
# BACHELOR THESIS

## Pooling hospital beds: A capacity allocation study within the Wilhelmina Kinderziekenhuis

Author
W.H.W.M. Otten

Date
10-07-2017

Supervisors
Ir. A.G. Leeftink
University of Twente, Centre for Healthcare Operations Improvement and Research

Dr. ir. N.J. Borgman
University of Twente, Centre for Healthcare Operations Improvement and Research

K.C. Proctor
UMC Utrecht, Program 'Verbouwing WKZ'

Wilhelmina Kinderziekenhuis

UNIVERSITY OF TWENTE.

# Preface

Before you lies the report of my Bachelor project at the Wilhelmina Kinderziekenhuis of UMC Utrecht. I hereby complete the last part of the Bachelor curriculum in Industrial Engineering and Management at the University of Twente. This project was conducted from April 2017 until July 2017. In this preface, I would like to thank everybody that helped with the realization of this research.

Immediately from the start of my Bachelor project, I noticed what a stimulating environment UMC Utrecht is. The willingness to grow as an organisation and to involve all patients, was something that I was amazed by. This made me enthusiastic and excited to have the opportunity to contribute to this organization. The principles of UMC Utrecht allow students to develop themselves both academically and socially.

First, there are many people within the Wilhelmina Kinderziekenhuis that cannot be left unmentioned. I would like to thank Kate Proctor for her guidance and support. She helped me get started and introduced me to many new faces. My thanks also go out to John Heijstek, Willem de Vries and Michel Zeilmaker. Their expertise and openness helped me to interpret the data and the results correctly. Furthermore, I would like to thank all staff that answered my questions during my project in the Wilhelmina Kinderziekenhuis. The enthusiasm and dedication that they put into their work inspire me greatly.

Second, I express my gratitude to the support coming from the University of Twente. I would like to thank Gréanne Leeftink for her role as first supervisor. When needed, she provided me with positive feedback to point me in the right direction. I would also like to thank my second supervisor Nardo Borgman, for providing useful tips regarding the content of my Bachelor report.

Lastly, I would like to thank my family for supporting me not only during this project, but the entire Bachelor curriculum over the past three years. By executing this Bachelor project, I want to show everybody what I am capable of.

Wouter Otten

Enschede, July 2017

# Management summary

## Motivation

Currently, the Wilhelmina Kinderziekenhuis (WKZ) is dealing with a shortage of operational hospital beds in the departments Children's ICU and Neonatal IC. Due to this shortage, too many requests for hospital beds are rejected since the hospital cannot accommodate all patients. Rejecting the patient also means that his or her operation must be cancelled as well. The high number of rejections goes hand in hand with a high occupancy rate over the two departments.

As of 2016, the WKZ has started renovating. This renovation process has given management the opportunity to investigate optimization possibilities. One of these possibilities is optimizing the allocation of single-person rooms, after an intensified collaboration between the departments Children's ICU and Neonatal IC. This collaboration is called the 'Harmonica' and will be operational in 2018.

## Research goal

The goal of this study is to deliver a substantiated advice for the WKZ on the allocation of single-person rooms for the future Harmonica. The research question that corresponds with this research goal is:

*"What is the optimal capacity allocation for the Neonatal IC, the Children's ICU and the hybrid given stakeholder preferences on the occupancy rate and the rejection probability?"*

We come to this advice by first analysing the current performance of the two departments. Then, we conduct a literature study on modelling methods and their applicability within the WKZ. Hereafter, we test several scenarios to provide the WKZ with a trade-off on capacity allocation.

## Results

We analysed the datasets of the NICU and PICU. Here, we focussed on the length of stay, the occupancy rate, the arrival intensity and the rejection probability. On average, patients on the NICU have a longer length of stay than on the PICU. Therefore, the turnover on the NICU is lower than on the PICU. The average occupancy rate on the NICU is 88.2%, while for the PICU this is 74.7% (Pelikaan) and 86.8% (Leeuw). These high numbers indicate that while both departments use their beds efficiently, there is a high likelihood for rejection at times. Furthermore, the NICU shows a constant distribution of arrivals, while Pelikaan and Leeuw experience more seasonal influences. The rejection probability on the NICU is approximately 7.3%, while the PICU has a 5.8% chance of rejecting patients.

After constructing a queueing model, we tested four scenarios. These scenarios are constructed after discussing with all stakeholders. Each scenario has three aspects of interest; the allocation of capacity, the average occupancy rate and the overall rejection probability. The results of our tested scenarios are shown in the Table 1.

| Scenario | Capacity allocation (NICU, Hybrid, PICU) | Occupancy | Rejection probability |
|---|---|---|---|
| **1. Current situation** | 32, 0, 35 | 82.1% | 6.2% |
| **2. Occupancy to capacity** | 28, 10, 29 | 85.5% | 2.6% |
| **3. Safety stock** | 30, 6, 31 | 84.7% | 3.6% |
| **4. Two of each** | 30, 4, 33 | 84.1% | 4.0% |

*Table 1: Experiment results*

## Recommendations

We recommend to allocate 28 NICU rooms, 10 hybrid rooms and 29 PICU rooms to the future Harmonica. This capacity allocation proves to be the most beneficial. The pooling of hybrid hospital rooms over the NICU and PICU has a large impact on the performance of the Harmonica. Furthermore, we recommend using this study as a substantiation for the empowerment of educating 'flexible' nurses, deployable for the future Harmonica. The availability of flexible nurses simplifies the planning process and reduces the shortage of staff. Our last recommendation is continuously monitoring the performance of the future Harmonica. This includes keeping track of the occupancy rate and the overall rejection probability. By continuously monitoring these indicators, the performance of the Harmonica can be compared with the performance of the current situation. Besides, after monitoring, management can decide to experiment with less or more hybrid rooms to determine their effect.

The suggestions for further research stem from our main findings. We suggest to optimize the capacity allocation via modelling. Here, maximum occupancy rates or minimum rejection probabilities can be found. Another suggestion is to extend the results of this study into staffing decisions. The hybrid policy allocates rooms on a tactical planning level, which requires staff to be deployed tactically as well. Finally, we suggest to increase the integration of staff deployment into bed occupancy rates. This way, a more realistic picture of the performance of both departments can be derived. Besides, it also provides opportunities for benchmarking occupancy rates across similar departments The Netherlands.

# Management samenvatting (Dutch)

## Motivatie

Momenteel kampt het Wilhelmina Kinderziekenhuis (WKZ) met een tekort aan operationele ziekenhuisbedden op de afdelingen Kinder IC en Neonatale IC. Vanwege dit tekort worden er te veel aanvragen voor een ziekenhuisbed afgewezen, omdat het ziekenhuis niet alle patiënten kan opvangen. Het weigeren van een patiënt houdt ook in dat zijn of haar operatie gecanceld moet worden. Het hoge aantal weigeringen gaat hand in hand met een hoge bezettingsgraad over de twee afdelingen.

Vanaf 2016 is de WKZ begonnen met renoveren. Dit renovatieproces heeft management de mogelijkheid gegeven om optimalisatiemogelijkheden te onderzoeken. Een van deze mogelijkheden is het optimaliseren van de toewijzing van eenpersoonskamers, na een verbeterde samenwerking tussen de afdelingen Kinder IC en Neonatale IC. Deze samenwerking heet de 'Harmonica' en zal vanaf 2018 operationeel zijn.

## Onderzoeksdoel

Het doel van dit project is om het WKZ een onderbouwd advies te presenteren over de toewijzing van eenpersoonskamers voor de toekomstige Harmonica. De onderzoeksvraag die overeenstemt met dit onderzoeksdoel is:

*"Wat is de optimale capaciteitstoewijzing voor de Neonatale IC, de Kinder IC en de hybride, gegeven de voorkeur van stakeholders op het gebied van de bezettingsgraad en de weigerkans?"*

We komen tot dit advies door eerst de huidige prestaties van de twee afdelingen te analyseren. Vervolgens voeren we een literatuurstudie uit wat betreft modelleringsmethoden en hun toepasselijkheid binnen het WKZ. Hierna testen we verschillende scenario's om het WKZ een afweging te bieden over capaciteitsverdeling.

## Resultaten

We hebben eerst de datasets van de NICU en PICU geanalyseerd. Hier lag onze focus op de verblijfduur, de bezettingsgraad, de aankomstintensiteit en de weigerkans. Gemiddeld verblijven patiënten op de NICU langer dan op de PICU. Dit resulteert in een lagere patiënt-omzet op de NICU dan op de PICU. De gemiddelde bezettingsgraad op de NICU bedraagt 88.2%, terwijl dit voor de PICU 74.7% (Pelikaan) en 86.8% (Leeuw) is. Deze hoge cijfers tonen aan dat hoewel beide afdelingen efficiënt gebruik maken van hun beddencapaciteit, er van tijd tot tijd een aanzienlijke weigerkans is. Daarnaast toont de NICU een constante verdeling van aankomsten, terwijl Pelikaan en Leeuw meer seizoensinvloeden ervaren. De weigerkans op de NICU bedraagt circa 7.3%, terwijl de PICU een geschatte 5.8% kans heeft op het afwijzen van patiënten.

Na het opstellen van een wachtrij-model hebben we vier scenario's getest. Deze scenario's zijn opgesteld na meerdere stakeholder-vergaderingen. Elk scenario bevat drie aspecten van belang; de capaciteitstoewijzing, de gemiddelde bezettingsgraad en de algemene weigerkans. De resultaten van de geteste scenario’s worden in Tabel 1 weergegeven.

| Scenario | Capaciteitstoewijzing (NICU, Hybride, PICU) | Bezetting | Weigerkans |
|---|---|---|---|
| **1. "Current situation"** | 32, 0, 35 | 82.1% | 6.2% |
| **2. "Occupancy to capacity"** | 28, 10, 29 | 85.5% | 2.6% |
| **3. "Safety stock"** | 30, 6, 31 | 84.7% | 3.6% |
| **4. "Two of each"** | 30, 4, 33 | 84.1% | 4.0% |

*Tabel 1: Resultaten van de experimenten*

## Aanbevelingen

We raden aan om 28 NICU-kamers, 10 hybride kamers en 29 PICU-kamers toe te wijzen binnen de toekomstige Harmonica. Deze capaciteitsverdeling blijkt het meest voordelig te zijn. Het 'poolen' van hybride ziekenhuiskamers over de NICU en PICU heeft een grote invloed op de prestaties van de Harmonica. Verder raden we aan om deze studie te gebruiken als motivatie voor het opleiden van 'flexibele' verpleegkundigen, inzetbaar voor de toekomstige Harmonica. De beschikbaarheid van flexibele verpleegkundigen vereenvoudigt het planningsproces en vermindert het personeelstekort. Onze laatste aanbeveling is het continu monitoren van de prestaties van de toekomstige Harmonica. Door voortdurend te controleren en te evalueren, kan de prestatie van de Harmonica worden vergeleken met de prestaties van de huidige situatie. Daarnaast kan management, na het monitoren, besluiten om met minder of meer hybride kamers te experimenteren om hiervan de effectiviteit te bepalen.

De suggesties voor verder onderzoek komen voort uit onze belangrijkste bevindingen. Wij suggereren om de capaciteitsverdeling via het modelleren te optimaliseren. Hier kunnen maximale bezettingsgraden of minimale afwijzingswaarschijnlijkheden worden gevonden. Een andere suggestie is de resultaten van deze studie uit te breiden tot personeelsbeslissingen. De hybride verdeelt ruimten op een tactisch planningsniveau, waardoor personeel ook tactisch moet worden ingezet. Onze laatste suggestie is een verhoogde integratie van personeelsinzet in bedbezettingscijfers. Op deze manier wordt een realistischer beeld van de prestaties van beide afdelingen bepaald. Daarnaast biedt deze verhoogde integratie ook mogelijkheden tot het benchmarken van bezettingsgraden over vergelijkbare afdelingen in Nederland.

# Table of Contents

# 1. Introduction

## 1.1 Context description

The Wilhelmina Kinderziekenhuis is the children's hospital of the University Medical Centre Utrecht (UMC Utrecht). Every year, approximately 5000 children are treated and 3000 babies are born in this hospital. UMC Utrecht, which is the overarching institute, is an academic hospital located in Utrecht, Utrecht. This hospital has over 12,000 employees, 1000 beds and is divided into 12 divisions (UMC Utrecht, 2017).

As of 2016, the WKZ has started with the renovation of its building which lies in the Northern part of the UMC complex. This renovation process has given management the opportunity to investigate optimization possibilities. One of these possibilities is optimizing the allocation of single-person rooms, after an intensified collaboration between the departments Children's ICU and Neonatal IC. This collaboration is called the 'Harmonica'.

This Bachelor assignment takes place within the renovation program of the WKZ, with the focus on the two earlier mentioned departments. The scope of this assignment are the divisions 'Leeuw' and 'Pelikaan' for the Children's ICU (PICU), and the Neonatal IC plus one High Care unit (NICU). 'Pelikaan' consists of two intensive care units, 'Leeuw' is the High Care unit. The Neonatal IC consists of three Intensive Care units. Furthermore, in the future Harmonica a fixed number of beds will be assigned to patients of the Prinses Maxima Centrum (PMC). These patients will fall under the PICU department.

In this chapter, we discuss the problem description, the research objective and the research questions of this Bachelor assignment in detail.

## 1.2 Problem description

Currently, the WKZ is dealing with a shortage of operational hospital beds in the departments Children's ICU and Neonatal IC. Due to this shortage, too many requests for hospital beds are rejected since the hospital cannot accommodate all patients. Rejecting the patient also means that his or her surgery must be cancelled as well. The high number of rejections goes hand in hand with a high occupancy rate over the two departments. However, the problem of a high occupancy rate is a complex problem which consists of multiple other problems. For this reason, a problem cluster is designed to create structure in the problem context and identify the so called 'core problem'. Besides that, the problem cluster also helps indicating the causes, effects and interrelationships of the problems stated. In Figure 1, the problem cluster is shown.

Figure 1 shows that the problem of a high occupancy rate can be divided into three causes. The first cause is a high fluctuation in demand for hospital beds. This fluctuation is a problem, since the peaks in demand cause the need for the WKZ to reject possible patients. The first underlying reason behind the high fluctuation is the planning regarding hospital beds. For the WKZ, it is difficult to predict the amount of hospital beds that are needed to accommodate every request. Especially for the Neonatal IC this is a challenge, because this department has to deal with emergency requests coming from outside the WKZ. No insight in demand due to emergency arrivals is the second cause for the high fluctuation in demand for hospital beds. The lack of cooperation between the departments Children's ICU and Neonatal IC can be seen as the cause of this bad planning. The last known cause of the problem cluster is the insufficient number of universal hospital rooms. This insufficiency currently makes it impossible for the departments to fully exploit the benefits of working together. This problem can also be described as the core problem of the problem cluster. The core problem is the problem that has no known cause and can be influenced by the researcher (Heerkens & van Winden, 2012).

The second cause for a high occupancy rate is the low number of operational hospital beds. Logically, with an insufficient amount of operational hospital beds, the WKZ is not able to accommodate every request that comes in. The first cause for the low supply of operational beds is the fact that the two departments cannot interchange hospital beds. Again, an insufficient number of universal hospital rooms is stated as the core problem. The second cause for this low supply, however excluded from the scope of this research, is the lack of specialized staff. For example, when there is a lack of nurses on the Children's ICU, beds cannot be opened since there is nobody to nurse the patient on that bed.

The third and last cause is the wrong number of hospital beds placed at each department. Financial and structural constraints make it impossible to build additional rooms just to accommodate all patients. Besides that, efficiency wise it would not be a smart decision to keep on building just to meet demand. Concluding, this third cause for the high occupancy rate is something that the researcher cannot influence. Therefore, this branch of the problem cluster goes beyond the scope of this research and will be excluded.

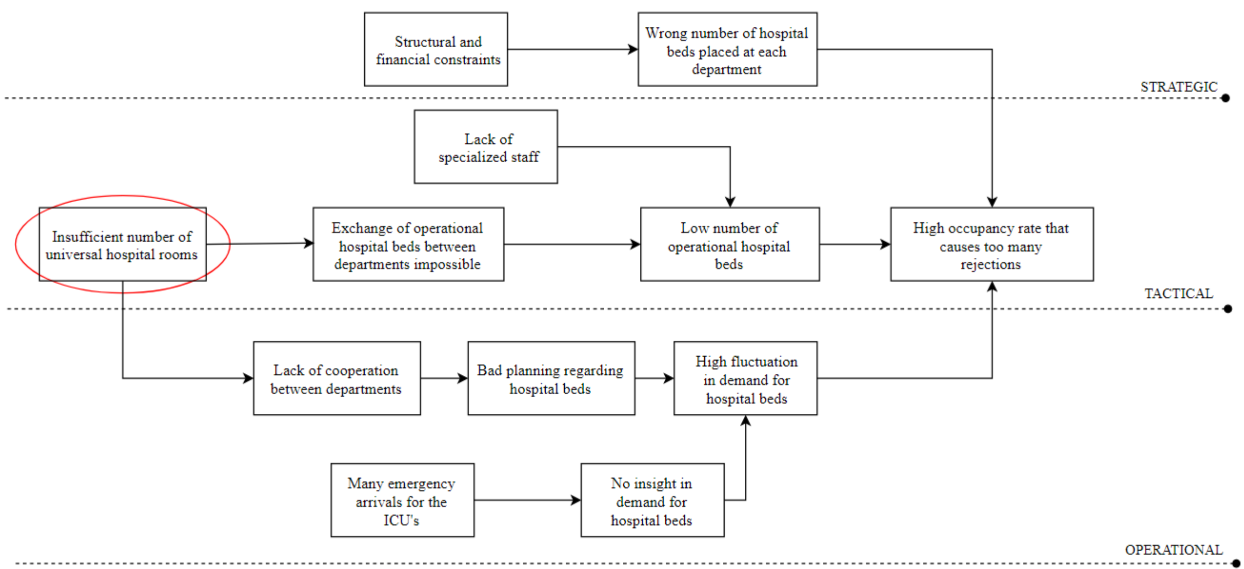



*Figure 1: The problem cluster*

## 1.3 Research objective

The aim of this project is to deliver a substantiated advice for the WKZ on the allocation of single-person rooms for the future Harmonica. In total, 67 rooms can be allocated over the NICU, Pelikaan and Leeuw. This allocation is dependent on factors such as the bed occupancy rate and the rejection probability.

