patient are not implemented in the model.
2) The HBC model is only applicable for surgery blocks from which patients are admitted to one ward. In this case the wards are specialty specific and the model has the information to assign patients to their preferred wards. If patients of a specialty can be admitted to multiple wards, the model does not know to which ward the patient must be admitted. Therefore, the model is not applicable for surgery blocks from which patients are admitted to various wards.

5.2.2. LIMITATIONS OF THE TECHNICAL DESIGN OF THE HBC AND NS MODEL

1) In the HBC model, patients are moved (misplaced) to another ward in case the bed capacity of their preferred ward is exceeded. The HBC model can only misplace patients between two wards and forecast the bed census for two wards at once. To make the model usable for more than two wards, the misplacement policy must be adapted.
2) The number of various surgical specialties and treating specialties (defined as patient types) in the HBC model is limited by the computation capacity of the computer. Only a limited number of surgical and treating specialties can be used. The number of patient types the computer can process is around 600.
3) The NS model cannot calculate the staffing levels with a flex pool for more than four wards. Many possibilities exist how flexible nurses are allocated to the wards and the NS algorithm calculates all these possibilities. If more wards are used in a case study (sharing flexible nurses), the number of possibilities rapidly increases. For more than four wards, too many possibilities need to be calculated and this is not possible with the technical design of the NS model. Nevertheless, a flex pool for more than four wards is difficult to implement due to organizational constraints.

5.3. INPUT REQUIREMENTS HBC MODEL

Figure 3 shows the working of the HBC and NS model. In this section we describe the requirements to calculate the bed census distributions with the HBC model. Figure 3 shows four different groups of input requirements for the HBC model: elective arrivals, acute arrivals, length of stay distributions and fixed input. We first discuss the distinction between elective and non-elective arrivals. In each section we describe why we need the information, how the models are used in the case study of Kortbeek et al. (2012a) and how the models are used in our case study. Limitations of the conceptual and technical design of the models are discussed in each section. If these limitations influence our case study, we describe the choices to use the models with knowledge of the limitations.

5.3.1. DISTINCTION BETWEEN ELECTIVE AND NON-ELECTIVE ARRIVALS

The conceptual HBC model makes a distinction between elective and acute patient arrivals admitted to a ward. The elective and acute patient arrivals can be divided in elective and acute patient types. The different patient types are the basis of the model and are used to distinguish between different patient characteristics. For each patient type, distributions are determined based on historical data. If more patient types are used, more specific distributions can be determined if sufficient historical data is available. Therefore, the choice of patient types influences the performance of the HBC model.

LIMITATIONS

A limitation of the technical design of the HBC model is that the number of patient types is restricted (see Section 5.2.2). A limitation of the conceptual model is that each patient type can only be admitted to one ward (see Section5.2.1). The HBC model needs to know to which ward a patient must be admitted.

Case study Kortbeek et al. (2012a)

In the case study of Kortbeek et al. (2012a) the acute patient types are based on the treating specialty and the elective patient types on surgical specialties. In their case study, the number of different treating and surgical specialties does not exceed the capacity of the technical design. Therefore, Kortbeek et al. (2012a) distinguish between the surgical specialties of elective patients. For each surgical specialty a patient type is created. More specific surgery distributions and length of stay distributions can be created if each surgical specialty becomes one patient type. Differences in length of stay distributions exists between surgical specialties because patients with a more invasive surgery will have a longer post-operative recovery time. Besides the elective patient types, the acute patients are subdivided into patient types based on their treating specialty and on their weekday and time of arrival. Hence, for every treating specialty (i.e. treating specialty ENT) 168 patient types exist (7 weekdays times 24 hours). They distinguish between these types to take disruptions in diagnostics and treatments that can occur during nights and weekends into account. Acute patients arriving outside office-hours and on weekend days may have a different length of stay than acute patients arriving during office-hours. Therefore, for each surgical specialty, only one patient type exists and for each treating specialty 168 patient types exist.

Case study WCC

In our case study a lot of different surgical and treating specialties exist. This results in small historical datasets of each specialty. We are restricted by the technical design and the size of our dataset and forced to group surgical or treating specialties. The conceptual model also has a limitation that each patient type can only be assigned to one ward. In our case study, patients of one specialty can be admitted to various wards. Therefore it is not possible to make one patient type for each specialty. The HBC model requires the preferred ward for each patient type.

By grouping all surgical specialties of patients admitted to the same ward, and all treating specialties of patients admitted to the same ward, we create large datasets and can calculate more reliable distributions. To work with the limitation that each patient type can only be assigned to one ward, we make the choice to group all surgical specialties and to group all treating specialties and give it the name of the ward. In this way, the HBC model has the information to which ward the patient type must be assigned. For example, a patient from the surgical specialty Neurosurgery, admitted to the Teenagers ward is grouped to the patient type Teenagers. Another patient from the same specialty of Neurosurgery, but admitted to the Older Children ward is grouped to the patient type Older Children. For the acute patient types, we make the same distinction in 168 acute patient types per treating specialty. Therefore, for each ward 168 acute patient types are created.

Influences of choices

Our choices for patient types influence on the applicability of the HBC model as a prediction tool and the different distributions described in this chapter. Due to the limitation of the HBC model that outflow from one surgery block to various wards is not possible, we made the choice to base patient types on the admission ward instead of the surgical specialty. This leads to the situation where the upcoming MSS cannot be used. It is not possible to make another choice for the patient types, because each patient type can only be admitted to one ward. Our choices also influence the surgery distributions, acute arrival distributions, length of stay distributions, admission day, and admission time distributions. These distributions can differ per specialty. The consequence of merging all specialties in the same patient type is that distributions are less specific and therefore less reliable.

5.3.2. Elective arrivals

The arrivals of elective patients are based on the upcoming MSS, surgery distributions, admission day distributions, and admission time distributions.

5.3.2.1. Master surgical schedule (MSS)

The MSS (an overview of the planned surgery blocks) set by the OR center is required to predict the bed census. Together with the surgery, admission day and time distributions the probability of the number of admissions and the day and time can be predicted.

Limitations

In the conceptual model, only admissions from one surgery block to one ward are possible, see (see Section 5.2.1). Therefore it is not possible to have patients admitted from one surgery block to various wards.

Case study Kortbeek et al. (2012a)

The case study of Kortbeek et al. (2012a) consists of a few patient types. Their case study contains specialty specific wards to predict hourly bed census. E.g., all patients from surgery blocks of Vascular Surgery will go to only one ward. Therefore Kortbeek et al. was able to determine the upcoming MSS.

Case study WCC

In the WCC it is not possible to determine the upcoming MSS from which patients will be admitted to the wards of the WCC. Many surgical specialties (i.e., ENT, Ophthalmology) exist where besides children and women also other patients are operated and admitted to a ward outside the WCC. Therefore outflow is possible from the surgical specialties to various wards in and outside the WCC. Due to the high variation in the outflow from various surgical specialties, it is not possible to use historical data to predict the outflow. The decision to create one patient type, also influences the use of the HBC model. Because patient types are not specified per surgical specialty, we cannot use the upcoming MSS with the distributions per patient type to predict the hourly bed census. Therefore we decided to base our MSS on historical data and only use the HBC model to indicate the improvements possible with the HBC model.

Recommendations

A method must be developed to admit patients from one surgery block to various wards. If patient types can be created and specific surgery distributions that can be used with the MSS, bed census can be predicted.

5.3.2.2. Surgery distributions

The surgery distributions are calculated for each elective patient type based on historical data of patients with an elective surgery. In the HBC model the upcoming MSS together with the surgery distributions are used to predict how many patients are admitted to a ward from a surgery block of a certain surgical specialty.

CASE STUDY KORTBEEK ET AL. (2012A)

The case study of Kortbeek et al. (2012a) determines the probabilities of how many patients are operated in one surgery block based on historical data of all elective patient types. They calculate the surgery distribution based on the realized surgeries of patients admitted to the wards. Therefore the probability of 0 surgeries performed in one block equals 0.

CASE STUDY WCC

In our case study a lot of surgical specialties exist. Due to the high variance in the number of patients operated and the small size of the dataset, it is not possible to calculate reliable surgery distributions per surgical specialty. Therefore, all surgical specialties are grouped to one patient type and for each ward one surgery distribution is calculated.

INFLUENCES OF CHOICES

The influence of the choice to group the surgery specialties per ward is that e.g. a surgery block of ENT with patients admitted to Teenagers and Older Children is now seen as two separate surgery blocks. In this case study, both surgery blocks have their own surgery distribution based on the historical admissions to the ward from this block. We make these distributions independent of each other. In reality, however, both patients come from the same surgery block and thus are dependent on each other. It is possible that the number of outflowing patients from both surgery blocks exceeds the maximum number of patients (max k) that is possible (in reality) to flow out of the original surgery block (ENT). This can result in more patients admitted to the wards of the WCC at the same time than in reality is possible.

Another influence of merging the surgical specialties and calculate a general surgery distribution on all specialties is that the distributions cannot be used with the upcoming MSS. The surgery distributions need to be calculated per surgical specialty to use it with an upcoming MSS.

RECOMMENDATIONS

A method must be developed to use the surgery distributions with the surgical schedule consisting of different surgery specialties from which patients can be admitted to multiple wards. If outflow from one surgery block to various wards is modeled in the HBC model, the surgery distributions must be calculated based on historical data and the MSS that was used. This results in surgery distributions where the probability of 0 surgeries is also calculated.

5.3.2.3. ADMISSION DAY AND TIME DISTRIBUTIONS

The HBC model needs admission day and time distributions to predict on which day and time a patient will arrive, depending on the surgery block in the MSS. The admission day distribution is the probability of a patient (of a certain type) to be admitted on day n. The admission time distribution is the probability of a patient (of a certain type) of being admitted at time t, given that the patient is admitted on day n. To calculate these distributions, the admission day and time of all elective patients (of a certain type) admitted to the ward must be known.

CASE STUDY KORTBEEK ET AL. (2012A)

The case study of Kortbeek et al. (2012a) specified the patient types on the surgical specialties. Therefore, they created specific admission day and time distributions per surgical specialty. The admission day distributions differ between specialties. For example, it is understandable that a patient that is admitted for Neurosurgery will be admitted earlier to the hospital than a patient admitted for a small surgery of specialty ENT.

Case study WCC and Influences of choices

In our case study we made the choice to group all surgical specialties into one patient type. Therefore, the admission day and time distributions are based on all surgical specialties. This leads to less specific and therefore less reliable admission day and time distributions.

Recommendations

To make the admission day and time distributions more specific, more patient types must be created based on the surgical specialties. If too many surgical specialties exist, one could consider to make groups of surgical specialties that have the same characteristics. The limitations of the models must be taken into account before grouping the specialties.

5.3.3. Acute arrivals

The HBC model requires arrival rates of acute patients to predict acute arrivals. These arrival distributions are based on historical admissions of acute patients.

Case study Kortbeek et al. (2012a)

Kortbeek et al. (2012a) make use of different acute patient distributions based on the treating specialty of the acute patient and the arrival weekday and timeslot. This results in 168 (24 hours * 7 days) different acute patient distributions per treating specialty.

Case study WCC and Influences of choices

In our case study too many treating specialties exist. Due to the high variance in arrivals of patients and the small size of the dataset, it is not possible to calculate reliable acute arrival distributions per treating specialty. Besides the high variance, the number of patient types is limited by the technical design of the HBC model. Therefore, to limit the number of patient types, the treating specialties are grouped. This results in a general acute arrival distribution for all treating specialties.

5.3.4. Length of stay (LOS) distributions

The LOS distributions consist of discharge day and discharge time distributions of elective and non-elective patient types. These distributions are specified per patient type and based on historical patient admission data. The HBC model uses the probabilities to predict how long patients will stay.

Limitations

A lot of patients move between wards for medical reasons. Sometimes patients are temporary absent. In the conceptual HBC model the temporary absence is not implemented. Therefore, the LOS of a patient must be determined per ward.

Case study Kortbeek et al. (2012a)

Kortbeek et al. (2012a) calculate the discharge day and time distributions based on historical LOS values. They use patient types based on surgical and treating specialties and the LOS distributions are therefore specialty specific. Patients with for example specialty Cardiac Surgery will have a different length of stay distribution than patients with specialty ENT.

Besides the specialty specific patient types, in their case study patients only were absent from a ward in case they went to the Intensive Care Unit. They chose to determine the historical LOS value on the wards in their case study by the last discharge date and time minus the earliest admission date and time. In this way, they include the absence of a patient (e.g. to the ICU) in the LOS on their wards.

