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OPTIMIZING THE SCHEDULING OF CARDIOTHORACIC ELECTIVE SURGERIES TO REDUCE THE VARIABILITY OF DEMAND FOR INTENSIVE CARE BEDS

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St Antonius

a santeon hospital

Management summary

Problem description

St. Antonius is a large hospital recognised for its expertise in heart, lung and cancer. In this project, we focus on the intensive care unit (ICU) of the hospital located in Nieuwegein.

The ICU has a high variability of demand for IC-beds during the week for the following reasons:

- General wards are full (thus, patients cannot flow out of the ICU, increasing the demand for beds).
- Highly variable and uncertain arrival of emergency patients.
- Complications of patients that are currently in ICU.
- Surgeries are scheduled without considering the length of stay (LOS) of the patients in the ICU.

At the beginning of the week, the bed occupation is low and during the week, this occupation increases. The reason is the hospital schedules elective surgeries without considering the LOS of the patients after surgery in the ICU. In addition, during the weekend patients that are recovered, they are relocated to the general wards and there is only inflow of emergency patients. Consequently, if we do not schedule elective surgeries considering the length of stay (in our case the postoperative care in the ICU), at the end of the week, the demand for IC-beds may be too high given the remaining capacity. As a result, surgeries are cancelled mostly at the end of the week. A cancelled surgery leads to two problems: reduced quality of healthcare and, financially speaking, inefficient use of capacity in the operating room.

We decided to focus this project on reducing the variability of demand for IC-beds for patients coming from cardiothoracic (CTC) elective surgeries because 47% of the total number of elective patients that need postoperative care in the ICU are coming from CTC-department.

Approach

We design a cyclical blueprint schedule with the most frequent CTC-elective surgery types (more than 25 samples per year). The cyclical blueprint schedule, in our case the cycles are fortnightly. In this schedule, we assign surgery types to operating rooms and days, afterwards, the operating room planner assigns a name of a patient with corresponding surgery type to the operating room slot. This system will help to reduce the variability of demand for IC-beds and further stipulate the relevance and practical value of academic scheduling methods in a healthcare setting.

We make a rough prediction of the length of stay of the most frequent CTC-elective patients in the ICU according to each surgery type. Besides, we want to consider outliers (patients who stayed in the ICU longer than expected) by having an open-ended prediction of the length of stay of the patients in the ICU, for each surgery type. Furthermore, for the remaining patients that are not included in the cyclical blueprint schedule, we calculate the probability distribution of the number of required beds depending on the flu seasonality.

To create the cyclical blueprint schedule, we use the constructive algorithm, so-called Best-fit, where we use the median length of stay of each surgery type in the ICU. We use a statistical convolution approach to calculate the demand distribution for beds per day based on the blueprint schedule. Then, we improve the blueprint schedule with what we refer to as data visualisation local search. We do a local search by plotting the probability distributions of the demand for IC-beds each day of the cycle and calculate the variability of demand for IC-beds. We evaluate which surgeries will affect the variability of demand for IC-beds by moving them to another day. We keep the new blueprint schedule when there is an improvement and then we continue doing this process with other surgeries until the variability per cycle is of one bed (two beds in case we plan 74 surgeries).

To evaluate the optimal schedule, we use Monte Carlo simulation. In all scenarios, we consider a randomized number of emergency patients and the number of beds needed for other patients (considering flu season and non-flu season). Our experimental variables are the number of surgeries planned, the duration of the surgery (fixed surgery time or variable), the capacity in the CTC-wards (infinite or finite) and whether we cluster certain surgery types.

Conclusions

The local search shows that variability of demand for IC-beds reduces by scheduling the surgery types with a long length of stay in the ICU at the end of the week, because those also have high variability in their length of stay.

After the experimentation, we conclude that the variability of the surgery duration does not influence the number of beds required or the number of cancellations because we can schedule one or at most two CTC-surgeries per operating room per day. When we cluster certain surgery types, we have to schedule fewer surgeries to meet the percentile we desire (it can be different in each experiment) and therefore we need fewer IC-beds. Another advantage of clustering is that the probability that we have a patient in the waiting list that we can assign to the time slot we are assessing is higher; hence, it reduces the probability of having an empty operating room. In the simulation, we also take into account the capacity in the CTC-wards and the flu season, which both may affect the capacity in the ICU.

The scientific contribution of this project is the generalised implementation plan for a blueprint schedule that any hospital, that wants to reduce the variability of demand for beds, can implement in departments where elective surgeries are long (in this project we proved that the generalised implementation plan works for scheduling long surgeries). Moreover, we proved the positive impact of clustering surgeries. We conclude that we can cluster two surgery types when they have similar LOS distribution and similar surgery duration.

The results of this project are useful to five different groups of people within the hospital:

- The managers have an incentive to start research to control the flow of patients in the CTC-wards after seeing the consequences of a bottleneck in the CTC-wards.
- The OR-planners perceive the effect of considering the postoperative care of the patients when we schedule the surgeries we can reduce the variability of demand for beds. Our

cyclical blueprint schedule will help the CTC OR-planner to schedule the surgeries considering the LOS of the patients.

- The doctors spot the idea of using data analysis to improve healthcare processes and are therefore motivated to put more effort into data collection. The cleaner and clearer the data, the easier it will be to improve the process.
- The nurse coordinator who assigns a bed to each patient will know in advance how many beds for each type of patient are needed and can reduce the stress of cancelling surgeries or pushing the patients to the general wards because the ICU is full.
- The patients' satisfaction will increase because the blueprint schedule will reduce the cancellations and the patients will have a better experience within the hospital.

Recommendations

We recommend the CTC OR-planner to implement the blueprint schedule, because the current mean number of beds needed for CTC-elective surgeries during a cycle is 9.5 and the standard deviation of 1.9 beds. With our blueprint schedule the mean number of beds needed is 8.8 and the standard deviation is 0.4 scheduling the same number of surgeries.

To improve data gathering we recommend standardizing surgery codes, facilitating the input of surgery duration and adding a checkbox that the doctors can select when a patient had complications during the admission into the department.

Outlook

We propose the following ideas for further research:

- Study the flow of patients from the hospital wards to the nursing houses or aftercare services to minimise bed blocking.
- Study the flow of patients of elective surgeries excluding CTC-surgeries that need postoperative treatment in intensive care.
- Make a more accurate prediction of the bed demand by differentiating the two types of ICU patients: those who need heart and lung support and those who only one of them.

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Judith Hernandez Mallol

Utrecht, February 2020

Glossary

Artificial variability	Variability caused by scheduling elective surgeries without considering the postoperative care needed for the patient.
Blocked bed	Bed that has the personnel to cover it but doctors decided to do not assign any patient because other patients need more care and we want to keep a high quality of care.
Closed bed	Bed in the department but we cannot assign a patient in it because there is no personnel to take care of it.
Elective patient	Scheduled patient, we consider it a non-urgent patient.
Emergency patient	Life-threatening patient. We cannot plan a surgery for these patients; we have to treat them as soon as we admit them in the hospital.
Intensive care unit (ICU)	Department of a hospital with the medical equipment and personnel to treat seriously injured or ill patients.
In-patient	A patient admitted to one of the wards in the hospital.
Length of stay (LOS)	Time (days/hours) that the patient stays in a hospital or in a certain department.
Occupied bed	Bed that has a patient assigned.
Opened bed	Bed with personnel assigned to take care of the patient who has assigned this bed.
Operating room (OR)	Room where the surgeries are performed. Equipment may differ for ORs.
Post anaesthesiology care unit (PACU)	Type of care inside the ICU where there are patients who need mechanical ventilation and control of the constants for a short period. Not more than 24h.
Ward	Group of rooms for patients who needs a similar kind of care. Also known as general patient wards.
P_i	*i*-th percentile

Contents

1 Project description

The intensive care department has a highly variable demand for beds. When the department is full, doctors cancel one or more elective surgeries with postoperative care in the intensive care unit (ICU), because we cannot ensure a bed for those patients after their surgery.

The high variability of bed demand in the ICU is due to several reasons. Among the most severe of them is the negligence of the length of stay of the patients, when planning a surgery, in the ICU. In this project, we aim to design a schedule of elective surgeries focusing on the cardiothoracic department (department with highest arrival rates) to reduce the fluctuation of demand for beds.

The project description has the following layout. Section 1.1, contains general information about the hospital. In Section 1.2, we list the reasons to perform this project. Section 1.3 describes the problem and Section 1.4 mentions the research objectives.

1.1 Context description

St. Antonius is a large hospital known for its recognised expertise in heart, lung and cancer treatment. It has eight locations around the region of Utrecht. There are two clinical hospitals located in Nieuwegein and Utrecht and one outpatient hospital in Woerden. St. Antonius Ziekenhuis (2018) has more than 5700 employees, 750 beds and 35 operating rooms.

St. Antonius is one of the seven top clinical hospitals that are part of Santeon. These hospitals work together to continuously improve medical care.

In this project, we focus on the ICU of the hospital located in Nieuwegein. The department has two types of care units according to the level of care the patient requires: intensive care unit (ICU) and post anaesthesiology care unit (PACU). In the ICU, we can differentiate two types of care: intensive care (IC) and medium care (MC).

Intensive care unit (ICU)

This unit accommodates the sickest patients who need mechanical ventilation and/or continuous control of their constants. In case they need both the patient is assigned to an IC-bed, but if the patient needs one of those he/she is admitted in a MC-bed. In this research, we will not differentiate between IC and MC because the data set provided considers both types of care in the ICU department.

Post anaesthesiology care unit (PACU)

This unit admits patients who need mechanical ventilation and/or continuous control of their constants for less than 24 hours after their surgery. After this time, doctors decide to transfer the patient to the general wards or if he/she still needs to be motorised to an IC/MC-bed.

1.2 Research motivation

There are two main reasons to perform this research: the number of cancellations and the shortage of IC-nurses.

During the weekend, there are no elective surgeries, which reduces the inflow of patients in the department. Moreover, doctors transfer patients who do not need intensive care to general wards. For that reason, at the beginning of each week, there are enough beds to cover the demand. However, during the week, the volume of IC-beds demand is increasing and sometimes at the end of the week, in case the department is full we have to cancel elective surgeries.

In the Netherlands, there is a shortage of IC-nurses and especially in the province of Utrecht. Added to this, in case a patient needs full-time supervision from the doctors and nurses, because of his/her medical condition, we have to block the bed next to him/her.

1.3 Problem description

Several reasons lead to a full ICU; Figure 1 mentions the most important ones.

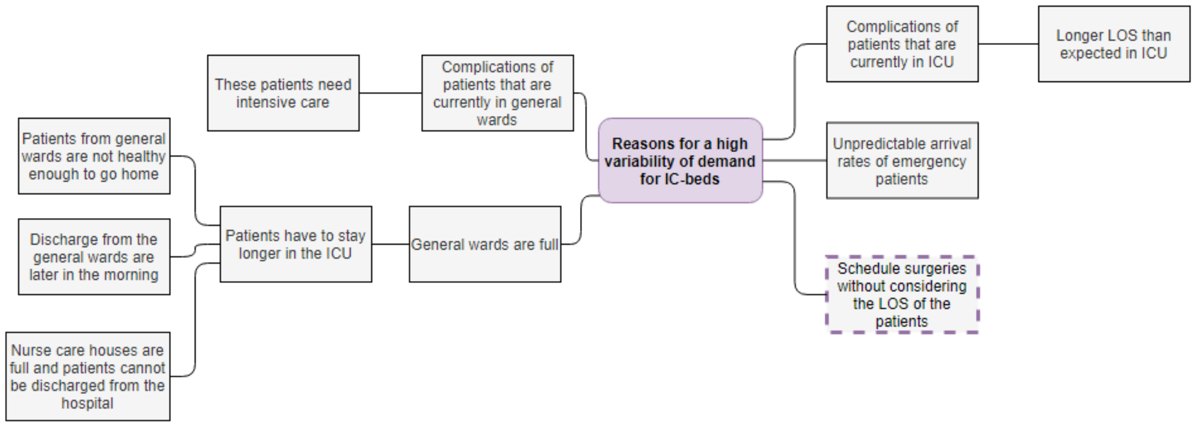


Figure 1. Reasons for a high variability of demand for IC-beds

According to McManus et al. (2003) and Kolker (2008), there are two types of variability in the ICU: natural and artificial:

Natural variability

We cannot control this variability in the intensive care department because is due to the unpredictable arrival rates of the patients coming from general wards of any speciality, patients coming from the emergency department and patients coming from other hospitals. Moreover, the length of stay (LOS) of patients that are currently in the department might be longer than expected due to complications.

Artificial variability

This variability comes from scheduling the elective surgeries without considering the length of stay of the patients during the postoperative care. The cardiothoracic department (CTC-department) schedules its surgeries a short time in advance. Consequently, the schedule is not efficient and besides, when we schedule the surgeries, we do not consider the LOS of the patients in ICU. The CTC-department has the highest arrival rates of elective patients in the ICU, so the performance of this department has a high impact on the variability of demand for IC-beds. The combination of high arrival rates and the absence of smart scheduling procedures in the CTC-department results in this department being the core of many cancellations.

On top of this, the doctors discharge patients during the morning in the general wards. Therefore, it is difficult to estimate the number of available beds in the general wards that we can use to relocate patients that do not need intensive care anymore. When we cannot relocate a patient, and the ICU is full, we have to cancel surgeries. Thus, the discharging of patients in the general wards influences the scheduling options in the ICU. We consider this an artificial form of variability because better communication between departments and a different working habit will reduce this variability. These two types of variability together lead to peaks of demand; Beliën and Demeulemeester (2007) explain that those would be smooth if we can control the artificial variability.

Problem statement:

The demand for beds in the ICU fluctuates. Normally it increases during the week, leading to capacity problems at the end of the week. Consequently, we have to cancel some elective surgeries that need postoperative care in ICU.

1.4 Research objectives

We will be able to solve the problem when we meet the following research objectives:

- Objective 1: Study of the current flow of patients through the ICU.
- Objective 2: Study of the current capacity strategy in the ICU.
- Objective 3: Select which model for optimizing the scheduling of surgeries to balance the demand for beds suits the situation in the ICU better.
- Objective 4: Develop and assess interventions for optimizing the scheduling of the CTC-surgeries.
    - A rough estimation of the LOS of the patients in the ICU according to their pathology with historical data.
    - Strategy to schedule surgeries and reduce the variability of demand for beds.
- Objective 5: Design experiment to assess the robustness of the schedule.
- Objective 6: Steps to implement a new scheduling strategy.

2 Context analysis

This chapter explains the current situation in the intensive care department. Section 2.1 describes the flow of the patients through the ICU and PACU, and the arrival rates of the patients. Section 2.2 contains a hierarchical decomposition of the resource capacity planning adapted to the intensive care situation. Section 2.3 describes the strategies that the ICU currently uses. Section 2.4 reports the different bottlenecks in the hospital. Section 2.5 explains the demarcation of the core problem.

2.1 Process and system description

The flow of patients in the intensive care department (Figure 2) has predictable (green arrow) and unpredictable (red arrows) inflow of patients. The dashed lines indicate the flow of patients that need more specialised care than expected due to their medical condition. The grey dashed arrows represents patients discharged from the hospital because they either need to go to another type of hospital (for example in case of attempted suicide, we transfer the patient to a psychiatric hospital) or they passed away.

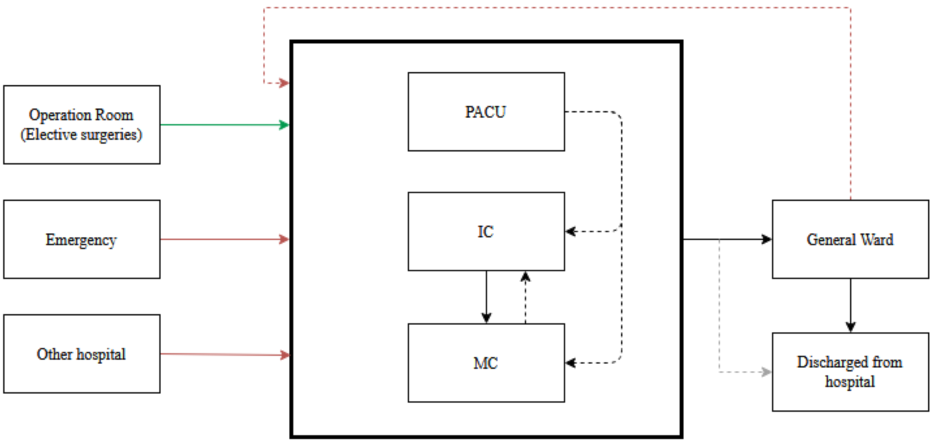


Figure 2. Flow of patients through the intensive care department

Elective surgery patients are predictable because, after the preoperative screening, doctors decide which postoperative care the patient will have. However, in case of complications during the surgery, a patient might need intensive care treatment. We consider these in the unpredictable arrival rate group.

The unpredictable flow of patients comes from the emergency department, from other hospitals or the general ward of the hospital. The last case is more likely to happen during winter due to the flu season. It is possible that a patient in a MC-bed has complications and goes to an IC-bed. In addition, PACU patients who did not recover enough, after 24 hours, go to ICU (IC/MC) instead of general wards.

The general path of a patient leaving the intensive care department is to a general ward and afterwards, the patient is discharged from the hospital to go home or to fo to nurse care houses.

We got data, from EPIC (software to store, organise and share electronic medical records), of all patients from the 1st of January 2018 until the 30th of June 2019 that were accepted in the intensive care unit. During this period, 4522 patients needed intensive care treatment. We will focus on patients from the CTC-department, for that reason, we divided the arrival rates into two groups: CTC-patients and the rest. Table 1 shows the arrival rates of the different types of accepted patients in ICU and PACU. This project focuses on scheduling elective surgeries from the CTC-department, which corresponds, to the 47% of the patients that needs intensive care treatment.

Table 1. Arrival rates to ICU of 4522 patients during the 1st January 2018 until 30th June 2019, data got from EPIC

Department	Patients from elective surgeries	Patients from emergency department general wards or other hospitals	Patients from emergency surgeries
CTC	2116 (47%)	236 (5%)	211 (5%)
Rest	1238 (27%)	721 (16%)	

2.2 Planning and control description

Figure 3 shows the ideal planning and control of resource capacity in the intensive care department, based on the framework for healthcare planning and control by Hans, et al. (2011).

On a strategic level, the hospital decides the number of personnel hired for the intensive care department and on this level. On a tactical level, the hospital decides on the number of beds open in the coming weeks and the cyclical blueprint schedule. On the operational offline level, we schedule the workforce and we assign elective patients to an operating room and day according to their surgery type. On operational online level, in case of a peak of demand, doctors will decide which elective surgery to cancel. This level also facilitates the coordination of the emergencies that need intensive care.

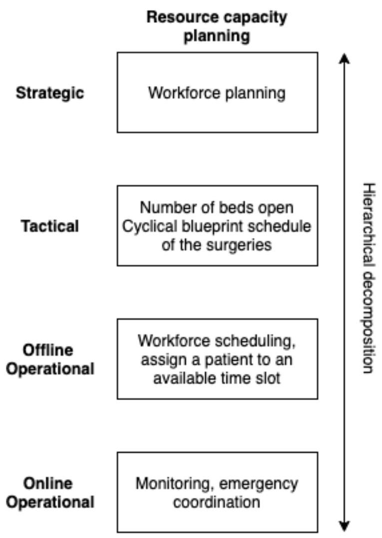


Figure 3. Framework for resource capacity planning

2.3 Definition and zero-measurement of performance

The current strategy consists of fixing a maximum discrete number of CTC-surgeries per day with postoperative care in the intensive care department (on Monday 12 surgeries and the rest of the working days 11 surgeries). In a normal week (without holidays), there are five operating rooms available per day for CTC-surgeries.

The hospital uses the rule of having at least two beds available for emergency patients in ICU because we can treat any kind of patient in this unit.

The current utilization of beds in the intensive care department is 73.6% with a standard deviation of 13.6% per day according to the files provided by the OK-IC Centrum department from 1st of January 2018 until 30th of June 2019.

2.4 Overview of the problems/bottlenecks

The productivity in the intensive care department would increase with the efficient flow of patients. In the hospital, there are several bottlenecks, that have a direct effect on the flow of patients within the hospital. There are three bottlenecks in the process from the scheduling of the patient until they leave the hospital after the surgery.

First bottleneck: Intensive care unit

When the intensive care unit is full, the flow of patients through this department is slower and the inflow of patients depend on the number of discharges in the department. The number of elective surgeries with postoperative care in the department will also depend on bed availability. The probability of having a bottleneck in this department increases due to the shortage of IC-nurses explained in Section 1.2.

Second bottleneck: General wards

When the general wards are full, patients cannot be moved to the wards because the ward is full. Consequently, they have to stay longer in the ICU, which is more expensive than a general ward and at the same time, this can lead to another bottleneck in the intensive care department. This problem especially affects the intensive care department, when the bottleneck is at the CTC-wards.

Third bottleneck: Nurse caring house

Some patients, especially patients from the CTC-department, when leaving the hospital need to go to nursing caring homes instead of home. These places work as a bridge between the hospital and home. There is a high demand, so when nurse caring homes are full, it affects the general wards and consequently the intensive care department.

2.5 Demarcation of the core problem

Part of the variability of intensive care beds is due to poor scheduling of surgeries. Consequently, some days there are empty beds (normally this happens at the beginning of the week) and other days we have to cancel surgeries because there is no space for these patients in the department (normally this happens at the end of the week).

The core problem is that the scheduling without considering the length of stay of the patients during the postoperative care, of elective surgery patients from the CTC-department leads to high variability in ICU-occupation, because the highest ICU-arrival rates are from patients coming from the CTC-department.

3 Literature review

The literature review includes four sections. Section 3.1 explains the goal and approach of this chapter. In Section 3.2, we choose a strategy on how to approach the length of stay of the patients in the ICU. Section 3.3 contains comparison models for scheduling the surgeries considering the LOS of the patient. Section 3.4 describes the conclusions of this literature research.