The Harmonica will consist of a NICU part, a PICU part and a 'hybrid' part. This 'hybrid' part will consist of rooms that are usable for both departments. For example, when there is a large demand for PICU beds, the hybrid provides the ability to accommodate this demand. Since the NICU and the PICU will have a fixed number of rooms assigned, the 'hybrid' part of the Harmonica will be of greatest interest. The advice to the WKZ is a trade-off between the capacity allocation, the bed occupancy and the rejection probability.

We come to this advice by first analysing the current performance of the two departments. Then, we conduct a literature study on modelling methods and their applicability within the WKZ. After this, we test several scenarios to provide the WKZ with a trade-off on capacity allocation.

## 1.4 Research questions and methodology

To accomplish the research objective, we conduct several research questions. By answering the research questions, we provide a stepwise approach towards a substantiated advice.

1. *What will the total patient flow for the Harmonica be and what bottlenecks are expected?*

Chapter 2 gives an indication of the patient flow for the future Harmonica. This patient flow includes patient data in terms of arrival patterns and average lengths of stay on the two departments. The first research question is answered by analysing this data. Since these two departments will start working together more intensively, it is relevant to know the total demand for hospital beds and where and when possible bottlenecks will occur. Furthermore, via informal interviews with medical staff and the management team of the WKZ, possible bottlenecks are identified.

2. *What models are known in literature for making 'resource capacity planning' decisions in health care organisations?*

Chapter 3 describes the methods and techniques for 'resource capacity planning' found in the literature. First, a theoretical framework is described which sets the boundaries for the literature study. This framework is the framework for health care planning and control by Hans et al. (2011). Within resource capacity planning, the term 'capacity dimensioning' can be used when describing this research project. Capacity dimensioning is a strategic, structural form of decision-making, and therefore it can also be applied for the allocation of hospital rooms. In Chapter 3, a literature study is conducted to answer the second research question. The general conditions and limitations of the different modelling methods are summarized.

3. *How can the model found in the literature be applied within the WKZ?*

In Chapter 4, we make the connection between the theoretical models from literature and practice. Logically, the situation within the WKZ has its own limitations and conditions for a model to be of use. Therefore, specific assumptions and simplifications are listed. A model is constructed to test scenarios and present a trade-off to the stakeholders of the WKZ. Each scenario is evaluated for its impact and effectiveness. Furthermore, throughout Chapter 4 we continuously validate and verify our queueing model.

4. *What is the optimal capacity allocation for the Neonatal IC, the Children's ICU and the hybrid given stakeholder preferences on the occupancy rate and the rejection probability?*

Chapter 5 delivers the WKZ recommendations and conclusions regarding the capacity allocation of single-person rooms. This is done by putting the results of Chapter 4 into perspective. Meaning, the impact of the scenarios on reality is discussed. Besides, Chapter 5 includes staffing into the decision of capacity allocation. Altogether, this chapter substantiates any eventual decision made by the WKZ.

Additionally, all research questions should have one methodology which helps to concretize the problem statement. The methodology of the above-mentioned research questions is chronologic. This means that first question 1 will be answered, then question 2, then question 3, and lastly question 4.

# 2. Current situation

This chapter gives an overview of the current situation on the departments of interest within the WKZ. Section 2.1 describes the current care trajectory of elective patients, in order to analyse how these are designed in the current situation. After this, Section 2.2 discusses all resources that are currently available to the two departments. The assumption is made that these current resources will be used in the future situation. Lastly, Section 2.3 analyses the current situation given performance indicators. This way, the bottlenecks are made visible.

## 2.1 Care process

This section discusses the logistics of elective patients on the departments NICU and PICU. The details of the general care trajectory need to be known when translating this situation to the future Harmonica.

In Figure 2, the care path of patients on the NICU is shown. The WKZ does not allow waiting lists or queueing for an available bed. Each patient request is either admitted or rejected. Figure 2 indicates that there are three types of arrivals for the NICU: arrivals from home, another hospital, or from within the WKZ. Internal deliveries take place on the obstetrics units. Neonates are hospitalized when the vital organs do not function properly. The NICU will monitor, support and if necessary take over the vital functions. Examples are the taking over of breathing, infusion therapy and monitoring brain functions. Neonates can be hospitalized on the NICU from a pregnancy period of at least 24 weeks (UMC Utrecht, 2017).

Patients arriving from outside the hospital are first received in the birth centre of the WKZ. Then, the patient is allocated to a care unit based on his or her condition. There are specific criteria when allocating a patient. For example, patients with an Intensive Care (IC) classification are in life danger, where organs cannot function autonomously without external help. The patient receives care on the unit that he or she is assigned to. After a while, the patient can either be redirected to a different department of the WKZ, or the dismissal procedure is started. These different departments are the Medium Care unit of the NICU and nursing departments. Once the dismissal procedure is completed, the patient leaves the WKZ. If the patient is fully recovered, the patient can go home with the parents. However, the NICU can also refer the patient to a peripheral hospital, more close to home.

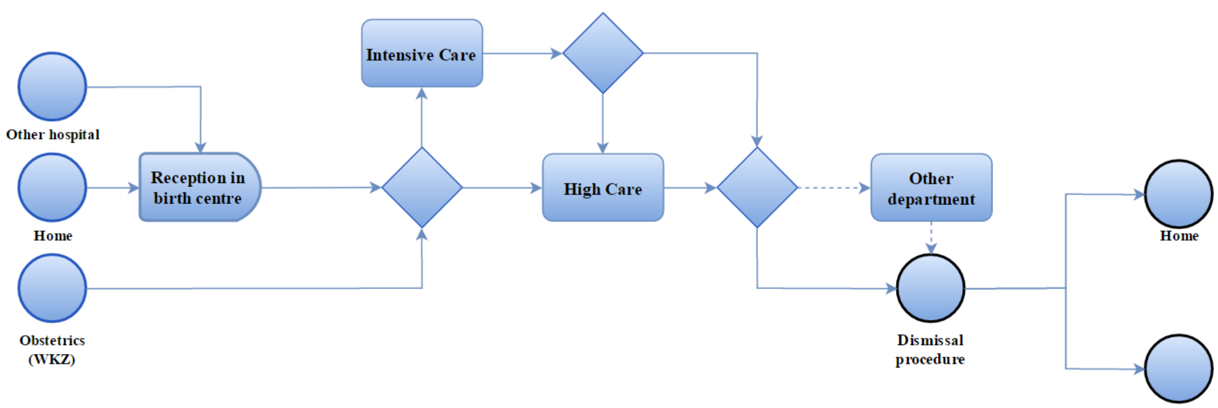



*Figure 2: NICU care trajectory*

The care trajectory of patients on the PICU has many similarities with Figure 2. Patients can either arrive from home, another hospital or from another department within the WKZ. The most frequent clinical condition of these patients is cardiologic, cardiothoracic or paediatric. Oncological, neurological, orthopaedical and chirurgical patients are other examples of clinical conditions being treated at the PICU.

If patients come from an internal source, they are directly transported towards their assigned care unit. Then, if a patient needs surgery, he or she is transported to an operation room next to the PICU department. Once this surgery is completed, the patient relocated to an Intensive Care or High Care unit. For example, if a patient with classification High Care (HC) is operated on his or her heart, and the surgery worsens the condition, the patient is relocated to an IC unit. Figure 3 displays the process flow at the PICU. Note that implicitly the units Pelikaan (IC) and Leeuw (HC) are integrated this figure as well. Again, after the treatment period on the IC or HC, the patient can either be referred to another hospital or sent home.

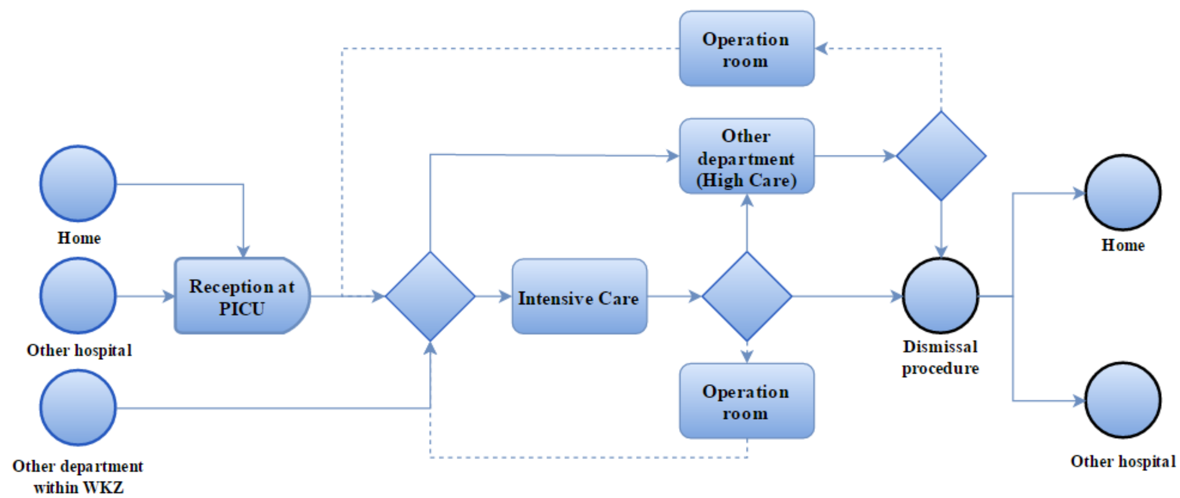



*Figure 3: PICU care trajectory*

## 2.2 Resources

In this section, the available resources to the two departments are discussed. We identify three types of resources that are relevant for the future Harmonica; hospital beds, medical staff and medical equipment. The renovation program of the WKZ has an impact on the resources available to the departments. Therefore, since the current situation differs from the future situation, an overview of both situations is given in this section.

### 2.2.1 Current situation

**Hospital beds**

The department NICU consists of three Intensive Care units and one High Care unit. Per unit, eight incubators are allocated. This means that a total of 32 incubators or places are available to nurse patients. If the Intensive Care units are full and a request comes in, the NICU checks if one of the neonates can be transferred to the High Care unit. This way, an extra space is created to accommodate a new arrival. This is also indicated in Figure 2. Furthermore, it is possible that patients of the PICU are allocated to the NICU when there is a shortage of places on the PICU. These patients are mostly new-born babies.

On the other hand, the PICU consists of two IC units (Pelikaan) and one HC unit (Leeuw). The Pelikaan has a capacity of 17 beds, while for Leeuw this number is 9. In contrast to the NICU, the PICU deals with many internal transfers. Examples of these internal transfers are patients that are transported from Leeuw to Pelikaan, Pelikaan to an operation room (OR) or Leeuw to a lower care unit. Hospital beds currently do not pose a restriction to the number of patients admitted to the WKZ. The current capacity could accommodate many more patients than there are now.

**Medical staff**

The medical staff on the NICU and PICU consists of doctors, doctor assistants, nurses, physician assistants, department assistants, poolers and fellows. This staff is very specialized to perform their individual tasks. To keep one hospital bed operational for 24 hours a day, 3.5 full time employees (FTE) are needed.

Staffing has a large influence on the occupancy rate. Both departments are currently facing a shortage in staff, which limits the number of operational beds. There is a national shortage of licenced nurses and not enough students are educated to become a nurse. When there is a shortage in nurses, beds cannot be operational and patient requests must be rejected. It is from a medical perspective not justified to nurse a group of patients with less nurses than required. For example, the Pelikaan can theoretically accommodate 17 patients, but in practice only 14 or 15 beds are structurally occupied due to a shortage of personnel. Unfortunately, it is currently not possible to allocate a PICU nurse on the NICU department or the other way around, due to specialisation issues. However, WKZ is investigating educational programmes to make this interchanging of nurses possible. For this research project, staffing issues are excluded.

**Medical equipment**

The medical equipment that is used by the two departments, can pose a restriction when planning capacity. The most important equipment used by the NICU that has an influence on the Harmonica, are the respiratory systems. Currently, the respiratory systems are not usable for the PICU department. Conversely, the PICU also makes use of specific respiratory systems that are not usable for the NICU. The WKZ is considering the option to invest in these systems that can be used on both departments. This way, in every single-person room such a system can be installed and less respiratory systems are needed. All other medical equipment will not form an issue, since these materials are sufficiently available.

### 2.2.2 Future situation

In the future situation, starting September 2019, the Harmonica allows the interchanging of beds between the two departments. This principle is called the 'pooling' of resources and will be further explained in Section 3.2.2. The WKZ has estimated that the current capacity in terms of hospital beds is needed for the future Harmonica.

The Harmonica will consist of three parts; a NICU part, a PICU part and a 'hybrid' part. A fixed capacity will be allocated to the NICU and PICU parts. The hybrid part is used to accommodate both NICU and PICU patients, based on short-term demand. This way, high peaks in demand on one department are offset by lower demand on the other department. Hence, the hybrid part will feature a fixed number of single-person rooms, but the ratio NICU-to-PICU rooms differs per time period.

Another development of interest is the impact of the new Princes Maxima Centrum (PMC). Starting from May 2018, a large group of PMC patients will be treated on the PICU department. This group consists of oncology patients only. For this group of patients, an estimated number of 9 beds is reserved in the future Harmonica. Table 2 shows an overview, to summarize the capacity statements made in this chapter so far.

| Unit | Estimated number of places needed |
|---|---|
| Pelikaan | 17 |
| Leeuw | 9 |
| PMC | 9 |
| NICU IC | 24 |
| NICU HC | 8 |
| Harmonica | 67 |

*Table 2: Estimated capacity allocation by the WKZ*

## 2.3 Performances

This section describes the performance of the current situation. By evaluating the performance of the two departments, we substantiate the problem statement of Section 1.2, and show where improvement opportunities are present. The following performance indicators are identified; length of stay, bed occupancy, arrival frequency and rejection probability. We substantiate the problem statement by visualising and evaluating datasets. Especially for medical staff, visualising the performance indicators gives an understanding of the problem context, and provides a tangible image of the current situation. The provided datasets by the NICU and PICU form the basis of the data analysis. The time horizon of these datasets stretches from 1-1-2014 until 31-12-2016. We interpret this data via informal interviews with heads of medical staff and management.

### 2.3.1 Length of Stay

The first performance indicator that we analyse is the length of stay. Every patient has a unique duration that he or she spends in the WKZ. The length of stay can be described as the service time of each patient. The length of stay per patient is determined as follows:

$$Length\ of\ Stay = Moment\ of\ dismissal\ from\ the\ hospital - Moment\ of\ hospitalization$$

When a patient switches beds, this is not seen as a new length of stay. For every patient on the two departments, the length of stay is calculated. This gives insight in the average duration of stay of patients on the two departments of interest. On average, the length of stay at the NICU is longer than on the PICU, because neonates require a longer period of care. The turnover on the PICU is therefore much higher than on the NICU. Figure 4 shows the distribution of the length of stay on the NICU.

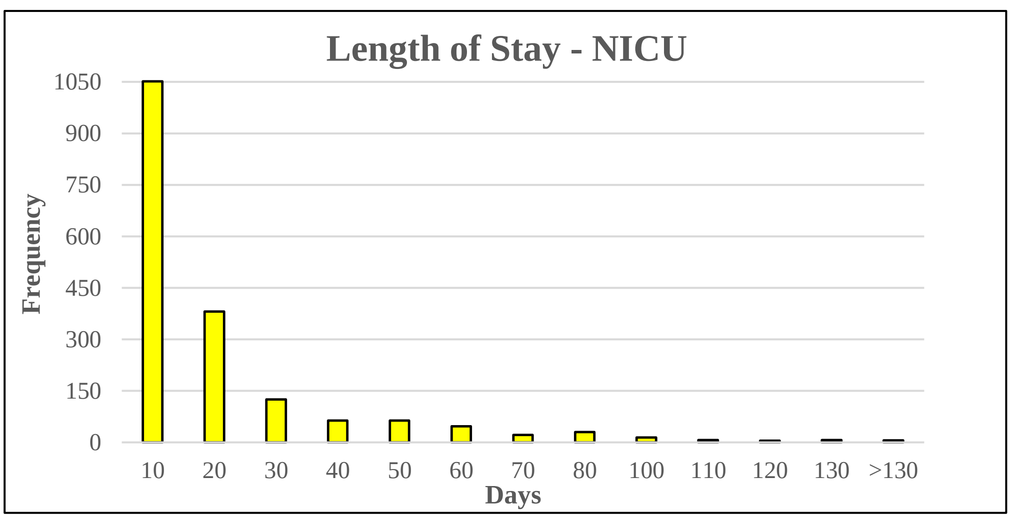



*Figure 4: Length of Stay on the NICU (n=1848, January 2014 – December 2016, UMC Utrecht)*

Figure 4 shows that the length of stay on the NICU appears to be negative exponentially distributed. Meaning, as the service time increases, the frequency of patients decreases. Most patients stay no more than ten days on the NICU. Neonates with a short duration of stay often have an infection, an oxygen deficiency or transition problems. However, when a neonate is born after 24 weeks of pregnancy, he or she needs a longer period of medical attention.