Case study WCC and Influences of choices

In the WCC, a substantial number of movements of patients occur and patients are absent on wards for a long period. Therefore it leads to overestimations of LOS if we determine the LOS in the same way as Kortbeek et al. (2012a). We adapt the data to determine the LOS on each ward per patient. We make several choices that determine the LOS on each ward: sometimes the LOS of a patient is fragmented; sometimes the LOS of a patient is merged. The data preparation is described in Appendix E. The data preparation leads to LOS distributions that differ from the real situation.

In our case study, we merged all surgical specialties and all treating specialties. Due to the merging, the LOS distributions are the same for patients of different surgical specialties and different treating specialties.

Recommendations

We recommend to implement the temporary absence of patients in the conceptual HBC model. If patients can be absent on wards, the determination of the LOS distributions will be easier. Also if more patient types can be used, the LOS distributions will be more reliable.

5.3.5. Fixed input requirement – bed capacity

The bed capacity of the wards is required for the misplacement policy. If the patient demand exceeds the bed capacity of a ward, patients can be misplaced to another ward.

5.4. Input requirements NS model

Figure 3 shows the working of the HBC and NS model. In this section we describe the requirements to calculate the staffing requirements with the NS model based on bed census predictions of the HBC model. Figure 3 shows three input requirements for the NS model: bed census predictions, start and end time working shifts and coverage requirements.

5.4.1. Bed census predictions

The bed census predictions per ward calculated with the HBC model are needed to calculate the staffing levels for both staffing policies: staffing on bed census predictions and flexible staffing.

5.4.2. Start and end time working shifts

Nurses work in shifts, therefore it is important to know the start and end time of the various working shifts. Section 2.3.2 describes the working shifts.

5.4.3. Coverage requirements

The coverage requirements consist of five different parameters: nurse-to-patient ratios, minimum coverage, coverage compliance, minimum number of nurses in a shift, and the minimum fraction of dedicated nurses. The nurse-to-patient ratios are described in Section 2.3.3 and indicate the number of patients a nurse can take care of. The minimum coverage is the value where the coverage may never fall below during a shift. The coverage is calculated by the ((number of nurses * ratio)/number of patients). The coverage compliance requirement indicates the percentage of time that the coverage should be higher than one (enough nurses to take care of patients according to the nurse-to-patient ratio). The minimum number of nurses in a shift indicate the number of nurses that need to be staffed in a shift on a ward. The minimum fraction of dedicated nurses indicates the fraction of nurses on a ward that are dedicated nurses (the other part consists of flexible nurses).

5.5. Conclusion

In the application of the HBC and NS model to the WCC, we encountered several limitations. The largest limitation is the inability to use the HBC model as a prediction tool in the WCC. The HBC model is not usable for surgery blocks from which patients can be admitted to various wards. In the case study of the WCC the MSS consists of surgery blocks from which patients can be admitted to all wards of the WCC. The HBC model needs surgery specific wards to allocate patients to their preferred ward.

Another limitation of the conceptual HBC model is that temporary absence or movements of patients cannot be modeled. Consequently, the case study of the WCC – with a lot of movements and absence of patients - led to choices that influence the performance of the HBC model.

A limitation of the technical design of the HBC model is a restriction to the number of patient types: the HBC model cannot process more than 600 patient types. For a case study with various surgery blocks and various treating specialties, it is desirable to make specific patient types. A restriction is that the size of the dataset per patient type must be large enough to calculate reliable distributions. In our case study we merged patient types admitted to the same ward. This influenced the applicability of the HBC model as a prediction tool and the results.

We made several decisions to apply the HBC and NS model to the WCC. In the next chapter we will validate the outcome of the HBC model to research the influence of the choices made in this chapter. We know that the HBC is not applicable as prediction tool, therefore we research the possibilities of the use of the HBC and NS model based on historical data. Due to the limitations of the model and the time needed for the input preparation, the choice is made to limit the scope of the study and work further with three wards instead of nine. These three wards are the age-specific pediatric wards: Teenagers, Older Children, and Pediatric Surgery and Infants. The choice for these three wards is made since these wards are comparable and the nurses deployed on these wards have the same qualifications.

6. EXPERIMENTATION

In Chapter 5 the limitations and solutions for applying the models to the WCC are described. In this chapter we indicate what improvements in nurse staffing are possible if the HBC and NS model can be applied. Due to the inability of the models to use as prediction tools, we apply the models to the three age-specific wards of the WCC based on historical data. Various experiments are executed to verify the best nurse staffing policy. Section 6.1 describes the input of the model. Section 6.2 describes the validation of the HBC model. Section 6.3 describes the experiments and Section 6.4 presents the results of the experiments. This chapter closes with a conclusion.

6.1. MODEL INPUT

To use the HBC model as a prediction tool, data is needed from the operating room (OK plus) and inpatient care (LOCATI) databases. This data is coupled for the years 2011 and 2012. The inpatient care database contains every admission in the hospital, specified for every movement of a patient. The operating room database contains every surgery performed in 2011 and 2012.

We calculated the input distributions for the HBC model based on historical data from 3 January 2011 to 1 July 2012. We want to forecast the bed census (and check the applicability) on the wards for the period 2 July 2012 to 30 December 2012. As discussed in Chapter 5, the HBC model cannot be used as a prediction tool due to the complex MSS used in the WCC. To predict bed census based on a period in the past, we derive the OR block planning based on historical patient admission data. We use an MSS following the surgery blocks where patients are admitted to the three wards in 2011 and 2012. Each day is divided in hourly time slots, so T = 24. The elective patients undergo surgery in one of the 31 ORs (I = 31). These surgeries are only executed on weekdays. The acute arrival, surgery, admission day, admission time, discharge day and discharge time distributions are estimated per specialty, see Chapter 5. The length of the Acute Admission Cycle (AAC) is set to one week. For acute patients, the discharge distributions are estimated per patient type and are clustered by admission time intervals: 0-8, 8-18 and 18-24 hours. The discharge day distributions are assumed to be equal for all patients from two days after admission.

As shown in Appendix A, each day consists of three shifts: a day, evening and night shift. In the model, the shift starts at the start of the next time slot. For example, if a shift starts at 7:30, the starting time slot in the model is eight. The shift also ends at the start of the next time slot, hence if a shift ends at 7:45, time slot seven is completely included. In the model, the working days are divided in three shifts: the day shift (8:00-15:00), the evening shift (15:00-23:00) and the night shift (23:00-8:00).

During the planning horizon of 182 days (2 July to 30 December 2012), 182 x 3 = 546 unique working shifts have to be staffed. In the NS model the staffing costs for float nurses (ω_f) can be set higher than the staffing costs for dedicated nurses (ω_d). In the AMC the intention is to roster registered nurses alternately as a float nurse or dedicated nurse. Therefore we set the staffing costs for float nurses equal to the staffing costs for dedicated nurses ($\omega_d = \omega_f$). In the AMC the minimum coverage requirement (β^k) is set on 0.70, the coverage compliance requirement (α^k) is set on 0.90, and at least two out of three nurses should be dedicated nurses ($\gamma^k = 2/3$).

In this case study, we perform experiments consisting of various combinations of wards. For these experiments we used three wards in total: Teenagers, Older Children, and Pediatric Surgery and Infants. These wards all have a bed capacity of 24 beds. The nurse-to-patient ratios are set by management and shown in Table 2.

Table 6 gives an overview of the historical data used for the determination of the input distributions. The input distributions are calculated for the period of 3 January 3 2011 to 1 July 2012. The choice of the patient types in this case study is described in Section 5.3.1.

Specialty/Patient type	**# Admissions**		**Average LOS (in days)**
	Elective admissions	**Acute admissions**	
Teenagers	808	1195	4.1
Older Children	615	1481	3.2
Pediatric Surgery and Infants	458	1524	4.7

TABLE 6: OVERVIEW HISTORICAL DATA FROM JANUARY 3, 2011 – JULY 1, 2012

We need different input parameters in order to run the HBC model and the NS model. Table 7 presents these input parameters.

Parameter	**Description**	**Value**
M^k	Capacity of ward k in the number of beds	24
T	Number of time intervals per day	24
$\lvert\tau\rvert$	Number of shift types	3
(b_1, b_2, b_3)	Shift start times	(8, 15, 23)
(l_1, l_2, l_3)	Shift durations	(7, 8, 9)
S^k	Minimum staffing levels	2
ω_d	Staffing cost dedicated nurse	1
ω_f	Staffing cost float nurse	1
α^k	Minimum coverage compliance	0.90
β^k	Minimum coverage	0.70
γ^k	Minimum fraction of dedicated nurses	0.67
$(r^1_{q,1}, r^1_{q,2}, r^1_{q,3})$	Nurse-to-patient ratio targets Teenagers	(4, 6, 12)
$(r^2_{q,1}, r^2_{q,2}, r^2_{q,3})$	Nurse-to-patient ratio targets Older Children	(4, 6, 8)
$(r^3_{q,1}, r^3_{q,2}, r^3_{q,3})$	Nurse-to-patient ratio targets Pediatric Surgery and Infants	(3, 4½, 6)

TABLE 7: INPUT PARAMETER SETTINGS

6.2. VALIDATION

We use the case studies introduced above to validate the model. We want to verify whether or not the choices made, as described in Chapter 5, are valid. We compare admission data of all patients to the outcome of the models. More specific, the bed census distributions of the HBC model are compared to the bed census percentiles of the admission data (retrieved from Locati). The distributions and percentiles are obtained on each weekday on hourly basis. We run the HBC model for half a year (2 July 2012 – 31 December 2012). The input distributions are based on the period January 2011 - June 2012. In total, the HBC model provides a bed census prediction for a period of 182 days (26 weeks).

The exact validation is executed over the period of 172 days. The Christmas holiday is excluded due to a deviating bed census. From 21 December 2012 to 31 December 2012 the Teenager ward was closed and patients were moved to Older Children. Hence, for the final validation of the bed census output, the period of 2 July – 20 December 2012 is used.

To validate the output of the HBC model, we compare the average bed census probabilities and the 90th percentile of the bed census probabilities to two sets of historical data. Two sets of historical data are used: (1) the original historical data and (2) the historical data of patients moved to their preferred ward (adapted). The original historical data contains misplacements, therefore the patients are registered on the misplaced ward. To obtain historical data of patients registered on their preferred ward, patients are moved to their preferred ward based on their age. Both sets of historical data are used for the validation of the HBC model.

Figure 4, Figure 5, and Figure 6 display the HBC model results for the bed census distributions of Teenagers, Older Children, and Pediatric Surgery and Infants respectively. We discuss the results per ward.

6.2.1. Teenagers

Figure 4 displays the results for the bed census distributions for the Teenagers ward on Tuesday and Wednesdays against historical data. To obtain these results, the HBC model is executed for two wards: Teenagers and Older Children. Therefore, the model has misplaced patients to the other ward (Older Children) in case of exceeding the capacity. Figure 4 shows an overestimation of the bed census predictions of the HBC model for both the average and the 90th percentile. Although the bed census predictions follow the patterns of the historical data, the HBC model does not predict the bed census precisely.

Additional to the results in Figure 4, we calculate the deviation of the average bed census results of the HBC model to the average bed census of the original historical data. The average deviation of the average bed censuses of the model compared to the average of the original historical data is 15%. The maximum deviation of the average results of the model is 32% higher than the average original data. The average bed census predicted by the model is never below the average of the historical data.

We assume that the HBC predictions are overestimated due to limitations of the conceptual HBC model: the inapplicability of the admission of patients from one surgery block to multiple wards and the inability of the HBC model to model the temporary absence of a patient on a ward. For this case study the first limitation leads to the choice to determine separate surgery distributions of the same specialty in surgery distributions for each ward. Therefore, multiple surgery distributions exist for one surgical specialty. These surgery distributions can result in more patients admitted to the wards from one surgery block than in reality is possible, leading to overestimation. The HBC predictions do follow the pattern of the historical data. A reason for this is that the MSS used in the HBC model is based on the surgery blocks that occurred in the past, therefore the timing of the surgery blocks corresponds with the historical data.

The second limitation leads to the necessity of an extensive input preparation of the patient admission data to get an overview of the LOS of patients. The input preparation is needed to calculate the discharge day and time distributions. In our input preparation patients move often between wards. We therefore made the choice to include or exclude (depends on the situation, see Appendix E) the stay of patients on other wards in the length of stay of patients on a certain ward. This results in possible over- or underestimated discharge day distributions. For the case study of Teenagers, the choices in the input preparation can lead to an overestimation of the discharge day distributions. This leads to longer stays of patients than in reality happened and consequently an overestimation of the number of patients on a ward.