3.1 Literature search goal and approach

The goal of the literature research is to select which model for surgery scheduling suits the situation in ICU (in St. Antonius, Nieuwegein) to balance the variability of demand for beds. For the literature research, we first look at similar master theses and PhD projects to select which keywords were important for my research, and we review the citations of the most interesting papers. Section 3.1.1 describes the approach to estimating the demand for beds in the ICU. Section 3.1.2 compares different models to schedule surgeries. Finally, in the conclusions, we decide what model we will use. For deciding whether a paper is relevant for my study, we read the abstract and the conclusions. Section 3.2 and 3.3 describe and compare the models that could fit our situation.

3.1.1 Estimation of the demand for beds in the ICU

To estimate the demand for beds in the ICU we use the following keywords: flow of patients, ICU occupancy, ward occupancy and healthcare management.

We found thirteen relevant papers: Kortbeek et al. (2015) consider bed occupancy and rejection of patients due to shortage of beds but they do not consider emergencies. Litvak et al. (2008) explain how to manage the overflow of patients in ICU but do not include internal emergency patients. Mc Manus et al. (2004) assess capacity problems and bed utilization. Harper (2002) and Ridge et al. (1998) describe CART analysis to determine which factors influence in the LOS of the patients. Harrison et al. (2005) make a model to estimate the LOS considering seasonal effects and days of the week but it is out of the scope of this project. In Section 3.2, we also discuss Kim and Horowitz (2002), Beliën and Demeulemeester (2007), Vanberkel et al. (2011b), Steins and Walther (2013), Mallor and Azcárate (2014), Troy and Rosenberg (2009), Kolker (2008).

3.1.2 Models to schedule CTC-surgeries

To improve the OR scheduling for CTC-surgeries we use the following keywords: master surgery scheduling, schedule surgeries, operating room planning, healthcare planning and optimization with simulation.

We found and compared the following sixteen papers: Cahill and Render (1999) and Min and Yih (2010) use simulation to predict the best schedule considering the ICU beds but according to Vanberkel et al. (2010), these are inexact and require a lot of time to develop. Van Oostrum et al. (2010) give an overview of the different strategies to schedule surgeries. Hans et al. (2016) and Van Houdenhoven et al. (2007) use a model to reduce variability and increase robustness while maximizing the capacity of the operating rooms but it does not consider the beds' availability after the surgery. Hans and Vanberkel (2012) schedule the surgeries to maximise the number of breaking points and have an OR for emergency surgeries as soon as possible. Kortbeek et al. (2014) consider non-stationary arrivals to incorporate the expected peak behaviour of walk-in demand. Beliën et al. (2009) use a MILP solution of multi-objective quadratic optimization problems. Zhang et al. (2019) do not use a cyclical blueprint surgery type's schedule and they schedule the surgeries considering the waiting list management. In Section 3.3, we also discuss Van Houdenhoven et al. (2008), Van Oostrum et al. (2006), Glerum (2014), Beliën (2009), Fügener et al. (2014), Schneider et al. (2019) and Hans et al. (2008).

3.2 Estimation of the demand for beds in the ICU

The utilization of ICU beds is a parameter that can provide an overview of how the department works. Troy and Rosenberg (2009) say that in departments like the ICU the higher the utilization the higher the probabilities of cancellation. According to Steins and Walther (2013), the admission rate depends on the current occupancy of ICU beds.

To estimate the LOS of the patient, Kim and Horowitz (2002), Beliën and Demeulemeester (2007) divide each group of patients into classes using a multinomial distribution. Each class corresponds to a certain LOS in ICU. For example as Vanberkel et al. (2011b), for surgery A, a certain patient has 65% of staying one night and 20% chances of staying two nights. However, Mallor and Azcárate (2014) say that in the statistical model we must consider the outliers. For example, a patient who stays 100 days in ICU uses the same amount of resources as 100 patients with LOS of one day each.

Kolker (2008) considers the total number of beds needed, according to the LOS of the patients (instead of considering the arrival rates).

3.3 Models to schedule CTC-surgeries

Van Houdenhoven et al. (2008) explain that when we schedule the elective surgeries considering the LOS of the patients in ICU, there is a reduction of cancellations and we reduce the variability for the demand of IC-beds.

Van Oostrum et al. (2006) group surgeries in three types: elective frequent, elective seldom and emergency procedures. To design the cyclical blueprint schedule the authors consider elective frequent surgeries because, in every cycle, there must be at least a one-time slot saved for each type of surgery. The model includes two phases. In the first phase, it schedules the surgeries considering the portfolio effect, however it does not consider the specialist and the operating room that can perform this type of surgery. The second phase consists of minimizing the demand of each type of bed, to do that, they fix the surgery type in an operating room day, but they move the days of the cyclical blueprint schedule to balance the demand for beds.

Glerum (2014) schedules the surgeries considering their LOS but not the frequency of the surgeries (in contrast with Van Oostrum et al. (2006), who do consider the frequency of the surgeries). The model considers two types of LOS: 7 days or longer. In the case of the ICU, every single day is important.

Beliën (2009) has three objectives in his model. The first one is about minimizing the sum of peaks in the bed occupancy and variance overall hospitalization units. The second one is about keeping the surgeon in the same OR and receive a penalty in case the surgeon has to move to another OR. The third objective is about designing the schedules as repetitive as possible, testing weekly and fortnightly schedules.

Fügener et al. (2014), after calculating the LOS assess the probability of p out of k patients who had surgery are in ICU in day n. The authors calculate it using binominal distribution. To determine the cyclical blueprint schedule, they consider four cost components: fixed costs, overcapacity costs, staffing costs, and additional weekend staffing costs.

Schneider et al. (2019) divide the surgeries into long and short. They use cluster algorithms to cluster surgeries. Their model considers patients which postoperative care is in ICU or general wards, for that reason they assess the probability that a patient with certain characteristics after surgery goes to the ICU or general wards. They also consider the probability that after X days, the patient is transferred from ICU to general wards. They use different techniques in simulated annealing to find a feasible neighbour solution: adding or removing a surgery group, swap two groups or two OR blocks. In this model, they also consider whether the OR has the equipment to perform the surgery. The downside of this model is that it takes seven hours to compute.

Hans et al. (2008) propose different constructive and local search heuristics to optimize the schedule of surgeries and take advantage of the portfolio effect. The solution to the robust surgery loading problem is to first use a constructive approach and then improve it using local search. In the study, the best approach is using regret-based random sampling and random exchange method as a local search.

None of the models described, consider the different types of beds ICU and PACU. However, some of them differentiate between ICU and general wards.

3.4 Conclusions

After the literature research, we decided to combine several approaches to meet the requirements and the current situation of the ICU in St. Antonius. To calculate the number of beds needed without considering the pathology of the patient we use Kolker (2008). We consider the outliers due to the reasoning in Mallor and Azcárate (2014). As explained in Section 3.2, we predict the LOS using a multinomial distribution. We calculate the number of elective patients in ICU as Vanberkel et al. (2011b). We assess the cyclical blueprint schedule using the same strategy as Hans et al. (2008), by first using a constructive approach and then use local search to improve the solution.

4 A rough estimation of the length of stay of the patients in the ICU

In this chapter, we explain how we estimate the length of stay of the patients. Section 4.1 gives an overview of the approach. Section 4.2 explains the most relevant data cleaning steps. Section 4.3, describes the strategy for estimating the length of stay for patients from the CTC-department and the number of beds needed for the rest of the patients. Section 4.4 shows how to include outliers in the probabilistic model. Section 4.5, shows the results of these calculations. Section 4.6 concludes the chapter.

4.1 Overview of the approach

We use historical data to estimate the length of stay (LOS) of the patients in the ICU. With this information, we will schedule the cardiothoracic surgeries to reduce the variability of the demand for IC-beds. We cannot predict when there will be emergency surgeries, patients coming from the emergency department, patients coming from general wards or other hospitals. Therefore, for all these patients and patients that are not coming from CTC-elective surgeries, we calculate the average number of beds they use. Consequently, we can know how many elective CTC-surgeries we can schedule.

4.2 Data cleaning

We perform data cleaning to modify the data set from EPIC into one clean and easily understandable data set which is tailored for our purposes.

The surgery number is the unique number of the data set, this is due to sometimes during the same admission the patient has several surgeries. In case the patient has several surgeries during one admission we combine the rows into one, and we consider the surgery that leads the patient to the ICU. For the diagnostic procedures that the data set considers them as surgeries, we add a column for diagnostics and move it there. Additionally, we verify that the day of the surgery is between the admission and the discharge of the patient in the hospital. If it does not match, we add these surgeries into a column for surgeries that did not cause the admission of the patient to the ICU.

We do this process with Excel because in case of several surgeries during the same admission period, we have to check which surgery brought the patient to the ICU first. Besides, doctors write the same surgery differently or with misspellings, or they use different surgery codes for the same type of surgery. I recommend the hospital to standardize these processes by having a list with all the different types of surgery, this improvement will facilitate the data cleaning.

We differentiate the emergency CTC-surgeries from the CTC-elective surgeries by combining the data set from EPIC with a file provided by the CTC-department. To do that, we design an algorithm that matches the surgery number of both files and adds the binary variable (emergency/elective) into the file from EPIC.

We calculate the age of the patients with the discharge date from ICU or PACU and the birthdate of the patient. We assume that a patient has passed away when the discharge department from the hospital is the ICU or PACU (exceptions are explained in Section 2.1).

We determine the flu season according to the data from the National Institute for Public Health and the Environment (2018-2019).

We calculate the LOS with the discharge day minus the admission day from the ICU or PACU. We repair the data of the patients with negative LOS (normally it is because we wrote the year wrong, or we swapped the month and the day). We did this, by looking at the logic of the admission and discharge date in the hospital and in the ICU, in case of doubt we delete the patient. Moreover, we delete patients with a LOS lower than two hours and discharged alive from the department. In case they need intensive care after the surgery, they could go to the recovery room (where the maximum stay is two hours). However, in case the patient is not coming from an operating room and needs intensive care treatment they stay more than two hours in the ICU.

The data set only records the last length of stay of a patient in the intensive care department during an admission. When a patient goes to general wards and then back to the ICU, the data set registers only the last length of stay. However, it considers a unique LOS when the patient goes to the operating room and then back to the ICU. This situation is not frequent but we should consider it in further research.

4.3 Experiment design

The length of stay (LOS) of patients is the number of nights the patient stays in the ICU or PACU. When we sent a patient to general wards at night (after seven o´clock in the evening or before six o´clock in the morning) most of the time it is because the ICU is full. This patient would have spent the night in the ICU and the next day he/she would have gone to the general wards. In these situations, we added one night to the LOS of those patients.

Section 4.3.1 explains how we calculate the LOS for elective surgeries from CTC-department and in Section 4.3.2 we explain what we do with the rest of the patients.

4.3.1 Elective cardiothoracic patients

According to experienced doctors, the type of surgery has an impact on the LOS of the patients in the ICU. We used the correlation tool in Excel to find the factors that could have an impact on the length of stay of the patients, but we could only find a weak correlation (less than 0.3) between the LOS and the pathology or the binary variable for a patient when passed away. The only factor that has a direct effect on the length of stay of the patients in the ICU and we can predict before the surgery is their pathology. For that reason, we grouped patients according to their pathology. Like Runnarsson and Singurpalsson (2019), to have bigger samples of patients and therefore increase the reliability of the results, we clustered, with a medical specialist, similar pathologies that have also similar recoveries.

We could not get the data of whether the patient had complications during his/her LOS in ICU, because we write this in the record of the admission of the patient but we could only know it going patient per patient through their records. However, we should consider implementing a checkbox in EPIC that medical personnel could check in case of complications. This implementation would lead to a more accurate prediction of the LOS of the patients.

We calculate the LOS of the patients with the historical data mentioned in previous chapters. For each group of patients, we assess the probability that they stay one night, two, etc. in ICU or PACU. To predict the LOS of the patients, we consider the first 95% of the patients, with lower LOS. For the remaining 5% we consider as an open-ended probability as we explain in Section 4.4.

4.3.2 Other patients

The project focuses on CTC-elective surgeries, therefore for the rest of the patients; we do not consider the specific LOS of each patient. In this case, we calculate the total number of beds that we need to treat those patients, without considering their arrival rates. We proved that there is seasonality because, during flu season, the demand for beds for these patients is higher.

During the first month of the dataset, we do not calculate the number of beds needed, because we do not know how many patients were admitted before 1st of January 2018 and were still in the ICU during January. We have 99% accuracy that the patients that are in ICU were accepted after the 1st of January 2018 if we start calculating the number of beds needed from 1st of February 2018 (99% of the patients have a LOS equal or smaller than 31 days).

4.4 Inclusion of outliers in the probabilistic model

There are patients with a much longer LOS in the ICU than expected, due to several complications. We consider these patients as outliers and we want to include them because even if it is uncommon, they need the same resources as any other patient for a longer period. For that reason, we decided to calculate the LOS of the patients according to their surgery type using the 95% of the patients that have the shortest LOS. We calculate as an open-ended probability the last 5% of the patients because we do not have enough outliers in our dataset to be able to make an accurate prediction.

Sometimes due to the number of samples of a certain surgery type, it is impossible to get exactly 95% of the patients with the shortest LOS. For that reason, to assess the tail of LOS for each surgery type, we consider the remaining percentage of patients that are not considered in Table 2. To calculate the probability that an outlier patient with certain surgery type stay exactly t days in the ICU we use Equation 2. In Equation 2, variable x is the remaining percentage that is not considered in Table 2 as it is described in Equation 1. We calculate the tail until the total percentage of the LOS of the surgery type is 100%. To know the length of the tail, we use Equation 2. For example, in case variable x is equal to 5%, the length of the tail (N) is 20 days. This means that after the day where the first 95% of the patients are included, we calculate the probability that a certain patient stays in the ICU for t days (we calculate t, for every day during 20 more days).

Figure 4 shows an example of cumulative distribution (in this case of surgery type 9) including the outliers probability.

$$x = 1 - \sum_{t=1}^{MaxLOS_{within\,95\%}} P(t) \quad (1)$$

$$P_{LOS}\left(MaxLOS_{within\,first\,95\%} + n\right) = \frac{x}{2^n} \; n \in \{1, \ldots, N\} \quad (2)$$

$$N = \frac{1}{2x} \quad (3)$$

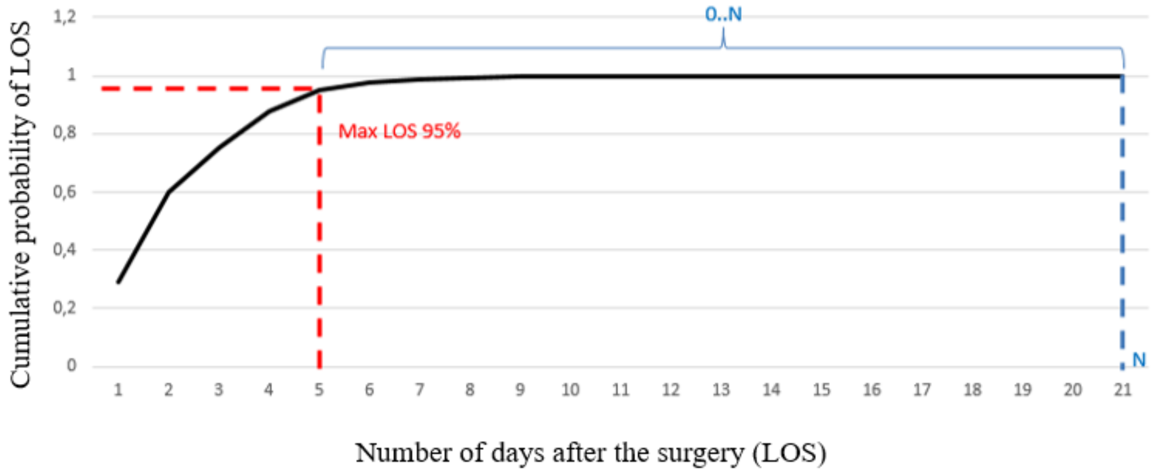


Figure 4. Cumulative LOS of Surgery type 9, data of 71 patients got from EPIC

4.5 Results

In this section, we present the results of the calculation of the LOS in case of the elective cardiothoracic patients (Section 4.5.1) and the number of beds that we need for the other patients that need intensive care (Section 4.5.2).

4.5.1 Elective cardiothoracic patients

Table 2 shows the probabilities of LOS (without the inclusion of outliers), excluding emergency patients, according to the type of CTC-surgery (including only samples which pathology or cluster of surgeries is bigger or equal than 25 patients). Table 24 (Annex A) contains the description of the surgeries that match the surgery ID. In a later stage of the project, we decided to exclude Surgerytype_7, because we do not use an operating room for this surgery.

Table 2. Probabilities of LOS according to the surgery of 2116 patients during the 1st January 2018 until 30th June 2019, data got from EPIC

Surgery ID	Length of stay in intensive care department (Days)																								
	1	2	3	4	5	6	7	8	9	10	11	12	13	15	16	18	20	22	23	24	28	32	34	36	44
Surgerytype_1	80%	10%	3%	2%																					
Surgerytype_2	86%	6%	3%																						
Surgerytype_3	43%	22%	12%	9%	4%	1%	3%	1%																	
Surgerytype_4	60%	13%	11%	4%	3%	2%	1%		1%																
Surgerytype_5	24%	37%	15%	2%	9%	7%								1%											
Surgerytype_6	5%	3%	5%	8%	5%	5%	16%	3%		3%			3%	3%	11%	3%	5%	3%	3%	3%			3%	3%	2%
Surgerytype_8	39%	19%	16%	9%				6%				3%								3%					
Surgerytype_9	2%	38%	16%	14%	11%	4%	1%	1%	1%		1%	1%	1%	1%	3%										
Surgerytype_10	24%	60%	16%																						
Surgerytype_11	29%	31%	15%	13%	7%																				
Surgerytype_12	27%	28%	11%	13%	2%	4%	2%	2%								2%		2%				2%			
Surgerytype_13	31%	19%	15%	15%			4%			4%										4%	3%				
Surgerytype_14	23%	41%	18%	5%		5%	9%																		
Surgerytype_15	95%																								

Elective CTC-surgeries do not have seasonality because these surgeries are planned a short time in advance. After all, the medical condition of the patient is critical.

4.5.2 Other patients

To consider the variability of the IC-beds, we find the distribution of the number of beds used. For these patients, we have seasonality depending on the flu season. To calculate the mean, standard deviation and mode we delete the weekends, public holidays and as months July and August (because it is the holiday season so the number of elective surgeries changes). We deleted those periods because we want to know the number of beds needed in a certain day when elective surgeries are scheduled. Moreover, the mean of unpredictable beds in those months is 16 and the mean during the non-flu season (excluding those months) is 18.48. Table 3 contains an assessment of 110 days during the flu season and 206 days during the non-flu season.

Table 3. Mean, standard deviation and mode of beds occupied during 110 days during flu season and 206 days non-flu season, data got from EPIC

	Flu season	Non-flu season
Mean	19.41	18.48
Standard deviation	3.02	3.38
Mode	18	17

We use Montgomery et al. (2012) to find the distribution that fits better the mean, standard deviation and mode of the data set. We did not find any distribution that fits the demand for IC-beds of other patients during flu season or non-flu season; therefore, we will use the probability density function (PDF) to generate random samples in Chapter 7. In Figure 5 and Figure 6, there are histograms of the number of beds occupied and the cumulative distribution during flu season and non-flu season respectively. For example, Figure 5 shows that 14.5% (18 days of the total number of days assessed, 110 days) of the time we need 18 beds for patients that are included in the group of other patients during flu season.

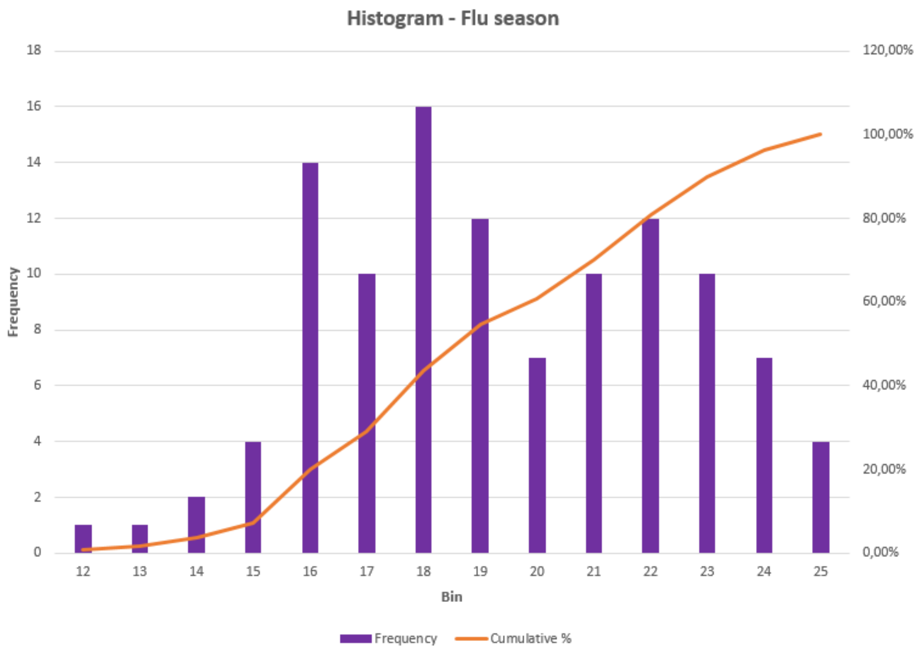


Figure 5. Histogram and cumulative distribution during flu season of number of beds occupied during 110 days for patients included in other patients group, data got from EPIC

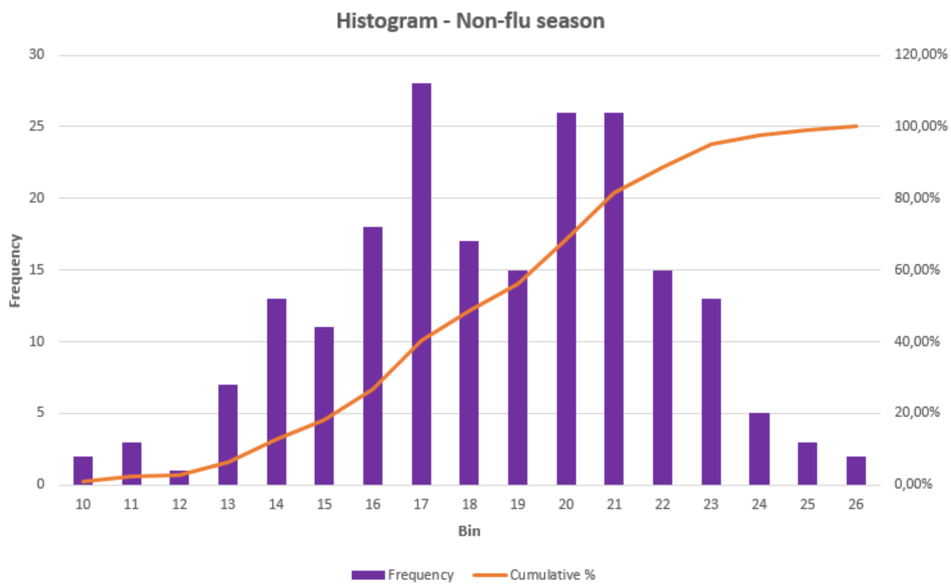


Figure 6. Histogram and cumulative distribution during non-flu season of number of beds occupied during 206 days for patients included in other patients group, data got from EPIC

4.6 Conclusions

In this chapter, we made a rough estimation of the LOS of the elective CTC-patients in the ICU and an estimation of the number of beds needed for the rest of the surgeries. First, we had to clean the data, we should improve the methodology of data collection to facilitate this process and have results that are more accurate in further researches. We use the results from the CTC-elective surgeries in the probabilistic model (Chapter 6). We use the number of beds needed for the group of *other patients* during the experiments (Chapter 7).We consider that in the future with more data the results from this chapter will be more accurate.