For the PICU we make a distinction between Pelikaan and Leeuw, for stakeholder preferences. Therefore, the performance indicators for Pelikaan and Leeuw are separately presented in this section. Figure 5 and Figure 6 present the length of stay performance for these two units. Again, the length of stay appears to be negative exponentially distributed for both units. On average, patients on the PICU spend no more than one week at either unit. Furthermore, the most frequent value in Figure 6 is two days. This is because Leeuw can serve as a post-IC or post-OR unit. Patients spend this period on Leeuw to recover before being dismissed from the WKZ.

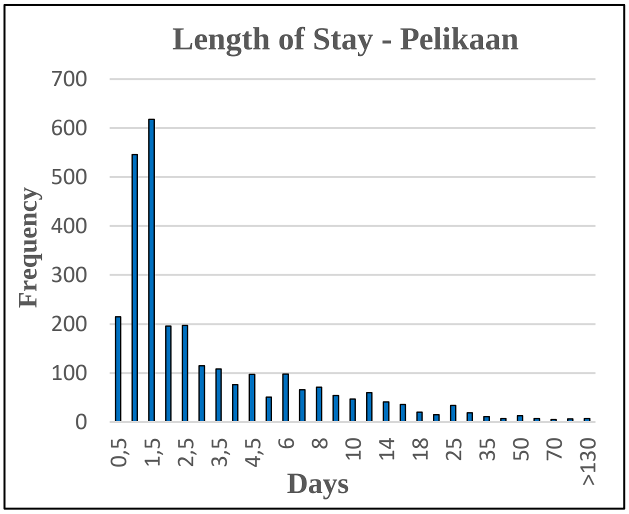



*Figure 5: Length of Stay on Pelikaan*
*(n=2588, January 2014 - December 2016, UMC Utrecht)*

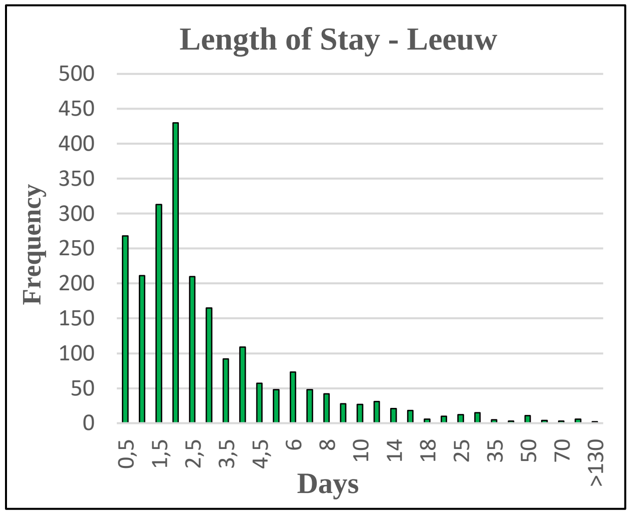



*Figure 6: Length of Stay on Leeuw*
*(n=2066, January 2014 - December 2016, UMC Utrecht)*

### 2.3.2 Occupancy rate

The second performance indicator we analyse is the occupancy rate. In Section 1.2, we indicated that a high occupancy rate is the cause for the high number of rejections in the WKZ. Now, we visualise and evaluate the occupancy rates to substantiate the problem cluster and the corresponding problem statement.

For both departments, the occupancy rates are calculated based on the lengths of stay and the theoretical capacity. Logically, with long lengths of stay, occupancy rates are higher. These occupancy rates are based on operational numbers, and not on financial numbers. Operational bed occupancies represent the actual utilization of inpatient healthcare facilities. This way, we prevent obtaining a distorted picture of the current situation. We use the following formula to calculate the occupancy rate:

$$Occupancy\ rate = \frac{\sum Lengths\ of\ stay\ in\ time\ period\ X}{\sum Bed\ days\ available\ in\ time\ period\ X} * 100\%$$

Since staffing issues are excluded from this research project, the theoretical capacity is used when determining occupancy rates. Therefore, the occupancy rates are not corrected for the number of beds that were ‘operational’. Hospital beds can only be operational when there is enough medical staff available to treat a patient. In terms of staffing, 3.5 full-time employees (FTE) are needed to keep a bed operational for

24 hours. The theoretical capacity is the maximum number of beds or places available to accommodate patients.

First, we analyse the occupancy rate on the NICU. Figure 7 presents the trajectory of the occupancy rate over the last three years. This figure shows that high occupancy rates are achieved over the measured time horizon. The average occupancy rate is 88.2%. Medical staff of the NICU state that they feel that this number represents the current situation accurately. Logically, when operating at a high occupancy rate, more patient requests are rejected. The red trendline indicates that occupancy on the NICU is rising steadily.

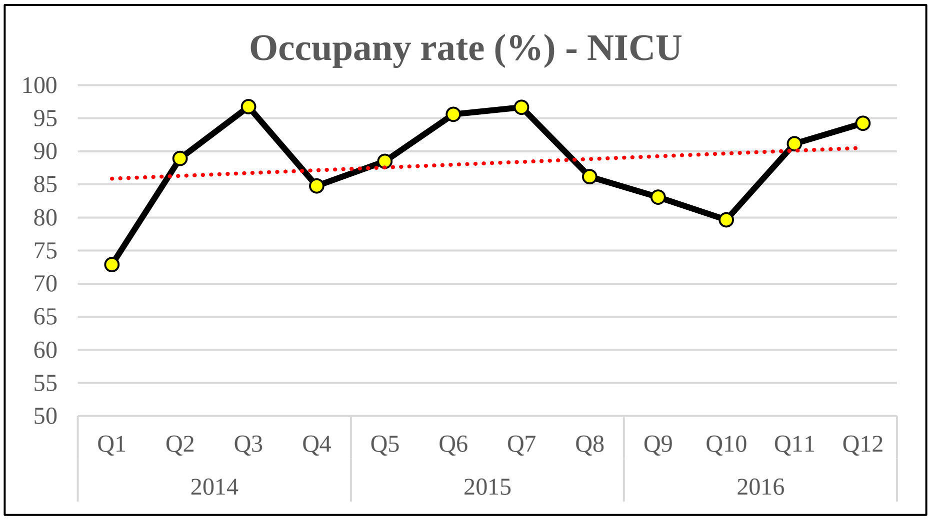



*Figure 7: Occupancy rate (%) on the NICU (n=1848, January 2014 - December 2016, UMC Utrecht)*

Next, we discuss the occupancy rates on the PICU. Figure 8 and Figure 9 show the occupancy rates for the two separate PICU units. Again, as on the NICU, high occupancy rates are achieved. The average occupancy on Pelikaan is 74.7% and on Leeuw 86.6%. An interesting example of a quarter with a high occupancy is Q12. In October to December, many patients with the RS virus were hospitalized at the WKZ. The RS virus is common in The Netherlands and mostly occurs in the winters. This virus causes an increase in patients to be treated at Pelikaan and Leeuw, which often have long durations of stay.

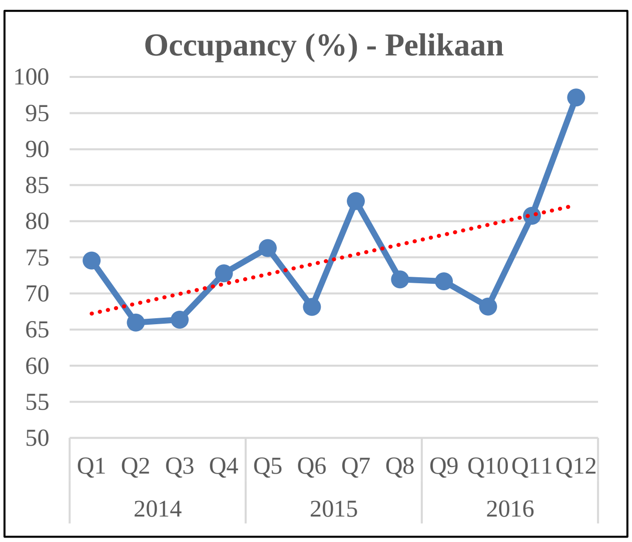



*Figure 8: Occupancy rate (%) on Pelikaan (n=2588, January 2014 - December 2016, UMC Utrecht)*

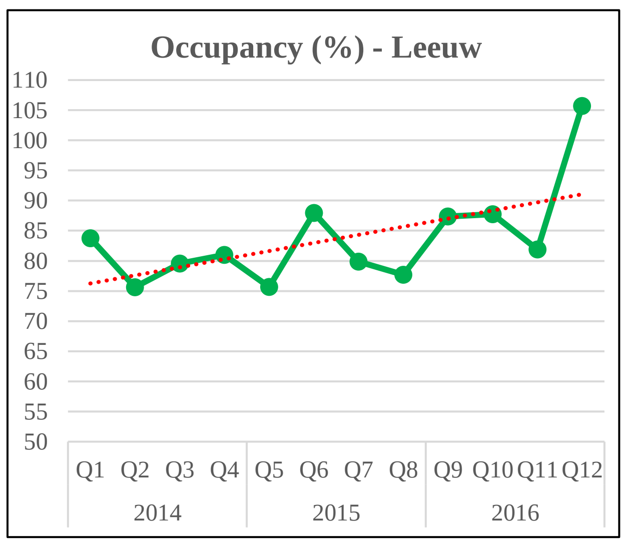



*Figure 9: Occupancy rate (%) on Leeuw (n=2066, January 2014 - December 2016, UMC Utrecht)*

Furthermore, as of Q10, Pelikaan and Leeuw started admitting respiratory care unit (RCU) patients. RCU patients have difficulty breathing, and can be assisted by means of a respirator. Figure 9 and Figure 8 visualize an exponential rise in occupancy rate due to this new patient group on the PICU. The red trendlines indicate that over the last three years, the occupancy has increased and are expected to continue to do so in the future.

In Figure 10, Figure 11, and Figure 12 the average occupancy per hour of the day is shown. This way, we provide an insight in the periods when it is structurally busy. As can be seen from all three figures, the occupancy rates are the highest in the nights and early mornings. This is because most patients get their transfer early in the morning. For example, the average occupancy on Pelikaan at 08:00 is 89.3%, compared to 79.6% at 18:00. Furthermore, Leeuw achieves percentages over 100% because at times more hospital beds than the theoretical capacity were deployed. However, these percentages do not reflect the work pressure on medical personnel. Especially for the PICU, during the day patients need much more medical attention. For the NICU this differs, since neonates do not have a day and night rhythm yet.

| NICU | |
|---|---|
| **Hour** | **Avg. Occupancy** |
| 00:00 | 87,1% |
| 01:00 | 87,3% |
| 02:00 | 87,4% |
| 03:00 | 87,6% |
| 04:00 | 87,7% |
| 05:00 | 87,9% |
| 06:00 | 88,0% |
| 07:00 | 88,1% |
| 08:00 | 88,2% |
| 09:00 | 88,1% |
| 10:00 | 87,9% |
| 11:00 | 87,6% |
| 12:00 | 87,1% |
| 13:00 | 86,6% |
| 14:00 | 86,3% |
| 15:00 | 85,9% |
| 16:00 | 85,8% |
| 17:00 | 85,8% |
| 18:00 | 86,0% |
| 19:00 | 86,1% |
| 20:00 | 86,4% |
| 21:00 | 86,6% |
| 22:00 | 86,8% |
| 23:00 | 92,2% |

*Figure 11: Occupancy NICU per hour (n=1848, January 2014 – December 2016, UMC Utrecht)*

| Pelikaan | |
|---|---|
| **Hour** | **Avg. Occupancy** |
| 00:00 | 79,8% |
| 01:00 | 88,8% |
| 02:00 | 88,9% |
| 03:00 | 89,0% |
| 04:00 | 89,1% |
| 05:00 | 89,2% |
| 06:00 | 89,3% |
| 07:00 | 89,3% |
| 08:00 | 89,3% |
| 09:00 | 89,0% |
| 10:00 | 88,4% |
| 11:00 | 84,5% |
| 12:00 | 82,8% |
| 13:00 | 82,1% |
| 14:00 | 80,2% |
| 15:00 | 79,7% |
| 16:00 | 79,7% |
| 17:00 | 79,6% |
| 18:00 | 79,6% |
| 19:00 | 79,6% |
| 20:00 | 79,6% |
| 21:00 | 79,6% |
| 22:00 | 79,7% |
| 23:00 | 79,8% |

*Figure 10: Occupancy Pelikaan per hour (n=2588, January 2014 – December 2016, UMC Utrecht)*

| Leeuw | |
|---|---|
| **Hour** | **Avg. Occupancy** |
| 00:00 | 105,8% |
| 01:00 | 106,0% |
| 02:00 | 106,1% |
| 03:00 | 106,1% |
| 04:00 | 106,1% |
| 05:00 | 106,1% |
| 06:00 | 106,1% |
| 07:00 | 105,8% |
| 08:00 | 106,0% |
| 09:00 | 105,9% |
| 10:00 | 105,2% |
| 11:00 | 103,0% |
| 12:00 | 102,7% |
| 13:00 | 102,0% |
| 14:00 | 101,1% |
| 15:00 | 101,2% |
| 16:00 | 101,2% |
| 17:00 | 102,7% |
| 18:00 | 102,7% |
| 19:00 | 103,0% |
| 20:00 | 105,4% |
| 21:00 | 105,7% |
| 22:00 | 105,9% |
| 23:00 | 105,9% |

*Figure 12: Occupancy Leeuw per hour (n=2066, January 2014 – December 2016, UMC Utrecht*

### 2.3.3 Arrival frequency

The third indicator that we discuss is the arrival frequency. By analysing the arrival frequency, we visualise the peaks and valleys in terms of demand for hospital beds. We do this by plotting the number of arrivals per quarter over the last three years. The sources of the arrivals are discussed in Section 2.1. Unlike the occupancy rates, the arrival frequency does take the number of operational hospital beds into account. This is because the provided dataset registers arrivals as follows:

$$Number\ of\ arrivals\ per\ quarter = \sum All\ patients\ hospitalised\ per\ quarter$$

The equation above shows that the arrivals are registered as hospitalised patients. However, not all patients that arrive at the WKZ can be admitted. For this research project, we do not see rejected requests for a bed as arrivals to the WKZ.

Figure 13 shows the arrival frequency of all patients on the NICU over the last three years. Due to the higher length of stay on the NICU, the average number of arrivals is less than on the PICU, as visible in Figure 14 and Figure 15. However, neonatologist Willem de Vries stated: “Other hospitals have started referring patients to our department, because our policy is to reject as few patients as possible” (de Vries, 2017). De Vries refers to the summer period where other hospitals ‘close’ beds. Resulting, throughout the year the NICU is structurally occupied. No seasonal trend is detected in Figure 13. As soon as a patient is dismissed from the WKZ, the designated spot is cleaned and prepared for the next arrival. A quarter with a lower number of arrivals is Q5. In this period, The Netherlands went through a period of low birth numbers. Hence, the NICU received less requests for an incubator. The same goes for Q8. This example shows that the number of ‘operational’ beds is not the only restriction for the number of hospitalizations in a period.

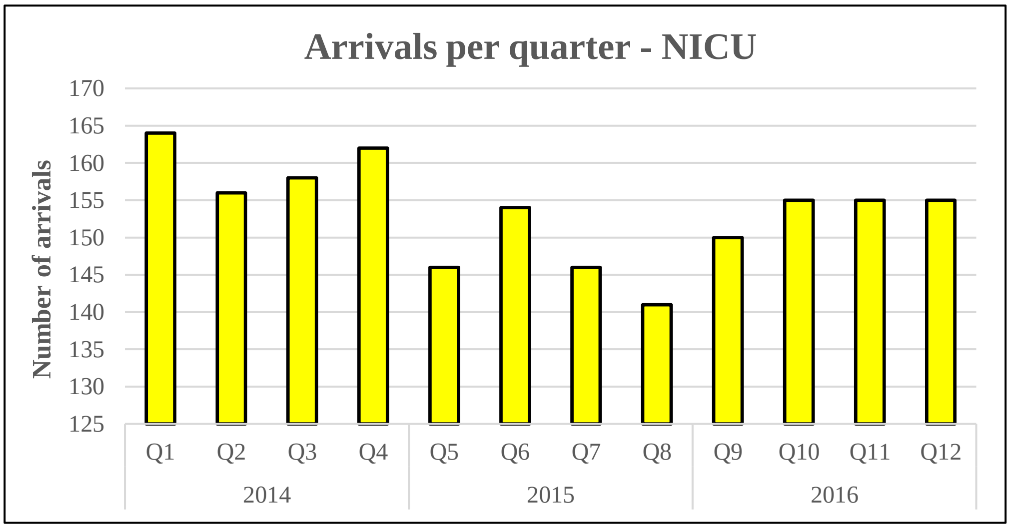



*Figure 13: Arrivals per quarter on NICU (n=1848, January 2014 - December 2016, UMC Utrecht)*

Figure 14 and Figure 15 provide insight in the arrival intensity on the PICU. On Pelikaan, the number of arrivals usually fluctuate between 175 and 225 per quarter. For Leeuw, the fluctuation is higher over the twelve quarters. Consistently, Q3, Q7 and Q11 have a lower number of arrivals. This quarter addresses the period July-October. The PICU admits less patients during the summer, because medical personnel are on vacation. Therefore, this shortage in staff causes the hospital to reject new arrivals. This is an example of a seasonal pattern on both Pelikaan and Leeuw.