Two other reasons for the deviating HBC predictions include: (1) misplacements to other wards do not correspond with reality and (2) input distributions are based on the entire dataset and less specific. Both situations can lead to an higher or lower bed census prediction compared to historical data. The misplacement policy in the HBC model differs from reality. In the historical data misplacements from and to other wards are included. In the case study of Teenagers, the HBC model only misplaced patients from and to Older Children. Besides the misplacement policy, the surgery, admission, and discharge distributions are not specified per specialty. In our case study the distributions are based on the entire dataset, therefore the distributions are less specific and this can also lead to a difference between the bed census predictions and the historical data.

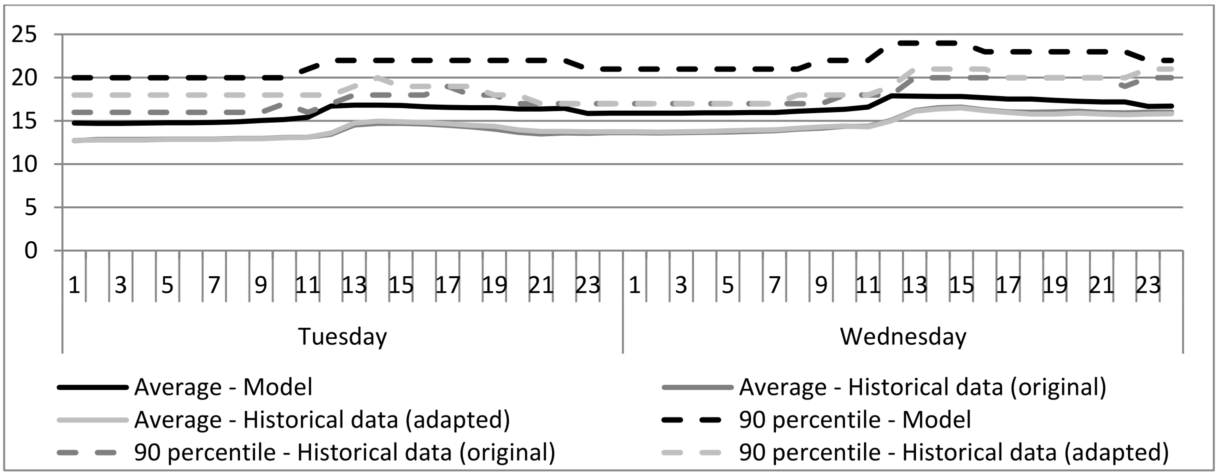

FIGURE 4: VALIDATION OF THE MODEL AGAINST HISTORICAL DATA (TUESDAY AND WEDNESDAY, WARD TEENAGERS) – INCLUDING MISPLACEMENTS FROM AND TO WARD OLDER CHILDREN

6.2.2. Older Children

Figure 5 displays the HBC model results for the bed census distributions for Older Children on Tuesdays and Wednesdays against historical data. The HBC model has misplaced patients to the other ward (Teenagers) in case of exceeding capacity. Figure 5 shows that the prediction of the average bed census by the HBC is almost the same as the historical data. The 90th percentile of the bed census predictions of the HBC model slightly differs from the historical data, but follows the same pattern.

The average deviation of the average bed census predicted by the HBC model is 3% compared to the average of the original historical data. The highest overestimation of the average bed census prediction is 9% in comparison to the average of the original historical data. The highest underestimation of the average bed census prediction is 6% compared to the average historical data.

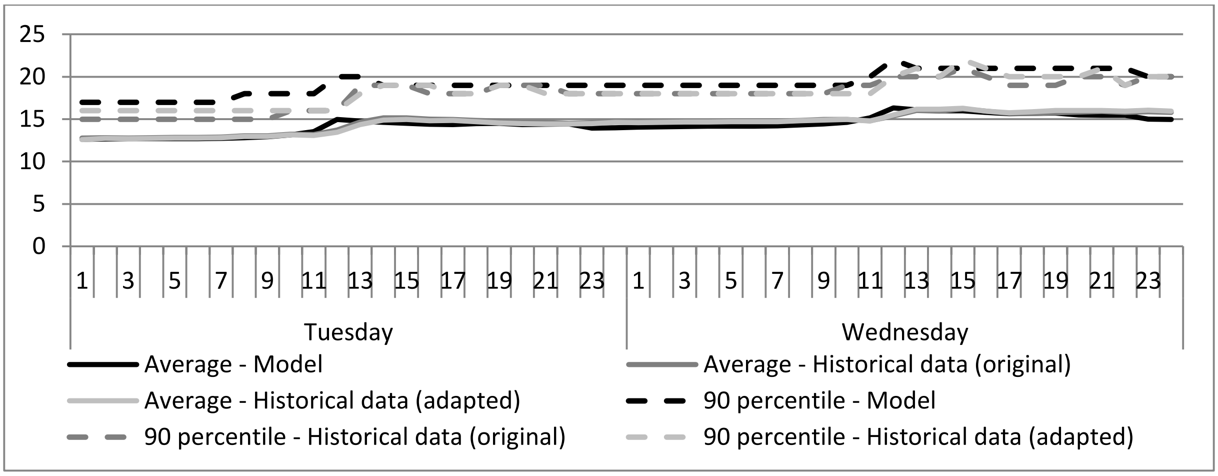

FIGURE 5: VALIDATION OF THE MODEL AGAINST HISTORICAL DATA (TUESDAY AND WEDNESDAY, WARD OLDER CHILDREN) – INCLUDING MISPLACEMENTS FROM AND TO WARD TEENAGERS

6.2.3. PEDIATRIC SURGERY AND INFANTS

Figure 6 displays the HBC model results for the bed census distributions for Pediatric Surgery and Infants on Tuesdays and Wednesdays with misplacements to and from Older Children. The average bed census predicted by the HBC model corresponds to the average bed census of both historical datasets. However, for the 90th percentile the HBC model overestimates the bed census for pediatric Surgery and Infants in comparison to the historical datasets.

The average deviation of the average bed census prediction is 4% compared to the average of the historical data. The highest overestimation of the average predicted bed census is 9% in comparison to the average of the original historical data. The HBC model underestimates the average bed census with a maximum of 7%.

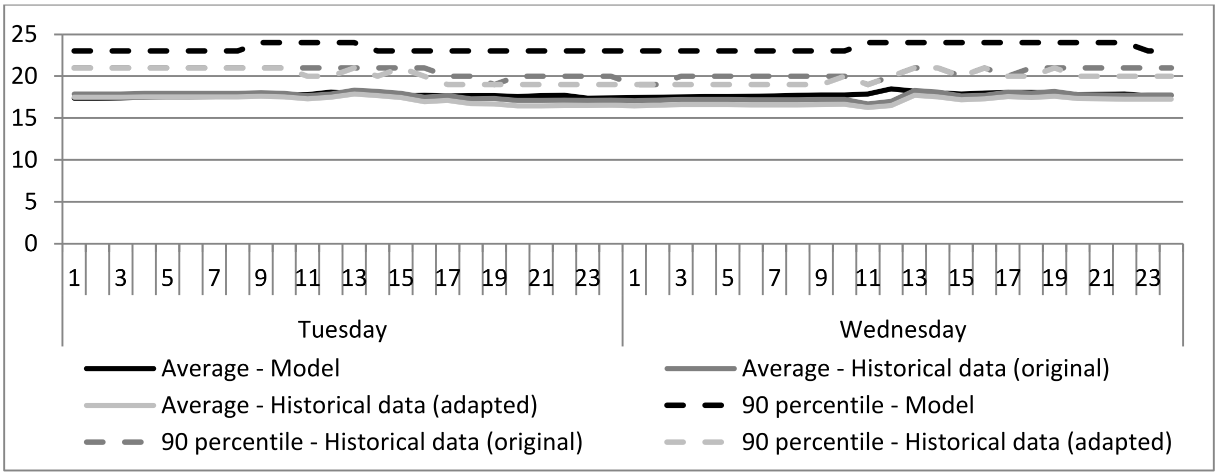

FIGURE 6: VALIDATION OF THE MODEL AGAINST HISTORICAL DATA (TUESDAY AND WEDNESDAY, WARD PEDIATRIC SURGERY AND INFANTS) - INCLUDING MISPLACEMENTS TO OLDER CHILDREN

Figures of the entire week (not shown here) show differences on Friday afternoon and Sunday morning. Differences exist on the Friday afternoon, as in reality, more patients are discharged just before the weekend. The discharge day distributions for both elective and non-elective patients are equal from two days after admission. For elective patients, the length of stay is independent of the day of admission and the day of discharge. Differences exist for the Sunday morning because in reality, patients are admitted to the wards on Sunday evenings. The model admits patients to the hospital during the entire Sunday. The time slot of admission of elective patients is independent of the day of the week, therefore the time slot of admission for elective patients is similar for weekdays and weekends.

The validation shows that the HBC model overestimates the bed census compared to reality. For some situations the HBC model underestimates the bed census. To indicate the improvements possible with staffing on bed census predictions, we decide to use this overestimated (and underestimated) bed census predictions. The following section presents the various experiments with the HBC and NS model.

6.3. EXPERIMENTS

This section describes the experiments executed with the NS model, based on the bed census predictions of the HBC model for the period 2 July – 30 December 2012. The NS model is also executed for the period 2 July – 30 December 2012, consisting of 182 days and therefore 546 working shifts. The input parameters of the NS model are shown in Table 7.

For all experiments, the NS model calculates the required number of nurses per day and per shift in order to reach a coverage compliance of 90%. The NS model consists of two methods: staffing on bed census predictions and flexible staffing, see Section 5.1.

We compare the results to the current staffing policy in the WCC to indicate what improvements are possible with each staffing method. The WCC currently staffs a fixed number of nurses in a shift. For each staffing policy, we calculate the number of required FTEs by:

$$\#\,\mathrm{FTE} = \text{total number of staffed hours} * \frac{\left(\dfrac{\text{number of days in a year}}{\text{number of days in the experiment}}\right)}{\text{number of deployable hours per FTE}}$$

In our case study the number of days in a year is 365, the number of days in the experiment is 182 and the number of deployable hours per FTE is 1525,7. The total number of staffed hours is calculated by:

$$\text{Total number of staffed hours} = \#\,\text{nurses staffed per shift} * \text{length of the shift (in hours)}$$

The number of FTEs required for the current staffing policy is calculated based on the number of nurses shown in Table 5. The number of nurses in Table 5 is based on the set nurse-to-patient ratios and expectations for the bed census of the head nurse.

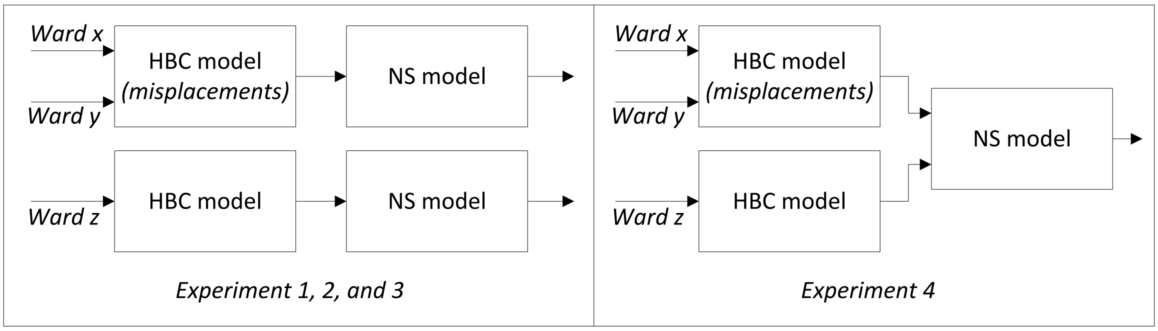

FIGURE 7: DIFFERENCES BETWEEN THE EXPERIMENTS

Figure 7 shows the various experiments and Table 8 shows the wards included in the experiments. In all scenarios we use three wards: ward x, y, and z. The HBC model can predict the bed census for two wards at once. Therefore, we predict the bed census of ward z separately and the bed census of ward x and y together. For ward x and y patients can be misplaced between the wards until the capacity of both wards is reached. For ward z it is not possible to misplace patients. If the bed capacity of ward z is exceeded, new patients are rejected. For each ward and each experiment the bed census predictions differ. This is due to whether it is possible to misplace patients to and from other wards.

In experiment 1, 2, and 3 only ward x and y share a flex pool and the staffing levels for ward z are calculated in isolation. The calculation of the nurse staffing levels differs in experiment 4 from experiment 1, 2, and 3. In experiment 4, the three wards share a flex pool of nurses.