5 Algorithm for scheduling surgery types

In Chapter 5, we build a cyclical blueprint schedule considering the median LOS of the patients in the ICU according to their type of surgery. Section 5.1 gives an introduction to the approach used to design the cyclical blueprint schedule. Section 5.2 assesses the frequency of each surgery type, based on the data gathered and the planning horizon of the cycle. Section 5.3 combines surgery types that fit in one OR-block and calculates the frequency of each OR-block. Section 5.4 schedules the surgeries first using best-fit algorithm minimizing the demand for IC-beds. Section 5.5 contains the limitations of this approach and Section 5.6 describes the conclusions.

5.1 Overview of the approach

The algorithm aims to schedule each surgery type according to its frequency during a two weeks cycle. Our algorithm design is a three steps process. First, we assess the frequency of each surgery type in the cyclical blueprint schedule as Vanberkel et al. (2011b). In this step we estimate the population frequency with our sample frequency. That assumption results in the requirement to have a sufficient amount of observations. For surgery types with fewer observations we advise to gather more data to retrieve a more accurate frequency estimates. When this step is executes, we can use the frequency estimates for each surgery type as input for the next step.

In the second step, we use the frequency to combine surgery types that fit in an OR-day using best-fit algorithm, so we assign the surgery type to the OR-block that is filled the most. We use the surgery durations (Table 4) provided by the CTC-surgeons. Surgerytype_7 does not need an OR, so we do not consider this surgery type in the cyclical blueprint schedule. For this project, we assume that the waiting lists are inexhaustible, and therefore there will always be a patient scheduled in each time slot of the frequent surgeries. With this strategy we increase the utility of the OR that are being used on a day.

Finally, we assign a day to each OR-block minimizing the demand for beds using best-fit algorithm. In this step, we also consider the portfolio effect to reduce the variability of demand for IC-beds, so when we assign surgeries we consider the variability of the surgery types. For that, we use the median and the variability of the probability distribution of the LOS of the patient in the ICU.

Table 4. Length of surgeries in hours, data provided by CTC-surgeons

Surgery ID	Length of surgery (hours)
Surgerytype_1	3
Surgerytype_2	4
Surgerytype_3	5
Surgerytype_4	5
Surgerytype_5	7
Surgerytype_6	8
Surgerytype_8	4
Surgerytype_9	6
Surgerytype_10	6
Surgerytype_11	5
Surgerytype_12	5
Surgerytype_13	5
Surgerytype_14	8
Surgerytype_15	4

5.2 Frequency of the surgeries and length of cyclical blueprint schedule

To design the cyclical blueprint schedule we consider the frequent surgeries explained in Section 4.3.1. The algorithm will also include infrequent surgeries and lung surgeries that do not need intensive care, but they need space in the ORs. We split those surgeries in long and short depending on the average duration of the surgery. We assume that the short infrequent surgeries go to PACU and we will schedule de long surgeries on Fridays. We do not have enough data to predict the LOS of the long surgeries that are not frequent; therefore, we schedule those surgeries on Friday so the impact in bed variability is lower. The reason for that is that during the weekend there are no elective surgeries, so patients can recover during the weekend without affecting the capacity for IC-beds during weekdays.

We decided to design a fortnightly cycle because it can contains at least one of each of the frequent surgery type and because a repetitive schedule is more practical and therefore easier to implement. We calculate the frequency using the probability distribution of each surgery type in a fortnightly schedule as described by Vanberkel et al. (2011b). Then, we calculate the number of time slots of each surgery type that we need to schedule in our cycle, with the percentile that we want to meet (Table 5).

Table 5. Frequency of each surgery type during a fortnightly cycle considering different percentiles

Surgery ID	Frequency of the surgeries during a biweekly cycle			
	60th percentile	65th percentile	70th percentile	75th percentile
Surgerytype_1	9	9	9	10
Surgerytype_2	26	28	29	29
Surgerytype_3	5	5	5	6
Surgerytype_4	6	7	7	7
Surgerytype_5	2	2	3	3
Surgerytype_6	1	1	1	1
Surgerytype_8	1	1	1	1
Surgerytype_9	2	2	2	2
Surgerytype_10	1	1	1	1
Surgerytype_11	2	3	3	3
Surgerytype_12	1	1	1	2
Surgerytype_13	1	1	1	1
Surgerytype_14	1	1	1	1
Surgerytype_15	2	2	2	2
Short surgeries	3	3	3	4
Long surgeries	1	1	1	1

We decided to use the number of surgeries needed to meet P_{75} as a running example. During the experimentation (Chapter 7) we will assess the variation of using different percentiles.

5.3 Group surgeries in OR-blocks

We assign each surgery type to an OR-day using an algorithm named Best-fit. With this strategy, we assign the surgery type to the operating room that is filled the most. To do that, first, we sort the surgeries from longest to shortest surgery time. Then we go through each OR-block and we assign the first surgery in the list of surgeries types to schedule. The next step is to search for another surgery that could fill the OR the most.

After assigning all the surgery types, we have the OR-blocks (Table 6) of one or two surgeries. OR_Block_2 (each OR_Block_2, contains two Surgerytype_2) has a frequency of 13 per two weeks. We decided to use one OR for these OR-blocks, consequently we have to schedule three of these surgery blocks in another OR. With this decision, we reduce the variability for bed demand because every day we will expect at least one OR_Block_2.

Table 6. Frequency of surgery combination that is assessed with data of 4522 patients during the time period from 1st January 2018 until 30th June 2019, data got from EPIC

OR-Block ID	Combination of surgeries	Frequency
OR_Block_1	[3,1]	6
OR_Block_2	[2,2]	13
OR_Block_3	[4,1]	4
OR_Block_4	[4]	3
OR_Block_5	[5]	3
OR_Block_6	[6]	1
OR_Block_7	[2,8]	1
OR_Block_8	[9]	2
OR_Block_9	[10]	1
OR_Block_10	[11]	2
OR_Block_11	[12]	2
OR_Block_12	[13]	1
OR_Block_13	[14]	1
OR_Block_14	[2,15]	2
Short surgeries (low frequency)		4
Long surgeries (low frequency)		1

Most of the surgery's take more than four hours and a few surgeries take less than four hours to perform. Therefore, most of the time we schedule one surgery per OR-block, so we recommend to have different starting time of the surgeries, in order to have an OR available for a possible emergency surgery.

5.4 Schedule OR-blocks to reduce variability for bed demand

To reduce the variability for bed demand we used a Best-fit algorithm to schedule each OR-block in an OR and day. To do that we used the median LOS of the patients in the ICU and a variability factor (Table 7). The variability factor described how fuzzy the empirical distribution of the LOS of the patients with that pathology is. We decided the variability factor according to the maximum LOS within the 95% of the patients with the shortest LOS minus the median. The variability is proportional to the difference mentioned above (Table 8).

Table 7. Decision for variability factor

Variability	Max LOS 95% - Median
0	[0,4]
1	[5,10]
2	[11,20]
3	>20

We schedule the surgery types using Best-fit algorithm to fill each bed as much as possible but at the same time considering the portfolio effect with the variability of the OR-blocks. With this strategy, we assign the surgery types with the highest variability in the same bed.

Table 8. Median and variability of the OR-blocks of the LOS in the ICU that is assessed with data of 4522 patients during the period from 1st January 2018 until 30th June 2019, data got from EPIC

OR-Block ID	Median LOS in IC		Variability
	1st patient	2nd patient	
OR_Block_1	2	0	1
OR_Block_2	1	1	0
OR_Block_3	0	0	1
OR_Block_4	0		0
OR_Block_5	2		2
OR_Block_6	8		3
OR_Block_7	1	PACU+1	3
OR_Block_8	3		2
OR_Block_9	2		0
OR_Block_10	2		0
OR_Block_11	3		3
OR_Block_12	3		3
OR_Block_13	2		1
OR_Block_14	1	0	0

The result of this algorithm leads to the following distribution of beds (Table 9). Table 10 shows the number of IC-beds and PACU-beds needed for CTC-elective frequent surgeries when we use this approach. Table 11 shows the resulting cyclical blueprint schedule.

Table 9. Assignment of bed to each surgery type of patient

	Day 1	Day 2	Day 3	Day 4	Day 5	Saturday	Sunday	Day 6	Day 7	Day 8	Day 9	Day 10	Saturday	Sunday
Bed1	2	2	2	2	2			2	2	2	2	2		
Bed2	2	2	2	2	2			2	2	2	2	2		
Bed3	3	3	3	3	3	3		14	14	2	2	2		
Bed4	5	5	5	5	5	5		3	3	2		12	12	12
Bed5	13	13	13	2	8			9	9	9	9	9	9	
Bed6	6	6	6	6	6	6	6	6	12	12	12	3	3	
Bed7		11	11	11	11			2	2	3	3	11	11	
Bed8								2	2	10	10			
PACU1	1	4	4	4	4			1	4	4	15	15		
PACU2		1	1	8	1				1	1	4	1		
PACU3			1							1				

Table 10. Number of IC-beds and PACU beds needed each day using Best-fit algorithm

	IC beds	PACU beds
Day1	6	1
Day2	7	2
Day3	7	3
Day4	7	2
Day5	7	2
Saturday	3	0
Sunday	1	0
Day6	8	1
Day7	8	2
Day8	8	3
Day9	7	2
Day10	7	2
Saturday	4	0
Sunday	1	0

Table 11. Cyclical blueprint schedule after Best-fit algorithm

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]
OR2	[3,1]	[4,1]	[4,1]	[4]	[4]	[14]	[4,1]	[2,2]	[4]	[11]
OR3	[5]	[11]	[3,1]	[11]	[3,1]	[3,1]	[2,2]	[4,1]	[2,15]	[3,1]
OR4	[13]		[5]	[2,8]	[5]	[9]	[12]	[3,1]	[9]	[12]
OR5	[6]	Short surgery	Short surgery	Short surgery	Long surgery	[2,2]	Short surgery	[10]		[2,15]

5.5 Limitations

The cyclical blueprint schedule has the following limitations:

- We use the median LOS of the patients in the ICU and PACU, so we do not consider outliers in this approach. In the next chapter, we will use a probabilistic model that leads to a more realistic distribution of beds.
- We consider a fixed surgery durations. During the experiments, we assess the impact of variable surgery durations on the cyclical blueprint schedule.

5.6 Conclusions

In this chapter, we designed a cyclical blueprint schedule following a three-steps process: assessing the frequency of the surgery types, cluster surgery types in OR-block and assign a day to each OR-block.

We will improve the cyclical blueprint schedule built in this chapter in the next chapter using a probabilistic model and local search.

6 Probabilistic model to assess the demand for beds by CTC-elective patients

In this chapter, we build a probabilistic model that calculates on a given day the demand for beds in the coming days for frequent CTC-elective patients that are currently in the ICU. Section 6.1 introduces the approach to the probabilistic model to calculate the demand for IC-bed by CTC-elective patients. Section 6.2 describes the probabilistic model from Vanberkel et al. (2011b). Section 6.3 shows our local search procedure. Sections 6.4 and 6.5 contain the result and the conclusions, respectively.

6.1 Overview of the approach

Our model aims to calculate the probability distribution that Y beds are occupied, for a period of T days for frequent (i.e. >25 patients of this type of surgery per year) CTC-elective patients that are currently in the ICU. Our approach follows the probabilistic model of Vanberkel et al. (2011b). The next step is to minimize the variability for bed demand using local search.

6.2 Probabilistic model to calculate the number of beds needed

To design the probabilistic model we used the sets, parameters and variables that are in Table 12, Table 13 and Table 14, respectively. This is the same model as Vanberkel et al. (2011b).

Table 12. Sets of the probabilistic model

Sets	
$\|J\|$	Total number of surgery groups
$\|Q\|$	Length (number of days) of the MSS
$\|I\|$	Number of ORs for CTC-surgeries

Table 13. Parameters of the probabilistic model

Parameters	
j	Surgery group of the patient {1…|J|}
q	Day in the MSS {1…|Q|}
i	OR {1…|I|}
z	Surgeries assigned in day of MSS q and to operation room i
m	Day to be assessed considering the cycle {1,2,…,Q,Q+1,Q+2,…}
x	Patients from OR i and day of MSS q that are still (today) in the ICU
k	Patients from OR i and day of MSS q that are still in the ICU after n days from today, $k \leq x$
L^j	Maximum LOS for specialty j
C^j	Maximum number of surgeries for specialty j that fit in one block i,q

Table 14. Variables of the probabilistic model

Variables	
d_n^j	Probability that a patient of specialty j who is still in ICU on day n, is to be discharged that day
$P^j(\mathrm{n})$	Probability that the LOS of a patient from specialty j is exactly n days long
c^j	Number of surgeries done in one block i,q
h_n^j	Number of patients still in ICU of specialty j after n days of the procedure
$\bar{h}_m^{i,q}$	Number of recovering patients of block i,q on day m
H_m	Discrete distribution for the total number of recovering patients on day m resulting from a single MSS cycle

In Equation 4, we calculate the conditional probabilities that a patient of speciality *j* who is in the ICU *n* days after the surgery, is discharged on that day. In the next step (Step 1 in Vanberkel et al. (2011b)), we assess the probability (Equation 5) of recovering patients from speciality *j* from a single OR block (which means from a specific OR in a specific day) using the binomial distribution. Equation 6 and Equation 7 assess the aggregate distribution of recovering patients following from a single cycle (Step 2 in Vanberkel et al. (2011b)). The last step of this probabilistic model is the steady-state distribution (Equation 9) of recovering patients (Step 3 in Vanberkel et al. (2011b)). Equation 8 determines the number of cycles that we have to convolute. In our case the longest LOS including the tail is 69 (Surgery type 6), so we will have to convolute $\left\lceil\frac{69}{10}\right\rceil$= 7 cycles.

$$d_n^j = \frac{P^j(n)}{\sum_{k=n}^{L^j} P^j(n)} \ \forall j, n \tag{4}$$

$$\mathrm{P}\left(\mathrm{h}_\mathrm{n}^\mathrm{j} = \mathrm{x}\right) = \begin{cases} \mathrm{P}\left(\mathrm{c}^\mathrm{j} = \mathrm{x}\right), \text{when } \mathrm{n} = 0 \\ \sum_{\mathrm{k}=\mathrm{x}}^{\mathrm{c}^\mathrm{j}} \binom{\mathrm{k}}{\mathrm{x}} \left(d_{n-1}^j\right)^{\mathrm{k}-\mathrm{x}} \left(1 - d_{n-1}^j\right)^{\mathrm{x}} P\left(\mathrm{h}_{\mathrm{n}-1}^\mathrm{j} = \mathrm{k}\right), \text{otherwise} \end{cases} \ \forall \mathrm{j}, \mathrm{n} \tag{5}$$

$$\bar{h}_m^{i,q} = \begin{cases} h_{m-q}^z, \ if \ q \le m < L^z + q \\ 0, otherwise \end{cases} \tag{6}$$

$$\mathrm{H_m} = \bar{\mathrm{h}}_\mathrm{m}^{1,1} * \bar{\mathrm{h}}_\mathrm{m}^{1,2} * \ldots * \bar{\mathrm{h}}_\mathrm{m}^{1,\mathrm{Q}} * \bar{\mathrm{h}}_\mathrm{m}^{2,1} * \ldots * \bar{\mathrm{h}}_\mathrm{m}^{\mathrm{I},\mathrm{Q}} \tag{7}$$

$$\mathrm{M} = \max_j \{L^j + x^j\} \ \forall j \tag{8}$$

$$H_q^{SS} = H_q * H_{q+Q} * H_{q+2Q} * \ldots * H_{q+\lceil M/Q \rceil * Q} \tag{9}$$

For more explanation, we refer to the model of Vanberkel et al. (2011b). Our objective is to reduce the variability of demand for IC-beds by scheduling the CTC-elective surgeries considering the LOS in the ICU. During weekends, there are no CTC-elective surgeries. Therefore, in our model, we do not calculate the steady-state distribution or the aggregate distribution of recovering patients during the weekends to reduce computational time.

6.3 Local search

To improve the current solution, we use data visualisation to assist our local search. The first step is to plot the results of the probabilistic model from the cyclical blueprint schedule built in Chapter 5 (Figure 7). During Mondays and the first Tuesday of this figure (days 1, 2 and 6) the demand for beds is less than the rest of the week. That is because during the weekend we discharge patients, from the ICU, but there are no elective surgeries planned, therefore, the inflow of this type of patients is zero.

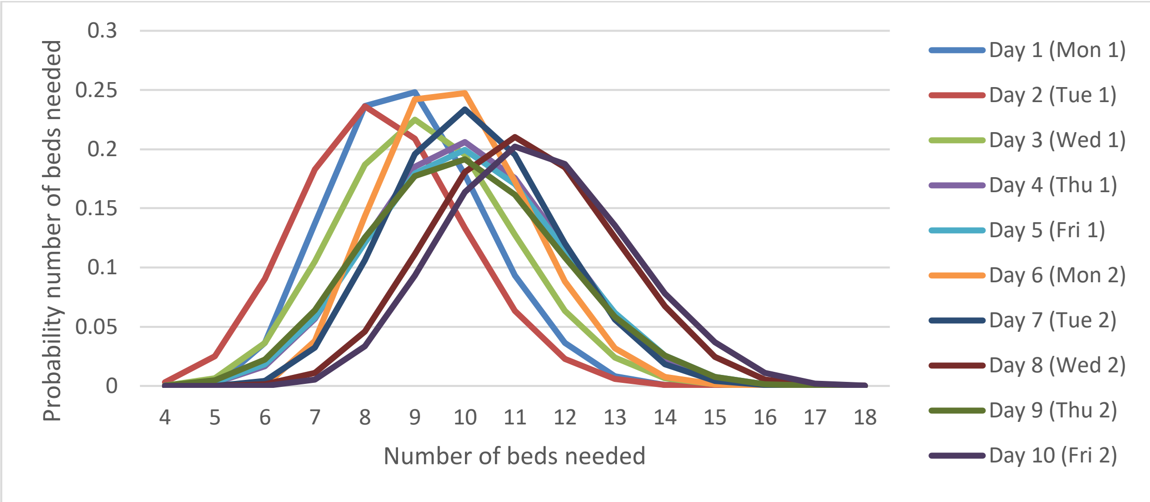


Figure 7. Probability distribution for number of beds needed in each day of the cyclical blueprint schedule

We also calculate the number of beds needed each day of the cycle with P_{80}, P_{85} and P_{90} (Figure 8).

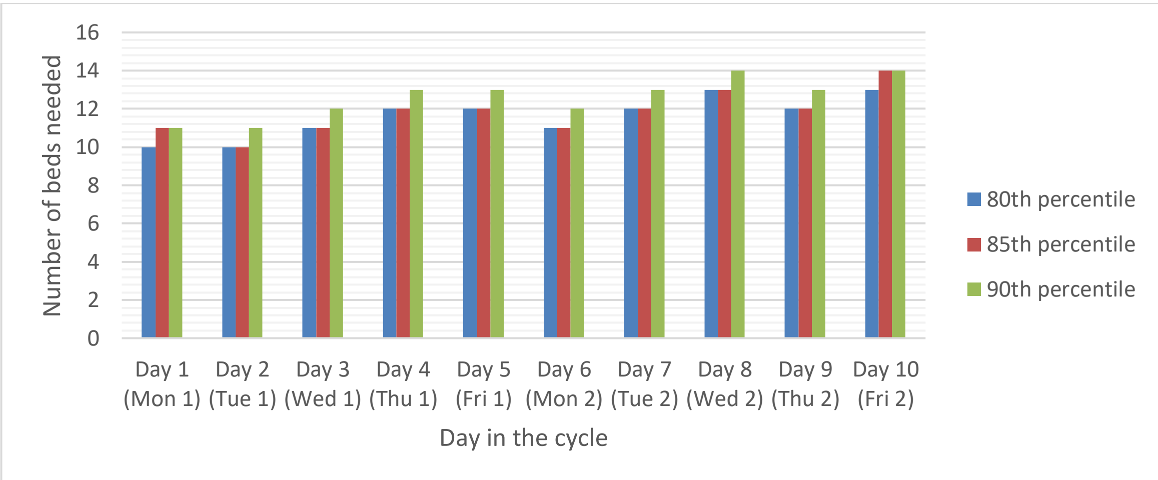


Figure 8. Number of beds needed each day of the cycle

After analysing the figure, we determine which OR-blocks, we should switch, to create a homogenous probability distribution of demand for beds in the ICU for every day of the cycle.