Furthermore, when considering the future Harmonica, we can make an interesting observation. As mentioned, the Harmonica allows the interchanging of hospital beds. This way, high demand on one department can offset low demand on the other department. Figure 13, Figure 14 and Figure 15 show the application of this principle. In Q5 the NICU dealt with a low number of arrivals, while the PICU saw a high number of patients arriving. This is the same for Q8. When the departments start working together more intensively, this proves to be an opportunity to reduce the number of rejections.

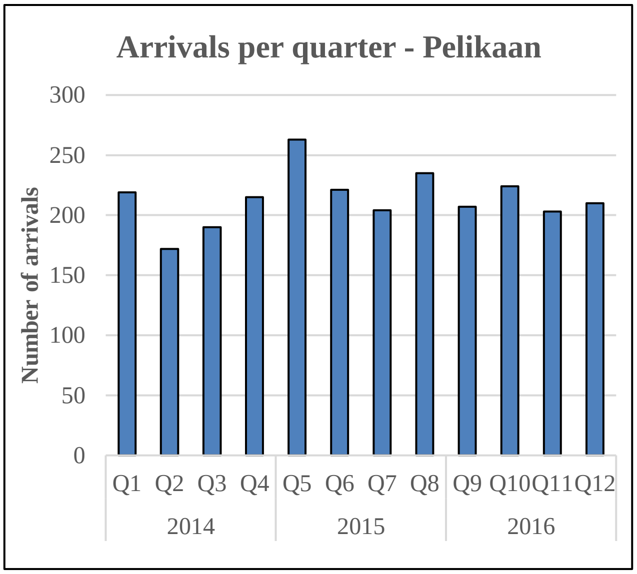



*Figure 14: Arrivals per quarter on Pelikaan*
*(n=2588, January 2014 - December 2016, UMC Utrecht)*

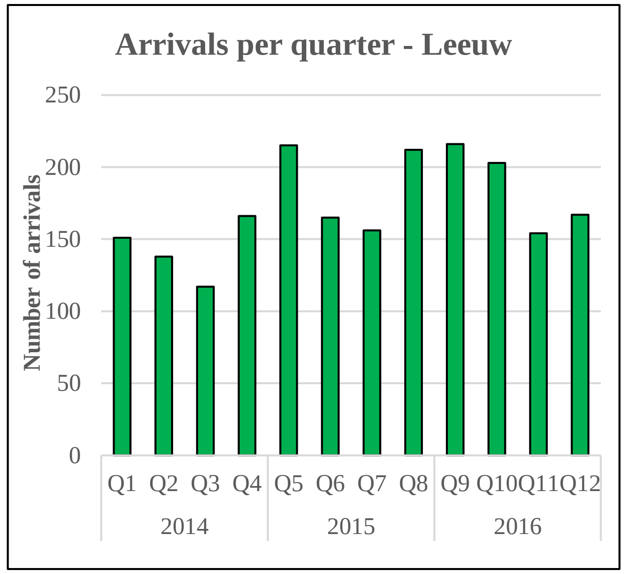



*Figure 15: Arrivals per quarter on Leeuw*
*(n=2066, January 2014 - December 2016, UMC Utrecht)*

### 2.3.4 Rejection probability

The last indicator we discuss is the rejection probability. This indicator measures the probability that an arriving patient is rejected treatment. Logically, every hospital ward strives to reject as few patients as possible. Every lost patient means lost revenue and a loss of goodwill. An arriving patient will only be rejected treatment if all operational hospital beds are occupied. Therefore, there is a positive correlation between the occupancy rate and the rejection probability. In the problem cluster, discussed in Section 1.2 we indicated that currently too many patients are rejected due to high occupancy rates. Furthermore, since this study excludes staffing issues, we observe the rejection probability as the probability that all theoretical hospital beds are occupied.

Unfortunately, we lack the necessary data to reliably represent the current rejection probability on the NICU and PICU. In Section 4.4.1 we will further discuss the rejection probability. Then, we will validate the output of our model with stakeholders.

## 2.4 Conclusion

In this chapter, we evaluate the current situation on the two departments of interest. We do this to give a substantiated answer to the research question: "*What will the total patient flow for the Harmonica be and what bottlenecks are expected?*" First, we visualize the care trajectory of patients on the NICU and PICU. This gives a structural picture of the patient flow for both the current situation and the future situation. Then, we identify all resources that are of relevance for the future Harmonica. Here, hospital beds, staffing issues and the medical equipment are discussed. This provides us with insight in the expected bottlenecks regarding resources. Lastly, we evaluate the performance of several indicators on the two departments. These indicators are the length of stay, the bed occupancy, the arrival frequency and the rejection probability over the last three years. This section visualizes the problem context and quantitatively supports the problem statement.

On average, patients on the NICU have a longer length of stay than on the PICU. Therefore, the turnover on the NICU is lower than on the PICU. For the PICU, most patients spend one to two days on Pelikaan or Leeuw. Long lengths of stay often indicate a high occupancy rate, which is reflected in the occupancy rates of the NICU and PICU. The average occupancy rate on the NICU is 88.2%, while for the PICU this is

74.7% (Pelikaan) and 86.8% (Leeuw). These high numbers indicate that while both departments use their beds efficiently, there is a high likelihood for rejection at times. The NICU shows a constant distribution of arrivals, while Pelikaan and Leeuw experience more seasonal influences.

After analysing the current situation, an intensified collaboration between the departments appears to be an improvement. In the future Harmonica, universal hospital rooms allow the interchanging of hospital beds. This way, high peaks in demand on one department can be offset by valleys on the other. This principle is called the pooling of hospital beds. This concept needs further explanation to identify all benefits and drawbacks. Furthermore, to determine the capacity layout, there are multiple modelling methods that are suitable to use. In Chapter 3, we conduct a literary study on which modelling method to use when determining the capacity layout for the future Harmonica.

# 3. Capacity dimensioning in literature

Now that the current situation has been analysed, a literature study will be conducted to find theoretical background on the main topic 'capacity dimensioning'. This chapter discusses the different models for capacity dimensioning that are found in existing literature. From the literature study, a method for modelling is selected. This can either be *Linear Programming (LP), Queueing* or *Simulation.* However, first a theoretical perspective is taken to delimit the extent of the literature study. This theoretical perspective is the hierarchical framework for health care planning and control, from a study by Hans et al. (2011).

## 3.1 Theoretical framework

With medical expenditures rising, there is an urging need for efficiency and effectiveness regarding processes in health care organisations. This calls for an organisation-wide planning and control mechanism. Within health care organisations, such a framework for planning and control differs from frameworks used in the manufacturing industry. This is due to the unique nature of the health care industry, and the problems that come with it. Examples of these problems are conflicts of interest between departments, a lack of training in resource allocation and the autonomously managed departments. However, an earlier study by Hans et al. (2011) constructed a framework for health care planning and control. "*Our framework integrates all managerial areas involved in health care delivery operations and all hierarchical levels of control, to ensure completeness and coherence of responsibilities for every managerial area*." This framework has been widely accepted and is used to form the theoretical perspective of this research project. The framework is discussed for its relevance to this project. In Figure 16 the framework is shown.

| | **Medical planning** | **Resource capacity planning** | **Materials planning** | **Financial planning** |
|---|---|---|---|---|
| **Strategic** | Research, development of medical protocols | Case mix planning, capacity dimensioning, workforce planning | Supply chain and warehouse design | Investment plans, contracting with insurance companies |
| **Tactical** | Treatment selection, protocol selection | ·Block planning, staffing, admission planning | Supplier selection, tendering | Budget and cost allocation |
| **Offline operational** | Diagnosis and planning of an individual treatment | Appointment scheduling, workforce scheduling | Materials purchasing, determining order sizes | DRG billing, cash flow analysis |
| **Online operational** | Triage, diagnosing emergencies and complications | Monitoring, emergency coordination | Rush ordering, inventory replenishing | Billing complications and changes |

← managerial areas →

↑ hierarchical decomposition ↓

*Figure 16: Hans et al. (2011) - Framework for health care planning and control*

On the horizontal axis, the four managerial areas of health care planning are shown. *Resource capacity planning* addresses the dimensioning, planning, scheduling, monitoring, and control of renewable sources. For this research project, all other managerial areas are excluded from the literature study. On the vertical axis, the hierarchical decomposition of the different planning levels is shown. The different levels are strategic, tactical, offline operational and online operational. Every level has its own time horizon and level of detail regarding decision-making. In the following section, each planning level is briefly discussed.

### 3.1.1. Strategic planning

The highest hierarchical level of decision-making is strategic planning. Strategic planning addresses structural decision making and is based upon aggregated information and forecasts. Once a strategic decision has been executed, it is not easily altered. This level of planning has the longest time horizon and often high expenditures are associated with the decisions made. For UMC Utrecht, the renovation program of the WKZ is an example of this form of planning. The number of single-person rooms that will be built is a strategic planning process. These rooms are made of bricks and mortar, and that sets the pace for decisions made at a lower planning level. Since this research project aims to give insight in the number of rooms that will be built, the strategic block of the framework is highlighted.

### 3.1.2. Tactical planning

Tactical planning addresses the strategic planning decisions on an intermediate time horizon. Tactical planning is more flexible than operational planning, but less detailed. Examples of this form of planning are staffing decisions, admission planning and budget allocation. For this research project, the tactical block has been highlighted alongside with the strategic block. This is because the number of single-person rooms that is built has an impact on the number of nurses that are scheduled. Given seasonal patterns, every patient per hospital room will have a fixed number of nurses assigned to it. Therefore, each additional room that is built indicates additional nurses to be deployed.

### 3.1.3. Offline operational planning

The lowest level of planning is called operational planning. The word ‘offline’ stands for decisions made *in advance*. This form of planning is short-term decision making, where capacity is set and the demand is known. This demand is based on the prediction of elective patient arrivals. Within the WKZ, day-to-day scheduling of staff and patients is done via offline operational planning. Staffing decisions made at a tactical level result in rostering of nurses on an operational planning level. However, the scope of this research does not focus on offline operational planning.

### 3.1.4. Online operational planning

Opposed to offline operational planning, online operational planning is *reactive*. This type of planning deals with unforeseen or unexpected events, such as the scheduling of emergency arrivals. When an emergency patient arrives, there must be an empty bed available. The emergency patient will have priority over an elective patient. Besides that, online operational planning also addresses replenishing depleted inventory, handling billing complications and triaging. For this research, the number of hospital rooms that is built, must accommodate a certain amount of emergency arrivals.

In Section 1.2 we applied the different levels of the abovementioned framework to the problem context of the WKZ. Figure 1 visualises the strategic, tactical and operational level of decision-making regarding capacity allocation. For example, the impact of IC patients that arrive on the NICU and PICU, is at an operational level of decision-making.

## 3.2 Concept matrix

Now that the theoretical framework has been discussed, the boundaries for the literature study are set. Within this literature study the centre of attention is on concepts, instead of the articles found. Therefore, this section describes a concept matrix where literature is assessed based on these concepts. In total, there are five concepts of relevance for this literature study. These concepts are:

- Capacity planning
- Pooling resources
- Queueing
- Linear Programming
- Simulation

First, the focus is on literature that describes capacity dimensioning or capacity planning in health care. This gives insight in the theoretical approach for making strategic resource planning decisions. However, in this literature study the type of medical resource is irrelevant. There is no difference if this resource is IC rooms, consultation rooms or another type of hospital room. Second, the application of 'pooling' in health care is described. The term *pooling* refers to the *"pooling of customer demands, along with pooling of the resources used to fill those demands"* in order to *"yield operational improvements."* (Cattani & Schmidt, 2005) Pooling resources then means grouping together resources to minimize variability or risk to increase profitability. This definition for pooling will from here on be used for the remainder of this report. Lastly, the literature on each modelling method is evaluated in combination with capacity dimensioning or pooling.

To conduct a successful literature study, a researcher must be selective when assessing articles. This selectiveness helps making the research more valid and reliable for future studies. Therefore, criteria for including or excluding articles in a literature study are drafted. In Table 3 these criteria for inclusion and exclusion are stated.

| Inclusion criteria | Exclusion criteria |
|---|---|
| Empirical papers with samples with medical institutes. These medical institutes can be large hospitals, clinics or smaller practices | Pre-2010 articles. Due to a large availability of articles, only articles after 2010 will fall under the scope of this literature study |
| Articles discussing *resource capacity planning* within health care. This is part of the health care planning and control framework | Articles that discuss medical planning, material planning or finance planning within health care. These three areas are the other managerial areas of the framework for health care planning and control |
| Articles discussing the methods *queueing, linear programming and/or simulation*. These models will help to get to an optimal solution | Articles that use other methods besides *queueing*, *linear programming* and *simulation* for optimization |
| Articles containing models those directly aim on the improvement of the performance of the process | Articles must be written in English |
| | Articles that discuss models that are not applicable in the healthcare industry |

*Table 3: Inclusion and exclusion criteria*

The criteria stated above are drafted from the theoretical perspective and common sense. Every criterion has its own contribution to the literature study. For example, by excluding all articles that discuss models for other industries except healthcare, it is guaranteed that the to-be-found model is applicable for the WKZ.

After selecting the five core concepts and drafting criteria, relevant articles can be searched for. All articles that add value to this research project are included into the literature study. This is done by constructing a concept matrix, where the articles are weighed and compared to arrive at a substantiated answer to a research question. In Figure 17, the concept matrix for this literature study is shown.

| | | | Concepts | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Author** | **Year** | **Title** | **Capacity (planning)** | **Pooling** | **Queuing** | **Mathematical Programming** | **Simulation** | **Evaluation** |
| Hulshof et al. | 2012 | Taxonomic classification of planning decisions in health care: A structured review of the state of the art in OR/MS | X | X | X | X | X | Every model must contain some slack capacity, due to emergency arrivals. 100% occupancy can never be achieved |
| Kozlowski et al. | 2012 | Discrete event simulation modelling for an improved patient flow at the Emergency Department | X | | | | X | A DES model is developed for decision-making for dimensioning the ED. Patient flow is visualised, what-if analyses are done |
| Rau et al. | 2013 | Using discrete-event simulation in strategic capacity planning for an outpatient physical therapy service | X | X | | | X | Advantages of DES are explained. Sensitivity analysis is done, the pooling of therapists proved to be beneficial for waiting times |
| Vanberkel et al. | 2012 | Efficiency evaluation for pooling resources in health care | X | X | X | | X | Discrete time slotted queuing model shows the trade-off between EOS and EOF. Simulation is used to fine-tune the results |
| " " | "" | " " " | | | | | | "Continuous time slotted queuing models are typically used to study the effects of pooling" |
| Li et al. | 2015 | Radiation queue: Meeting patient waiting time targets | X | X | X | X | | Queuing framework is proposed for considering time slots as servers and to pool patients to reduce the total number of time slots. |
| " " | "" | " " " | | | | | | Mixed-integer programming is used for capacity allocation and pooling optimization |
| Joustra et al. | 2010 | To pool or not to pool in hospitals: A theoretical and practical comparison for a radiotherapy outpatient department | | X | X | | X | Pooling queues is efficient when offering one type of service. High performance targets for urgencies make separation more beneficial |
| Hulshof et al. | 2013 | Tactical resource allocation and elective patient admission planning in care processes | X | | | X | | The described MILP model is useful for tactical resource allocation. Queuing results are often based on steady-state assumptions. |
| " " | "" | " " " | | | | | | This model can be of interest for dynamic decision-making such as staffing for the future Harmonica, or the number of beds allocated. |
| Chaussalet et al. | 2010 | Towards effective capacity planning in a perinatal network centre | X | | X | | | Queuing models require minimum data (arrival patterns + LoS) to estimate the number of beds for given levels of service. |
| " " | "" | " " " | | | | | | Model used takes issue of overflow into account. Rejection probability is set out against the number of cots (or capacity). |
| Song et al. | 2015 | The diseconomies of queue pooling: An empirical investigation of emergency department length of stay | | X | X | | | Improved flow management benefits are larger than the longer wait time predicted to arise from nonpooled queues |
| Green | 2011 | Queueing theory and modelling | X | | X | | | Queueing models are easy and cheap to develop and use, fast to run, do what-if analyses, identify trade-offs and aid decision-making |
| Monks et al. | 2016 | A modelling tool for capacity planning in acute and community stroke services | X | | | | X | Planning models that rely on average occupancy only will greatly underestimate bed requirements as they overlook variability |
| Green et al. | 2015 | A study of New York City Obstetrics Units demonstrates the potential for reducing hospital inpatient capacity | X | | X | | | Capacity needs are estimated on the probability of delay experienced by patients. Queueing applicable for other inpatients units as well |

*Figure 17: Concept matrix*

The concept matrix assesses twelve articles for their relevance. The concept matrix also has an 'Evaluation' section, where a brief description of every article regarding its relevance for this literature study is stated. This evaluation is focussed on finding the contribution of every article to the research question: "*What models are known in literature for making 'resource capacity planning' decisions in health care organisations?"* In the following section, the main literary findings of every concept are discussed.