Experiment	**Ward x**	**Ward y**	**Ward z**	***Wards sharing a flex pool***
1	Teenagers	Older Children	Pediatric Surgery and Infants	*Teenagers* *Older Children*
2	Older Children	Pediatric Surgery and Infants	Teenagers	*Older Children* *Pediatric Surgery and Infants*
3	Teenagers	Pediatric Surgery and Infants	Older Children	*Teenagers* *Pediatric Surgery and Infants*
4	Teenagers	Older Children	Pediatric Surgery and Infants	*Teenagers* *Older Children* *Pediatric Surgery and Infants*

TABLE 8: EXPERIMENTS EXECUTED

6.4. RESULTS

Table 9 provides an overview of the results of the various experiments. This table presents the average coverage compliance for staffing on bed census predictions and flexible staffing. The table also shows the number of FTEs needed for the current staffing policy, staffing on bed census predictions and the flexible staffing policy.

DISCLAIMER: *due to an error in the technical design of the NS model, the number of FTE of the flexible staffing policy presented in Table 9 can be wrong. Due to the complexity of the flexible staffing method of the NS model, an upper and lower bound are calculated. This is done to be able to find or approximate the optimal solution. The upper bound model resulted in some errors.*

Therefore it is possible that the upper bound model resulted in a lower value for the required number of nurses than needed to reach the coverage compliance requirement. This can lead to wrong conclusions for finding the optimal or non-optimal solution.

Experiment	Current staffing	Staffing on bed census predictions			Flexible staffing		
	FTE	FTE		Average coverage	FTE		Average coverage
	#	#	Δ		# (float)	Δ	
1	74.7	74.2	-0.5	0.99	73.7 (2.5)	-1.0	0.98
2	74.7	74.3	-0.4	0.99	73.7 (7.8)	-1.0	0.98
3	74.7	74.3	-0.4	0.99	73.5 (8.6)	-1.2	0.98
4	74.7	74.2	-0.5	0.99	72.7 (9.1)	-2.0	0.98

TABLE 9: NUMERICAL RESULTS WITH Δ RELATIVE TO CURRENT STAFFING, AVERAGE COVERAGE INDICATES THE AVERAGE COVERAGE COMPLIANCE OF THE THREE WARDS. CURRENT STAFFING POLICY IS BASED ON FIXED NUMBER OF NURSES PER SHIFT, SEE TABLE 5

The performance measurement in Chapter 3 showed that the coverage compliance of 90% is not reached in the WCC with the current staffing policy. If staffing levels are based on predictions of the variation in bed census, an average coverage compliance of much higher than 90% can be reached. This happens because in case the coverage compliance was slightly violated, an additional nurse was staffed, which increases the coverage compliance due to the size of the ratio.

Besides the consistent high coverage compliance, the required number of FTEs decreases for both staffing policies of the NS model compared to the current staffing policy with fixed staffing levels. By using a flex pool (flexible staffing policy), less buffer capacity is needed to protect against demand fluctuations. Therefore, fewer nurses are needed in comparison to the required number of nurses when staffing on bed census predictions. Flexible staffing in experiment 4 shows the largest reduction in the number of FTEs (2 FTEs) compared to the current staffing policy, while achieving an average coverage compliance of 98%. Due to the additional flexibility of having three instead of two allocation wards for flexible nurses in experiment 4, an additional saving can be reached compared to the other experiments.

Appendix A shows the number of FTEs of nurses in 2012 on each ward. The total number of FTEs of Teenagers, Older Children, and Pediatric Surgery and Infants is 71.1. Information is unavailable on the number of FTEs of nurses in education for pediatric nurse that work on the different wards. These nurses count after a period in the nurse-to-patient ratios. This declares the difference between the required number of FTEs for the current staffing policy of 74.7 and the available number of FTEs of 71.1. Therefore, we assume that more than 71.1 FTEs are available for the three wards of the WCC and the required number of FTEs for the flexible staffing policy (72.7) is available.

Figure 8 shows the staffing levels for the day shifts for scenario 4 from Monday 16 July – Sunday 12 August 2012. This figure shows the differences between the current staffing policy, staffing on bed census predictions, and flexible staffing. The current staffing levels are lower in the weekend than the staffing levels calculated for the other staffing policies. More nurses in the dayshifts of the weekends are needed in the current staffing policy to reach a coverage compliance of 90%. This figure also shows the difference between staffing on bed census predictions and flexible staffing. In some day shifts (e.g. Thursday 19 July), less buffer capacity is required for the flexible staffing policy to protect against bed census fluctuations. Therefore fewer nurses are needed compared to staffing on bed census predictions.

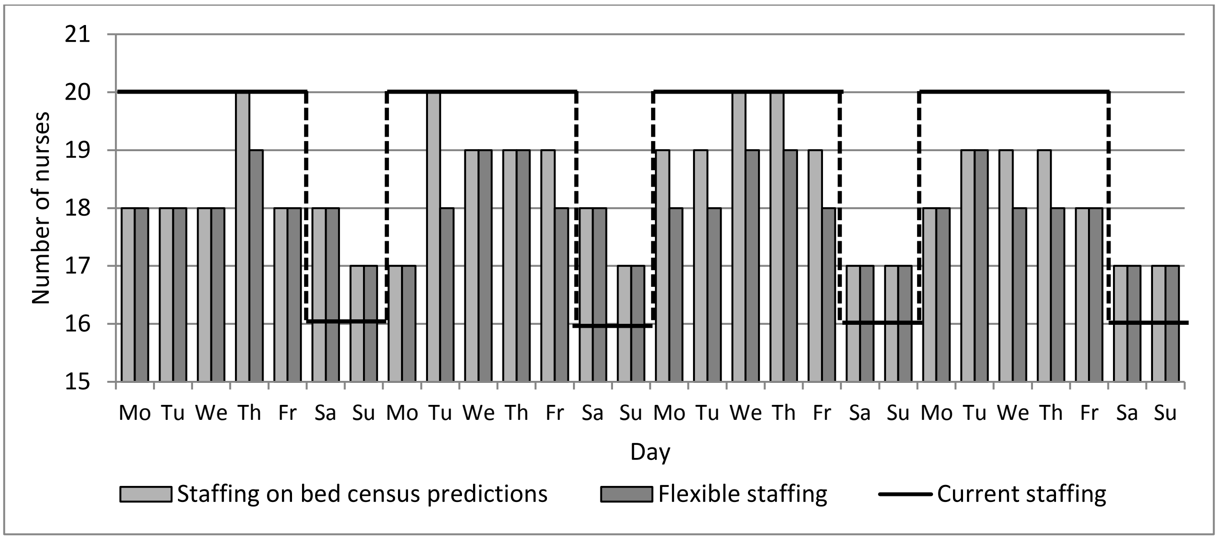

FIGURE 8: STAFFING LEVELS FOR DAY SHIFTS FOR SCENARIO 4 FROM MONDAY JULY 16 – AUGUST 12, 2012.

6.5. CONCLUSION

This chapter describes the outcomes of the application of the HBC and NS model to the WCC. The validation of the HBC results shows the influence of the encountered limitations of the conceptual HBC model. The HBC model overestimates the bed census in a high percentage of the time.

The HBC predictions are used for the determination of the staffing levels to indicate the improvements possible with the two staffing methods of the NS model. We performed four experiments consisting of various combinations of wards. The results of the experiments show that minimizing overstaffing and understaffing by flexible nurse staffing is possible. With flexible nurse staffing a high quality of care can be guaranteed with minimum staffing costs.

The situation of flexible nurse staffing for the three wards (Teenagers, Older Children, and Pediatric Surgery and Infants) leads to the same coverage compliance as the other experiments and the largest decrease in required FTEs. A reduction of 2 FTEs is possible compared to the current staffing policy applied in the WCC.

Due to the knowledge that the HBC model overestimates the bed census for these experiments, larger improvements in the required number of FTEs can be possible if the HBC model predictions are more precise. The difference in the required number of FTEs of the two staffing methods of the NS model and the current staffing policy will be larger than the differences in Table 9.

7. CONCLUSION AND RECOMMENDATIONS

This chapter addresses the conclusions, limitations and recommendations of this study. In Section 7.1 the final conclusions are described. Section 7.2 provides an overview of the limitations of this study. This chapter closes with recommendations for both practice and the further development of the models.

7.1. CONCLUSION

The main objective of this study was:

Research the potential of applying the available mathematical models, which are developed for flexible nurse staffing for the surgical inpatient care units of the AMC, to minimize overstaffing and understaffing in the Women's and Children's Inpatient Clinic

In order to reach the research objective it was important to gain insight in the planning horizons of the OR planning, the patient admission planning and nurse staffing. Knowledge of these processes is important to make decisions of how to develop a prototype for a decision support tool applicable to the WCC.

The performance measurement of the WCC showed a fluctuating bed census during the week, between and within shifts. Since the current staffing policy consists of staffing of a fixed number of nurses per shift and the bed census fluctuates between shifts, this indicates that improvements are possible in the nurse staffing policy. The performance measurement also indicates that over- and understaffing occurred in 2012. In all day shifts in 2012 on all wards of the WCC, the average coverage compliance was 70% without senior nurses and 82% with senior nurses. The coverage guidelines are set on 90%. This shows that nursing coverage guidelines are not reached in the WCC and improvements are needed in the nurse staffing policy.

The literature review shows that a lot of research is conducted addressing the topic of nurse staffing and rostering. Less literature is found, however on the specific area of determining the efficient nurse staffing levels per day based on expected patient demand. In previous studies performed in the AMC, models are developed that predict bed census (Kortbeek et al. 2012a) and apply a nurse staffing policy (Kortbeek et al. 2012b) on these predictions. In this study, the applicability of these models - the HBC and NS model – is examined by applying them to a new case study.

During the application of the HBC and the NS model to the WCC, several limitations were encountered. The first limitation is the non-applicability of the HBC model as a prediction tool. The HBC model cannot mimic the outflow of patients from one surgery block to multiple wards. Although the HBC and NS model have several limitations, we made decisions to indicate possible improvements if the models are applied to the WCC. We adapted the data and made choices how to use the surgery schedule for our case study. We limited our scope from nine to three wards. We compared staffing on demand predictions and flexible staffing to the current staffing policy in the WCC.

Several scenarios were executed consisting of various combinations of three wards of the WCC: Teenagers, Older Children, and Pediatric Surgery and Infants. These wards are the largest wards in the WCC. The results show that by applying staffing on demand predictions or flexible staffing a coverage compliance of 90% can be reached. We calculated the required number of FTEs for each staffing policy. Besides the high coverage, also a decrease in the required number of FTEs is possible when either applying staffing on demand predictions or flexible staffing.

Therefore, predicting bed census and anticipating on unpredicted fluctuations in bed census by flexible staffing results in a high coverage compliance with a possible reduction in the required number of FTEs. However the flexible staffing model is not yet applicable in the WCC. Therefore we recommend to further study the applicability of the models. We recommend the AMC to study how nurse staffing can be improved based on bed census patterns in historical data. This will be a starting point to improve nurse staffing. If the HBC and NS model are adapted in the upcoming years, these models can be used to determine the optimal nurse staffing levels in the WCC.

7.2. LIMITATIONS OF THIS STUDY

During this study, limitations were encountered in the data used in the performance measurement and of the HBC and NS model.

(1) Data used for the performance measurement
The required data provided for the performance measurement was unreliable. Specific data about the registration of worked hours of nurses was unavailable. It was also unclear when senior nurses provided care for patients or worked in the office and which nursing types provided care for patients. In reality, some nursing types are included in the nurse-to-patient ratios after working e.g. one month on a ward. In the analysis this is not included since specific information of each individual nurse was missing. Therefore the current performance measurement can show more understaffing than in reality occurred. Aside from the registration of worked hours, the bed census data was unreliable. Sometimes, nurses registered the admission time or discharge time of patients too late. Therefore, on some hours the number of patients exceeds the capacity of the wards.

(2) Limitations of the HBC and NS model
The limitations of the HBC and NS model are extensively described in Section 5.2. To use the HBC and NS model for the case study in the WCC, several assumptions were made. The most important limitation of this study was the determination of the upcoming MSS. Due to both the fact that in the WCC patients are operated by different surgical specialties and patients from these surgical specialties can be admitted to multiple wards, the upcoming MSS cannot be obtained. Therefore, the HBC model cannot be used in the WCC as a prediction tool for the bed census of the upcoming period. In this case study, the MSS was determined based on the realized surgeries of the patients admitted to the wards of the case study.

7.3. Recommendations

This section describes recommendations for the AMC and recommendations for the further development of the models.