The criteria that we use to switch two OR-blocks is to schedule the surgery types with long LOS and high variability of LOS at the end of the week. Thereafter, we compensate the number of surgery blocks filled each day by scheduling the surgery blocks with patients that normally only need to go to PACU. We explain the reasoning for switching each pair of surgery blocks and the results after each step in Annex C.

6.4 Results

Table 15 shows the resulting cyclical blueprint schedule of the probabilistic model and the local search. Figure 9 contains the probability distribution of beds each day of the cycle. To determine the variability of demand we plot Figure 10, where we can see the number of beds needed each day according to the percentile we want to meet. Considering P_{85} the variability of demand for IC-beds in Figure 10 comparing it to the result before local search (Figure 8) there is a reduction of variability of 2 IC-beds. We decided to schedule the long surgery (an elective surgery with low frequency in the group of CTC-surgeries) on Day 10, to compensate the uncertainty of the LOS of this patient we decided to reduce the demand distribution for IC-beds in this day. Our objective is to reduce the variability of the demand for IC-beds and in Table 16 we show the variability for bed demand after each step in the local search. The last row from Table 16 is the variability from the blueprint schedule in Table 15.

Table 15. Cyclical blueprint surgery type's schedule after the probabilistic model and the local search

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]
OR2	[3,1]	[3,1]	[4,1]	[4]	[4]	[14]	[4,1]	[10]	[4]	[13]
OR3	[2,2]	[11]	[3,1]	[11]	[3,1]	[3,1]	[2,2]	[4,1]	[2,15]	[4,1]
OR4	[11]	[5]	[5]	[2,8]	[5]	[9]	[12]	[3,1]	[9]	[12]
OR5	[6]	Short surgeries	Short surgeries			[2,2]	Short surgeries	[2,15]	Short surgeries	Long surgery

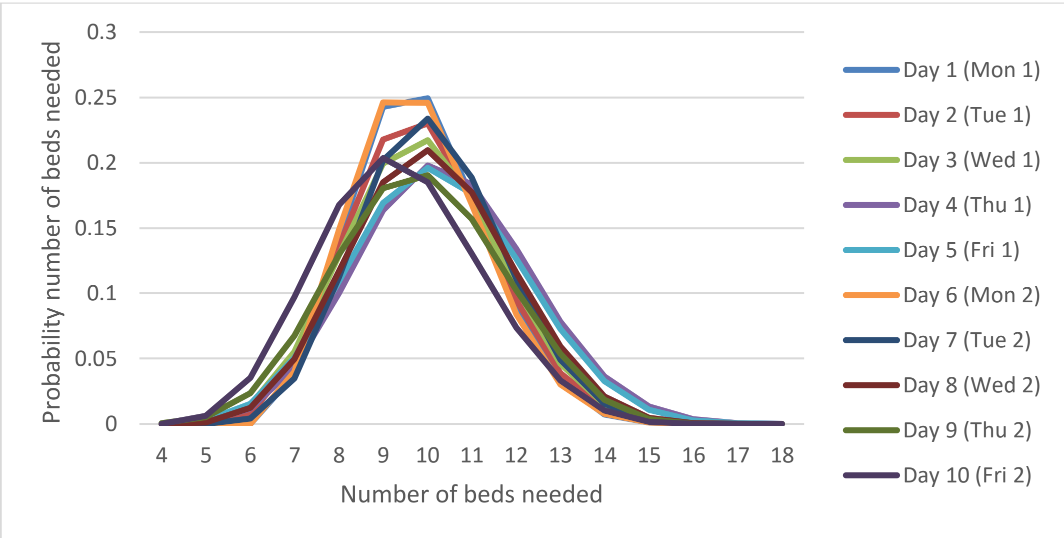


Figure 9. Probability distribution of the demand for IC-beds depending on the day of the cycle

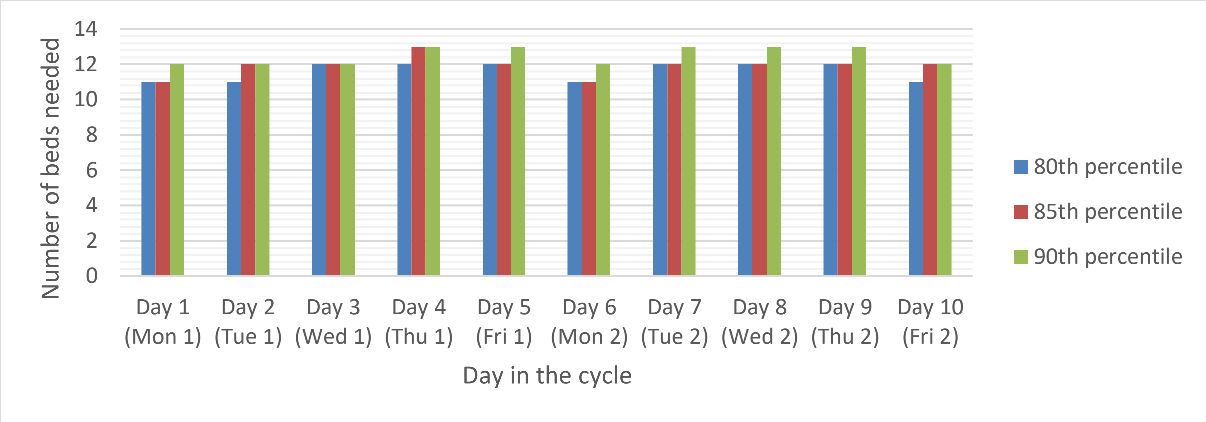


Figure 10. Demand of beds needed each day of the cycle with different percentiles

Table 16. Range of IC-beds that we need to cover the demand during the different days in the cycle blueprint schedule, during each step of the local search and the difference between the maximum and the minimum values in the range

Step in local search	Percentile	Value	Range
Local search 0	80th	3	[10,13]
	85th	4	[10,14]
	90th	3	[11,14]
Local search 1	80th	3	[10,13]
	85th	3	[11,14]
	90th	3	[11,14]
Local search 2	80th	3	[10,13]
	85th	3	[11,14]
	90th	3	[11,14]
Local search 3	80th	3	[10,13]
	85th	3	[11,14]
	90th	3	[11,14]
Local search 4	80th	2	[10,12]
	85th	2	[11,13]
	90th	2	[11,13]
Local search 5	80th	1	[11,12]
	85th	2	[11,13]
	90th	1	[12,13]

Following a discussion with the doctors, we decided to consider the 85th percentile (P_{85}) of the demand for beds for each day during the cycle. We made a trade-off between having a large number of beds empty thus being more certain that all patients will have a bed and facing an increased risk of cancellations yet having higher bed utilization in the ICU. High occupation for IC-beds means that more patients are treated in our hospital when the number of beds stays the same.

The running time of the algorithm of Chapter 5 and the model of Chapter 6 to obtain the probabilistic model for the number of beds needed in each day during the cyclical blueprint schedule is 3 minutes.

6.5 Conclusions

With the probabilistic model, we predict the number of beds needed for CTC-elective patients that are in the ICU after a period of T days. After a local search using data visualisation, we decide that the cyclical blueprint schedule of the surgeries is good enough to test during the experimentation. During the local search, we prove that when we schedule surgeries with long LOS at the end of the week, we reduce the demand for IC-beds during the week and it is easier to reduce the variability of demand for IC-beds.

7 Experiment design

In this chapter, we test the robustness of the model with different experiments, modifying several variables. Section 7.1 introduces our sensitivity analysis. Section 7.3 describes the different variables we choose to modify and the reason for choosing those. Section 7.4 explains the results of the experiments. Section 7.5 enumerates the limitations of the experimental design. Section 7.6 describes the conclusions we get from this chapter.

7.1 Introduction

To test the robustness of our model we decided to do a sensitivity analysis using Monte Carlo simulation. A simulation will also help us to see the impact of each variable during the cycle. We can simulate a realistic scenario by adding emergency CTC-surgeries and the category of other patients to the simulation.

We decided that each experiment consists of 1000 replications and each replication lasts 280 days (20 cycles). Each replication uses different random seeds, but for each experiment, we use the same sequence of random seeds.

We simulated the baseline scenario shown in Chapters 5 and 6 to assess whether or not to include emergency patients in the experimentation. In 13.19% of the replications during there is one emergency CTC-surgery during working hours and in 1.64% of the replications there are two emergency CTC-surgeries. Therefore, we decided to include emergency CTC-surgeries in our experiments.

7.2 Modelling of emergency CTC-surgeries

In this section, we explain how we represent the arrival of emergency CTC-patients that need surgery in our simulation. Figure 11 shows the histogram of the number of emergency CTC-surgeries that are in one cycle. We assess the empirical distribution of the number of emergency CTC-surgeries per cycle to generate random emergency CTC-surgeries. We do not consider seasonality, because the emergency surgery distribution is consistent during the year.

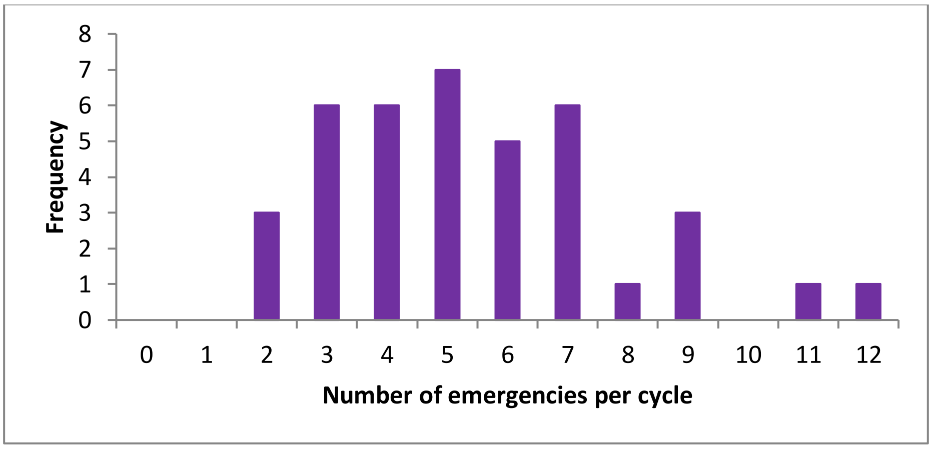


Figure 11. Histogram of number of emergency CTC-surgeries per cycle (14 days), combining data from EPIC and a file provided by CTC-department

Each emergency arrival is independent so once we have the number of emergency CTC-surgeries we set the arrival rate following a Poisson distribution (with lambda equals to the number of surgeries taking place in that cycle divided by the length of the cycle, which is 14 days). In this step, we determine the number of emergency surgeries that will arrive in our simulation during the day we are assessing.

The arrival time of an emergency patient at the hospital on that day follows a uniform distribution, that is, an emergency does not depend on the time of the day. We assume that the emergency CTC-surgery starts as soon as the patient arrives at the hospital and has a diagnosis. Emergency surgeries will affect our scheduled surgeries in case they arrive during working hours (that is when elective surgeries are planned). We assume that the duration of emergency surgeries follows a normal distribution with a mean of 5.5 hours and a standard deviation of 2 hours.

In case we have an emergency during working hours, we calculate the number of free hours available at the ORs for that day. We assign emergency surgeries to the first available OR. Consequently, if other surgeries were planned in that OR, we will have to reassign them to another operation room. We consider there will be a cancellation if the number of free hours in the OR with the most available time is less than 5 hours (90% of the mean duration of one emergency surgery).

7.3 Experimental variables

During the experiments, we assess the impact of the experimental variables on the variability of the required number of beds. In this section, we describe these variables and explain their relevance to our study.

Combining the number of planned surgeries (according to the chosen percentile) with the choice of clustering certain surgery types or not, we assess the best cyclical blueprint schedule for each scenario, using the steps explained in Chapters 5 and 6. We show the resulting cyclical blueprint schedules in Annex D. The simulation running time when clustering certain surgery types is 2 minutes and 15 seconds.

In Table 17, we describe the list of experiments with the experimental variables that we explain in the following subsections. We run each experiment with the data from other patients during flu season and non-flu season (as we described in Section 4.5.2, we have different probability distributions for patients considering the flu seasonality).

Table 17. Description of the variables for each experiment

Experiment	Surgery time	Nr of surgeries planned	Capacity in CTC-wards	Clustering surgery types
Experiment 1	Fixed	74 (75th percentile)	Finite	No
Experiment 2	Fixed	65 (75th percentile)	Finite	Yes
Experiment 3	Fixed	74 (75th percentile)	Infinite	No
Experiment 4	Fixed	65 (75th percentile)	Infinite	Yes
Experiment 5	Variable	74 (75th percentile)	Finite	No
Experiment 6	Variable	65 (75th percentile)	Finite	Yes
Experiment 7	Variable	74 (75th percentile)	Infinite	No
Experiment 8	Variable	65 (75th percentile)	Infinite	Yes
Experiment 9	Fixed	70 (70th percentile)	Finite	No
Experiment 10	Fixed	62 (70th percentile)	Finite	Yes
Experiment 11	Fixed	70 (70th percentile)	Infinite	No
Experiment 12	Fixed	62 (70th percentile)	Infinite	Yes
Experiment 13	Variable	70 (70th percentile)	Finite	No
Experiment 14	Variable	62 (70th percentile)	Finite	Yes
Experiment 15	Variable	70 (70th percentile)	Infinite	No
Experiment 16	Variable	62 (70th percentile)	Infinite	Yes
Experiment 17	Fixed	68 (65th percentile)	Finite	No
Experiment 18	Fixed	61 (65th percentile)	Finite	Yes
Experiment 19	Fixed	68 (65th percentile)	Infinite	No
Experiment 20	Fixed	61 (65th percentile)	Infinite	Yes
Experiment 21	Variable	68 (65th percentile)	Finite	No
Experiment 22	Variable	61 (65th percentile)	Finite	Yes
Experiment 23	Variable	68 (65th percentile)	Infinite	No
Experiment 24	Variable	61 (65th percentile)	Infinite	Yes
Experiment 25	Fixed	64 (60th percentile)	Finite	No
Experiment 26	Fixed	57 (60th percentile)	Finite	Yes
Experiment 27	Fixed	64 (60th percentile)	Infinite	No
Experiment 28	Fixed	57 (60th percentile)	Infinite	Yes
Experiment 29	Variable	64 (60th percentile)	Finite	No
Experiment 30	Variable	57 (60th percentile)	Finite	Yes
Experiment 31	Variable	64 (60th percentile)	Infinite	No
Experiment 32	Variable	57 (60th percentile)	Infinite	Yes

7.3.1 Fixed vs. variable surgery time

We assess the difference between the number of cancellations and the number of beds needed (in our simulation). In case we use surgery duration mentioned in Table 4 and using the mean and the standard deviation of each surgery type (Table 18).

Table 18. Mean and standard deviation of the length of each surgery type, data from all the surgeries during 2019 provided by OK-IC Centrum department

Surgery ID	Length of surgery (hours)	
	Mean	Standard deviation
Surgerytype_1	3.00	0.25
Surgerytype_2	3.60	0.40
Surgerytype_3	4.43	0.52
Surgerytype_4	3.37	0.88
Surgerytype_5	5.25	1.25
Surgerytype_6	7.08	0.92
Surgerytype_8	2.65	1.35
Surgerytype_9	6.02	0.37
Surgerytype_10	4.83	1.17
Surgerytype_11	4.03	0.68
Surgerytype_12	4.42	0.58
Surgerytype_13	5.30	0.3
Surgerytype_14	5.93	1.98
Surgerytype_15	3.43	0.43

7.3.2 Clustering surgery types

We test the performance of our model when we cluster surgery types with the same fixed length of surgery (Table 4) and similar LOS in the ICU (Table 2). If we can schedule several surgery types in the same time slot, the OR-planner would have more flexibility assigning patients to OR-blocks. We decided to cluster surgery types 3 and 11, surgery types 5 and 14 and surgery types 12 and 13. We show the combination of cluster ID and surgery ID in Table 19.

Table 19. Description of the surgery types that are in each surgery cluster-ID

Cluster ID	Surgery ID	
SurgeryCluster_A	Surgerytype_1	
SurgeryCluster_B	Surgerytype_2	
SurgeryCluster_C	Surgerytype_3	Surgerytype_11
SurgeryCluster_D	Surgerytype_4	
SurgeryCluster_E	Surgerytype_5	Surgerytype_14
SurgeryCluster_F	Surgerytype_6	
SurgeryCluster_G	Surgerytype_8	
SurgeryCluster_H	Surgerytype_9	
SurgeryCluster_I	Surgerytype_10	
SurgeryCluster_J	Surgerytype_12	Surgerytype_13
SurgeryCluster_K	Surgerytype_15	

Table 20 shows the resulting probability distribution of the LOS of the patients in the ICU according to their Surgery Cluster ID. Table 21 shows the mean and the standard deviation of the duration of the surgery, according to its Surgery Cluster ID. Table 22 shows the number of times that we have to schedule each Surgery Cluster ID, according to the percentile of surgeries planned in the schedule we want to include. In Table 22 we also show the number of elective surgeries with low frequency (we group them in short surgeries and long surgeries). We will use this data to determine the cyclical blueprint schedule and afterwards we use the chosen cyclical blueprint schedule during the simulation.

Table 20. Probability distribution of the LOS of the patients in the ICU according to their Surgery cluster of 2116 patients from the 1st January 2018 to the 30th June 2019, data retrieved from EPIC

Cluster ID	1	2	3	4	5	6	7	8	9	10	11	12	13	15	16	18	20	22	23	24	28	34	36	44
SurgeryCluster_A	80%	10%	3%	2%																				
SurgeryCluster_B	86%	6%	3%																					
SurgeryCluster_C	39%	25%	13%	10%	5%	1%	2%																	
SurgeryCluster_D	60%	13%	11%	4%	3%	2%	1%		1%															
SurgeryCluster_E	22%	38%	15%	4%	7%	7%	2%																	
SurgeryCluster_F	5%	3%	5%	8%	5%	5%	16%	3%		3%			3%	3%	11%	3%	5%	3%	3%	3%		3%	3%	2%
SurgeryCluster_G	39%	19%	16%	9%				6%				3%								3%				
SurgeryCluster_H	2%	38%	16%	14%	11%	4%	1%	1%	1%		1%	1%	1%	1%	3%									
SurgeryCluster_I	24%	6%	16%																					
SurgeryCluster_J	27%	25%	12%	14%	2%	3%	3%	2%		1%						1%		3%		1%	1%			
SurgeryCluster_K	95%																							

Table 21. Mean and standard deviation of the length of each cluster of surgery types, data from all the surgeries during 2019 provided by OK-IC Centrum department

Cluster ID	Length of surgery (hours)	
	Mean	Standard deviation
SurgeryCluster_A	3.00	0.25
SurgeryCluster_B	3.60	0.40
SurgeryCluster_C	4.23	0.63
SurgeryCluster_D	3.37	0.88
SurgeryCluster_E	5.75	1.85
SurgeryCluster_F	7.08	0.92
SurgeryCluster_G	2.65	1.35
SurgeryCluster_H	6.02	0.37
SurgeryCluster_I	4.83	1.17
SurgeryCluster_J	4.77	0.65
SurgeryCluster_K	3.43	0.43

Table 22. Frequency of each surgery cluster during a fortnightly cycle with different percentiles

Cluster ID	Frequency of the surgeries during a biweekly cycle			
	60th percentile	65th percentile	70th percentile	75th percentile
SurgeryCluster_A	9	9	9	10
SurgeryCluster_B	26	28	29	29
SurgeryCluster_C	3	4	4	4
SurgeryCluster_D	6	7	7	7
SurgeryCluster_E	1	1	1	2
SurgeryCluster_F	1	1	1	1
SurgeryCluster_G	1	1	1	1
SurgeryCluster_H	2	2	2	2
SurgeryCluster_I	1	1	1	1
SurgeryCluster_J	1	1	1	1
SurgeryCluster_K	2	2	2	2
Short surgeries	3	3	3	4
Long surgeries	1	1	1	1

7.3.3 Capacity in the CTC-wards

To visualise the impact of the flow of patients in the ICU in case we have infinite capacity in general wards. Our focus is on the flow of patients from the CTC-department; therefore, we simulate what would happen with infinite capacity in the CTC-wards. Nurses gathered the number of patients that we could not move to general wards because those were full. We assess the empirical distribution of the number of CTC-patients per day from 14th of May 2018 until 22nd of October 2019. We do not consider seasonality, because the situation is similar all over the year. In our experiments, we generate a random number of patients that should leave the ICU, following an empirical distribution with the data provided.

7.3.4 Number of surgeries planned

Table 5 shows all the different surgeries that we should plan to meet the percentile we choose. Table 22 shows the same information plus the clustering of certain surgery types. During the experiments, we test P_{75}, P_{70}, P_{65} and P_{60}. The setup of these experiments are in Table 5 and Table 22.

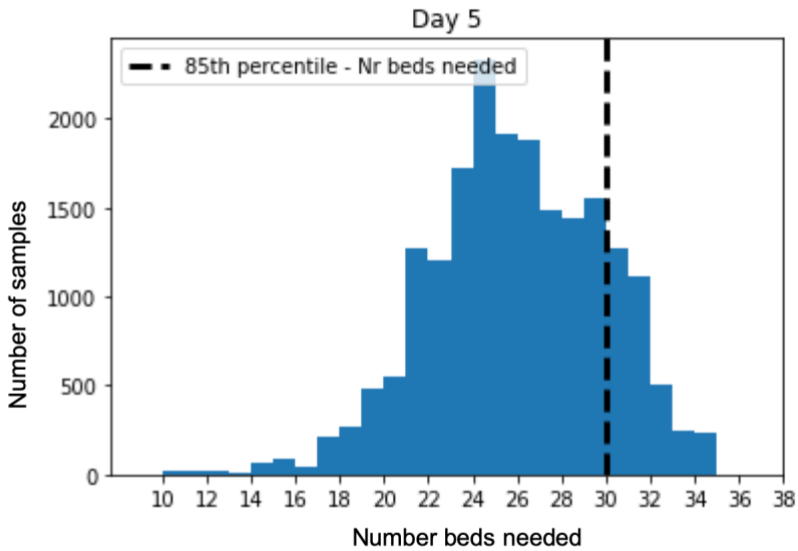
7.3.5 Implementation of other patients considering flu seasonality

The number of beds needed for other patients (which are the patients that are not frequent CTC-elective surgeries) is variable depending on the flu season. Consequently, each experiment is tested during the flu season and the non-flu season, using the probability distribution in Figure 5 and the probability distribution in Figure 6 respectively.