### 3.2.1 Capacity dimensioning

The literature study is primarily focussed on capacity dimensioning or capacity planning. However, the term 'capacity dimensioning' is not common in the literature. Therefore, the term 'capacity planning' is used to find relevant literature on this topic. As mentioned earlier, capacity dimensioning lies in the strategic level of resource capacity planning. Capacity dimensioning is a long-term decision-making process which has influence on the lower hierarchical levels. Resulting, operational performances come from decisions made at a strategic level.

In this research, the number of single-person rooms to build is dimensioned. Hulshof et al. (2012) take a general perspective on capacity dimensioning and suitable methods to use. These methods are computer simulations, heuristics, Markov processes, mathematical programming, queueing and literary reviews. Each method will have its own benefits and drawbacks when dimensioning capacity in health care. These benefits and drawbacks will be discussed in Section 3.2.3, 3.2.4 and 3.2.5. More specifically, the capacity decisions made can have an impact on other, interdependent care units. Therefore, the capacity should be balanced across the care units. Furthermore, this article stresses the importance of slack capacity when considering bed occupancy. They state that due to randomness in the number of arrivals and the length of stay, care units can never operate at a 100% occupancy rate. Care units also deal with emergency patients that can arrive at any time. Within the WKZ, the principle of slack capacity applies as well. The NICU and PICU aim to achieve the highest possible occupancy, while minimizing the number of rejections. As mentioned, each rejection results in lost revenue and a loss of goodwill. This co-dependency between the occupancy and rejections must be acknowledged and used when planning capacity. Lastly, a fixed occupancy rate can never be the guideline when determining capacity. This will result in many rejections or excessive delays. The desirable occupancy level should be calculated as a complex function of the service mix, the number of beds and the length of stay distribution. This statement is justified by Monks et al. (2016), which claim that "*planning models that rely on average occupancy only will greatly underestimate bed requirements as they take insufficient account of variability*."

The other articles do not address capacity dimensioning or planning this specifically. However, one vision is shared amongst all articles. There is an urging need for efficiency and effectiveness due to increasing demand and expenditures in health care.

### 3.2.2 Pooling resources

The term 'pooling' has been described in Section 3.2 as the *pooling of customer demands, along with pooling of the resources used to fill those demands"* in order to *"yield operational improvements."* This section describes the main findings regarding the pooling of resources in the health care industry.

A large amount of research investigates the applications, benefits and drawbacks of pooling in the manufacturing industry. However, the application of pooling in the health care industry is a more recent practice. Vanberkel et al. (2010) provide insight in the trade-off between economies of scale and economies of focus. In economies of scale, all resources are pooled and the result is a reduction in variability due to a portfolio effect. The portfolio effect means adding more assets to a portfolio to decrease the risk. On the other hand, economies of focus results in less complexity and more focus on a limited range of services.

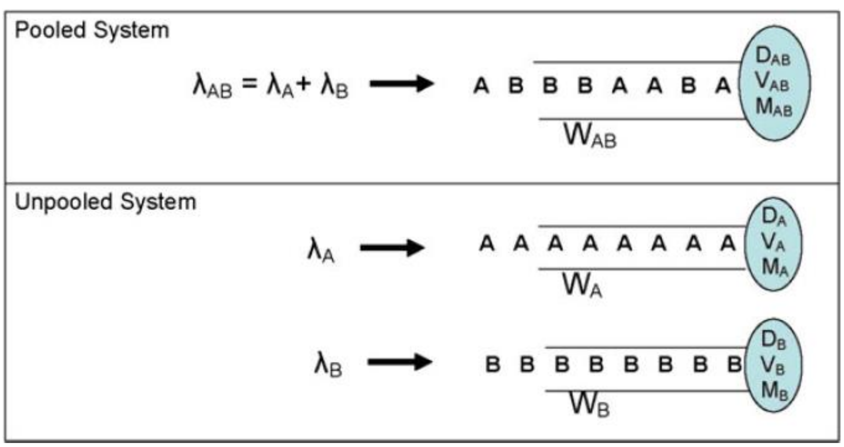



*Figure 18: Vanberkel et al. (2010) – Pooled and unpooled systems*

Vanberkel et al. (2010) propose a discrete time slotted queueing model to evaluate the trade-off between economies of scale and economies of focus. Figure 18 shows the basics of a pooled system versus an unpooled system. Every system has its own expected waiting time (W) average appointment length (D), variance of appointment length (V) and number of rooms (M). The article concludes by mentioning that the benefits of pooling differ per clinic load, proportional size of the patient groups, bed division and variability in appointment length.

Another study by Joustra et al. (2010) states that pooling two separate queues is generally perceived to be efficient. Pooling is useful when offering one type of service. This is because customers can then be processed by any server from a pool, instead of waiting for a specific server to become available. For this research project, since the Harmonica allows the interchanging of beds, pooling seems to be efficient. However, when high performance targets for urgent patients are set, separation of queues might be more beneficial. An example is when 80% of the patients must have their first consultation within five calendar days after the date of referral. In the study by Joustra et al. (2010), separation even slightly improves the performance in terms of mean waiting time service levels.

Additionally, later research by Song et al. (2015) shows that unpooled systems at an Emergency Department deliver improved flow management benefits. These benefits outweigh the longer waiting times that unpooled systems create. This is because physicians have greater ownership over patient flow and the resources needed to smooth flow through the Emergency Department. However, in that study the type of resource is 'physicians' opposed to the 'single-person rooms' of this research project.

Now that the findings of 'capacity dimensioning' and 'pooling resources' have been discussed, the literature regarding the methods for capacity decision-making can be evaluated.

### 3.2.3 Queueing

The queueing theory was first introduced in 1904 by Erlang, with its application for the Danish telephone system. Erlang wanted to know how many servers were necessary to prevent the customers from waiting too long for an available circuit. When realizing that the minimization of waiting times was applicable to other fields, this theory was further developed.

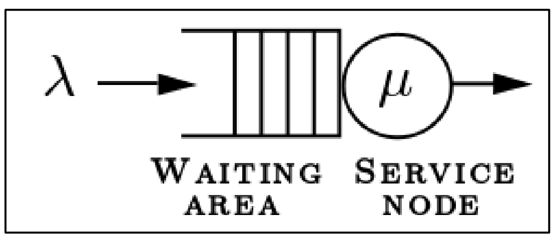



*Figure 19: Basic queueing model*

Nowadays, there are multiple queueing models for every type of queue. The most basic form of queueing is called the M/M/1-model, where arrivals are Poisson distributed and service times are exponentially distributed. The arrival intensity has the parameter $\lambda$ and the service duration has the parameter $\mu$. Figure 19 shows a visualisation of this queueing model. Arrivals can either be directly processed by a server or must join the queue waiting for service. An important assumption when constructing queueing models is a steady-state, where parameters such as the arrival intensity are constant on the long-term.

There are many literary articles that show the practical application of queueing theories in medical institutes. Logically, every case study requires its own application of a queueing model to generate a solution. However, there is a general understanding of the benefits of queueing models. Green (2011) states that queuing models are easy and cheap to develop, fast to run, support what-if analyses, identify trade-offs and aid decision-making. Queueing can be used in long-term capacity planning.

An earlier study by Chaussalet et al. (2010) queueing is used for capacity planning on the Neonatal IC and the High Dependency Unit. This study tested several scenarios to estimate the optimal number of cots to place at the care units. The number of beds is set out against the rejection probability, which serves as a capacity planning tool. A drawback of this study is the use of one year's worth of data. This excludes possible seasonal or periodic variations in demand which have influence on capacity. However, this study states that benefits of queueing are minimum data requirements, only random arrival patterns and lengths of stay, to estimate the capacity needed to attain a service level. In a similar study, Green et al. (2015) show the practical application of queueing on obstetrics units.

An important statement from Vanberkel et al. (2010) is that continuous time slotted queueing models are typically used to study the effects of pooling. Since Intensive Care units are open day and night, these care units do not empty at night and therefore only continuous time slotted queueing models should be used.

But there are also drawbacks to the use of queueing models in practical situations. Firstly, the simplicity of queuing models is often criticised. The level of detail is often limited and dynamic environments are often not suited for queueing. Furthermore, queueing models are based on assumptions regarding reality. Examples are the assumption of a steady-state, no balking or reneging from a queue or the 'First Come First Served' (FCFS) queue discipline (Li, Geng, & Xie, 2015).

### 3.2.4 Linear Programming

Another method of modelling suitable for capacity planning is linear programming. Linear programming is an optimization method with makes use of mathematical models. The first linear programming formulation stems from World War II, where in 1939 Kantorovich proposed a mathematical model to reduce army expenditures. However, literature on the term 'linear programming' in combination with 'capacity planning' or 'pooling' is scarce. Therefore, the term 'mathematical programming' is used to find a larger pool of relevant articles.

Li et al. (2015) propose a Mixed-Integer Linear Programming (MILP) model for linear accelerator (LINAC) capacity allocation and case-mix optimization. This is done to meet the targets regarding waiting times (WTT) per patient. However, before mathematical programming, a queueing model is applied to pool patient types and reduce the total number of LINAC time slots needed to meet the WTT.

A model for tactical resource allocation via MILP, which aims to achieve equitable access and treatment duration for patient groups, is proposed by Hulshof et al. (2013). Besides equitable access, the model also strives to serve the strategically agreed number of patients. This model can also be used for allocation of beds for departments, staffing and other tactical decision-making processes. The objective function is shown in the following equation, where $\beta$ represents the weight per patient in the queue and $W$ the number of patients in the queue at the start of time period $t$:

$$\min \sum_{j \in J} \sum_{n=0}^{\infty} \sum_{t \in T} \beta_j^n W_{j,t}^n$$

Mathematical programming is useful for optimization in dynamic situations. This is because this form of programming is iterative, where weights are constantly updated and optimal solutions are determined. However, there are also drawbacks to this method of modelling. For example, in dynamic businesses, the use of only one objective such as the minimization of costs is too focussed. Furthermore, LP models assume linearity between an objective function and the constraints. However, in practice this is not always the case.

### 3.2.5 Simulation

The last modelling technique that can be used for capacity decision-making is simulation. Using simulation, the reality is imitated, "*to examine a problem often not subject to direct experimentation*" (Merriam-Webster, 2017). Different scenarios can be tested to gain insight in processes or to provide a solution towards stakeholders. Popular simulation programs are Technomatrix Plant Simulation, MATLAB and SIMUL8.

Kozlowski et al. (2012) propose a discrete event simulation model, to help dimensioning the Emergency Department. Via the simulation model, patient flow has been visualized and what-if analyses are done. Monks et al. (2016) make use of a simulation model within the acute and community stroke services. A scenario is tested where acute and rehab beds are pooled, which provided efficient results. Simulating indicated that an increase from 10 to 14 acute stroke unit beds reduces the number of patients experiencing delays from 1 in every 7 patients to 1 in every 50. Rau et al. (2013) show via simulation that the pooling of therapists is beneficial in an outpatient physical therapy centre. Concluding, there are many advantages when using simulation models for capacity decision-making. It is transparent, flexible to express process dynamics and logic, suitable for complex problems and it can include individual attributes. This modelling method is usually used to fine-tune the results gained from queueing practices. Therefore, a basic knowledge of queueing is required when starting a simulation program.

The drawbacks of simulation are that this method is often time consuming, it takes expertise to build, data requirements are high and it can be expensive to develop.

## 3.3 Relevance for this research

In the previous section, the main findings for each of the five concepts are discussed. The concepts 'capacity dimensioning' and 'pooling' and their applications are explained and the methods for modelling are evaluated. In this section, the relevance of the findings regarding this research project is discussed.

The literature study is mainly focussed on capacity dimensioning. Hospitals should never strive for 100% bed occupancy on a care unit, due to randomness in the number of arrivals and the lengths of stay. Furthermore, a fixed occupancy rate can never be the guideline when determining capacity. In the case of the WKZ, there are many emergency patients arriving at the NICU and PICU. Therefore, there must be slack capacity to accommodate these arrivals. A trade-off will be presented to determine the exact capacity, instead of a fixed occupancy rate. This trade-off shows the trajectory of the factors 'rejection probability', the 'occupancy rate' and the 'number of single-person rooms'.

Pooling is found to be useful when offering one type of service. All customers can then be processed from a pool of servers, where waiting time is significantly reduced. Other results are a reduction in variability due to the portfolio effect. The pooling results are often referred to as economies of scale. Unpooled systems result in more focus and less complexity. In the future, the Harmonica in the WKZ facilitates the interchanging of beds between departments. Beds are drawn from a large pool of universal beds. This way, high peaks in demand on department A are offset by lower demand on department B. This offsetting causes a reduction in variability for the Harmonica.

The first modelling method reviewed from literature is queueing. Queueing is used as capacity planning tool, where the rejection probability is set out against physical capacity. Queueing models are easy to develop, require minimum data and support what-if analyses, but there are many simplifications and assumptions that come with this method. The Harmonica will require unique simplifications and assumptions, but queueing models can support much desired what-if analyses.

MILP models are useful for capacity allocation of LINACs and case-mix optimization. This is done to meet the patient waiting time targets. However, the WKZ does not allow waiting times. Via MILP, tactical resource allocation model can be provided. Concluding, linear programming is most suited for dynamic situations such as bed allocation or staffing decisions.

Simulation is a common method for capacity-planning decisions. This method for modelling is transparent, supports scenario testing and is a fine-tuner, but developing a model is time-consuming and is most suited for complex problems. For the Harmonica, scenarios must be tested and transparency is preferred, but the might not be the most efficient modelling method.

## 3.4 Conclusion

This literature study starts with the theoretical framework, which sets the boundaries for the literature study. Within the framework for health care planning and control, we highlight the strategic and tactical blocks of resource capacity planning. After that, we construct a concept matrix for literature on five concepts to evaluate articles for their relevance. Eleven articles all have their contribution towards the research question: "*What models are known in literature for making 'resource capacity planning' decisions in health care organisations?"* Per concept, we summarize the main literary findings. However, the WKZ is a unique environment with its own specifications. Therefore, the previous section indicates the relevance of the concept-findings towards this research project.

The aim of the literature study is to identify the models used for 'resource capacity planning' and evaluate their pros and cons. The 'pooling' of hospital beds will be used in the future Harmonica, and therefore the modelling method should support this technique. Queueing is an easy-to-use method which does not require much data for capacity decision-making. It is based on assumptions such as the steady-state and simplifies the reality into a model. Linear programming is an iterative method which is useful in dynamic environments. In every LP model, an objective function is either maximized or minimized. Simulation is an imitation of reality, which provides a transparent and flexible view on process dynamics and logic. This method is often used to fine-tune the results gained from queueing.

In Chapter 2, we perform a data analysis of the two departments. This data will be used as input for the model constructed in Chapter 4. When we consider the available data and evaluate the results of the literature study, the most suitable modelling method used for this research project will be *Queueing*. We base this decision on three factors; the WKZ environment, the time horizon and the available data. First, since the allocation of single-person rooms is a long-term decision, steady-state assumptions must be made. Meaning, in the future the environment of the Harmonica is assumed to be constant. This indicates a strategic and tactical decision-making context. In general, queueing models are more suitable for steady-state environments than LP models or simulation programs. Although LP models result in a more optimal solution and simulation programs provide more detail and transparency, queueing is more suitable for the situation at hand. Second, the ease to develop a queueing model within the time horizon of this project increases validity and precision. Queueing models are fast to develop, opposed to simulation programs. Lastly, queueing models require little input to generate a steady-state output and support in decision-making. Therefore, given the simplicity of the provided datasets, queueing seems more practical than simulating or linear programming. The next chapter constructs a queueing model with assumptions and simplifications suited for the Harmonica. We test several scenarios and present the trade-off for the WKZ.

# 4. Queueing model

In Chapter 3 we provided a theoretical background on queueing in healthcare. We showed the application of queueing, alongside with the benefits and drawbacks of this modelling method. Now, the practical use of a queueing model is analysed in this chapter. A specific queueing model is developed that is adjusted to the environment of the WKZ. Using this model, we can deliver the WKZ a trade-off on capacity allocation for the future Harmonica. Section 4.1 lists assumptions and simplifications that are needed when translating the reality into a theoretical model. Section 4.2 describes the relevant input data that is used for the queueing model. The data analysis done in Chapter 2 forms the substantiation of this section. Section 4.3 describes the scenarios that are tested with the queueing model, which are determined via stakeholder meetings. After the testing phase, Section 4.4 shows the results of the tests and evaluates the outcomes. Section 4.5 concludes by summarizing the main findings. These main findings will form the basis for the recommendations in Chapter 5.