7.3.1. Recommendations for the AMC

7.3.1.1. Recommendations for staffing on demand predictions

The HBC and NS models are not yet applicable as tools to predict bed census and staff on these predictions. We are not yet able to decide how many nurses need to be staffed on each shift and how many nurses should be staffed in a flex pool. Therefore we recommend to start with analysis of historical bed census to determine how many nurses should be staffed in a shift. We analyzed the bed census in 2012 and we recommend to analyze the bed census in 2013. We recommend to adapt nurse staffing levels based on bed census differences during the week and between shifts. In this case, staffing levels can be matched on patterns of historical bed census data. We saw in 2012 that the number of nurses staffed on Mondays and Tuesdays on Teenagers and Older Children may be set lower compared to Wednesdays and Thursdays. Currently, the same number of nurses are staffed from Monday to Friday. We recommend to analyze how many nurses can be reduced and staff a flexible nurse on these shifts to react on fluctuations in demand. The WCC already started with the further analysis to adapt the nurse staffing levels op bed census patterns during the week. We recommend to evaluate the nurse staffing situation on the wards monthly or quarterly to analyze whether improvements are possible. If nurse staffing decisions are adapted, we also recommend to evaluate these decisions with the management of the wards.

7.3.1.2. Recommendations for flexible nurse staffing in practice

The determination of the number of nurses to staff as flexible nurses with the NS model is not yet possible for the WCC. Nonetheless, we recommend to start with a type of flexible staffing: the assignment of nurses of overstaffed wards to understaffed wards. The AMC already made a start with the assignment of nurses to understaffed wards (see Section 2.4.3). We recommend to make the situation of under- or overstaffing on wards more transparent and stimulate nurses to help their colleagues on understaffed wards. We recommend to research the required qualifications of nurses to work on different wards before assigning a nurse to another ward.

To successfully implement flexible staffing in practice, three aspects are important. First, to successfully implement flexible staffing, nurses should be involved in the decision whether or not to implement flexible staffing. Employees of different levels in the organization must be involved in the implementation plan. Second, nurses should accept the nurse-to-patient ratios. Nowadays, in the AMC discussions arise about the nurse-to-patient ratios. Disagreement exists that the ratios do not take the different workloads per patient into account and are set too low because the ratios do not correspond to the workload, etc. If nurses agree with the nurse-to-patient ratios they can accept the rostering decisions based on the nurse-to-patient ratios. Third, we recommend to communicate the flexible deployment of nurses as a hospital policy. Clearly communicated expectations result in less resistance against flexible deployment.

7.3.1.3. Recommendations for data registration

We recommend to improve the registration of the deployment of nurses on wards to improve analysis of the current performance. Improvements are possible in the registration of worked hours of senior nurses, temporary deployed nurses and nurses allocated to an understaffed ward. As stated in Chapter 3 in the data the distinction is not made whether senior nurses provided care for patients or worked in the administration. To execute more reliable analysis about over- and understaffing in the wards, we recommend to split the registration level for worked hours in the database Cognos RENO in two levels: worked hours in patient care and worked hours in administration. An additional level can also be added for worked hours as a supervisor. Besides this, temporary personnel is only registered on a monthly basis, it is recommended to register temporary personnel also on daily and hourly basis. Nurses allocated to an understaffed ward are now registered on the ward where they are contracted, instead of on the ward where they actually have worked. We recommended to register the deployment of nurses on the ward where they have worked. If the management of the WCC starts with the flexible deployment of nurses, it becomes more important to correctly register the worked hours of nurses (in a flexpool) on the ward where they have worked.

7.3.1.4. Recommendations based on context analysis

The WCC planners make rosters for the nurses and take the required staffing levels into account. Sometimes (head) nurses adapt nurse rosters. In this way, the WCC planners cannot control their own rostering process and guarantee that the required number of nurses is staffed per shift. We recommend to set guidelines that it is not allowed to adjust the rosters without consultation the planning office.

Due to the different nursing types and personal rostering preferences of the nurses, nurse rostering is a time consuming task. The nurse staffing model can support the planning office by determining the required staffing levels. We recommend to ease the rostering process and set a general guideline for rostering various nursing types shown in Chapter 3.

The boxplots shown in Chapter 3 show a large variability in bed census. With the flexible staffing method the staffing can respond to variability in demand. To match supply and demand in the WCC efficiently, we recommend to minimize the internal variability in bed census. We recommend to study the admission planning of patients to analyze the influence of these admissions on the variability in bed census. The admission of patients can possibly be spread out more during the weeks. The planning of OR-blocks has a large influence on the variation in bed census on the wards. It is recommended to study how the OR blocks influence the bed census and on which days the OR blocks should be scheduled to achieve less variation in bed census.

7.3.1.5. Recommendations for the use of the models

The boxplots of the bed census on the wards show that currently none of the wards use their full bed capacity. We recommend to use the HBC model to determine the optimal bed capacity of the wards in the WCC. Additionally, we advise to recalculate the required bed capacity as soon as the merge of the Children's Clinic with the VUmc is finalized.

The performance measurement in Chapter 3 shows that improvements are possible in the staffing policy of all wards of the WCC. In this study, we analyzed the three largest wards of the Children's Clinic. We recommend to apply the HBC and NS model to the six other wards in the WCC. We advise to execute more experiments for various configurations of wards in the WCC to evaluate the improvements possible with flexible nurse staffing.

7.3.2. Recommendations for further development of the models

First, we recommend to build a decision support tool combining the data preparation, the HBC model and the NS model. The combination of these models will fasten the application of the models. We recommend to design a user friendly-interface to make it usable for the nurse planners. The AMC wants to implement a new hospital information system. To ease the application of the models we advise to research the options to automatically retrieve the required data from the hospital information system for executing the models. One part of the calculations of the input distributions for the HBC is already automated. We recommend to research different case studies to get insight in the differences in the data preparation before automating the whole process. With this research we showed that differences exist in the data used for our case study compared to the data used in the case study of Kortbeek et al. (2012a).

Second, we recommend to make the HBC model applicable for surgery blocks from which patients are admitted to several wards. In this study, several choices are made in the setting of patient types to apply the model with surgery blocks from which patients are admitted to several wards. These choices led to the inapplicability of the HBC as a prediction tool based on the upcoming MSS and lead to overestimations of bed census predictions. Therefore, further research should focus on the possibilities to allow patients operated in the same surgery blocks and admitted to multiple wards.

Third, we recommend to adapt the HBC model to make it applicable for more wards and hospitals. One limitation of the model is that it is not applicable for more than two wards due to the misplacement policy of the model. If the HBC model is used for more than two wards, the misplacements of patients between wards must be analyzed. Based on that situation, a choice must be made of how to formulate the misplacement policy for more than two wards.

Fourth, the HBC and NS model forecast on a large time horizon. This horizon is based on the time that the OR block planning comes available. On an intermediate time horizon a more specific OR planning (which already contains planned patients) can be used to improve the bed census forecasts. A few days before surgery it is known how many and which patients are operated in which surgery block. With this information, a more precise prediction can be made for the bed census.

Fifth, we recommend to model the temporary absence of a patient on a ward in the HBC model. Some patients are temporary admitted to another ward (e.g. ICU) or are temporary discharged to home. Due to a lot of movements of patients between wards, it is desirable to model the temporary absence of a patient and to model the return as the same patient.

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APPENDIX A: TABLES AND FIGURES CONTEXT ANALYSIS

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APPENDIX B: FIGURES OF OVERSTAFFING AND UNDERSTAFFING PER WARD

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Appendix C: Detailed summary hourly bed census model

This appendix provides the detailed summary copied from the article on the hourly bed census prediction model of Kortbeek et al. (2012a).

Demand predictions for elective patients

Model input. The demand predictions for elective patients will be based on the following input parameters.

Time. An MSS is a repeating blueprint for the surgical schedule of S days. Each day is divided in T time intervals. Therefore, we have time points $t = 0, \ldots, T$, in which $t = T$ corresponds to $t = 0$ of the next day. For each single patient, day n counts the number of days before or after surgery, i.e., $n = 0$ indicates the day of surgery.

MSS utilization. For each day $s \in \{1, \ldots, S\}$, a (sub)specialty j can be assigned to an available operating room i, $i \in \{1, \ldots, I\}$. The OR block at operating room i on day s is denoted by $b_{i,s}$, and is possibly divided in a morning block $b^M_{i,s}$ and an afternoon block $b^A_{i,s}$, if an OR day is shared. The discrete distributions c^j represent how specialty j utilizes an OR block, i.e., $c^j(k)$ is the probability of k surgeries performed in one block, $k \in \{0, 1, ..., C^j\}$. If an OR block is divided in a morning OR block and an afternoon OR block, c^j_M and c^j_A represent the utilization probability distributions, respectively. Such shared OR blocks are not explicitly included in our formulation, given that these can be modeled as two separate (fictitious) operating rooms.

Admissions. With probability e^j_n, $n \in \{-1, 0\}$, a patient of type j is admitted on day n. Given that a patient is admitted on day n, the time of admission is described by the probability distribution $w^j_{n,t}$. We assume that a patient who is admitted on the day of surgery is always admitted before or at time ϑ_j; therefore, we have $w^j_{0,t} = 0$ for $t = \vartheta_j + 1, \ldots, T - 1$.

Discharges. $P^j(n)$ is the probability that a type j patient stays n days after surgery, $n \in \{0, \ldots, L^j\}$. Given that a patient is discharged on day n, the probability of being discharged in time interval $[t, t + 1)$ is given by $m^j_{n,t}$. We assume that a patient who is discharged on the day of surgery is discharged after time ϑ_j, i.e., $m^j_{0,t} = 0$ for $t = 0, \ldots, \vartheta_j$.

Single surgery block. In this first step, we consider a single specialty j operating in a single OR block. We compute the probability $h^j_{n,t}(x)$ that n days after carrying out a block of specialty j, at time t, x patients of the block are still in recovery. Note that admissions can take place during day $n = -1$ and during day $n = 0$ until time $t = \vartheta_j$. Discharges can take place during day $n = 0$ from time $t = \vartheta_j + 1$ and during days $n = 1, \ldots, L^j$. Therefore, we calculate $h^j_{n,t}(x)$ as follows:

$$h^j_{n,t}(x) = \begin{cases} a^j_{n,t}(x) & \text{if } n = -1 \text{ and } n = 0, t \leq \vartheta_j, \\ d^j_{n,t}(x) & \text{if } n = 0, t > \vartheta_j \text{ and } n = 1, \ldots, L^j, \end{cases}$$

where $a^j_{n,t}(x)$ represents the probability that x patients are admitted until time t on day n, and $d^j_{n,t}(x)$ is the probability that x patients are still in recovery at time t on day n.

Single MSS cycle. Next, we consider a single MSS in isolation. From the distributions $h^j_{n,t}$, we can determine the distributions $H_{m,t}$, the discrete distributions for the total number of recovering patients at time t on day m, $m \in \{0, 1, 2, \ldots, S, S+1, S+2, \ldots\}$, resulting from a single MSS cycle.

Steady state. In this step, the complete impact of the repeating MSS is considered. The distributions $H_{m,t}$ are used to determine the distributions $H^{SS}_{s,t}$, which are the steady state probability distributions of the number of recovering patients at time t on day s of the cycle, $s \in \{1, \ldots, S\}$.

Demand predictions for acute patients

Model input. The demand predictions for acute patients are based on the following input parameters:

Time. The AAC is the repeating cyclic arrival pattern of acute patients with a length of R days. For each single patient, day n counts the number of days after arrival.

Admissions. An acute patient type is characterized by patient group p, $p = 1, \ldots, P$, arrival day r and arrival time θ, which is for notational convenience denoted by type $j = (p, r, \theta)$. The Poisson arrival process of patient type j has arrival rate λ^j.

Discharges. $P^j(n)$ denotes the probability that a type j patient stays n days, $n \in \{0, \ldots, L^j\}$. Given that a patient is discharged at day n, the probability of being discharged in time interval $[t, t+1)$ is given by $\tilde{m}^j_{n,t}$. By definition, $\tilde{m}^j_{0,t} = 0$ for $t \leq \theta$.

Single patient type. In this first step we consider a single patient type j. We compute the probability $g^j_{n,t}(x)$ that on day n at time t, x patients are still in recovery. Admissions can take place during time interval $[\theta, \theta+1)$ on day $n = 0$ and discharges during day $n = 0$ after time θ and during days $n = 1, \ldots, L^j$. Therefore, we calculate $g^j_{n,t}(x)$ as follows:

$$g^j_{n,t}(x) = \begin{cases} \tilde{a}^j_t(x) & \text{if } n = 0, t = \theta, \\ \tilde{d}^j_{n,t}(x) & \text{if } n = 0, t > \theta \text{ and } n = 1, \ldots, L^j, \end{cases}$$

where $\tilde{a}^j_t(x)$ represents the probability that x patients are admitted in time interval $[t, t+1)$ on day $n = 0$, and $\tilde{d}^j_{n,t}(x)$ is the probability that x patients are still in recovery at time t on day n.