7.4 Results

In this section, we discuss the results of the different experiments and we assess the impact of modifying the variable settings. We calculate the number of beds needed every day, using a histogram, we need to cover the demand for IC-beds with P_{85}. For example, Figure 12 shows the histogram of the demand for beds after all the replications of Experiment 28 during flu season and on the first Friday of the cycle (Day 5). The dashed black vertical line is the number of beds needed to cover the demand for IC-beds with P_{85}, in this case, are 30 beds.

Figure 12. Example histogram of Experiment 28 during flu season on the first Friday of the cycle



Aside from the number of beds needed, we also calculate the number of cancellations per day. For example, in case of an emergency surgery occupying one OR, there is a cancellation if we cannot reschedule the planned surgery, or surgeries, in another OR. With this strategy, only Experiment 1 and Experiment 9 during the flu season (74 surgeries planned, finite space and without clustering some surgery types) require one cancellation if we want to cover the P_{90} (this value is zero for lower percentiles).

In the following subsections, we compare the experimental results of the number of beds needed to do not reject any patient with P_{85}. We will assess the impact of the different variables during flu season and then, separately, see the differences in the demand for IC-beds during flu season and non-flu season.

7.4.1 Fixed vs. variable surgery time

Table 23 shows on the left all the experiments with fixed surgery duration and on the right all experiments with variable surgery time. For example, Experiment 1 and Experiment 5 (both first row experiments in each table) have the same settings except the surgery time that in one case is variable and in the other is fixed. With this comparison, we can see the impact of the variable in the simulation. All experiments have barely any variation from using fixed and variable surgery times, which is likely due to slack in remaining available OR-time in the fixed surgery time planning.

Table 23. Comparison experiment results using fixed vs. variable surgery time
(this 8 means that during 8 days of the 10 working days cycle we need 35 beds)*

Experiment	Nr of beds needed FIXED surgery time							
	29	30	31	32	33	34	35	36
Experiment 1							8 *	2
Experiment 2				3	7			
Experiment 3				1	8	1		
Experiment 4		3	7					
Experiment 9						4	6	
Experiment 10				5	5			
Experiment 11				5	5			
Experiment 12		6	4					
Experiment 17						9	1	
Experiment 18				6	4			
Experiment 19			1	8	1			
Experiment 20		8	2					
Experiment 25					2	8		
Experiment 26			1	8	1			
Experiment 27		1	9					
Experiment 28	2	8						

Experiment	Nr of beds needed VARIABLE surgery time							
	29	30	31	32	33	34	35	36
Experiment 5						1	8	1
Experiment 6				3	7			
Experiment 7				1	8	1		
Experiment 8		3	7					
Experiment 13						5	5	
Experiment 14				5	5			
Experiment 15				5	5			
Experiment 16		7	3					
Experiment 21						9	1	
Experiment 22				6	4			
Experiment 23			2	7	1			
Experiment 24		8	2					
Experiment 29					2	8		
Experiment 30			2	8				
Experiment 31			3	7				
Experiment 32	2	8						

We decided to take the mean of the number of beds needed in each experiment to see the tendency of the demand for IC-beds. Figure 13 shows the number of beds needed according to each experiment. The experiments that we compare, have the same experimental variables except for the surgery duration (the orange line shows variable duration and the purple line fixed surgery duration). In Figure 13, we also added the minimum and the maximum number of beds that are open in the ICU.

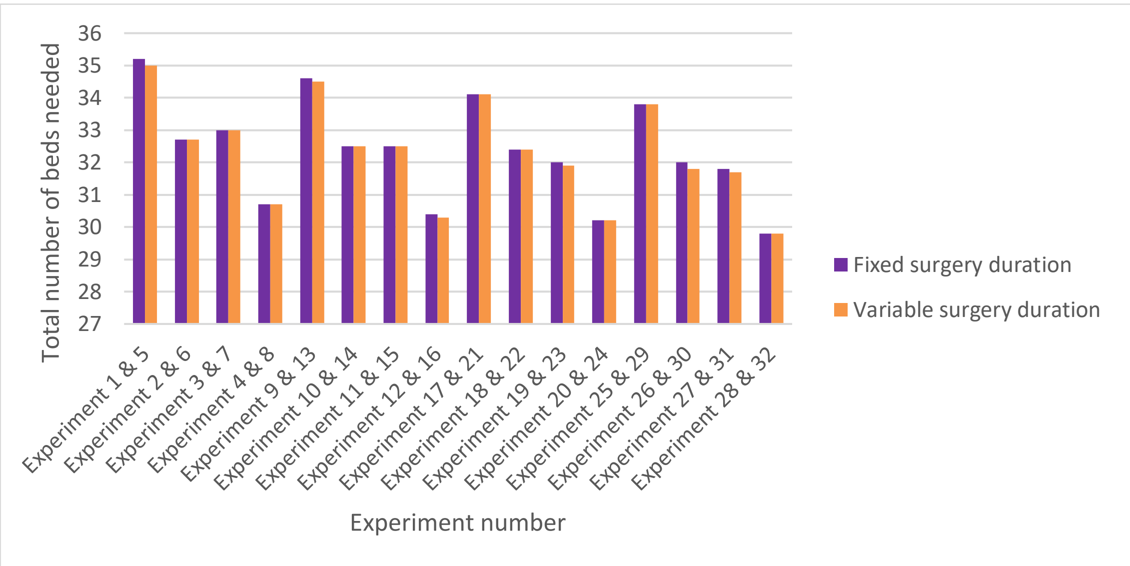


Figure 13. Total number of beds needed comparing experiments with fixed and variable surgery durations

7.4.2 Clustering surgery types

Figure 14 shows the comparison between the required number of beds *with* clustering certain surgery types and *without* clustering them. As before, the difference between the experiments with the orange and the purple line is only the variable that we are assessing. We decided to delete the experiments with variable surgery duration because as we have shown in Subsection 7.4.1 there is almost no difference between fixed and variable surgery duration. In Figure 14 we see that the difference between clustering and not clustering is around two beds. The meandering shape in both cases is due to the difference in the number of beds needed with finite and infinite capacity in the CTC-wards.

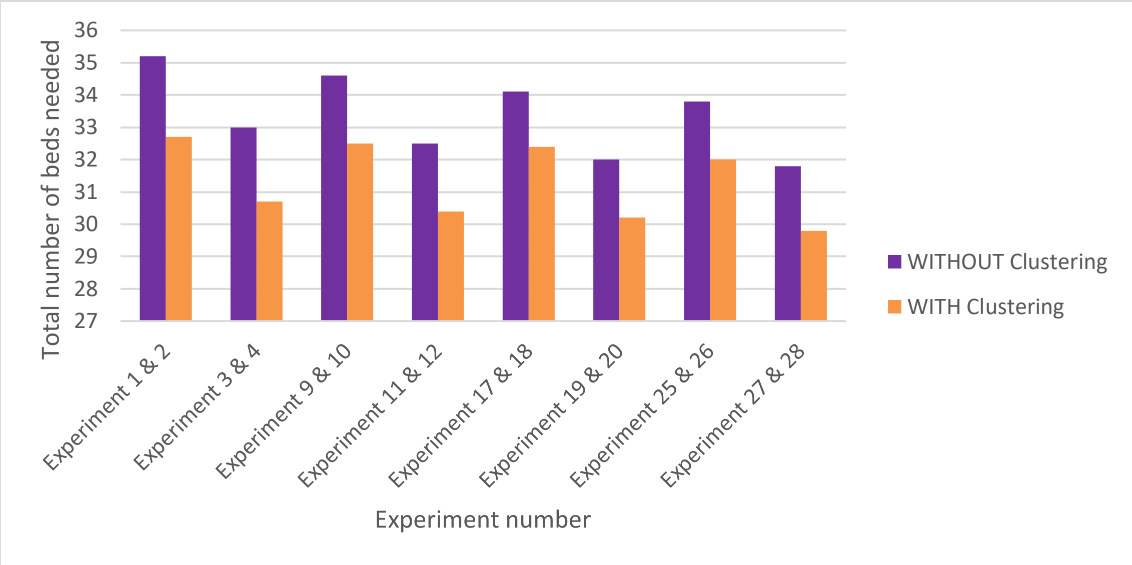


Figure 14. Total number of beds needed comparing experiments with clustering surgeries and without clustering surgeries

7.4.3 Capacity in the CTC-wards

Figure 15 visualises the difference between having an *infinite* or *finite* capacity in the CTC-wards. As before, we do not include the experiments with variable surgery duration because as we prove in Subsection 7.4.1 there is almost no difference between fixed and variable surgery duration. Comparing the experiments with the same experimental variables except for the one we are assessing there is a difference of approximately two beds. In this case, the meandering shape in both scenarios is due to the difference in the number of beds needed *with* clustering surgeries or *without* clustering surgeries.

There are clear similarities between Figure 14 and Figure 15 because the mean number of beds needed per day in the cycle changes on the decimal. In both cases, there is a difference of approximately two beds when we modify the variable we are assessing.

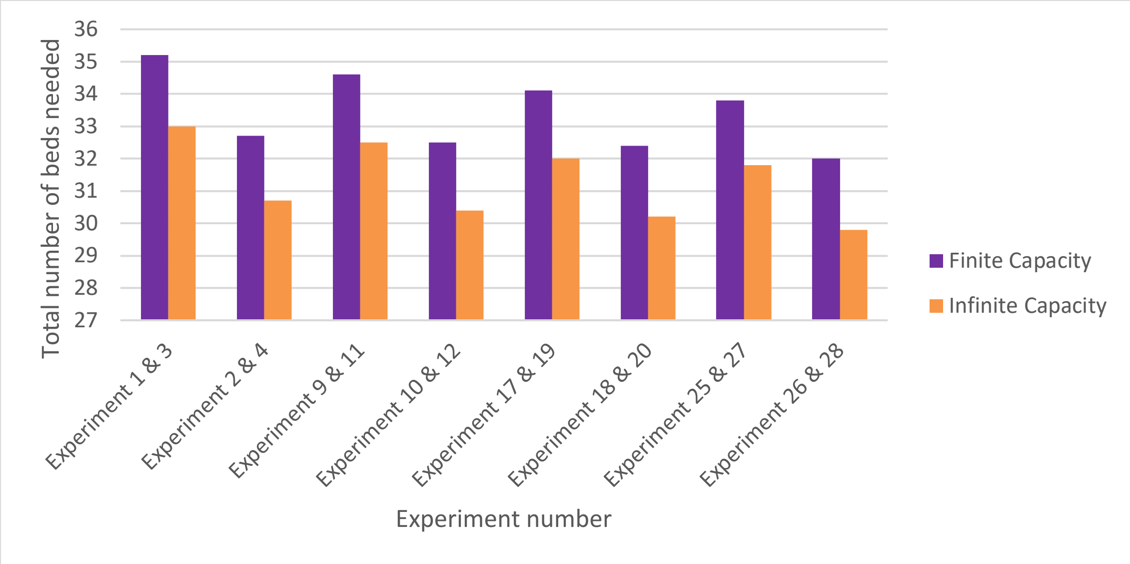


Figure 15. Total number of beds needed comparing experiments with finite and infinite capacity in the CTC-wards

7.4.4 Number of surgeries planned

Figure 16 and Figure 17 show the demand for IC-beds according to the number of CTC-elective surgeries planned per cycle. In these graphs, we rounded to the closest, the mean number of beds needed because beds are (positive) integers (you need the bed, or you do not). Normally, we schedule around 63 surgeries per cycle, which means that the difference between clustering or not is of two bed. As we see in both figures, the difference is up to two beds and the demand for IC-beds increases after the 70th percentile of the surgeries planned. The other cases where the demand for IC-beds increases is due to the proportional increase of surgeries planned.

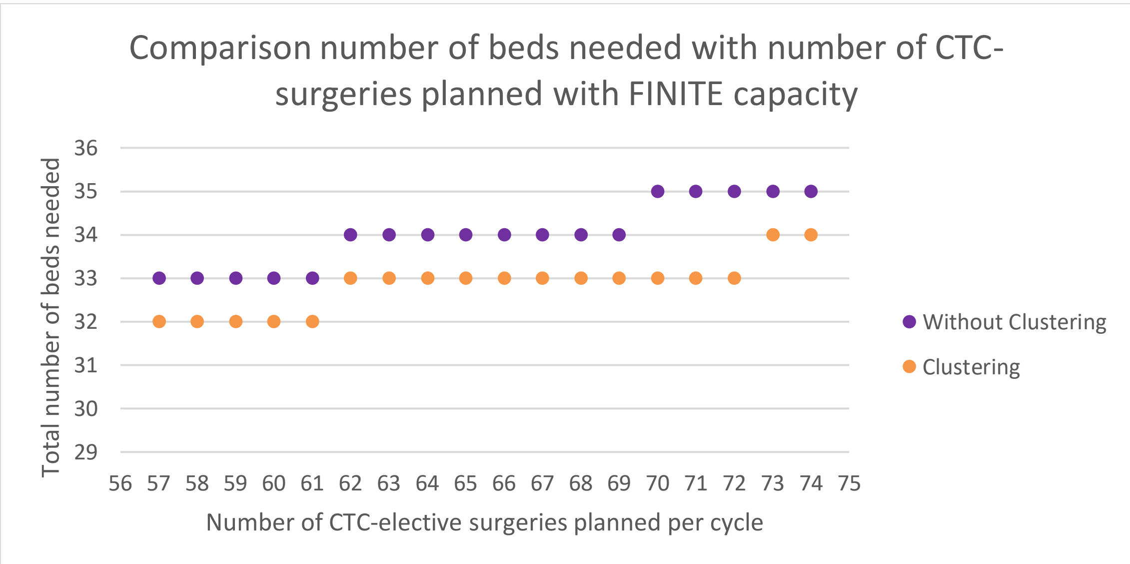


Figure 16. Number of beds needed according to the number of surgeries planned considering finite capacity in CTC-wards

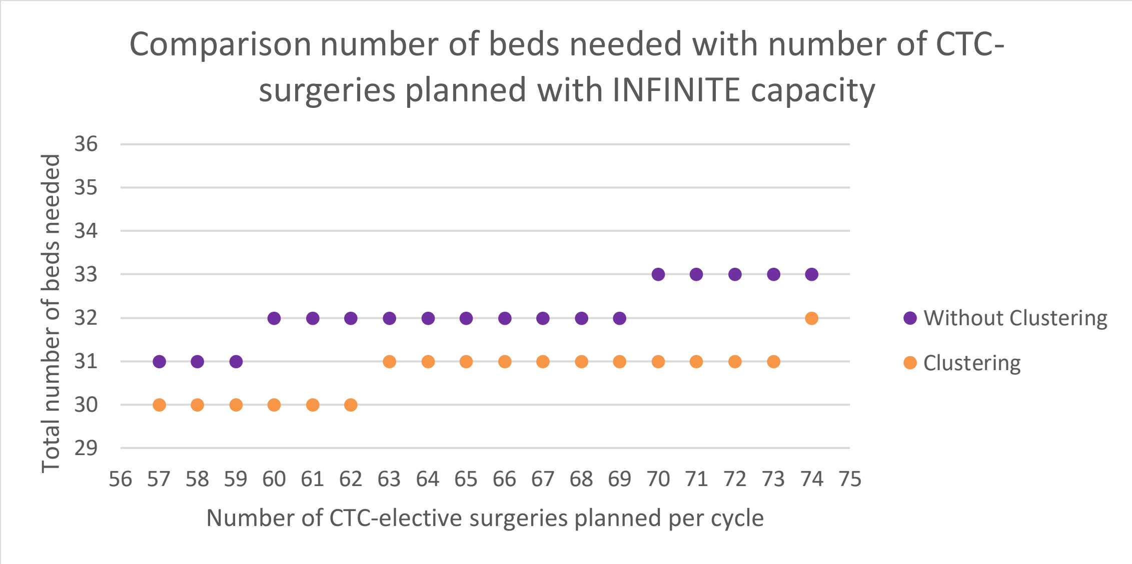


Figure 17. Number of beds needed according to the number of surgeries planned considering infinite capacity in CTC-wards

7.4.5 Implementation of other patients considering flu seasonality

Figure 18 shows the difference between the beds needed for each experiment depending on the flu season. About one bed less is needed during the non-flu season than during flu season.

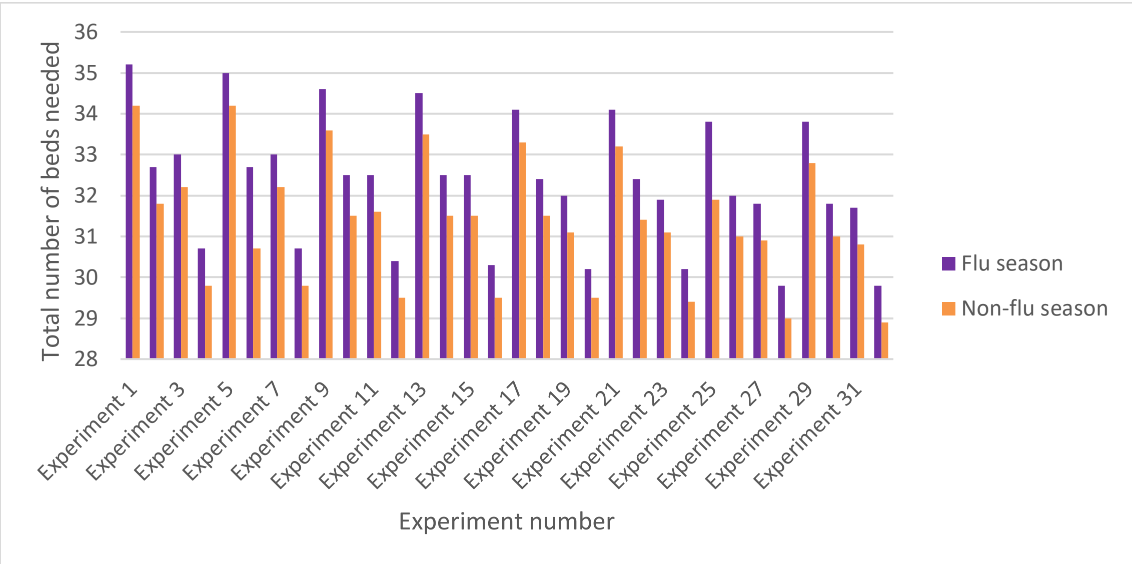


Figure 18. Total number of beds needed comparing experiments during flu season and non-flu season

7.5 Limitations

The following limitations influence the reality of the flow of patients in the ICU compared to our simulation:

- There are decisions that the staff takes daily which might change according to the demand for IC-beds.
- We do not consider the surgeries that we cancelled because the patient got sick or did not show up.

- We do not consider the fluctuations of open beds, especially during flu season because the staff is sick or other variable capacity restriction. However, we consider that the number of beds needed for the category of other patients is larger during the flu season.

7.6 Conclusions

In conclusion, the surgery time does not affect the simulation because most of the surgeries are long, so we schedule one surgery per OR-block. Consequently, the variability of this surgery does not influence the simulation. The running time of 3 minutes and 15 seconds, using variable surgery time is longer than without using it (2 minutes and 15 seconds). Therefore, we advise that for further research we should consider fixed surgery times for CTC-elective surgeries. The following variables have a clear impact on the demand for IC-beds:

- Clustering surgery types. When we cluster similar surgery types, we need fewer beds because some of the surgery types need one OR-block each to meet the percentile of the number of surgeries scheduled. However, when we cluster them, we need one OR-block for the clustering group. The advantage of clustering surgeries is that different types of patients can be scheduled in the OR-block and therefore the chances of having a patient that fits the surgery type is higher.
- Capacity in CTC-wards. When we assume that the CTC-wards have infinite capacity, we need approximately one bed less in the ICU. The managers should consider this finding because an IC-bed is more expensive than a bed in CTC-wards.
- The number of surgeries planned. Depending on the percentile of the distribution of the number of surgeries we want to meet, the number of surgeries that we plan is different. This has a direct impact on the number of cancellations of CTC-elective surgeries, for example, if we want to meet P_{75} of surgeries planned without clustering the surgery types and with finite capacity in CTC-wards; there are chances of having a cancellation if we consider having a bed for P_{90} of the patients.
- Flu season. During flu season, we expect in general one more bed to be occupied than during the non-flu season. We should be aware of this when we plan surgeries. However, we plan CTC-elective surgeries a short time in advanced because they are patients of high risk, so they cannot wait for months to have surgery.

8 Conclusion and recommendations

The chapter of conclusions and recommendations contains three sections. Section 8.1 explains the conclusions of the project. Section 8.2 describes the recommendations after the study. Section 8.3 explains the steps to implement the cyclical blueprint schedule. Section 8.4 contains further research options.

8.1 Conclusion

The first step was to determine the root causes of the perceived problem of variability of demand for IC-beds. We spent some days with the nurse coordinators from the ICU, doctors and the OR-planners from the CTC-department and the person responsible for planning the surgeries from the rest of the departments. After this, we determined that we could reduce the variability for bed demand in the ICU if we control the CTC-elective surgery schedule.

To schedule the surgeries considering the LOS of the patients in the ICU and thereby control the demand for beds, we need to first clean the data to be able to forecast the LOS. We decided to include outliers using an open-ended distribution.

To design our cyclical blueprint schedule we construct an initial solution using a constructive approach (best-fit algorithm bed scheduling using the median of the LOS of the patients in the ICU) and then improve the solution with local search (switching surgeries using data visualisation tools). We use a statistical convolution approach to calculate the number of beds needed for CTC-elective surgery patients based on the blueprint schedule.