## 4.1 Assumptions and simplifications

When constructing a queueing model that represents reality as accurately as possible, assumptions and simplifications need to be made. These assumptions and simplifications are part of conceptual models. Robinson (2008) identifies five elements of a conceptual model; understanding the problem situation, determining the project objectives, identifying model inputs and outputs, and determining the model content via assumptions and simplifications. We discuss the inputs of the queueing model in Section 4.2. The objectives of the queueing model are identified in Section 1.3 and the problem situation is contextualised in Section 2.3. This way, we cover all aspects of the conceptual model. Regarding assumptions and simplifications, queueing models are less visual and detailed than simulation models and therefore need to be described as precisely as possible. Furthermore, as the WKZ is considering implementing one of our proposed scenarios, we must ensure that every aspect of reality is covered.

### 4.1.1 Assumptions

Researchers make assumptions for aspects of reality that are uncertain of believed to be true. Robinson (2014, p. 82) states that these assumptions fill in gaps in our knowledge about the real world. However, the model must maintain a representative level of detail, so that conclusions can be drawn from the tested scenarios. Below, the assumptions for the queueing model are listed.

1. The arrivals are Poisson distributed (with rate $\lambda$) and the interarrival times are exponentially distributed (with rate $1/\lambda$). All arrivals are independent of each other.
2. The introduction of the Harmonica does not affect the arrival process of patients.
3. The servers are the single-person rooms (or hospital beds) on a department.
4. The service times have a lognormal distribution. The service time (with mean $1/\mu$) is the length of stay for an individual patient on either the NICU, the Pelikaan or Leeuw. The dismissal procedures are independent of each other.
5. The expected case mix distribution of future patients is known.
6. The pool of customers yet to arrive at the WKZ is infinite.
7. The allocation of idle hospital beds is FCFS, meaning that the patient that requested treatment first has priority over customer requests of a later timestamp.
8. As mentioned in Section 2.2.1, we assume that in the future situation there will be no restriction on other resources than hospital rooms. Staffing issues are excluded from the scope of this research, while medical equipment is sufficiently available. Therefore, we assume that medical staff is always deployable and there are no shortages or breakdowns of equipment.

### 4.1.2 Simplifications

In this section, we list the relevant simplifications for the queueing model. Simplifications are an abstraction of the real world, "*which enable more rapid model development and use, and improve transparency*" (Robinson, 2014). However, these simplifications must not decrease the validity or credibility of any model. Hence, to establish a sufficient level of credibility, the scope and level of detail of a model must be adjusted to stakeholder preferences. Therefore, we constructed the simplifications by discussing with stakeholders of the WKZ.

1. The server experiences no delay when finishing the service of one customer and starting service with the next customer. Immediately after a customer is processed by a server, a new arrival can be processed by this server.
2. The WKZ does not allow any queueing for hospital beds. Therefore, the maximum number of patients in the system is equal to the number of servers in the system. Meaning, if a request for a hospital bed arrives when all beds are occupied, this request is rejected. The absence of a queue also indicates that the possibility of balking, reneging and jockeying is excluded.
3. No distinction is made between elective and emergency patients regarding capacity allocation.
4. Pre-emption, or stopping service to start servicing an emergency patient, is not allowed.
5. Staffing issues are excluded from the queueing model. Resulting, the number of operational servers is not affected by the deployment of staff.

Now that we listed the assumptions and simplifications, we give the notation for our queueing system. The queueing model that we use for scenario testing is a M/G/c/c-model. The $M$ stands for a Poisson arrival process with interarrival times that are exponentially distributed. The $G$ states that service times have a general distribution. The first $c$ stands for the number of servers that are operational, while the second $c$ indicates that no queueing for hospital beds is allowed, as the maximum number of customers in the system is equal to the number of servers operational.

### 4.1.3 Conceptual model validation

We conclude Section 4.1 with conceptual model validation. Since the conceptual model forms a means of communication between all parties, validation is essential. First, the assumptions can be validated by assessing both the confidence and impact of every assumption. If the impact of an incorrect assumption is high, it endangers the validity of the conceptual model. Therefore, we constructed the assumptions mostly from theory on statistics and discussions with stakeholders. This convinces us of the correctness of the assumptions of the real world. The effect of an incorrect assumption is therefore minimized as well. Second, since the simplifications are established with the stakeholders, we make sure that the stakeholders have confidence in our conceptual model. Altogether, by executing the actions above, we establish a viable blueprint for our queueing model.

## 4.2 Input data

In this section, we discuss the input data that is used for our queueing model. Input data are quantitative data and is derived from the central information system of UMC Utrecht called HiX. As mentioned in Section 2.3, this historical data has a time horizon from 1-1-2014 until 31-12-2016. We interpret this data through discussion with the IT team and through visualization with graphs. By doing this, we transform the data to information. The performance evaluation in Section 2.3 is based on this approach. We discuss the following input parameters; arrival rate, service time and number of servers in the system. Hereafter, we validate whether the data used for input is accurate enough for decision-making processes.

### 4.2.1 Parameter estimation

Capacity dimensioning is a strategic decision-making process. On the long-term, both the input and output parameters of the queueing model are assumed to be in steady-state. Meaning, the parameters that are estimated are assumed to attain the same values in the upcoming years.

First, we estimate the parameter for the arrival rate of patients. We give an overview of the raw data used for this estimation in Appendix A. The probability distribution of patient arrivals is Poisson with rate λ. This parameter λ is the rate in which patients arrive consecutively per unit of time. The average time until the next patient arrives has mean 1/ λ and is called the interarrival time. We estimate the parameter λ by applying the formula presented by Winston (2004):

$$\text{Estimated arrival rate} = \lambda(\text{est.}) = \frac{n}{\sum_{i=1}^{n} t_i}$$

Here, $n$ stands for the total number of arrivals and $t_i$ is the interarrival time between arrival $i$ and arrival $i$+1. For the NICU, Pelikaan and Leeuw we estimate the arrival rate by applying this formula. Table 4 gives an overview. On average, the Pelikaan experiences the highest intensity in terms of patient arrivals.

| Unit | Arrival rate (λ) in days | Interarrival time (1/λ) in days |
|---|---|---|
| **NICU** | 1.6882 | 0.5923 |
| **Pelikaan** | 2.3519 | 0.4252 |
| **Leeuw** | 1.8856 | 0.5303 |

*Table 4: Arrival parameters*

Second, we estimate the mean time to complete service, which we also refer to as length of stay. The service times are exponentially distributed with rate µ. This parameter µ is the rate in which patients finish their treatment and are dismissed per unit of time. The mean time to complete service or the average length of stay is 1/µ. We estimate the parameter µ by applying the formula presented by Winston (2004):

$$\text{Estimated service rate} = \mu(\text{est.}) = \frac{n}{\sum_{i=1}^{n} s_i}$$

Here, $n$ stands for the number of patients and $s_i$ represents the service time of each patient. Table 5 gives an overview of the service parameters per unit. Neonates require a longer period of care than patients on the PICU. Patients on the Leeuw are dismissed the fastest, since Leeuw mostly serves as a post-OR unit. Even though the arrival rate on the NICU is the lowest, the mean time to complete service is much higher than on Pelikaan and Leeuw. This explains the high occupancy rates that are achieved on the NICU.

| Unit | Mean time to complete service (1/µ) in days | Service rate (µ) in days |
|---|---|---|
| **NICU** | 16.8631 | 0.0594 |
| **Pelikaan** | 4.5590 | 0.2193 |
| **Leeuw** | 3.9538 | 0.2529 |

*Table 5: Service parameters*

Besides the parameters of the current units, we must estimate the parameters of the future PMC patients as well. The WKZ states that in 2018, yearly 2,600 nursing days of treatment will be used for PMC patients. The PICU, who will accommodate these patients, estimates that the average service time (1/µ) will be seven days. Resulting, the $\lambda$ of the PMC is: $\left(\frac{2600}{7}\right) * \frac{1}{365} \approx 1.0176\ \text{PMC patients/day}$. PMC patients have oncological conditions and therefore require a longer per0069od of care. Regarding capacity allocation, the PICU estimates that 9 single-person rooms are needed to accommodate PMC patients.

Lastly, we describe the number of servers in our queueing model. The number of servers is the physical capacity in terms of single-person rooms. Single-person rooms will replace room nursing in the future Harmonica. There will be 67 single-person rooms, similar to the current capacity, from which currently 35 are assigned to the PICU and 32 to the NICU, as described in Section 2.2.1. Opposed to the arrival rate and mean time to complete service, we vary the allocation of servers. The experiment settings of the number of servers are further described in Section 4.3.

### 4.2.2 Data validation

The input data has a large impact on the accuracy and reliability of the output. Therefore, it is important that the modeller validates whether the data used as input is accurate enough. We validated the input data by discussing the provided Excel sheets with the IT team. By visually checking the datasets, we ensured that the data is in the right format. Besides, it is important that an appropriate statistical distribution is selected when modelling. As an example, we show Figure 20 where the Poisson distribution is plotted against the arrival frequencies on the Pelikaan. Overall, the observed values are close to the expected values. Hence, the Poisson distribution is appropriate for the arrivals on the Pelikaan. Appendix B further discusses the fitting of statistical distributions to the empirical data that we received.

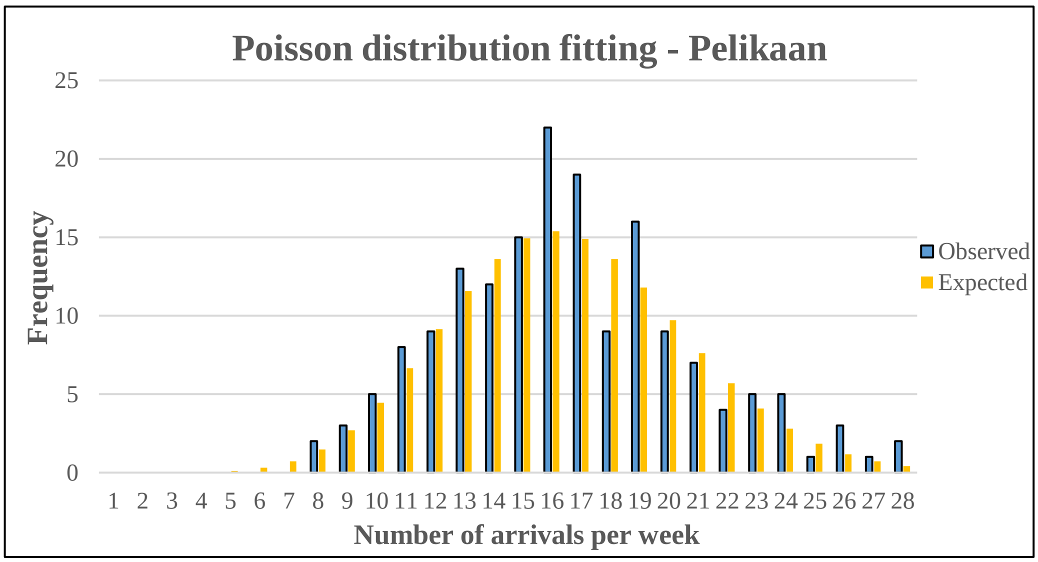



*Figure 20: Poisson distribution fitting on Pelikaan arrival data (n=2588, January 2014 - December 2016, UMC Utrecht)*

Hereafter, we conducted additional data validation steps. Within the datasets, we excluded all duplicates and cells that were missing values. Furthermore, we got an explanation for outliers in the length of stay by discussions with heads of department. These stakeholders are of great value when interpreting input data.

We acknowledge that historical data does not provide the best indication for the future. Historical data cannot predict trends in future arrivals or new epidemics. However, by choosing a three-year time horizon we ensure that any seasonal trends are included and more accurate averages are calculated.

## 4.3 Scenario description

Now that we constructed the conceptual model, we can discuss the scenarios that are of interest to the WKZ. We see every scenario as a capacity allocation, which includes the number of rooms assigned to either the NICU, the PICU or the hybrid. The total sum of single-person rooms always equals 67, which is the maximum number of rooms available. Each scenario results in an occupancy rate and rejection probability.

We test the scenarios with the program QtsPlus, which is an application within Excel. QtsPlus is a simple and understandable program suitable for testing different scenarios. The scenarios are conducted after several stakeholder meetings. Within the capabilities of QtsPlus, the stakeholders stated their preference towards certain scenarios.

Now, we visualise the future situation for the Harmonica. Figure 21 gives an overview of the queueing model which identifies the arrivals and servers. The NICU and PICU will have a fixed number of single-person rooms assigned. The hybrid will have a fixed number of rooms assigned as well, but these rooms are both deployable for the NICU and PICU. This pooling effect makes the hybrid attractive for the WKZ. High demand on one department can be offset by low demand on the other department. Hence, the hybrid will function as a buffer for both the NICU and PICU. Concluding, each scenario influences the parameter $\mu_c$, which is the maximum number of servers for each unit.

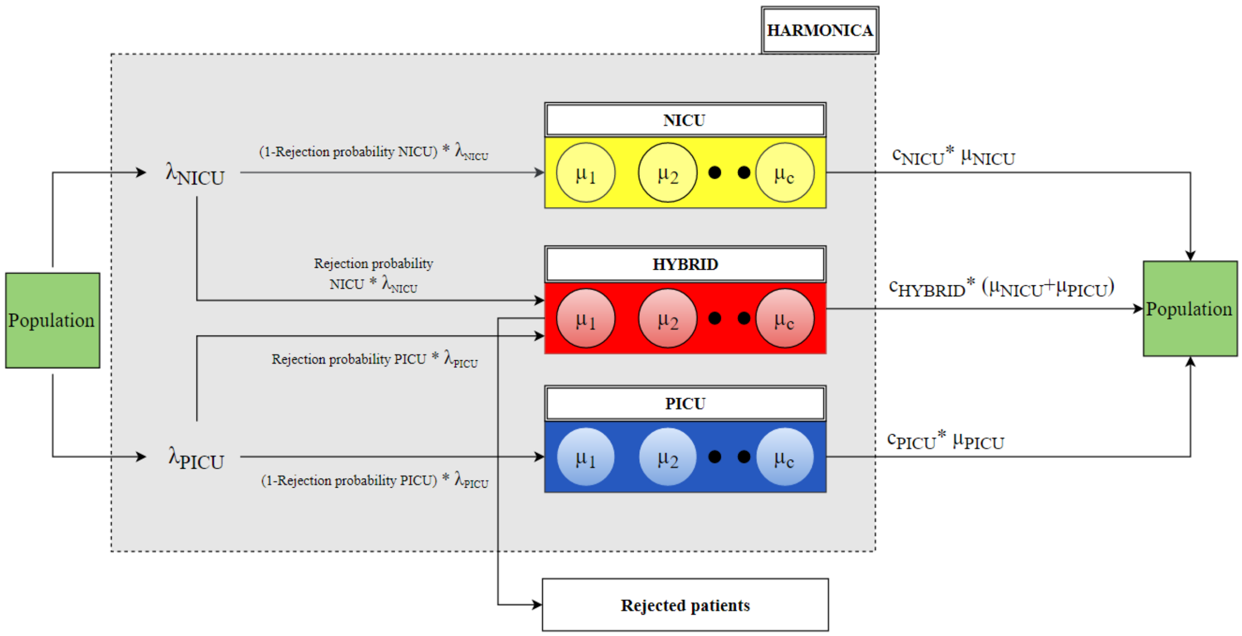



*Figure 21: Visualized queueing model for the Harmonica*

The parameter $\lambda_{PICU}$ is calculated as follows: $\lambda_{PICU} = \lambda_{Pelikaan} + \lambda_{Leeuw} + \lambda_{PMC} = 5.2551\ patients/day$. Furthermore, if the NICU or PICU is fully occupied, patients are referred to the hybrid. Therefore, this hybrid also has an arrival intensity. We determine the parameter $\lambda_{HYBRID}$ as follows: $\lambda_{HYBRID} = (\lambda_{NICU} * rejection\ prob.on\ the\ NICU) + (\lambda_{PICU} * rejection\ prob.on\ the\ PICU)$. However, since the rejection probability depends on the allocated capacity, $\lambda_{HYBRID}$ differs per scenario. Note, the rate in which patients are rejected treatment on the hybrid is the rate in which patients are rejected on the Harmonica.

Furthermore, we estimate the average service time on the hybrid as well. We do this by constructing the following formula:

$$Average\ service\ time\ on\ the\ hybrid = \left(\frac{Rate\ of\ rejected\ patients\ on\ the\ NICU}{\lambda_{HYBRID}} * \frac{1}{\mu}\ NICU\right) + \left(\frac{Rate\ of\ rejected\ patients\ on\ the\ PICU}{\lambda_{HYBRID}} * \frac{1}{\mu}\ PICU\right)$$

The average service time on the hybrid depends on the type of patients that arrive. If there are more PICU than NICU patients on the hybrid, the lengths of stay tend to be shorter. The parameter $\mu_{HYBRID}$ differs per scenario, because each scenario allocates the capacity differently, which impacts the rate of rejected patients on the NICU and PICU. In the following section, we describe the four scenarios we test in detail.

### 4.3.1 Scenario 1: "Validation and verification"

The first scenario that we test is the capacity allocation of the current situation. Based on the current situation, we allocate 32 rooms to the NICU, 35 to the PICU and 0 to the hybrid. This allocation has been determined by management of the WKZ before the start of this research project. Table 6 shows an overview.

| Unit | Number of single-person rooms |
|---|---|
| **NICU** | 32 |
| **Hybrid** | 0 |
| **PICU** | 35 |

*Table 6: Capacity allocation based on current situation*

We also use this scenario to validate the constructed queueing model for the WKZ. The values that the queueing model returns must approximately be the same values as in the real world. As the QtsPlus model returns occupancy rates as output, we compare this output with the values described in Section 2.3.2. This type of validation is called black-box validation. Overall, black-box validation ensures that the model has sufficient accuracy to meet the objectives of this queueing study. Figure 22 visualises the principle of black-box validation. Section 4.4.1 discusses the results of the black-box validation.