Single cycle. Now, we consider a single AAC in isolation. From the distributions $g^j_{n,t}(x)$, we can determine the distributions $G_{w,t}$, the distributions for the total number of recovering patients at time t on day w, $w \in \{1, \ldots, R, R+1, R+2, \ldots\}$, resulting from a single AAC.

Steady state. In this step, the complete impact of the repeating AAC is considered. The distributions $G_{w,t}$ are used to determine the distributions $G^{SS}_{r,t}$, the steady state probability distributions of the number of recovering patients at time t on day r of the cycle, $r \in \{1, \ldots, R\}$.

Demand predictions per care unit

To determine the complete demand distribution of both elective and acute patients, we need to combine the steady state distributions $H_{s,t}^{SS}$ and $G_{r,t}^{SS}$. In general, the MSS cycle and AAC are not equal in length, i.e., $S \neq R$. This has to be taken into account when combining the two steady state distributions. Therefore, we define the new IFC length $Q = LCM(S, R)$, where the function LCM stands for *least common multiple*. Let $Z_{q,t}$ be the probability distribution of the total number of patients recovering at time t on day q during a time cycle of length Q:

$$Z_{q,t} = H^{SS}_{q \bmod S + S\cdot\mathbb{1}_{(q \bmod S=0)},t} \otimes G^{SS}_{q \bmod R + R\cdot\mathbb{1}_{(q \bmod R=0)},t} \,,$$

where $\otimes$ denotes the discrete convolution function. Let U^k be the set of specialties j whose operated patients are (preferably) admitted to unit k, $k \in \{1, \ldots, K\}$, and V^k the set of acute patient types j that are (preferably) admitted to unit k. Then, the demand distribution for unit k, $Z_{q,t}^k$, can be calculated by exclusively considering the patients in U^k and V^k.

Bed census predictions

We translate the demand distributions $Z_{q,t}^k$ into bed census distributions $\hat{Z}_{q,t}$, $k = 1, \ldots, K$, the distributions of the number of patients present in each unit k at time t on day q. To this end, we require an allocation policy ϕ that uniquely specifies from a demand vector $\mathbf{x} = (x_1, \ldots, x_K)$ a bed census vector $\hat{\mathbf{x}} = (\hat{x}_1, \ldots, \hat{x}_K)$, in which x_k and $\hat{x}_k$ denote the demand for unit k and the bed census at unit k, respectively. Let $\phi(\cdot)$ be the function that executes allocation policy ϕ. Let $\hat{Z}_{q,t}^k$ denote the marginal distribution of the census at unit k given by distribution $\hat{Z}_{q,t}$. With a care unit capacity of M^k beds at unit k, we obtain

$$\hat{Z}_{q,t}(\hat{\mathbf{x}}) = \big(\hat{Z}_{q,t}^1(\hat{x}_1), \ldots, \hat{Z}_{q,t}^K(\hat{x}_K)\big) = \sum_{\{\mathbf{x}|\hat{\mathbf{x}}=\phi(\mathbf{x})\}} \Big\{\prod_{k=1}^{K} Z_{q,t}^k(x_k)\Big\}. \tag{1}$$

We do not impose restrictions on the allocation policy ϕ other than specifying a unique relation between demand $\mathbf{x}$ and census configuration $\hat{\mathbf{x}}$. Recall that the underlying assumption is that a patient is transferred to his preferred unit when a bed becomes available. The policy ϕ also reflects the priority rules that are applied for such transfers. As an illustration, we present an example for an inpatient care facility with two care units of capacity M^1 and M^2 respectively:

$$\phi(\mathbf{x}) = \begin{cases} (x_1, x_2) & \text{if } x_1 \leq M_1, x_2 \leq M_2, \\ (M_1, \min\{x_2 + (x_1 - M_1), M_2\}) & \text{if } x_1 > M_1, x_2 \leq M_2, \\ (\min\{x_1 + (x_2 - M_2), M_1\}, M_2) & \text{if } x_1 \leq M_1, x_2 > M_2, \\ (M_1, M_2) & \text{if } x_1 > M_1, x_2 > M_2. \end{cases} \tag{2}$$

Under this policy patients are assigned to their bed of preference if available and are otherwise misplaced to the other unit if beds are available in the second unit.

APPENDIX D: DETAILED SUMMARY NURSE STAFFING MODEL

This appendix provides the detailed summary copied from the article on the nurse staffing model of Kortbeek et al. (2012b).

Staffing requirements

Corresponding with the bed census prediction model, we consider a planning horizon of Q days ($q = 1, \ldots, Q$), during which each day is divided in T time intervals ($t = 0, 1, \ldots, T-1$). The set of working shifts is denoted by $\mathcal{T}$, where a shift τ is characterized by its start time b_τ and its length ℓ_τ. Within the time horizon, (q, t) is a unique time interval and (q, τ) a unique shift. For notational convenience, $t \geq T$ indicates a time interval on a later day, e.g., $(q, T+5) = (q+1, 5)$. For each of K inpatient care units, with the capacity of unit k being M^k beds, staffing levels have to be determined for each shift (q, τ).
We consider two types of staffing policies: 'fixed' and 'flexible' staffing. Under fixed staffing, the number of nurses working in unit k during shift (q, τ), denoted by $s^k_{q,\tau}$, is completely determined in advance. In the flexible case, 'dedicated' staffing levels $d^k_{q,\tau}$ per unit are determined, together with the number of nurses $f_{q,\tau}$ available in a flex pool. The decision regarding the particular units to which the float nurses are assigned is delayed until the start of the execution of a shift. We assign float nurses to one and the same care unit for a complete working shift, to avoid frequent hand-overs, which increase the risk of medical errors. Thus, we obtain staffing levels $s^k_{q,\tau} = d^k_{q,\tau} + f^k_{q,\tau}$, $k = 1, \ldots, K$, where $f^k_{q,\tau}$ denotes the number of float nurses assigned to unit k from the available $f_{q,\tau}$. Taking into account the current bed census and the predictions on patient admissions and discharges, the allocation of the float nurses to care units at the start of a shift is decided according to a predetermined assignment procedure. We denote such an assignment procedure by π.
Our goal is to determine the most cost-efficient staffing levels such that certain quality-of-care constraints are satisfied. Because float nurses are required to be cross-trained, it is likely that these staff members are more expensive to employ. To be able to differentiate such costs, we therefore consider staffing costs ω_d for each dedicated nurse who is staffed for one shift and ω_f for each flexible nurse. Next, the nurse-to-patient ratio targets during shift (q, τ) are reflected by $r^k_{q,\tau}$, indicating the number of patients a nurse can be responsible for at any point in time. To keep track of the compliance to these targets, we define the concept 'nurse-to-patient coverage', or shortly 'coverage'. With x^k the number of patients present at unit k at a certain time (q, t), $b_\tau \leq t < b_\tau + \ell_\tau$, the coverage is given by $r^k_{q,\tau} \cdot s^k_{q,\tau}/x^k$. Thus, a coverage of one or higher corresponds to a preferred situation.

Starting from the following quality-of-care requirements as prerequisites, we will formulate the fixed and flexible staffing models by which the most cost-effective staffing levels can be found:

(i) **Staffing minimum.** For safety reasons, at least S^k nurses have to be present at care unit k at any time.

(ii) **Coverage minimum.** The coverage at care unit k may never drop below β^k.

(iii) **Coverage compliance.** The long-run fraction of time that the coverage at care unit k is one or higher is at least α^k. We denote the expected compliance at care unit k during shift (q, τ) by $c^k_{q,\tau}(\cdot)$; the arguments of this function depend on which staffing policy is considered.

(iv) **Flexibility ratio.** To ensure continuity of care, at any time, the fraction of nurses at care unit k that are dedicated nurses has to be at least γ^k.

(v) **Fair float nurse assignment.** The policy π, according to which the allocation of the available float nurses to care units at the start of a shift is done, has to be 'fair'. Fairness is defined as assigning each next float nurse to the care unit where the expected coverage compliance during the upcoming shift is the lowest.

Fixed staffing

When only dedicated staffing is allowed, there is no interaction between care units. Therefore, the staffing problem decomposes in the following separate decision problems for each care unit k, and each shift (q, τ):

$$\min \quad z_F = \omega_d s_{q,\tau}^k \tag{1}$$

$$\text{s.t.} \quad s_{q,\tau}^k \geq S^k \tag{2}$$

$$s_{q,\tau}^k \geq \left\lceil \beta^k \cdot M^k / r_{q,\tau}^k \right\rceil \tag{3}$$

$$c_{q,\tau}^k \left(s_{q,\tau}^k, r_{q,\tau}^k \right) \geq \alpha^k \tag{4}$$

The constraints (2), (3), and (4) reflect requirements (i), (ii), and (iii), respectively. Let $X_{q,t}^k$ be the random variable with bed census distribution $\hat{Z}_{q,t}^k$ counting the number of patients present on care unit k at time (q, t). Then, the coverage compliance in (4) can be calculated as follows:

$$\begin{aligned} c_{q,\tau}^k \left(s_{q,\tau}^k, r_{q,\tau}^k \right) &= \mathbb{E}\left[\frac{1}{\ell_\tau} \sum_{t=b_\tau}^{b_\tau+\ell_\tau-1} \mathbb{1}\left(X_{q,t}^k \leq s_{q,\tau}^k \cdot r_{q,\tau}^k \right) \right] \\ &= \frac{1}{\ell_\tau} \sum_{t=b_\tau}^{b_\tau+\ell_\tau-1} \sum_{x=0}^{s_{q,\tau}^k \cdot r_{q,\tau}^k} \hat{Z}_{q,t}^k(x). \end{aligned}$$

Observe that $\sum_{x=0}^{s_{q,\tau}^k \cdot r_{q,\tau}^k} \hat{Z}_{q,t}^k(x)$ reflects the probability that with staffing level $s_{q,\tau}^k$ and under ratio $r_{q,\tau}^k$ the nurse-to-patient ratio target is satisfied during time interval $[t, t+1)$. The optimum of (1) is found by choosing the minimum $s_{q,\tau}^k$ satisfying constraints (2) and (3), and increasing it until constraint (4) is satisfied.

Flexible staffing

The next step is to formulate the flexible staffing model. Note that for requirements (i) and (ii), the constraints are similar to those for fixed staffing. Under the assumption $\omega_d \leq \omega_f$, we can replace $s_{q,\tau}^k$ by $d_{q,\tau}^k$ in (2) and (3). Due to the presence of a flex pool, the care units cannot be considered in isolation anymore. Hence, constraint (4) has to be replaced. An assignment procedure has to be formulated that fulfills requirement (v), and this assignment procedure influences the formulation of the constraint for requirement (iii). In addition, a constraint needs to be added for requirement (iv).
For an assignment procedure π that allocates the float nurses to care units at the start of a shift (q, τ), let $g_{q,\tau}^\pi(\mathbf{dv}, f, \mathbf{y})$ be the vector of length K denoting the number of float nurses assigned to each care unit, when f flex nurses are available to allocate, the number of staffed dedicated nurses equals $\mathbf{dv} = (d^1, \ldots, d^K)$, and the census at the different care units at time (q, b_τ) equals $\mathbf{y} = (y^1, \ldots, y^K)$. A vector of the type $\mathbf{y}$ reflects what we will call a *census configuration.*

Let π^* denote the assignment procedure that ensures constraint (v). The assignment procedure π^* depends on $\mathbf{dv}_{q,\tau}$, $f_{q,\tau}$, and $r_{q,\tau}^k, k = 1, \ldots, K$, and therefore the coverage as well. Hence, requirement (v) gives a constraint of the form $c_{q,\tau}^k(\mathbf{dv}_{q,\tau}, f_{q,\tau}, r_{q,\tau}^k) \geq \alpha^k$.