We used Monte Carlo simulation to create scenarios using different experimental variables. The simulation also evaluates the robustness of the blueprint schedule by including the patients that are planned with the blueprint schedule, the emergency surgeries and the remaining patients that need intensive care (during flu season or non-flu season).

We recommend the CTC OR-planner to implement the blueprint schedule because the current mean number of beds needed for CTC-elective surgeries during a cycle is 9.5 and a standard deviation of 1.9 beds. With our blueprint schedule, the mean number of beds needed is 8.8 and the standard deviation is 0.4.

The results of this project are useful to five groups of people within the hospital:

- The managers have an incentive to start research to control the flow of patients in the CTC-wards after seeing the consequences of a bottleneck in the CTC-wards.
- The OR-planners perceive the effect of considering the postoperative care of the patients when we schedule the surgeries we can reduce the variability of demand for beds. Our cyclical blueprint schedule will help the CTC OR-planner to schedule the surgeries considering the LOS of the patients.
- The doctors spot the idea of using data analysis to improve healthcare processes and are therefore motivated to put more effort into data collection. The cleaner and clearer the data, the easier it will be to improve the process.

- The nurse coordinator who assigns a bed to each patient will know in advance how many beds for each type of patient are needed and can reduce the stress of cancelling surgeries or pushing the patients to the general wards because the ICU is full.
- The patients' satisfaction will increase because the blueprint schedule will reduce the cancellations and the patients will have a better experience within the hospital.

The scientific impact of this project is the process to get the cyclical blueprint schedule. We can follow the same steps as we did in this project (see Section 8.3 for more details) to reduce the variability of demand for beds in departments where at most two surgeries per OR-day are scheduled. We recommend implementing it in departments in which surgeries are long because the reason of not having high number of cancellations due to variability in surgery duration in the experiments is because we can plan at most two surgeries per OR-block. However, we cannot prove that the methodology used in this thesis is effective when many surgeries are scheduled in an OR-block.

Moreover, we proved the impact of a good clustering of surgery types. We conclude that we can cluster two surgery types when they have similar LOS distribution and similar surgery duration.

8.2 Recommendations

We divide the recommendations into two groups: recommendations regarding the scheduling system and recommendations to improve data gathering.

8.2.1 Recommendations regarding the scheduling system

We recommend the CTC OR-planner to use a cyclical blueprint schedule to reduce the fluctuations for the demand of IC-beds. This tool will help the CTC OR-planner to assign patients that need frequent surgery types (we schedule these surgeries more than 25 times per year) to an OR-block.

In the cyclical blueprint schedule, we dedicate one OR to surgeries type-2. With this decision, we reduce the variability of demand for IC-beds. Moreover, the surgeons and the OR-planner knows that every working day there is at least one OR dedicated to surgeries type-2.

In February 2020, the CTC-wards are working in full capacity because they have enough nurses to keep all the beds open. We saw that during this period, the flow of patients is more fluent and we need fewer IC-beds to cover the demand. Therefore, we will give two pieces of advice to the management board and they can choose according to their future decision, based on whether the CTC-wards will continue working with full capacity or they will close some beds.

On one hand, if the situation is as before February 2020, we recommend using the cyclical blueprint schedule in Table 35. The cyclical blueprint schedule clusters certain surgery types and schedules 61 surgeries per cycle (P_{65} of the distribution of the surgeries planned). This situation will correspond to experiment 18 where we need between eight and nine beds for CTC-elective surgeries and the remaining beds, where the total number of IC-beds needed has a mean of 34.5 and standard deviation of 0.5 during the flu season. During the non-flu season, the total number of IC-beds that we need to meet the P_{85} according to the simulation has a mean of 33.5 and a standard deviation of 0.5 IC-beds.

On the other hand, if the CTC-wards work with full capacity, we could schedule 65 surgeries per cycle (P_{75} of the distribution of the surgeries planned). Table 32 corresponds to the cycle blueprint schedule in this situation and therefore, we cluster certain surgery types. This situation will be similar to experiment 4 because it is similar to having an infinite capacity in CTC-wards. In this case, we would need between nine and ten beds per day for CTC-elective surgeries, and the mean and the standard deviation of the number of IC-beds needed during flu season is 30.7 and 0.5, respectively. During non-flu season, the total number of IC-beds that we need to meet the P_{85} according to the simulation has a mean of 29.8 and a standard deviation of 0.4.

8.2.2 Recommendations to improve data gathering

Three main points help to improve data gathering and have a more accurate prediction of the flow of patients through the hospital:

- Standardise the surgery codes. When a surgeon has to select the surgery of the patient, there should be a list where he/she can select the surgery. If the surgery is not on the list, the surgeon should write it by hand but then someone from the software department should add it to the list. With this strategy, we would avoid typos and it will facilitate the cleaning data process.
- Facilitate the input of the surgery duration. The software should have a tool to determine when one surgery starts and finishes automatically without human interaction (for example when the patient enters the OR starts and when he/she exits, the surgery is finished). The software should at least be able to reject negative surgery durations.
- Adding a checkbox that the doctors should select when a patient had complications during admission into the department. Therefore, we will be able to predict the probability of complications and forecast a more accurate length of stay.

8.3 Implementation plan

We can generalise the implementation plan because we can follow these steps to reduce the variability of bed demand in any department of any hospital:

1. Assess the problem and determine whether a cyclical blueprint schedule will reduce the variability of demand for bed in the department we are evaluating. Focus the scope of the project.
2. Data gathering and data cleaning.
3. Determine which surgery types will be included in the cyclical blueprint schedule. Assess the probability distribution and the seasonality of the LOS of the patients according to the type of surgery.
4. Assess the probability distribution and the seasonality of the number of beds that we need for patients who are not included in step 3.
5. Determine the length of the cycle. Assess the probability distribution of the elective surgeries (the ones we consider in step 3) scheduled in a cycle.

6. We assess which surgery types can be scheduled in the same OR-block (same day and OR) according to the surgery duration.
7. Determine the cyclical blueprint schedule using the median of the LOS of the patients and the variability of the LOS. We allocate a patient to a bed using Best-Fit algorithm, during the number of days determined by the median and we determine the day of the surgery.
8. We apply the probabilistic model of Vanberkel et al. (2011b).
9. We use data visualisation as a local search. Therefore, we plot the outcome of the cyclical blueprint schedule and we assess which surgeries should we switch to reduce the variability of bed demand. We recommend to schedule surgeries with long LOS at the end of the week (normally these types of surgeries have also high variable LOS).
10. Make a simulation to test different possible scenarios, modifying the experimental variables. Test the robustness of the cyclical blueprint schedule by adding the patients admitted in the department but are not included in the cyclical blueprint schedule.

Once we think that our cyclical blueprint schedule is good enough we show all the parts involved the advantages of using logistics in the scheduling of surgeries. In our case, this would be personnel from the CTC-department (especially the OR-planner of the CTC-department) and the personnel from the ICU.

11. Assess the future changes in the involving departments. In our case, evaluate the number of opened beds in ICU and CTC-wards. This will have a direct impact on the number of surgeries we recommend to schedule.
12. Schedule the preoperative screening on time to have a patient that fits the characteristics and we can assign him/her to the OR-block that we are assessing.
13. Inform the doctors that at the beginning of implementing the cyclical blueprint schedule there will be elective patients from the department we are assessing that were not schedule following the cyclical blueprint schedule. Therefore, we recommend during the number of cycles we used to calculate the aggregate distribution in step 7 has more capacity than the recommended.

We proved that the implementation plan is good when the surgery types, included in the cyclical blueprint schedule, have a long surgery duration. Therefore, we recommend implementing this plan in departments where at most two surgeries are scheduled in one OR-day.

In particular, in this project, we want to show the employees the improvements of using the cyclical blueprint schedule, therefore we want to show Figure 19 and Figure 20 where we can see the current situation during a random cycle (we selected the CTC-elective surgeries from the 25th of November 2019 to the 6th of December 2019). We compare these figures, with the ones of the selected cyclical blueprint schedule to see the improvements.

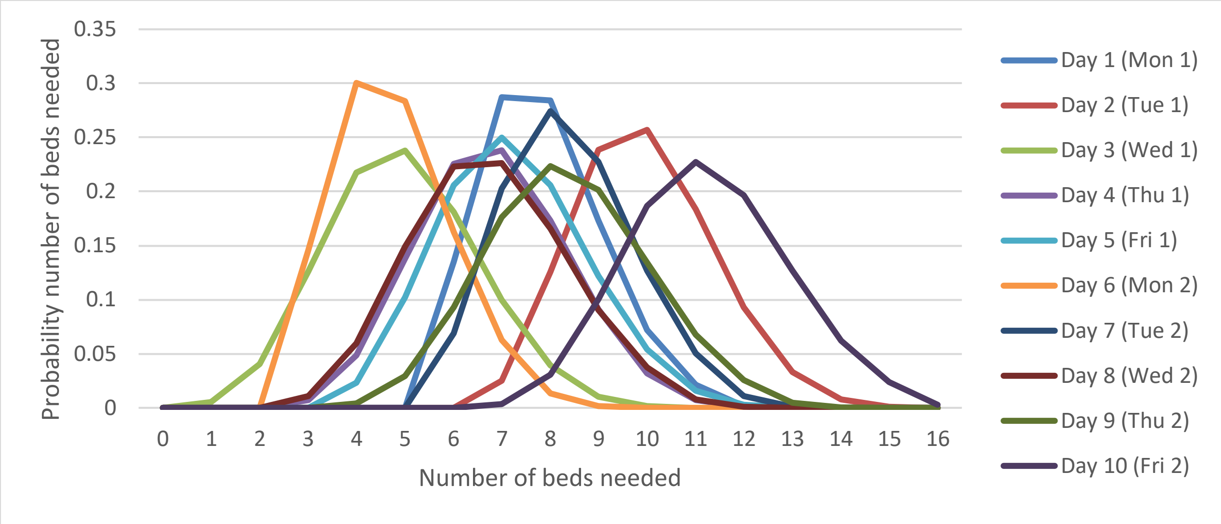


Figure 19. Probability distribution for number of beds needed on each day from 25th November 2019 to the 6th December 2019

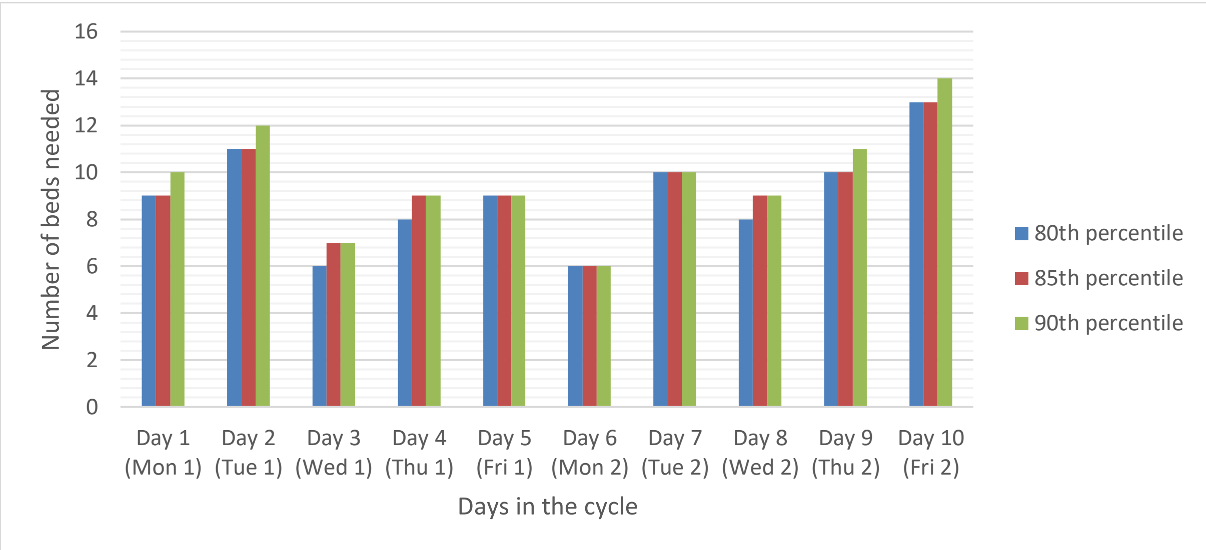


Figure 20. Number of beds needed each day of the cycle from 25th November 2019 to the 6th December 2019

8.4 Further Research

In this section, we suggest the following ideas for further research:

- Study the flow of patients through the CTC-wards. During the experimental research, we prove that without the bottleneck in the CTC-wards we could reduce the demand for IC-beds by around two beds per day.
- Study the flow of patients through the *verzorgingstehuis* (nursing houses). Sometimes CTC-patients that could leave the hospital and go to nursing houses (because they are not healthy enough to go home) have to stay longer in the CTC-wards because the nursing houses are full.

- Study the flow of patients through the *hartkatheterisatiekamer* that is not an OR but we do certain surgeries in that room. We should analyse the patients that are going from this room to CTC-wards or the ICU.
- Study the flow of patients through different wards in the hospital. We should make an independent assessment for each ward because departments are working independently.
- Study the flow of patients of elective surgeries from the rest of the departments (excluding the CTC-department) that need postoperative treatment in intensive care. However, most of the time those patients can go to PACU. Nowadays, they are controlling this because the hospital uses the same OR-planning department for all the departments except the CTC-surgeries and they have a policy with the ICU that a specific number of patients that need postoperative intensive care can be scheduled per day.
- The ICU has two types of beds: intensive care (IC) if they need heart and lung support and medium care (MC) if they only need one of the two. We could make a more accurate prediction of the bed demand if we could differentiate between them.
- In this project, we include the patients who passed away in the LOS of the patients according to the surgery type. In the future, we could assess these mortality rates and include them in our model (and exclude them from the distribution of the LOS of the patient in the ICU according to the surgery type).

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Annex C

In this annex, we explain the steps and the reasoning we made to decide which OR-blocks we switch.

Before the local search, we have the results shown in Figure 7 and Figure 8. These graphs show that the number of beds needed the second day of the cycle is lower, compared to the rest (because there are only three operating rooms filled). Therefore, we decided to move the OR-block with the OR-block [2, 2] from Day 8 to Day 2. Table 25 shows the resulting cyclical schedule after switching two surgeries.

Table 25. Cyclical blueprint surgery type's schedule after first time of moving one OR-block

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]
OR2	[3,1]	[4,1]	[4,1]	[4]	[4]	[14]	[4,1]	[10]	[4]	[11]
OR3	[5]	[11]	[3,1]	[11]	[3,1]	[3,1]	[2,2]	[4,1]	[2,15]	[3,1]
OR4	[13]	[2,2]	[5]	[2,8]	[5]	[9]	[12]	[3,1]	[9]	[12]
OR5	[6]	Short surgery	Short surgery		Long Surgery	[2,2]	Short Surgery	Short surgery		[2,15]

Figure 21 and Figure 22 show the results from moving the OR-block mentioned above. After this modification, the number of surgeries scheduled in Day 2 and Day 8 are more similar and therefore the probability distribution of demand for IC-beds for this two days are more aligned with the rest of the days in the cycle.

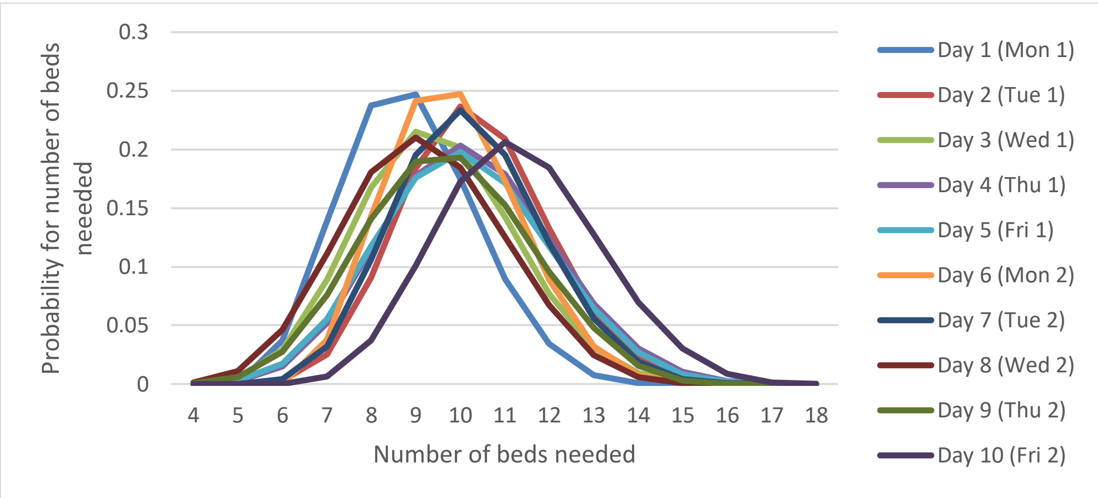

Figure 21. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (after first time of moving one OR-block)

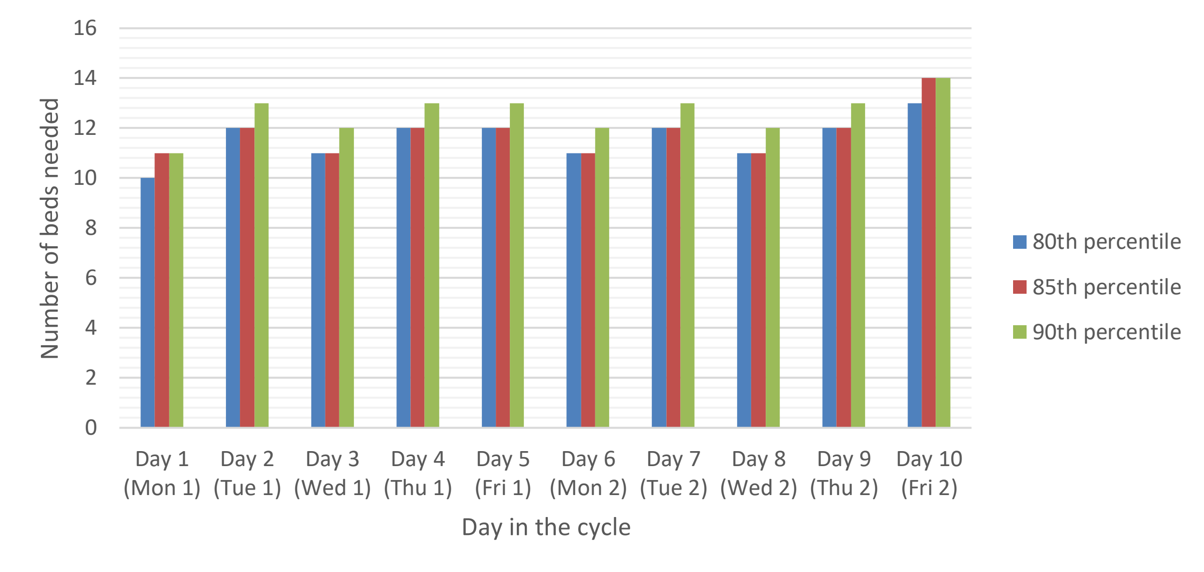

Figure 22. Number of beds needed every day in the cyclical blueprint schedule (after first time of moving one OR-block)

The next decision was to switch two OR-blocks to move the OR-block with high variability to a Friday and therefore control the variability. We decided to move OR-block with surgery type 13 that has high variability and long LOS in the ICU in to a Friday, to take advantage that during the weekend there are no elective surgeries. Our decision is switch the OR-block with surgery_type_13 in Day 1 with OR-block with surgerytype_11 in Day 10. Table 26 shows the cyclical blueprint surgery type's schedule after the second modification.

Table 26. Cyclical blueprint surgery type's schedule after second time of switching two OR-blocks

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]
OR2	[3,1]	[4,1]	[4,1]	[4]	[4]	[14]	[4,1]	[10]	[4]	[13]
OR3	[5]	[11]	[3,1]	[11]	[3,1]	[3,1]	[2,2]	[4,1]	[2,15]	[3,1]
OR4	[11]	[2,2]	[5]	[2,8]	[5]	[9]	[12]	[3,1]	[9]	[12]
OR5	[6]	Short surgery	Short surgery		Long surgery	[2,2]	Short surgery	Short surgery		[2,15]

Figure 23 and Figure 24 show the results after the probabilistic model using the cycle shown in Table 26. This change does not modify much, but we think that keeping the surgeries with high variability in Friday will have a high impact when we decide to switch two other OR-blocks.