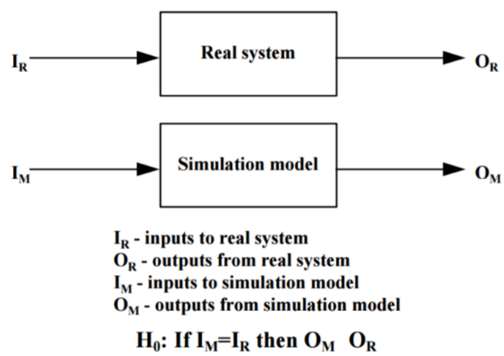



*Figure 22: Black-box validation (Robinson, 2014)*

However, Robinson (2014) discourages solely relying on black-box validation. This leads to inaccuracy of the model, but also the temptation to tweak outputs to specific scenarios. The practice of checking if the content of the model is true to reality, is called white-box validation. Feedback during stakeholder meetings delivered us the white-box validation our model needs. This form of validation is an indirect form of conceptual model validation. Hence, our queueing model has the credibility it needs when being used for decision-making. Finally, by continuously comparing the QtsPlus model to our conceptual model, we include verification into our queueing model.

### 4.3.2 Scenario 2: "Occupancy to capacity"

The second scenario we test is the allocation of capacity based on the current occupancy rates. Over the last three years, we estimated the occupancy rates in Section 2.3.2. The aim of this scenario is to test whether expressing the current occupancy in needed capacity is beneficial. First, we allocate capacity to the NICU and PICU based on the current occupancy of these departments. Then, the remaining number of rooms are assigned to the hybrid. Note that, as mentioned, 9 rooms are reserved for PMC patients. Table 7 shows an overview. Now, the hybrid has 10 single-person rooms assigned. Of these 10 rooms, 4 rooms come from the NICU and 6 rooms come from the PICU.

| Unit | Current occupancy | Number of single-person rooms |
|---|---|---|
| **NICU** | 88.2% | $88.2\% * 32 = 28$ |
| **Hybrid** | - | 67 – 28 – 29 = 10 |
| **PICU** | 74.7% + 83.6% | $(74.7\% * 16) + (83.6\% * 10) + 9 = 29$ |

*Table 7: Capacity allocation based on current occupancy rates*

### 4.3.3 Scenario 3: "Safety stock"

In the third scenario, we include the standard deviation in occupancy rates. We do this by adding the standard deviation to the current occupancy rates. This way, both departments have the standard deviation as a buffer to accommodate patients in busy periods. Again, we assign the remaining number of rooms to the hybrid. Table 8 shows an overview. In this scenario, the hybrid has 6 single-person rooms assigned. Of these 6 rooms, 2 rooms originate from the NICU and 4 rooms from the PICU.

| Unit | Current occupancy | Standard deviation | Number of single-person rooms |
|---|---|---|---|
| **NICU** | 88.2% | 7.0% | $95.2\% * 32 = 30$ |
| **Hybrid** | - | - | 67 – 30 – 31 = 6 |
| **PICU** | 74.7% + 83.6% | 8.5% + 7.9% | $(83.2\% * 16) + (91.5\% * 10) + 9 = 31$ |

*Table 8: Capacity allocation based on current occupancy rates plus buffer*

### 4.3.4 Scenario 4: "Two of each"

The last scenario we test is put forward by the stakeholders. Heads of the departments, team leaders and data analysts stated their preference during a stakeholder meeting. Their preferred hybrid consists of 4 single-person rooms. Meaning, both the NICU and PICU allocate 2 rooms to the future hybrid. The stakeholders base this allocation on seasonal peaks in demand, such as the period with the RS virus. Table 9 shows an overview.

| Unit | Number of single-person rooms |
|---|---|
| **NICU** | 32 – 2 = 30 |
| **Hybrid** | 2 + 2 = 4 |
| **PICU** | 35 – 2 = 33 |

*Table 9: Capacity allocation based on stakeholder preferences*

To summarize, we test scenarios where the hybrid has either 0, 4, 6 or 10 single-person rooms assigned. We test the four constructed scenarios in the following section, using the queueing model described in Section 4.1.

## 4.4 Scenario testing

After constructing the queueing model and describing the scenarios, we test our four selected forms of capacity allocation. Each capacity allocation has its effect on the occupancy rate and rejection probability on the future Harmonica. By evaluating and comparing the outcomes of each scenario, we provide the WKZ with a trade-off to support their decision making. After all, this research serves as an advice instead of a prescription.

### 4.4.1 "Validation and verification"

In the first scenario, we use the current capacity allocation as input. This is part of the black-box validation of our queueing model. For the PICU, we validate the QtsPlus queueing model by taking the average occupancy rate of the Pelikaan and Leeuw, described in Section 2.3.2. Table 10 presents the outputs in terms of occupancy rates.

Together with stakeholders of the NICU and PICU, we verified our queueing model by reviewing the assumptions and simplifications. This way, we searched for an explanation for the difference in output. For example, the data analysis in Section 2.3.2 does not include the increasing population of PMC patients in the future. For the queueing model however, the PMC parameters are based on the future patient flow. Therefore, it makes sense that the PICU percentages are slightly overestimated, as PMC patients are also included. Furthermore, the queueing model assumes that a server is directly available when completing service. In practice, time is needed to clean up and prepare the place for the next patient. Meaning, the servers in the queueing model can treat more patients per time unit than reality allows. Lastly, the lognormal distribution of service durations is not recognised in QtsPlus when modelling. Appendix B describes that QtsPlus makes no distinction between distributions except the exponential distribution. Resulting, QtsPlus assigns an arbitrary distribution to the service durations.

We believe that the current layout of the queueing model comes closest to representing reality. Therefore, we conclude by stating that our queueing model is valid enough for testing the scenarios and delivering the trade-off to the WKZ.

| Unit | Output of data analysis | Output of the queueing model | Difference |
|---|---|---|---|
| **NICU** | 88.2% | 82.5% | - 5.7% |
| **PICU** | 79.2% | 81.7% | + 2.5% |

*Table 10: Black-box validation of the queueing model*

As the output of the queueing model slightly differs from reality, our focus is on the incremental improvements or diminishments instead of absolute numbers when comparing scenarios. Since staffing issues are excluded from this research project, absolute numbers will always provide a distorted image of the situation. Therefore, especially when delivering a trade-off, the individual differences between scenarios are more representative.

QtsPlus estimates the fraction of time that the system is fully occupied, denoted as $p_c$. Meaning, at these times an arriving patient will be rejected treatment. Table 11 shows an overview of the fraction of time that there is a probability for rejection, estimated by QtsPlus. Logically, because the NICU has a higher occupancy, there is a higher likelihood for rejection on this department.

| Unit | Number of single-person rooms allocated | Rejection probability $p_c$ |
|---|---|---|
| **NICU** | 32 | 7.3% |
| **PICU** | 35 | 5.8% |

*Table 11: Rejection probabilities in current situation*

Both departments strive to reject as few patients as possible. Multiplying the arrival rate $\lambda$ with the rejection probability $p_c$ gives us the number of rejected patients per time unit. With the QtsPlus output, we can estimate the yearly rejections on the Harmonica. Assuming an arrival intensity of 5.2551 patients per day, the future Harmonica rejects approximately 111 PICU patients per year. For the NICU, the estimated number of rejected patients is 48. Altogether, estimating the yearly number of rejected patients provides us with a tangible image of the current situation. The rejection probabilities have been validated by discussing with stakeholders.

To evaluate the bed occupancy for each scenario, we take the weighted average occupancy. Meaning, we include the allocation of rooms to each department into the Harmonica occupancy calculation. This weighted average is constructed as follows:

$$
\begin{aligned}
&Weighted\ average\ occupancy \\
&\qquad = \left(\frac{NICU\ rooms\ allocated}{67} * NICU\ occupancy\right) \\
&\qquad + \left(\frac{Hybrid\ rooms\ allocated}{67} * Hybrid\ occupancy\right) \\
&\qquad + \left(\frac{PICU\ rooms\ allocated}{67} * PICU\ occupancy\right)
\end{aligned}
$$

The weighted average occupancy of the first scenario is: $\frac{32}{67} * 0.825\% + \frac{35}{67} * 0.817\% = 82.1\%$.

### 4.4.2 "Occupancy to capacity"

To test the second scenario, we must establish the parameters for the hybrid. The $\lambda$ is calculated as follows: $\lambda_{HYBRID} = (1.6882 * 0.1454) + (5.2551 * 0.1587) = 1.08\ patients/day$. Meaning, the hybrid sees 1.08 patients arrive per day due to the fully occupied NICU and PICU. The average service time on the hybrid $\frac{1}{\mu}$ is: $\left(\frac{0.2455}{1.08} * 16.8631\ days\right) + \left(\frac{0.8344}{1.08} * 5.7723\ days\right) = 8.29\ days/patient$.

Overall, the second scenario shows interesting results. This scenario allocates the 67 single-person rooms based on the occupancy rates that were achieved over the last three years. Figure 23 shows the probability distribution of present patients on the hybrid. It is most likely that there are eight patients present on the hybrid. In Appendix C, we visualise all probability distributions for the scenarios that are tested.

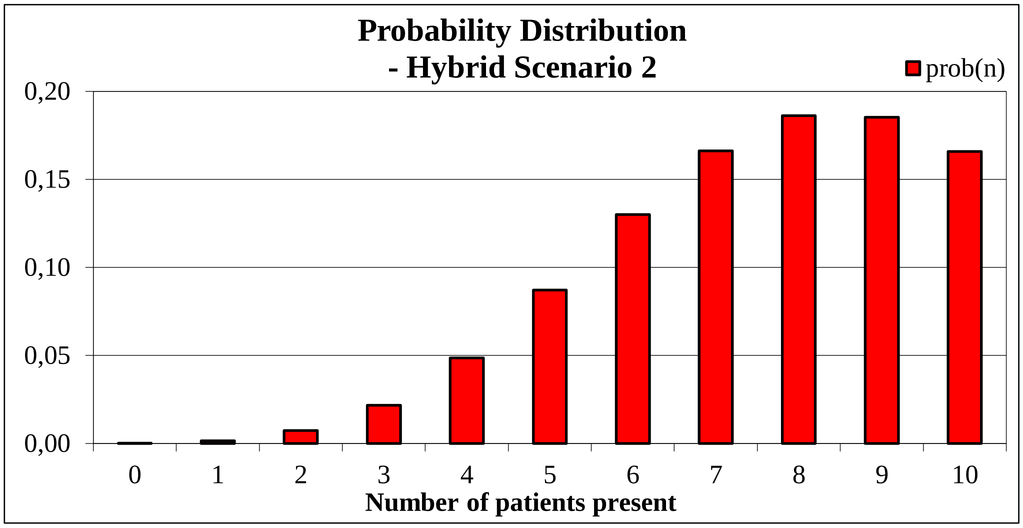



*Figure 23: Probability distribution of Hybrid patients, scenario 2*

Table 12 summarizes the main findings of the second scenario. High occupancy rates are achieved on both the NICU and PICU. The weighted average occupancy rate on the Harmonica is in this scenario 85.5%. Furthermore, 16.6% of the time the hybrid is fully occupied. We find the rejection probabilities from Figure 23 and Appendix C, by identifying the probability corresponding with the rightmost value on the X-axis.

| Unit | Number of single-person rooms allocated | Occupancy | Rejection probability $p_c$ |
|---|---|---|---|
| **NICU** | 28 | 86.9% | 14.5% |
| **Hybrid** | 10 | 74.7% | 16.6% |
| **PICU** | 29 | 88.0% | 15.9% |

*Table 12: Main findings of scenario 2*

In the second scenario, the NICU rejects 89 patients per year and the PICU rejects 305 patients per year. To estimate the number of rejected patients on the hybrid, we multiply the arrival rate $\lambda_{HYBRID}$ with the corresponding rejection probability $p_c$. Resulting, the second scenario causes the hybrid to reject 65 patients. In other words, of the 394 patients that arrive at the hybrid, 65 are rejected treatment. This indicates that 65 patients are rejected on the Harmonica per year. However, these rejection numbers are a rough estimation, since we cannot completely validate the output. Due to the exclusion of a personnel factor, the rejection numbers are in fact underestimated. In the future, we expect that Harmonica will reject a higher number of patients, due to a lack in available nurses and therefore operational hospital rooms.

### 4.4.3 "Safety stock"

The third scenario includes a buffer in capacity. Now, the hybrid has six rooms operational. Resulting, the parameters of the hybrid are: $\lambda_{HYBRID} = 0.81\ patients/day$ and $\frac{1}{\mu} = 8.24\ days/patient$.

Table 13 shows an overview of the third scenario. The weighted average occupancy achieved on the Harmonica is 84.7%. Furthermore, the rejection probabilities on the NICU and PICU decrease compared to the second scenario. However, the hybrid faces a 30.8% chance of rejecting possible arrivals.

| Unit | Number of single-person rooms allocated | Occupancy | Rejection probability $p_c$ |
|---|---|---|---|
| **NICU** | 30 | 84.8% | 10.6% |
| **Hybrid** | 6 | 76.5% | 30.8% |
| **PICU** | 31 | 86.2% | 11.9% |

*Table 13: Main findings of scenario 3*

The safety stock reduces the total number of rejected patients. In the third scenario, the NICU rejects 65 patients, while the PICU rejects 228 patients. Instead of ten single-person rooms, the hybrid now has six rooms assigned. Resulting, the hybrid and therefore the Harmonica, reject 90 patients on a yearly basis.

### 4.4.4 "Two of each"

The last scenario we test is constructed after discussing with stakeholders. In this scenario, both the NICU and PICU allocate two single-person rooms to the hybrid. Resulting, the hybrid has four rooms operational. This estimation by management is based on common sense and experience with patient demand. For example, the PICU might need two extra beds during the RS virus season. The parameters of the hybrid are: $\lambda_{HYBRID} = 0.63\ patients/day$, $\frac{1}{\mu} = 8.93\ days/patient$. Compared to the other scenarios, the average service time on the hybrid is the highest. Meaning, the hybrid accommodates a higher percentage of NICU patients than in the other scenarios.

Table 14 presents the main findings of the fourth scenario. The hybrid has a 44.3% rejection probability for future arrivals. This high number comes from the hybrid having only four rooms operational and the corresponding likelihood of full occupancy. Furthermore, the weighted average occupancy rate is 84.1%.

| Unit | Number of single-person rooms allocated | Occupancy | Rejection probability $p_c$ |
|---|---|---|---|
| **NICU** | 30 | 84.8% | 10.6% |
| **Hybrid** | 4 | 78.0% | 44.3% |
| **PICU** | 33 | 84.1% | 8.5% |

*Table 14: Main findings of scenario 4*

In the fourth scenario, the NICU yearly rejects 89 patients, while the PICU rejects 163 patients. In this scenario, the hybrid and therefore the Harmonica thus reject 101 patients per year.

### 4.4.5 The trade-off

Now that we have discussed the main findings of each scenario, we present the trade-off. Here, the four tested scenarios are weighed against each other. The trade-off is between the allocated capacity, the bed occupancy and the overall rejection probability. To assess the occupancy of each scenario, we take the weighted average. For the overall rejection probability, we construct the following formula:

$$Rejection\ prob.\ on\ the\ Harmonica = \frac{Rate\ of\ rejected\ patients\ on\ the\ Hybrid}{Total\ arrival\ rate\ of\ patients\ on\ the\ Harmonica}$$

$$= \frac{\lambda_{HYBRID} * p_c\ (Hybrid)}{\lambda_{NICU} + \lambda_{PICU}}$$

In case a hybrid department is operational, a patient that is rejected from the NICU or PICU, might still be admitted on the hybrid. If the hybrid is also fully occupied, this patient is rejected and leaves the hospital. The formula divides the rate of patients that are rejected from the hybrid, by the total arrival rate on the Harmonica. This provides us with the overall rejection probability of the Harmonica. For example, the rejection probability of the second scenario is calculated as follows: $\frac{1.0799 * 0.1659}{1.6882+5.2551} = 0.0258 = 2.6\%$. The first scenario divides the rate of rejected patients on the NICU and PICU, by the total arrival rate of the NICU and PICU.

In Table 15 we present the trade-off to the WKZ.

| Scenario | Capacity allocation (NICU, Hybrid, PICU) | Occupancy | Rejection probability |
|---|---|---|---|
| **1. Current situation** | 32, 0, 35 | 82.1% | 6.2% |
| **2. Occupancy to capacity** | 28, 10, 29 | 85.5% | 2.6% |
| **3. Safety stock** | 30, 6, 31 | 84.7% | 3.6% |
| **4. Two of each** | 30, 4, 33 | 84.1% | 4.0% |

*Table 15: The trade-off*

From Table 15, we identify that there is a trend in the rejection probability. When allocating less single-person rooms to the hybrid, the overall rejection probability on the Harmonica rises. The scenario with the least number of rooms assigned to the hybrid, has the highest rejection probability; 4.0%. The rejection probability continues to rise when allocating less capacity to the hybrid. When less capacity is assigned to the hybrid, the Harmonica has more difficulty dealing with peaks in demand.