However, assignment procedure π^* depends on the census configuration $\mathbf{y}$ at time (q, b_τ), so calculation of the coverage compliance first requires the computation of $c^k_{q,\tau}(\mathbf{dv}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau}; \mathbf{y})$, which describes the coverage compliance, given that at the start of shift (q,τ) census configuration $\mathbf{y}$ is observed. Then, the coverage compliance is given by:

$$c^k_{q,\tau}\left(\mathbf{dv}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau}\right) = \sum_{\mathbf{y}} \left\{ c^k_{q,\tau}\left(\mathbf{dv}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau}; \mathbf{y}\right) \prod_{w=1}^{K} \hat{Z}^w_{q,b_\tau}(y^w) \right\}.$$

Using $c^k_{q,\tau}(\mathbf{dv}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau}; \mathbf{y})$, the assignment policy π^* satisfying requirement (v) is the one that satisfies:

$$g^{\pi^*}_{q,\tau}(\mathbf{dv}_{q,\tau}, f_{q,\tau}, \mathbf{y}) = \max_{\left\{f^1_{q,\tau},\ldots,f^K_{q,\tau} : \sum_k f^k_{q,\tau} = f_{q,\tau}\right\}} \min_k \; c^k_{q,\tau}\left(\mathbf{dv}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau}; \mathbf{y}\right). \tag{5}$$

Applying policy π^* provides $s^k_{q,\tau}(\mathbf{y})$, the number of nurses staffed at care unit k if census configuration $\mathbf{y}$ is observed at the start of shift (q,τ). Hence, the flexible model for each shift (q,τ) is the following:

$$\begin{aligned}
\min \quad & z_E = \omega_f f_{q,\tau} + \sum\nolimits_k \omega_d d^k_{q,\tau} && && (6)\\
\text{s.t.} \quad & d^k_{q,\tau} \geq S^k, && \text{for all } k, && (7)\\
& d^k_{q,\tau} \geq \left\lceil \beta^k \cdot M^k / r^k_{q,\tau} \right\rceil, && \text{for all } k, && (8)\\
& c^k_{q,\tau}\left(\mathbf{dv}_{q,t}, f_{q,\tau}, r^k_{q,\tau}\right) \geq \alpha^k, && \text{for all } k, && (9)\\
& d^k_{q,\tau} \geq \gamma^k \cdot s^k_{q,\tau}(\mathbf{y}), && \text{for all } k, \mathbf{y}, && (10)\\
& s^k_{q,\tau}(\mathbf{y}) = d^k_{q,\tau} + g^{k,\pi^*}_{q,\tau}\left(\mathbf{dv}_{q,\tau}, f_{q,\tau}, \mathbf{y}\right), && \text{for all } k, \mathbf{y}. && (11)
\end{aligned}$$

Constraints (7)–(11) reflect (i)–(v), respectively. Finding the optimum for (6) requires the computation of $c^k_{q,\tau}(\mathbf{dv}, f_{q,\tau}, r^k_{q,\tau}; \mathbf{y})$ by considering every sample path of census configurations during a shift. For realistic instances, this is computationally too expensive to find the optimal solution for $d^1_{q,\tau}, \ldots, d^K_{q,\tau}, f_{q,\tau}$ in a reasonable amount of time. Therefore, two approximations are proposed. The first approximation is obtained by deriving the probability distribution for the maximum number of patients present during each shift and then finding the optimal staffing for this maximum census. In this case, the number of patients present is overestimated, and subsequently the required staffing levels are overestimated; thus we obtain an upper bound on the staffing requirements. In the second approximation we reassign the float nurses to the care units at the start of each time interval. Because this provides more flexibility to align the float nurse allocation to the current census, we obtain an underestimation of the required staffing levels. As such, a lower bound on the actual staffing requirements is found. Finally, comparing the lower and upper bound solutions and the solution for the fixed model provides us with (an approximation of) the optimal solution of the flexible staffing model. To be more specific, the upper bound solution guarantees that the constraints are satisfied in the flexible staffing model. When the lower bound solution coincides with the upper bound or the fixed staffing solution, we are sure to have found the optimal solution. Otherwise, the lower bound also provides an error bound.

Upper bound model. Based on the observed maximum census configuration $\mathbf{x} = (x^1, \ldots, x^K)$ during a shift, let π^{up} be the assignment policy that allocates the nurses from the flex pool to the care units in which the nurses deficiency is the highest:

$$g^{\pi^{up}}_{q,\tau}(\mathbf{dv}_{q,\tau}, f_{q,\tau}, \mathbf{x}) = \max_{\left\{f^1_{q,\tau},\ldots,f^K_{q,\tau} : \sum_k f^k_{q,\tau} = f_{q,\tau}\right\}} \min_k \; \frac{r^k_{q,\tau} \cdot (d^k_{q,\tau} + f^k_{q,\tau}) - x^k}{r^k_{q,\tau}}.$$

Let $\hat{W}^k_{q,\tau}(x)$ be the probability that during shift (q,τ) the maximum census level that occurs at care unit k is x patients. These probabilities are derived by analogy with the derivation of $\hat{Z}^k_{q,\tau}(x)$ in Kortbeek et al. To obtain the upper bound, for $b_\tau \leq t < b_\tau + \ell_\tau$, we approximate the original distribution $\hat{Z}^k_{q,t}(x)$ by $\hat{W}^k_{q,\tau}(x)$. Let $\bar{X}^k_{q,\tau}$ be the random variable with distribution $\hat{W}^k_{q,\tau}$ that reflects the maximum number of patients on care unit k during shift (q,τ). To see that this approximation leads to an upper bound on the required staffing levels, observe that $\bar{X}^k_{q,\tau} \geq X^k_{q,t}$, for $b_\tau \leq t < b_\tau + \ell_\tau$, so that for every time interval of a shift the census is overestimated, and thus staffing requirements are overestimated.
Because we use the same census distribution in every time interval during a shift, the coverage compliance over a shift $\bar{c}^k_{q,\tau}(\mathbf{dv}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau})$ is calculated by:

$$\bar{c}^k_{q,\tau}\left(\boldsymbol{d}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau}\right) = \sum_{\boldsymbol{x}} \left\{ \mathbb{1}\left(x^k \leq r^k_{q,\tau} \cdot s^k_{q,\tau}(\boldsymbol{x})\right) \cdot \prod_{w=1}^{K} \hat{W}^w_{q,\tau}(x^w) \right\},$$

where $s^k_{q,\tau}(\mathbf{x})$ is the number of nurses staffed at care unit k for shift (q,τ) under assignment policy π^{up}, when the maximum observed census configuration is $\mathbf{x}$. Summarizing, for each shift (q,τ), we have:

$$\min \quad z_U = \omega_f f_{q,\tau} + \sum\nolimits_k \omega_d d^k_{q,\tau} \tag{12}$$

$$\text{s.t.} \quad d^k_{q,\tau} \geq S^k, \qquad \text{for all } k, \tag{13}$$

$$d^k_{q,\tau} \geq \left\lceil \beta^k \cdot M^k / r^k_{q,\tau} \right\rceil, \qquad \text{for all } k, \tag{14}$$

$$\bar{c}^k_{q,\tau}\left(\mathbf{dv}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau}\right) \geq \alpha^k, \qquad \text{for all } k, \tag{15}$$

$$d^k_{q,\tau} \geq \gamma^k \cdot s^k_{q,t}(\mathbf{x}), \qquad \text{for all } k, \mathbf{x}, \tag{16}$$

$$s^k_{q,\tau}(\mathbf{x}) = d^k_{q,\tau} + g^{k,\pi^{up}}_{q,\tau}\left(\mathbf{dv}_{q,\tau}, f_{q,\tau}, \mathbf{x}\right), \qquad \text{for all } k, \mathbf{x}. \tag{17}$$

The optimum of (12) is identified by first finding the solution space for $d^k_{q,\tau}, k = 1, \ldots, K$, using constraints (13) and (14), as well as the optimal solution of the fixed staffing model, and, then finding the solution space for $f_{q,\tau}$ using constraint (16). Next, complete enumeration over the obtained solution space is applied, which can be done quickly for realistic situations.

Lower bound model. For the lower bound model, we assume that we are allowed to reconsider the nurse-to-care-unit assignment at the start of every time interval. To observe that this relaxation leads to a lower bound on staffing requirements, note that with a given number of nurses, a higher coverage compliance can be achieved than in the original model. The assignment procedure π^{low} is executed at the start of each time interval, and the coverage compliance can thus be calculated per time interval. The coverage compliance over a shift $\underline{c}^k_{q,\tau}(\mathbf{dv}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau})$ can then be calculated by:

$$\underline{c}^k_{q,\tau}\left(\boldsymbol{d}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau}\right) = \frac{1}{\ell_\tau} \sum_{t=b_\tau}^{b_\tau+\ell_\tau-1} \sum_{\boldsymbol{x}} \left\{ \mathbb{1}\left(x^k \leq r^k_{q,\tau} \cdot s^k_{q,t}(\boldsymbol{x})\right) \cdot \prod_{w=1}^{K} \hat{Z}^w_{q,t}(x^w) \right\}.$$

where $s^k_{q,t}(\mathbf{x})$ is the number of nurses staffed at care unit k for time interval $[t, t+1)$ on day q under assignment policy π^{low}, when census configuration $\mathbf{x}$ is observed at time (q,t).
Since π^{low} is executed at every time interval, it is based on the census configuration at the start of that time interval. A nurse from the flex pool gets staffed on the unit where the nurse deficiency is the highest:

$$g^{\pi^{low}}_{q,t}\left(\mathbf{dv}_{q,\tau}, f_{q,\tau}, \mathbf{x}\right) = \max_{\left\{f^1_{q,t}, \ldots, f^K_{q,t} : \sum_k f^k_{q,t} = f_{q,\tau}\right\}} \min_k \frac{r^k_{q,\tau} \cdot (d^k_{q,\tau} + f^k_{q,t}) - x^k}{r^k_{q,\tau}}.$$

As a result, for each shift (q, τ), we have:

$$\min\ z_L = \omega_f f_{q,\tau} + \sum_k \omega_d d^k_{q,\tau} \tag{18}$$

$$\text{s.t. } d^k_{q,\tau} \geq S^k, \qquad \text{for all } k, \tag{19}$$

$$d^k_{q,\tau} \geq \left\lceil \beta^k \cdot M^k / r^k_{q,\tau} \right\rceil, \qquad \text{for all } k, \tag{20}$$

$$\underline{c}^k_{q,\tau}\left(\boldsymbol{d}_{q,\tau}, f_{q,\tau}, r^k_{q,\tau}\right) \geq \alpha^k, \qquad \text{for all } k, \tag{21}$$

$$d^k_{q,\tau} \geq \gamma^k \cdot s^k_{q,t}(\boldsymbol{x}), \qquad b_\tau \leq t < b_\tau + \ell_\tau,\ \text{for all } k, \boldsymbol{x}, \tag{22}$$

$$s^k_{q,t}(\boldsymbol{x}) = d^k_{q,\tau} + g^{k,\pi^{low}}_{q,t}\left(\boldsymbol{d}_{q,\tau}, f_{q,\tau}, \boldsymbol{x}\right), \qquad b_\tau \leq t < b_\tau + \ell_\tau,\ \text{for all } k, \boldsymbol{x}. \tag{23}$$

The optimum of (18) is found by first finding the solution space for $d^k_{q,\tau}, k = 1, \ldots, K$, using constraints (19) and (20), and the optimal solution of the fixed staffing model, and, second, the solution space for $f_{q,\tau}$ using constraint (22). Next, complete enumeration over the obtained solution space is applied, which can be done quickly for realistically sized instances.

Flexible staffing levels. The upper and lower bound models were formulated to be able to find, or otherwise approximate, the optimal solution of the flexible staffing model. In this section, we discuss how the solutions of the fixed model, as well as the upper and lower bound models, can be used to select the best staffing configuration. Two questions need to be answered: (1) did we find the optimal solution for the flexible staffing model, and, (2) which staffing configuration should be selected as the best solution?
Let us first discuss question (1). Observe that $z_L \leq z_U$ and $z_L \leq z_F$. When $z_L = z_U$ the upper and lower bounds coincide so that the optimal solution is found. When $z_L < z_U$, but $z_L = z_F$, the optimal solution is also found because, in this case, we are sure that flexible staffing cannot improve upon fixed staffing. In other cases, we are not sure whether or not the optimal solution has been identified; it is then of interest to identify a bound on the distance between the optimal and the obtained solution.
The consideration involved when answering question (2) is to select the solution with the lowest optimal objective value, while it assures that the constraints (7)–(11) of the flexible staffing model are satisfied. For the solution of the lower bound model, we are uncertain whether constraints (7)–(11) are satisfied; therefore, we never select this solution. In addition, when $z_F = z_U$, as a tie breaker, we choose the solution that achieves the highest minimum coverage compliance.

Let us denote with S_F, S_U, and S_L the optimal staffing configurations in the fixed, upper, and lower bound models, respectively. We now provide an overview of the different cases:

(a) $z_L = z_F = z_U$. The optimal solution is found; if $\min_k \overline{c}^k_{q,\tau}(\cdot) \geq \min_k c^k_{q,\tau}(\cdot)$, S_U is selected as the best staffing configuration, otherwise S_F.