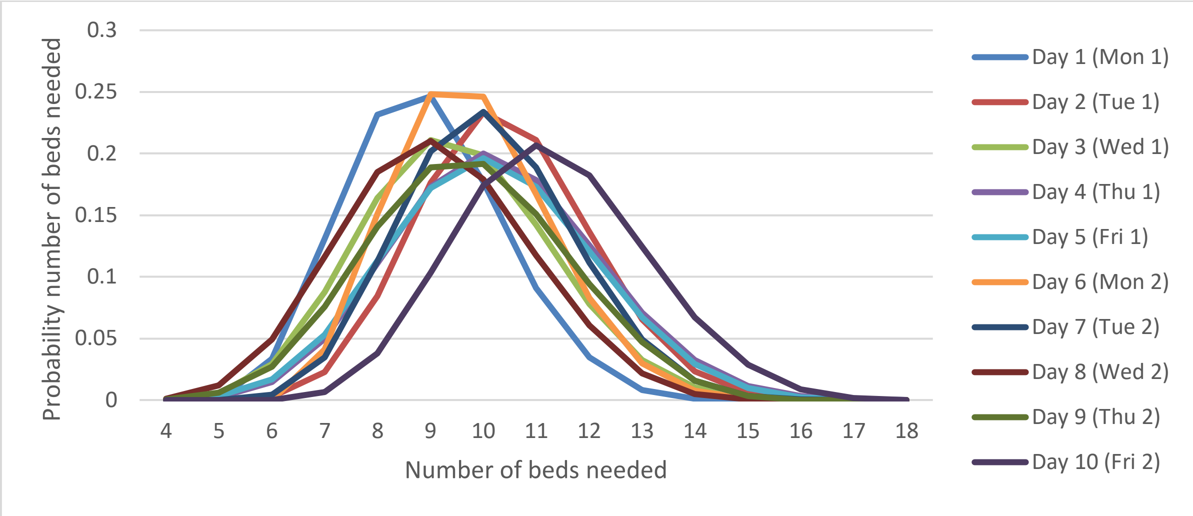

Figure 23. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (after switching two-time two OR-blocks)

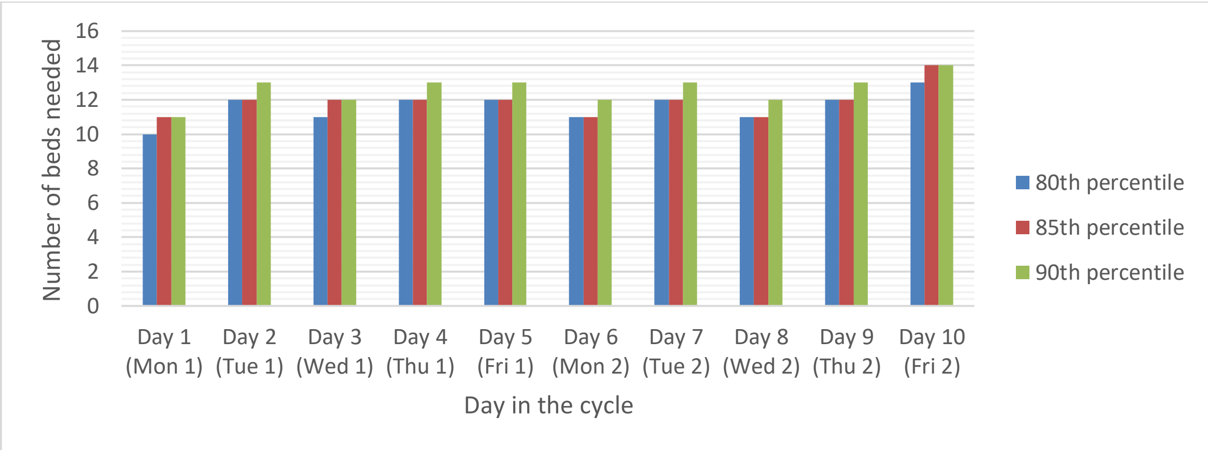

Figure 24. Number of beds needed every day in the cyclical blueprint schedule (after switching two-time two OR-blocks)

The next step is to increase the number of beds needed in Day 1 and consequently reduce it in another day. To do that we switched OR-block [5] from Day 1 with OR-block [2, 2] from Day 2. Table 27 shows the cyclical blueprint surgery type's schedule after switching those surgery blocks.

Table 27. Cyclical blueprint surgery type's schedule after third time of switching OR-blocks

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]
OR2	[3,1]	[4,1]	[4,1]	[4]	[4]	[14]	[4,1]	[10]	[4]	[13]
OR3	[2,2]	[11]	[3,1]	[11]	[3,1]	[3,1]	[2,2]	[4,1]	[2,15]	[3,1]
OR4	[11]	[5]	[5]	[2,8]	[5]	[9]	[12]	[3,1]	[9]	[12]
OR5	[6]	Short surgery	Short surgery		Long surgery	[2,2]	Short surgery	Short surgery		[2,15]

Figure 25 and Figure 26 show the results of the probabilistic model using the blueprint schedule shown in Table 27. The demand for beds on Day 1 has increased and it is more similar to the demand of the other days from the cycle. We keep this modification because if we compare the probability distributions between the different days is more similar than before.

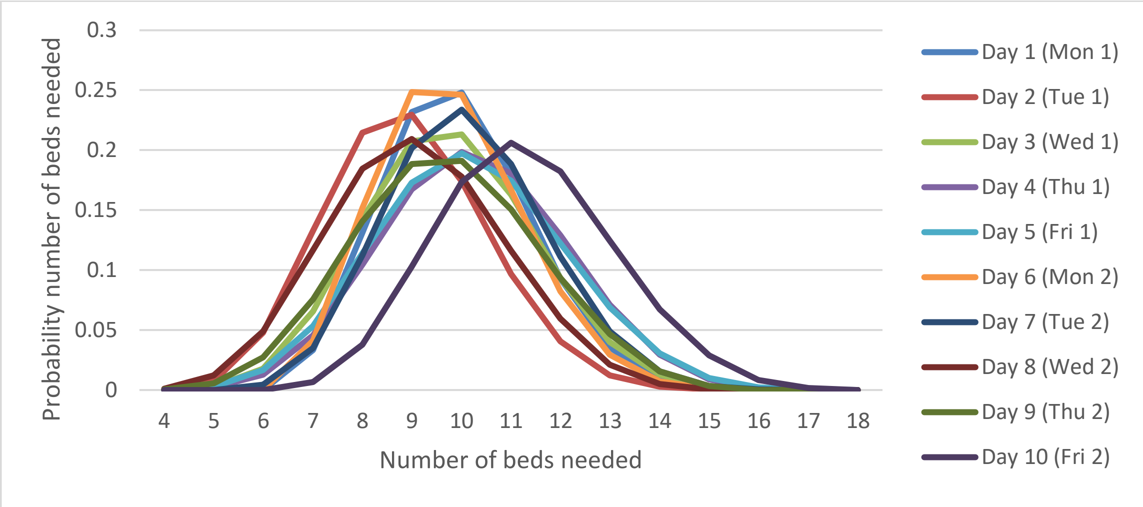

Figure 25. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (after switching three-time two OR-blocks)

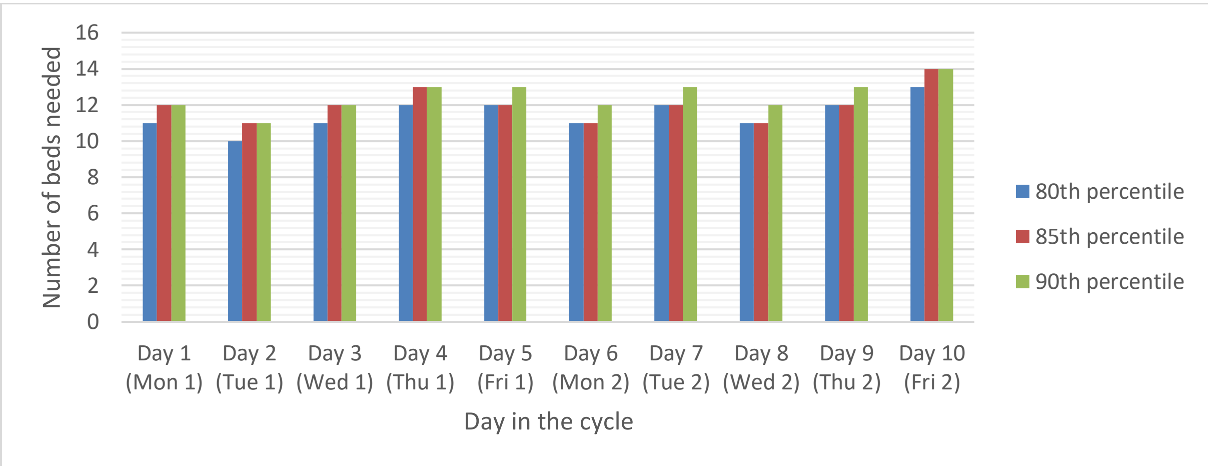

Figure 26. Number of beds needed every day in the cyclical blueprint surgery type's schedule (after switching three-time two OR-blocks)

We saw that the demand of beds on Day 10 and its probability distribution is higher than the other days of the cycle. The demand for beds in Day 8 is lower so we decided to move OR-blocks [2, 15] from Day 10 to Day 8. The resulting blueprint schedule in Table 28. We decided to do this, also because surgery type 15 is a lung surgery and we schedule these type of elective surgeries on Wednesdays or Thursdays.

Table 28. Cyclical blueprint surgery type's schedule after fourth time of switching two surgeries

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]
OR2	[3,1]	[4,1]	[4,1]	[4]	[4]	[14]	[4,1]	[10]	[4]	[13]
OR3	[2,2]	[11]	[3,1]	[11]	[3,1]	[3,1]	[2,2]	[4,1]	[2,15]	[3,1]
OR4	[11]	[5]	[5]	[2,8]	[5]	[9]	[12]	[3,1]	[9]	[12]
OR5	[6]	Short Surgery	Short surgery		Long surgery	[2,2]	Short surgery	[2,15]		Short surgery

Figure 27 and Figure 28 show the results of the probabilistic model using the cycle in Table 28. With this modification, we reduce the demand for beds for Day 10 and the probability distribution of demand for IC-beds on Day 8 aligns with the other days of the cycle.

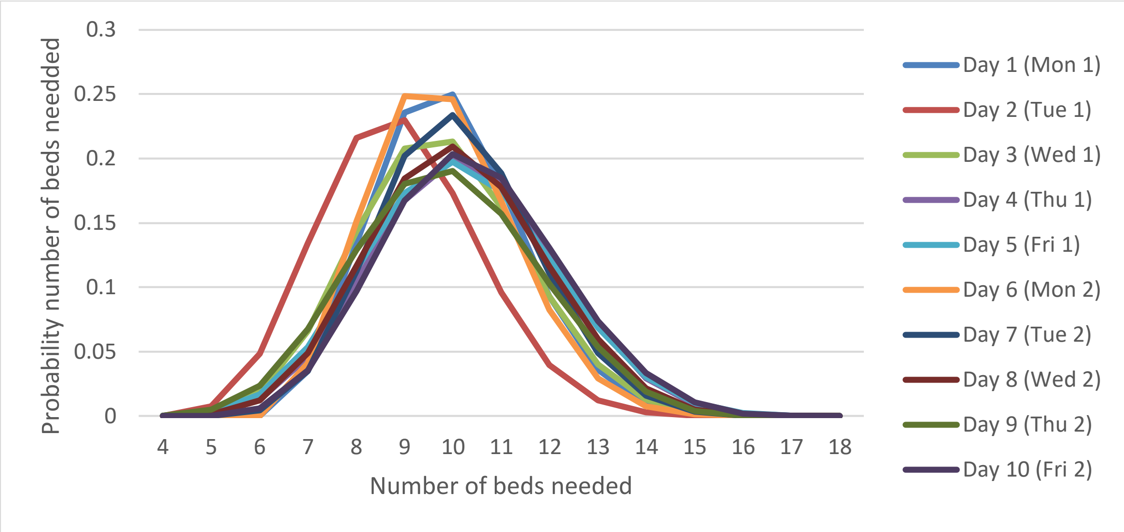

Figure 27. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (after moving for the fourth-time one OR-block)

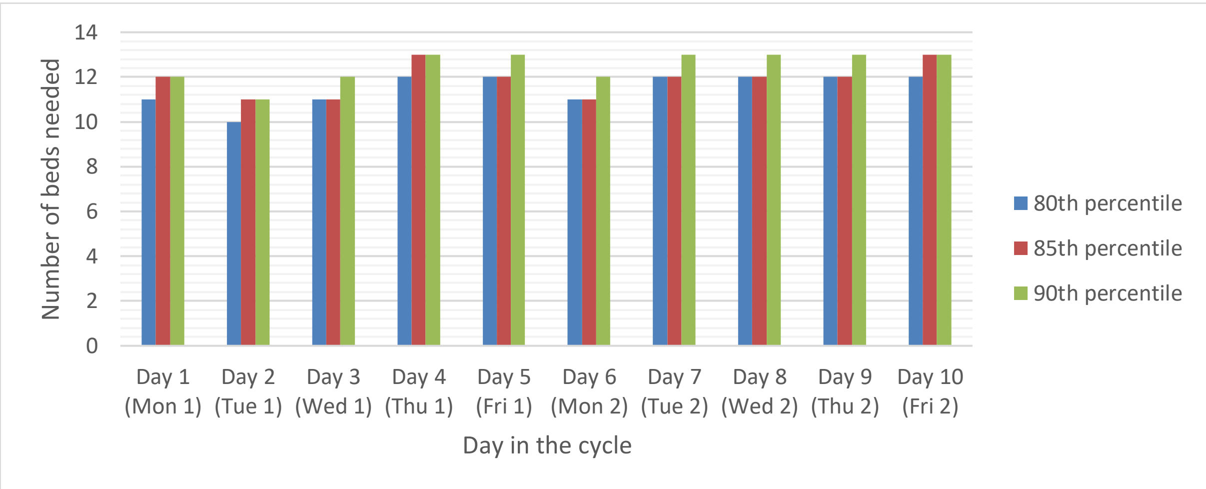

Figure 28. Number of beds needed every day in the cyclical blueprint schedule (after moving for the fourth-time one OR-block)

The last modification is to increase the demand of beds in Day 2 to reduce the variability of that the results are shown in Section 6.4.

Annex D

In this Annex we show the resulting cyclical blueprint schedule depending on the percentile of the number of surgeries that we want to plan and depending if we cluster certain surgery types or not.

Planning P_{70} of the surgeries without clustering certain surgery types

Table 29. Cyclical blueprint surgery type's schedule with 70 surgeries planned after local search

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]
OR2	[3,1]	[4,1]	[14]	[4,1]	[10]	[11]	[4,1]	[11]	[4]	[13]
OR3	[5]	[2,2]	[4]	[2]	[3,1]	[3,1]	[11]	[4,1]	[9]	[4,1]
OR4	[6]	[3,1]	[5]	[2,15]	[8]	[9]	[2,15]	[3,1]	[5]	[12]
OR5	[2,2]	Short surgeries			Short surgeries	[2,2]	Short surgeries			Long surgery

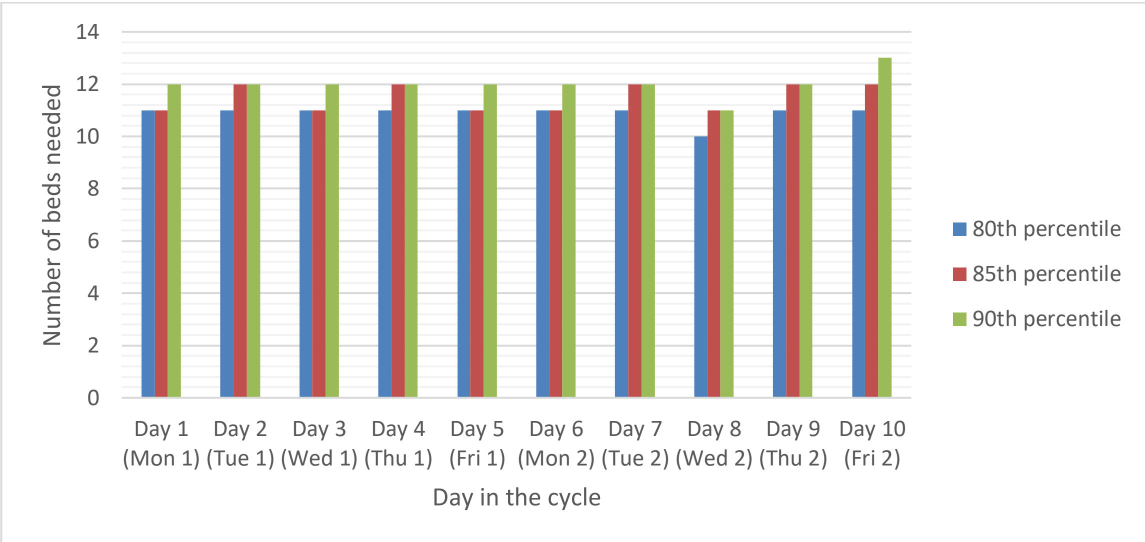

Figure 29. Number of beds needed every day in the cyclical blueprint schedule (70 surgeries planned, no clustering)

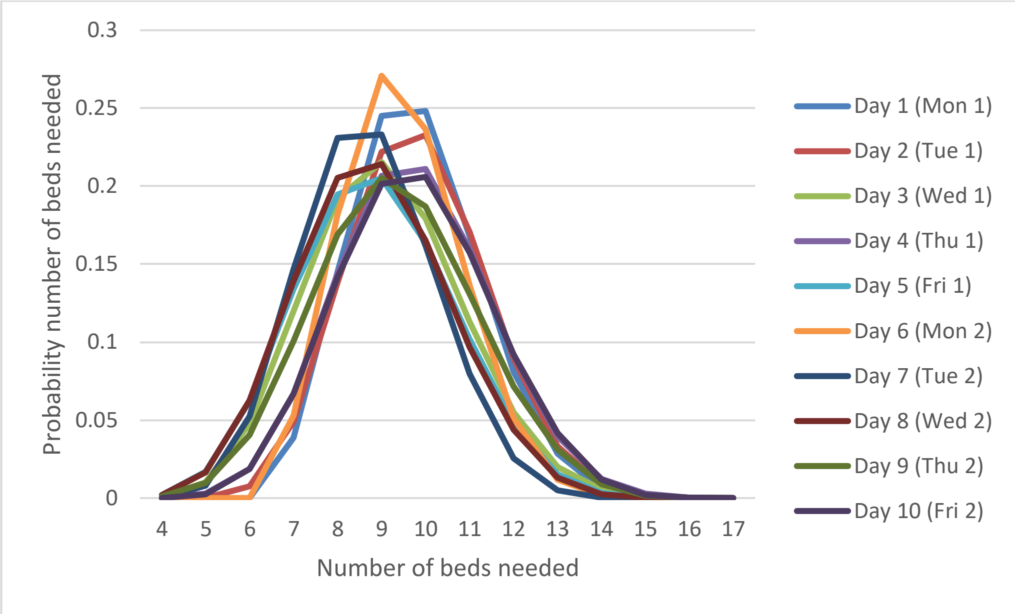

Figure 30. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (70 surgeries planned, no clustering)

Planning P_{65} of the surgeries without clustering certain surgery types

Table 30. Cyclical blueprint surgery type's schedule with 68 surgeries planned after local search

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]
OR2	[14]	[4,1]	[10]	[4]	[11]	[11]	[4,1]	[11]	[4,1]	[13]
OR3	[5]	[2,2]	[3,1]	[2,15]	[3,1]	[3,1]	[2,15]	[4,1]	[5]	[8]
OR4	[6]	[4]	Short surgeries	[9]	[4]	[2]	[2]	[3,1]	[12]	[9]
OR5	[2]	Short surgeries			Long surgeries	[3,1]		[2]		Short surgeries

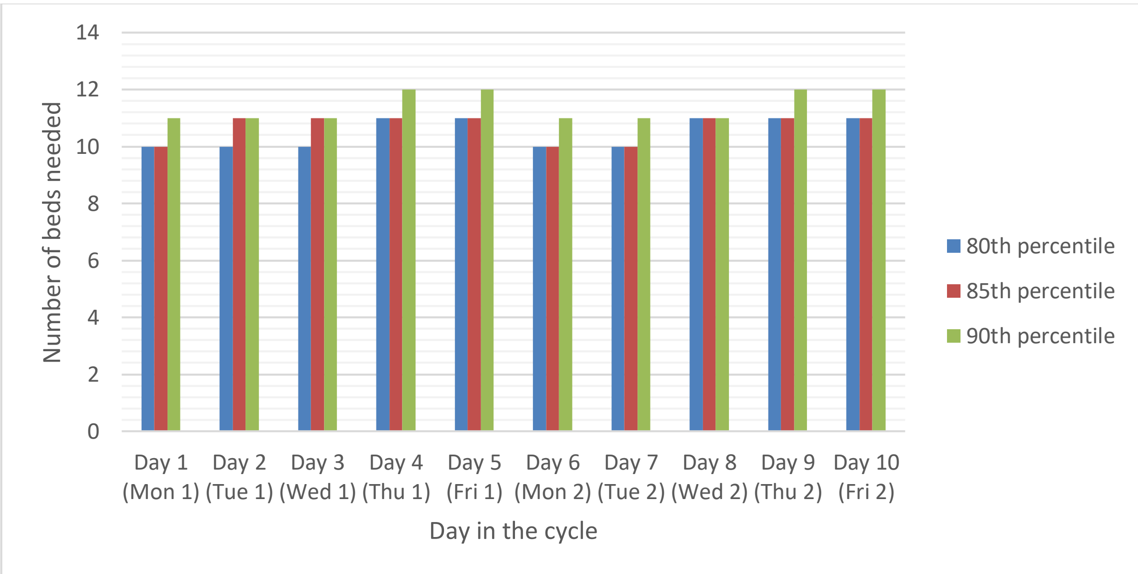

Figure 31. Number of beds needed every day in the cyclical blueprint schedule (68 surgeries planned, no clustering)

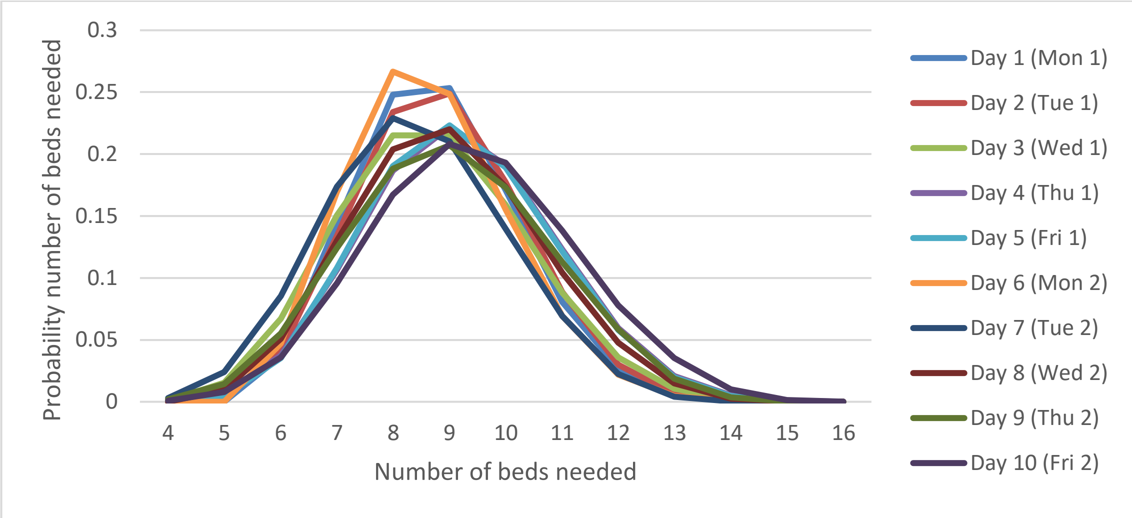

Figure 32. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (68 surgeries planned, no clustering)

Planning P60 of the surgeries without clustering certain surgery types

Table 31. Cyclical blueprint surgery type's schedule with 64 surgeries planned after local search

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]	[2,2]
OR2	[14]	[4,1]	[10]	[4,1]	[9]	[11]	[4,1]	[3,1]	[15,15]	[13]
OR3	[2]	[2,2]	[3,1]	[4]	[8]	[3,1]	[2]	[11]	[5]	[12]
OR4	[6]	[4]	Short Surgeries	[2]	[5]	[9]	[3,1]	[4,1]	Short Surgeries	Long surgeries
OR5	[3,1]	Short Surgeries				[2]				

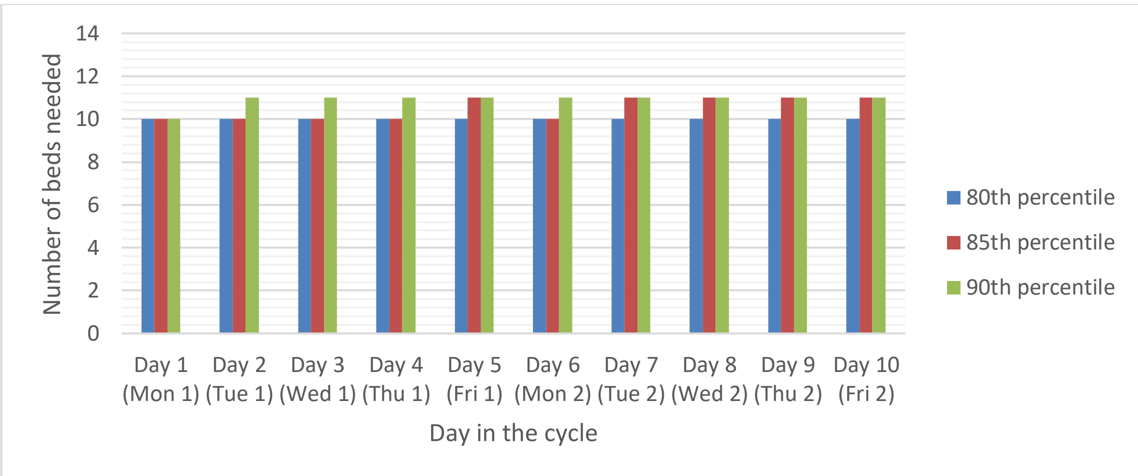

Figure 33. Number of beds needed every day in the cyclical blueprint schedule (64 surgeries planned, no clustering)

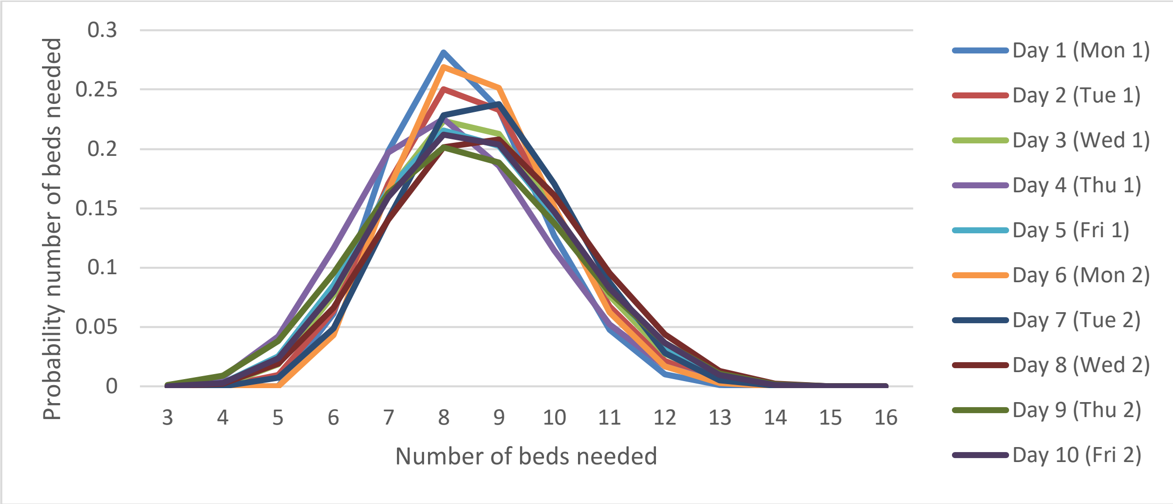

Figure 34. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (64 surgeries planned, no clustering)

Planning P75 of the surgeries clustering certain surgery types

Table 32. Cyclical blueprint surgery type's schedule clustering some surgery types with 65 surgeries planned after local search

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]
OR2	[C,A]	[B,K]	[D,A]	[D,A]	[D,A]	[I]	[D,A]	[B]	[D,A]	[J]
OR3	[B,K]	[D,A]	[E]	[H]	[E]	[C,A]	[B,B]	[C,A]	[B]	[C,A]
OR4	[F]	[B]	[B]	Short surgeries	Long surgery	[B]	[D]	Short surgeries	[H]	[G]
OR5						Short surgeries				Short surgeries

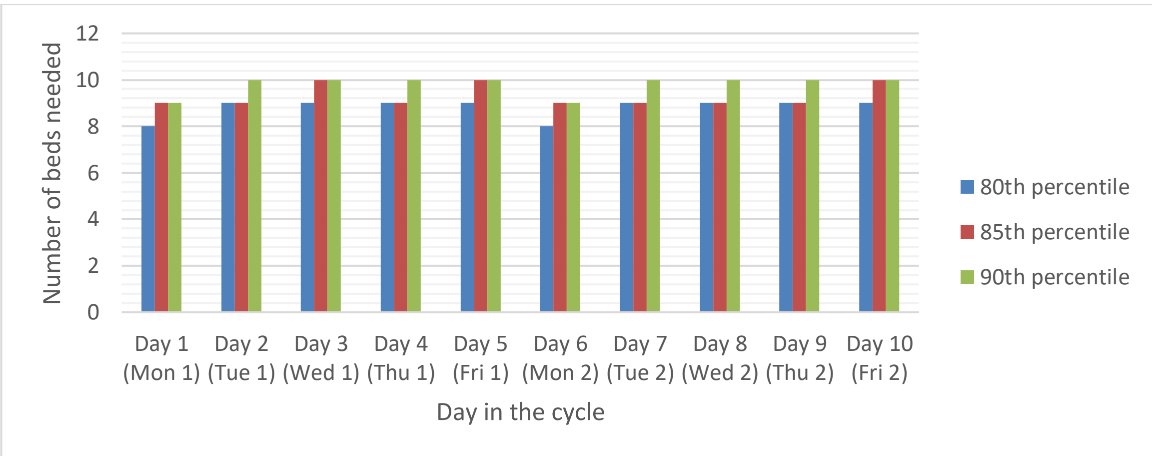

Figure 35. Number of beds needed every day in the cyclical blueprint schedule (65 surgeries planned, clustering some surgeries)

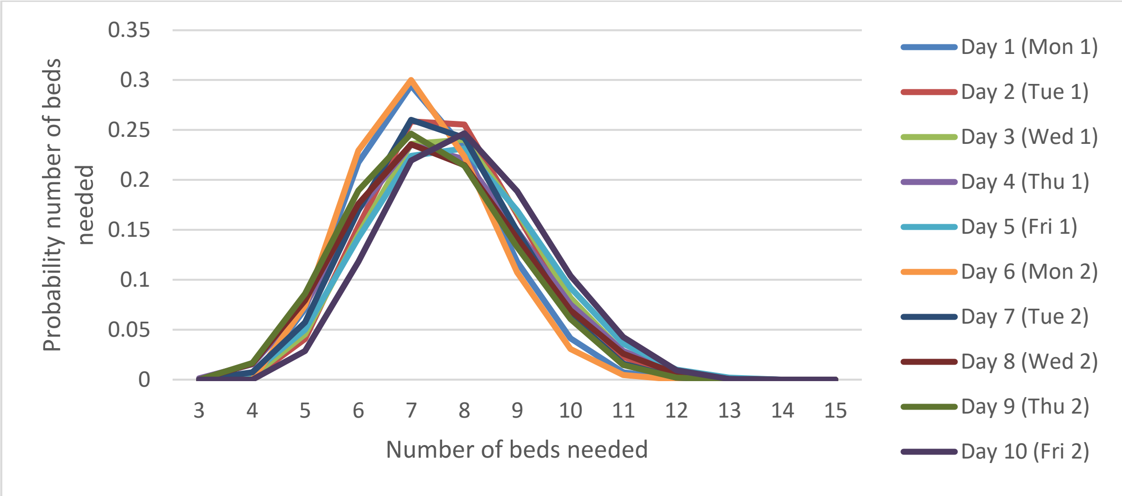

Figure 36. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (65 surgeries planned, clustering some surgeries)

Planning P_{70} of the surgeries clustering certain surgery types

Table 33. Cyclical blueprint surgery type's schedule clustering some surgery types with 62 surgeries planned after local search

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]
OR2	[C,A]	[D,A]	[D,A]	[D,A]	[D,A]	[B,B]	[D,A]	[B,K]	[B,B]	[J]
OR3	[H]	[B,K]	[I]	[H]	[E]	[C,A]	[B,B]	[C,A]	[D]	[C,A]
OR4	[F]	[D]	Short surgeries		Long surgery	Short surgeries	[B]	Short surgeries		[G]
OR5										

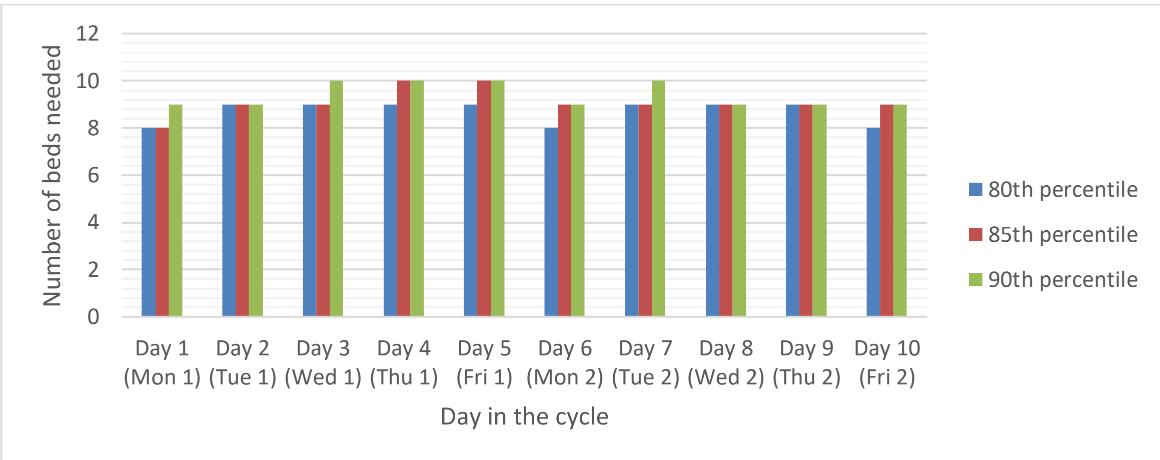

Figure 37. Number of beds needed every day in the cyclical blueprint schedule (62 surgeries planned, clustering some surgeries)

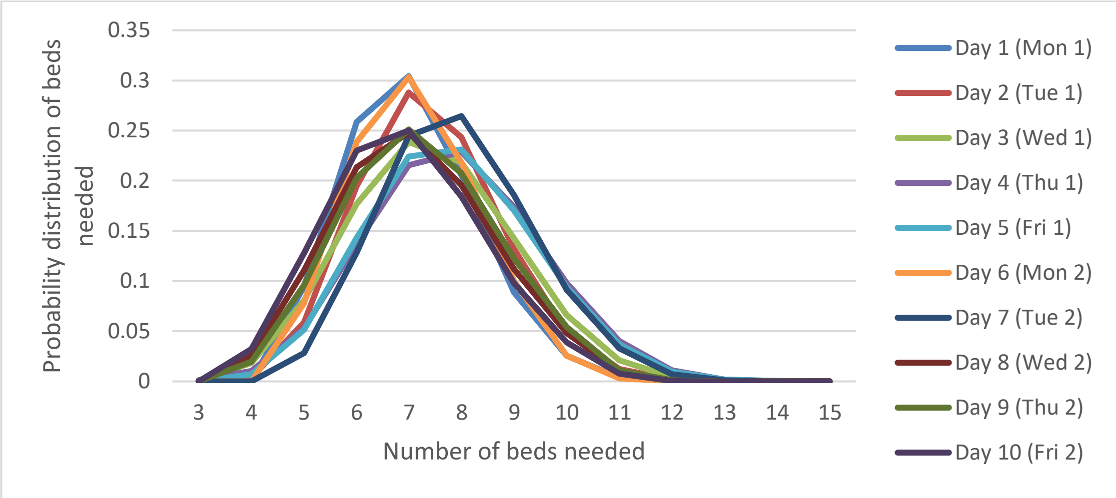

Figure 38. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (62 surgeries planned, clustering some surgeries)

Planning P_{65} of the surgeries clustering certain surgery types

Table 34. Cyclical blueprint surgery type's schedule clustering some surgery types with 61 surgeries planned after local search

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]
OR2	[C,A]	[D,A]	[D,A]	[D,A]	[D,A]	[B,B]	[D,A]	[B]	[B,K]	[J]
OR3	[C,A]	[D]	[B]	[H]	[I]	[C,A]	[B,B]	[C,A]	[E]	[H]
OR4	[F]	[B,K]	Short surgeries		Long surgery	Short surgeries	Short surgeries		[D]	[G]
OR5										

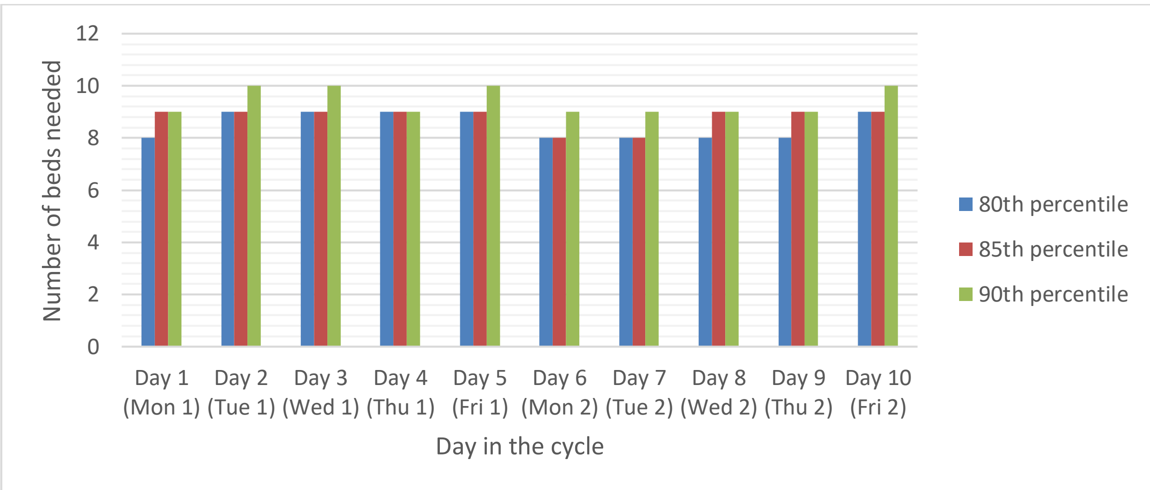

Figure 39. Number of beds needed every day in the cyclical blueprint schedule (61 surgeries planned, clustering some surgeries)

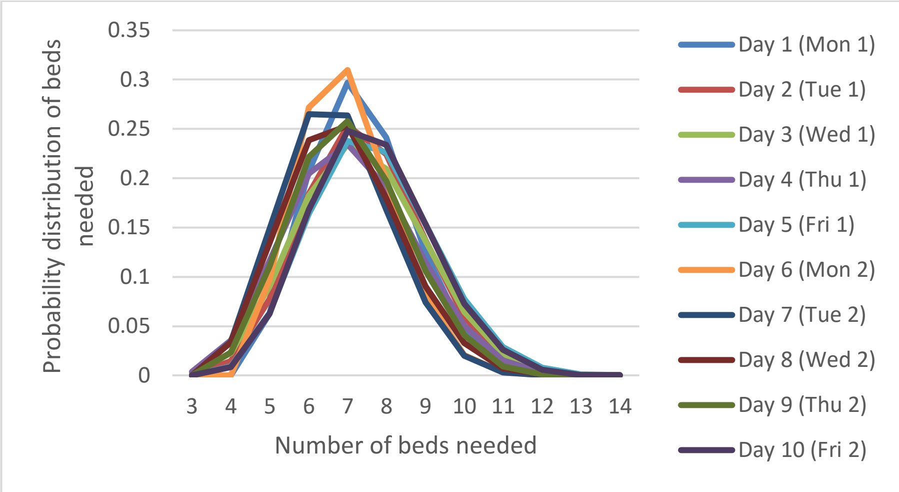

Figure 40. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (61 surgeries planned, clustering some surgeries)

Planning P_{60} of the surgeries clustering certain surgery types

Table 35. Cyclical blueprint surgery type's schedule clustering some surgery types with 57 surgeries planned after local search

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
OR1	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]	[B,B]
OR2	[E]	[D,A]	[D,A]	[D,A]	[D,A]	[B,B]	[C,A]	[C,A]	[B]	[J]
OR3	[B]	[D,A]	[I]	Short surgeries	[H]	[C,A]	[B,K]	Short surgeries	Short surgeries	[G]
OR4	[F]	[B,K]			Long surgery	[D,A]				[H]
OR5										

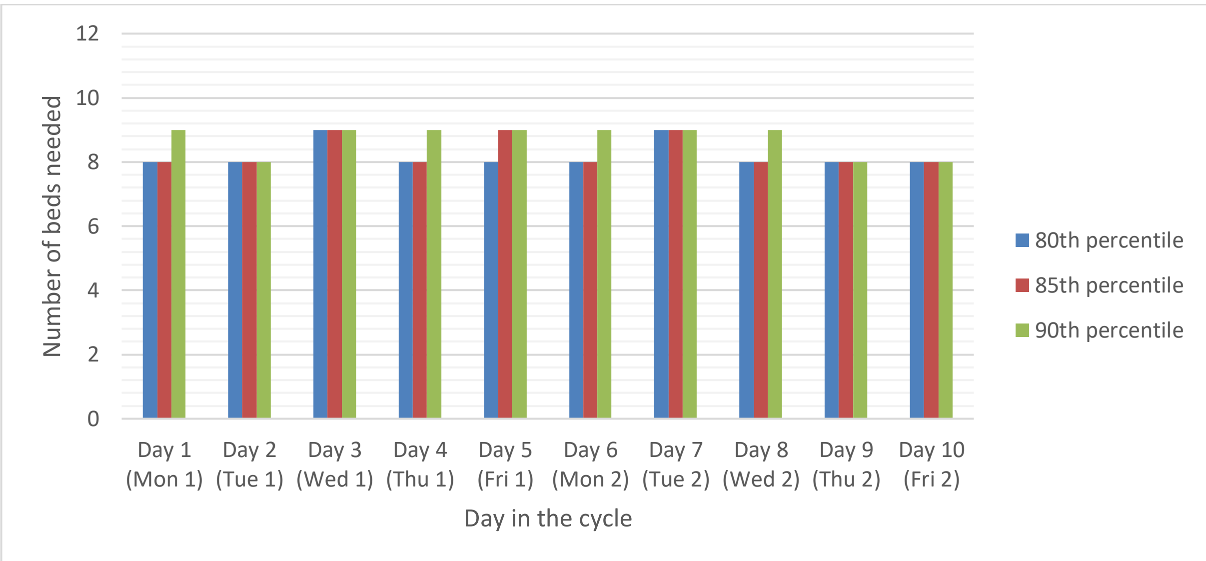

Figure 41. Number of beds needed every day in the cyclical blueprint schedule (57 surgeries planned, clustering some surgeries)

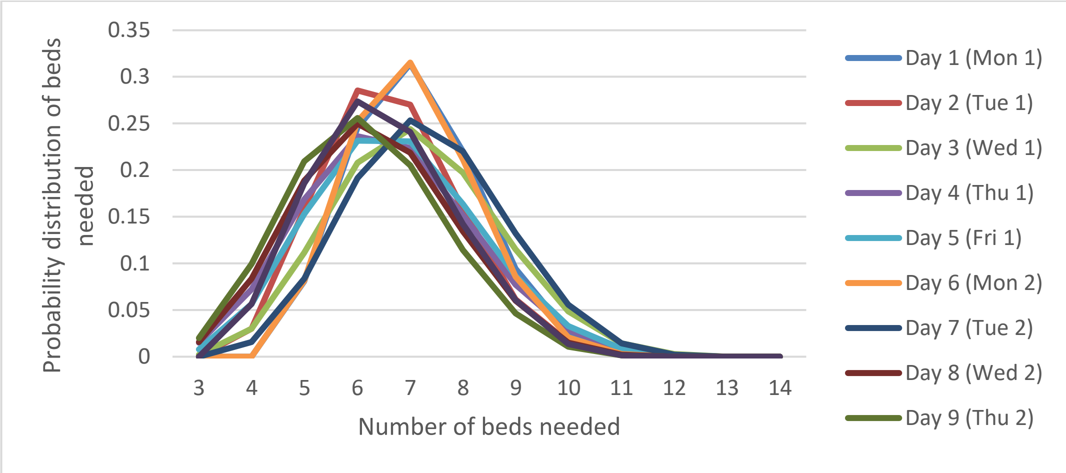

Figure 42. Probability distribution of number of beds needed for each day in the cyclical blueprint schedule (57 surgeries planned, clustering some surgeries)