(b) $z_L = z_U < z_F$. The optimal solution is found; S_U is selected.

(c) $z_L = z_F < z_U$. The optimal solution is found; S_F is selected.

(d) $z_L < z_F = z_U$. Uncertain whether the optimal solution is found; if $\min_k \overline{c}^k_{q,\tau}(\cdot) \geq \min_k c^k_{q,\tau}(\cdot)$, S_U is selected, otherwise S_F. The bound on the error margin is $z_U - z_L$.

(e) $z_L < z_U < z_F$. Uncertain whether the optimal solution is found; S_U is selected; the error bound is $z_U - z_L$.

(f) $z_L < z_F < z_U$. Uncertain whether the optimal solution is found; S_F is selected; the error bound is $z_F - z_L$.

APPENDIX E: INPUT PREPARATION

The first step in the input preparation is the merging of the patient admission data with the surgery data. In the AMC, data is gathered from Locati and OK-plus. Locati contains all admissions to the hospital, OK-plus contains all surgeries performed in the hospital. If a patient has more surgeries during an admission, only the first surgery during an admission is used. After the data of Locati and OK-plus is merged, one will have an overview of all patient admissions and for each admission whether an elective surgery took place or not.

A part of the input preparation is already automated in Delphi Embarcadero RAD studio. If an overview is available of all admissions, including the patient type, admission ward, admission date and time and discharge date and time, the automated part of the input preparation (the 'inputwriter') can be started. We want to know the urgency of the surgery since we only want to include the elective surgeries. In case of an elective surgery, the operating room and day must be known as well. An overview of the data requirements is given in Table 10 and an example of the input for the 'inputwriter' is shown in Table 11. The 'inputwriter' calculates all input distributions for the HBC model. The output of the 'inputwriter', the upcoming surgical schedule and the bed capacity of the wards, are direct input for the HBC model.

Patient number
Admission date and time
Discharge date and time
Ward
Specialty
Operating room number
Surgery start date and time
Surgical specialty
Urgency of surgery (acute, semi-acute, elective)

TABLE 10: DATASTRUCTURE OVERVIEW

Since one part of the input preparation is already automated, it would be ideal if the whole input preparation could be automated. If patient admission and surgery data can be automatically retrieved from the hospital information database and an input file for the HBC model can be produced automatically, the data preparation for the HBC model can be executed faster. Before automating the whole process, limitations of both models as stated in Section 5.2 must be taken into account.

INPUT PREPARATION FOR THE WCC

The determination of an overview as given in Table 10 for the WCC is a challenge. In the WCC, many patients move between wards. For example, children admitted for surgery and chemotherapy are often replaced. A common clinical pathway of a surgical child is: ward X – OR – Recovery Room – PIC – ward X. A common clinical pathway of an oncological child is: ward X – Pediatric Oncology – ward X. Therefore, the determination of the length of stay and the determination of the admission day of patients in the WCC is a challenge. Choices need to be made on how to prepare the input data for ward X if a patient arrives two times (or more) on ward X during one admission. To mimic reality as good as possible, decisions are made for splitting the admission into separate admissions. The length of stay of patients on wards other than ward X are included in or excluded from the length of stay on ward X. The flowcharts in Figure 9 and Figure 10 show the steps of the input preparation. For the determination of the admission and discharge day of patients on ward X, the following choices are made:

1. Some patients stay in the day center (DAY), recovery room (RR) or go for temporary discharge (TEM) during an admission in the WCC. The length of stay of a patient on DAY, RR or TEM between two admissions on ward X is included in the length of stay on ward X. The choice is based on the assumption that a bed stays reserved for the time the patient was away from ward X.
2. Some patients stay less than 24 hours on another ward. We assume that this bed stays reserved for the time the patient was away from the ward. Therefore the time (less than 24 hours) on other wards is included in the length of stay on ward X.
3. Some patients stay more than 24 hours on another ward. This time is excluded from the length of stay of the patient on ward X. In this case, the admission of the patient to ward X is split in two (or more) admissions. If the patient is an elective patient, the surgery is only coupled to one of the admissions, one sub admission becomes elective and the other sub admission becomes non-elective. This sub admission becomes non-elective, since the surgery can only be coupled to one admission.

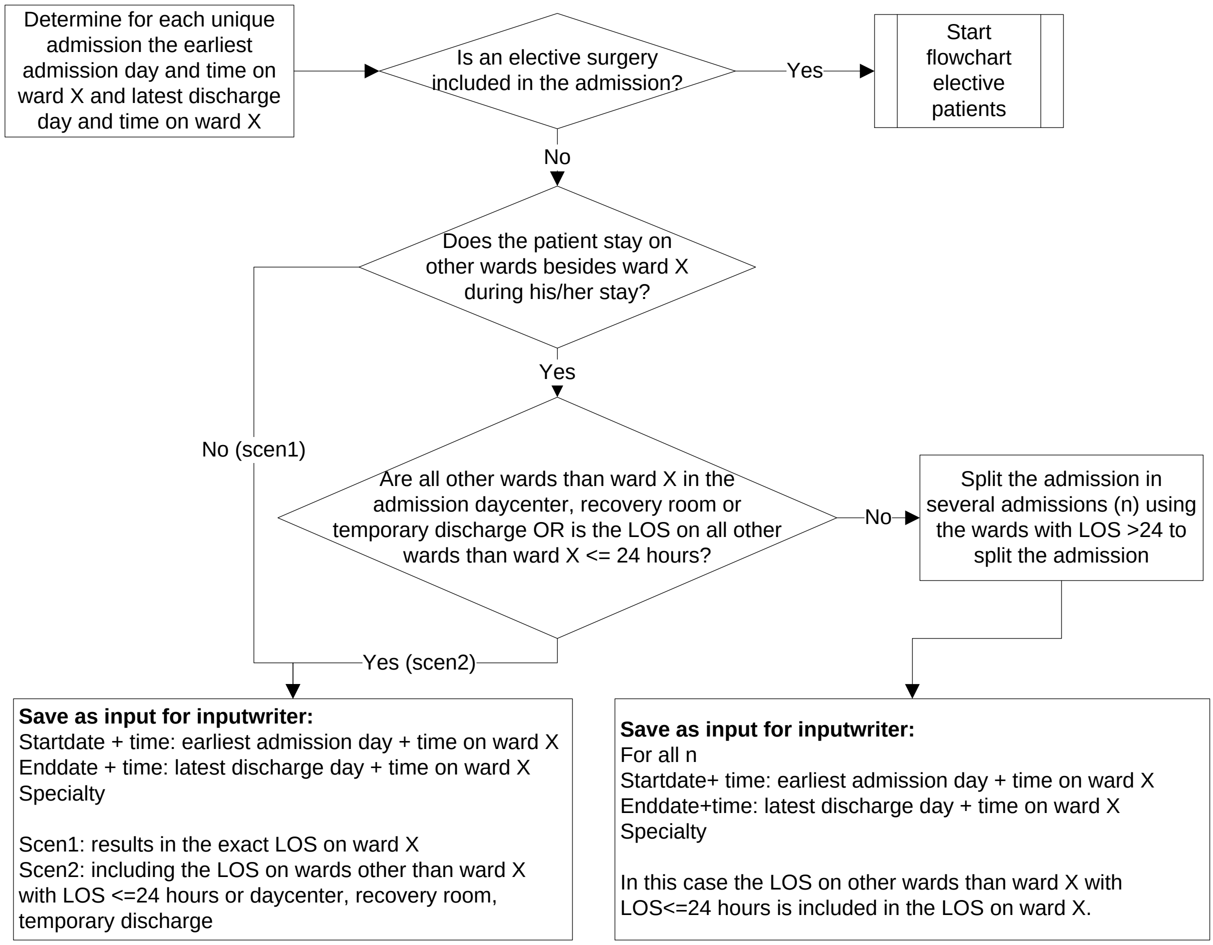

FIGURE 9: FLOWCHART OF INPUT PREPARATION FOR THE INPUT WRITER MODEL. THE FLOWCHART OF ELECTIVE PATIENTS STARTS IN FIGURE 10.

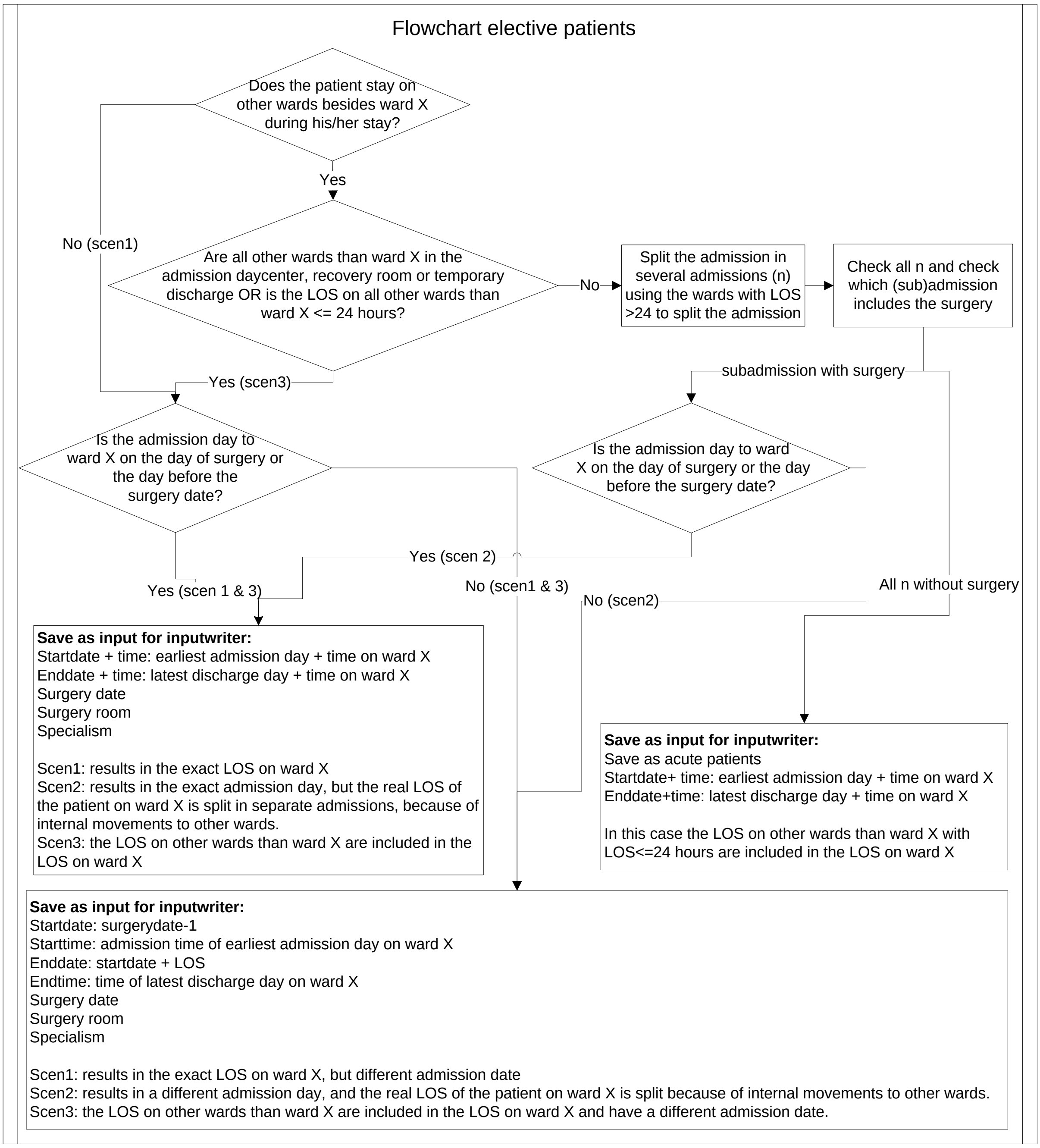

FIGURE 10: FLOWCHART OF INPUT PREPARATION FOR THE INPUT WRITER MODEL FOR ELECTIVE PATIENTS

Admission number	Patient type	Surgery (yes/no)	OR nr	Surgery date	Admission date	Discharge date	Adm. time slot	Disch. Time slot	Ward	North/ South
11_231	TEE	0	None	None	14-1-'11	18-1-'11	19	14	7	N
11_232	TEE	1	2	16-2-'11	15-2-'11	23-2-'11	9	15	7	N
…	…	…	…	…	…	…	…	…	…	…

TABLE 11: EXAMPLE INPUT FOR THE AUTOMATED INPUT PREPARATION TOOL