We notice that the second scenario appears to be the best option. Here, the average occupancy is the highest and the overall rejection probability is the lowest. Meaning, there is little chance that if a patient is rejected on the NICU or PICU, he or she is rejected on the hybrid as well. This scenario allocates the 67 rooms based on the average occupancy of the last three years. We believe that the pooling principle is the reason for the performance of this scenario. The second scenario allows the pooling of ten single-person rooms over the NICU and PICU. Hence, a large buffer is available to deal with peaks and valleys in patient demand. Furthermore, the pooling of rooms has a tactical planning horizon, since seasonal demand forms the basis for the allocation of hybrid rooms to the NICU and PICU.

## 4.5 Conclusion

In this chapter, we put the theoretical knowledge gained in Chapter 3 into practice. Our goal is to answer the research question: "*How can the model found in the literature be applied within the WKZ?"* Due to the unique environment of the WKZ, a queueing model for decision-making must be well-adjusted. First, we start by listing the necessary assumptions and simplifications for our queueing model. By continuously getting feedback from stakeholders, we validate our conceptual model. This way, our queueing model represents reality as accurately as possible. Then, we estimate the arrival and service parameters of the NICU, Pelikaan, Leeuw and PMC. Again, we include a validation step in this section. Hereafter, we visualise the future Harmonica and the corresponding queueing model. We describe each scenario regarding capacity allocation and why we select this scenario. Our method of applying a constructed queueing model is integrally applicable for all wards within UMC Utrecht.

Section 4.4 tests the scenarios to assess their impact and effectiveness. We measure the occupancy rates and rejection probabilities for the NICU, hybrid and the PICU. Finally, we present the trade-off where the scenarios are compared with each other. As mentioned, our focus is on the relative differences between scenarios.

From the trade-off, we identify that the second scenario provides the best results. Here, the average occupancy is the highest and the overall rejection the lowest. In this scenario, 28 rooms are assigned to the NICU, 10 to the hybrid, and 29 to the PICU. However, assigning ten rooms to the hybrid may prove to be difficult in practice, as will be pointed out in Chapter 5. In the next chapter, we provide the WKZ with several recommendations based on the outcomes of the scenario testing.

# 5. Conclusion and recommendations

In this chapter, we present conclusions and recommendations to the WKZ. In the previous chapter, we summarized and evaluated the main findings of each scenario. Now, we put these findings into perspective. Logically, each scenario has its impact and effectiveness. Besides, each form of capacity allocation requires its own implementation program and large financial expenses are associated. First, Section 5.1 presents the conclusions of this report. Hereafter, Section 5.2 provides the WKZ with recommendations regarding capacity allocation and staffing issues. Then, Section 5.3 states the limitations of this study. Lastly, Section 5.4 indicates the possibilities for further research. These recommendations for further research are based on our findings and are placed within the context of the WKZ.

## 5.1 Conclusions

In this section, we present the conclusions of this report. By summarizing the conclusions of each chapter, we indicate the development of knowledge within this study. We restate the research questions, which formed the guiding principle of each chapter.

1. "*What will the total patient flow for the Harmonica be and what bottlenecks are expected?*"

Chapter 2 analyses the current performance of the NICU and PICU. Here, we visualise the current lengths of stay, the occupancy and the arrival patterns. The data analysis indicates that both departments faced high occupancy rates over the last three years; 88.2%, 74.6% and 83.6%. In the future, these rates are expected to rise steadily. The occupancy rates can be explained by long lengths of stay and the occasional peaks in patient demand. Although staffing issues are excluded from this research, we cannot ignore the impact of capacity allocation on personnel. In the future Harmonica, 3.5 FTE are needed to keep one single-person rooms operational 24 hours per day. Lastly, we identify that an intensified collaboration between the NICU and PICU seems beneficial, because both departments experience peaks and valleys in patient demand. Improvement opportunities arise when considering the pooling of hospital beds in a 'hybrid' setting.

2. "*What models are known in literature for making 'resource capacity planning' decisions in health care organisations?*"

Chapter 3 provides a substantiation for the modelling method of choice. We select eleven relevant literary articles that contribute to this decision. Linear programming is useful in dynamic environments due to its iterative nature, but too elaborate for the objective of this research project. Simulation is transparent and flexible, but more useful when fine-tuning the results of a queueing model. We select queueing as modelling method to deliver the trade-off to the WKZ. Steady-state assumptions must be made and the ease of development is of importance when considering the time-horizon of this research project.

3. "*How can the model found in the literature be applied within the WKZ?*"

Chapter 4 constructs a queueing model adjusted to the environment of the WKZ. With this queueing model, we test four scenarios determined via stakeholder meetings. Hereafter, we compare the scenarios by presenting a trade-off on capacity allocation, occupancy and the rejection probability. We identify that the second scenario provides the best results; 85.5% occupancy and 2.6% rejection probability. In this scenario, 28 rooms are assigned to the NICU, 10 rooms to the hybrid and 29 rooms to the PICU. Allocating more rooms to the hybrid increases the pooling effect.

## 5.2 Recommendations

The research objective of this Bachelor report was to deliver a substantiated advice for the WKZ on the allocation of single-person rooms for the future Harmonica. We constructed the following research question: "*What is the optimal capacity allocation for the Neonatal IC, the Children's ICU and the hybrid given stakeholder preferences on the occupancy rate and the rejection probability?"* Now, after testing the scenarios and presenting the trade-off, we can deliver an advice to the WKZ.

We recommend the Harmonica to consist of 28 NICU rooms, 10 hybrid rooms and 29 PICU rooms. Of the 10 hybrid rooms, we advise to allocate the ratio NICU-to-PICU rooms on a tactical planning level. Meaning, based on expected demand, management need to decide how many NICU and PICU rooms are needed within the hybrid. For example, management can decide to allocate the hybrid in a 2:8 form or a 3:7 form in the winter period, to cope with the RS virus. Note that these hybrid rooms will physically be located at both the NICU or PICU. No separate unit is created for the hybrid. The '28-10-29' capacity allocation proves to be the most beneficial. This allocation achieves the highest occupancy, while obtaining the lowest rejection probability overall. The pooling of hybrid hospital rooms over the NICU and PICU has a large impact on the performance of the Harmonica.

Allocating capacity greatly influences staffing decisions for the NICU and PICU. With 10 hybrid rooms, each department must be able to deploy $28 + 10$ and $29 + 10$ nurses to accommodate peaks in demand. However, current specialisations make it impossible for a NICU nurse to treat a PICU patient and vice versa. Hence, initiatives are started to educate 'flexible' nurses. Having nurses deployable for both departments, simplifies the planning process and reduces the shortage of staff. We recommend using this study as a substantiation for the empowerment of educating 'flexible' nurses, deployable for the future Harmonica. Other medical institutes such as the Leids Universitair Medisch Centrum (LUMC) and the Sophia Children's Hospital already apply this principle (Heijstek, 2017). On the short-term, Heijstek (2017) suggests to start with 'flexible' HC-staff. HC-staff on the NICU and PICU both have the specialization 'Kinderaantekening', which provides the opportunity for nurses to work at both departments.

Our last recommendation is continuously monitoring the performance of the future Harmonica. This includes measuring the overall rejection probability, the bed occupancy and the allocation of capacity within the hybrid. By continuously monitoring these indicators, the performance of the Harmonica can be compared with the performance of the current situation. Robinson (2014) describes this process as solution validation. Another part of solution validation is testing whether the implemented solution is truly the most suitable. Meaning, since there is no separate unit for the hybrid, management can decide to experiment with less or more hybrid rooms to determine their effect. Implementing such an alternative scenario requires a follow-up study, which we discuss in Section 5.4.

## 5.3 Discussion

Now, we discuss the limitations of this study, since these have influenced the interpretation of our findings. Moreover, limitations are drawbacks for the application to practice and generalizability. In this section, we acknowledge the limitations and their impact on this research project. We conclude this section by making the connection between existing literature and the results of this study.

First, we used datasets containing patient data from January 2014 until December 2016 for our queueing model. With this input data, we tested scenarios and provided the trade-off for the WKZ. However, the datasets and the corresponding parameters do not provide any guarantee for the future. The datasets are only a snapshot of the current problem context. Future arrivals or new epidemics are unforeseen events that are not included in the datasets. These future events can influence the arrivals or lengths of stay in such a way, that a different capacity allocation is more suitable. We dealt with this drawback by assuming that the expected case mix distribution of future patients is known. Besides, we also acknowledge the fact that by choosing a larger time horizon, more accurate parameters could have been estimated. A longer time horizon might influence the most suitable capacity allocation for the WKZ.

Second, due to the time horizon of this study, the personnel-factor could not be included into this study. Staffing decisions have high financial consequences for both the NICU and PICU. For example, we calculated the occupancy rates by using the theoretical capacity of beds. Here, we could not include the beds that were 'closed' due to a shortage in staff. Resulting, we dealt with lower occupancy rates than the WKZ achieves in reality. Overall, including the deployment of staff results in obtaining a more accurate picture of the problem context. Besides, including staffing issues also increases the validity of the queueing model used for scenario testing. This limitation provides an opportunity for a follow-up study, discussed in Section 5.4.

Third, queueing is a relatively rigid method of decision-making. Queueing models use steady-state parameters and assumptions are required. For example, the queueing model in QtsPlus makes no distinction between the remaining distributions when rejecting the exponential distribution for service times. As Section 4.4.1 described, the appropriate lognormal distribution cannot be selected. QtsPlus assigns a 'general' distribution to the service times. The output parameters of QtsPlus can therefore not be completely validated. Another example is the queueing discipline. For all arrivals, QtsPlus assumes that patients are serviced FCFS. In practice, emergency patients will always have priority over elective patients when assigning bed capacity. This rigidness has impact on the application of the queueing model in practice.

Fourth, we reflect on our decisions and assumptions that influence the interpretation of the results. For example, we decided to select queueing as method for the scenario testing and evaluation. However, we hereby limit ourselves in a matter of detail, visualisation and consequently transparency for stakeholders. A combination of simulation and queueing for scenario testing could have been more beneficial, but given the time constraints we decided to just use queueing. Another example is our decision to focus on the relative differences between scenarios. By using relative differences instead of absolute numbers, we create difficulty for the WKZ to compare the future situation to the current situation. Due to the validity of the QtsPlus output, we use relative differences for the evaluation of scenarios.

Lastly, after the testing the scenarios and evaluating the results, we can compare our results with existing literature. In Chapter 3, we describe the application of pooling and queueing in medical institutes. Here, Joustra et al. (2010) stated that pooling is generally conceived to be efficient. As the results in Section 4.4.5 indicate, we proved that pooling in medical institutes is beneficial when considering the future Harmonica. Even though we do not state absolute numbers, the incremental differences between scenarios indicate the effect of pooling. Furthermore, the literature accurately describes both the benefits and drawbacks of queueing when modelling. Throughout this research project, we experience identical benefits and drawbacks, such as quick development and rigidness.

## 5.4 Further research

The findings of this study provide multiple opportunities for further research. In this section, we state the most relevant suggestions. Logically, these suggestions are placed within the context of this research study.

In Section 4.4, we tested four forms of capacity allocation. However, the 67 single-person rooms can be allocated in many more styles. A follow-up study for optimizing the capacity allocation is one of our suggestions for further research. Optimization models such as LP models can deliver maximum occupancy rates or minimum rejection probabilities within the set boundaries. LP models can quickly evaluate many different scenarios for their effectiveness (University of Twente, 2014). However, this requires keeping the input data, the assumptions and simplifications constant. Some urgency comes with this matter, since the Harmonica will be operational in 2018.

Another possibility for a follow-up study is extending the results of this study into staffing decisions. In Section 2.3.2 we illustrated the occupancy per quarter and per hour or the day. During busy periods, the departments require more staff to treat the patients. A result of Section 2.3.2 is that in the morning the bed occupancy is the highest. Now, the hybrid allocates rooms to the NICU and PICU on a tactical planning level. Based on seasonal demand, management decides how many hybrid rooms are required to accommodate all NICU and PICU demand. Therefore, the rostering of staff should also happen on a tactical planning level. This includes temporary capacity expansions such as overtime or hiring staff. Altogether, the framework for health care planning and control by Hans et al. (2011) is an excellent approach to further investigate these staffing methods. This framework also supports strategic and operational decision-making for the deployment of staff.

Moreover, we suggest to improve the integration of staff-deployment with bed occupancy. Meaning, calculating and evaluating occupancy rates that are corrected with the number of 'operational' hospital beds. During this research project, we noticed that there is room for improvement on this matter. By improving the integration of staff, a more realistic image of the operational occupancy is obtained. Besides, it provides opportunities for benchmarking across all Intensive Care units in The Netherlands. The datasets used in this study can be used as a starting reference. Applying a personnel-factor on the data analysis of Chapter 2 is our last suggestion for further research.

# References

Cattani, K., & Schmidt, G. (2005). The pooling principle. *INFORMS Trans Educ*, 17-24.

Chaussalet, T., Asaduzzaman, M., Adayemi, S., Chahed, S., Hawdon, J., Wood, D., & Robertson, N. (2010). Towards effective capacity planning in a perinatal network centre. *Archives of Disease in Childhood - Fetal and Neonatal Edition* .

de Vries, W. (2017, Mei 1). Data-analyse NICU. (W. Otten, Interviewer)

Green, L. (2011). Queuing Theory and Modelling. *Graduate School of Business* .

Green, L., & Liu, N. (2015). A Study of New York City obstetrics units demonstrates the potential for reducing hospital inpatient capacity. *Medical Care Research and Review*, 168-186.

Hans, E., van Houdenhoven, M., & Hulshof, P. (2011). *A Framework for Health Care Planning and Control.*

Heerkens, H., & van Winden, A. (2012). Core Problem. In *Geen Probleem* (pp. 47-49). Business School Nederland.

Heijstek, J. (2017, Juni 12). Flexible staff. (W. Otten, Interviewer)

Hulshof, P., Boucherie, R., Hans, E., & Hurink, J. (2013). Tactical resource allocation and elective patient admission planning in care processes. *Health Care Management Science*, 152–166.

Hulshof, P., Kortbeek, N., Boucherie, R., Hans, E., & Bakker, P. (2012). Taxonomic classification of planning decisions in health care: A structured review of the state of the art in OR/MS. *Health Systems*, 129–175.

JMP Statistical Software. (2017). *Likelihood, AICc, and BIC*. Retrieved from JMP: https://www.jmp.com/support/help/13-1/Likelihood_AICc_and_BIC.shtml

Joustra, P., van der Sluis, E., & van Dijk, N. (2010). To pool or not to pool in hospitals: A theoretical and practical comparison for a radiotherapy outpatient department. *Annals of Operations Research*, 77–89.

Kozlowski, D., Mogensen, C., & Petersen, N. (2012). Discrete event simulation modelling for an improved patient flow at the Emergency Department. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*.

Li, S., Geng, N., & Xie, X. (2015). Radiation Queue: Meeting Patient Waiting Time Targets. *IEEE Robotics & Automation Magazine*, 51 - 63.

Merriam-Webster. (2017). *Simulation*. Retrieved from Merriam-Webster: https://www.merriam-webster.com/dictionary/simulation

Monks, T., Worthington, D., Allen, M., Pitt, M., Stein, K., & James, M. (2016). A modelling tool for capacity planning in acute and community stroke services. *BMC Health Care Services Research*.

Rau, C.-L., Tsai, P.-F., Liang, S.-F., Tan, J.-C., Syu, H.-C., & Jheng, Y.-L. C.-S.-S. (2013). Using discrete-event simulation in strategic capacity planning for an outpatient physical therapy service. *Health Care Management Science*, 352–365.

Robinson, S. (2004). Appendix 4: Statistical distributions. In S. Robinson, *Simulation: The practice of model development and use.* John Wiley & Sons, Ltd.

Robinson, S. (2008). Conceptual Modelling for Simulation Part I: Definition and Requirements. *The Journal of the Operational Research Society*, 278-290.

Robinson, S. (2014). Conceptual Modelling. In S. Robinson, *Simulation: The practice of model development and use* (pp. 82-92). Palgrave Macmillan.

Robinson, S. (2014). Data collection and analysis. In S. Robinson, *Simulation: The practice of model development and use* (pp. 139-149). Palgrave Macmillan.

Robinson, S. (2014). Verification, validation and confidence. In S. Robinson, *Simulation: The practice of model development and use* (pp. 251-267). Palgrave Macmillan.

Song, H., Tucker, A., & Murrell, K. (2015). The Diseconomies of Queue Pooling: An Empirical Investigation of Emergency Department Length of Stay. *Management Science*.

UMC Utrecht. (2017). *Neonatologie*. Retrieved from Het WKZ: http://www.hetwkz.nl/nl/Ziekenhuis/Afdelingen/Geboortecentrum/Neonatologie

UMC Utrecht. (2017). *Organisatie*. Retrieved from UMC Utrecht: http://www.umcutrecht.nl/en/Over-ons/Organisatie

University of Twente. (2014, November). Linear Programming. Enschede.

Vanberkel, P., Boucherie, R., Hans, E., Hurink, J., & Litvak, N. (2010). Efficiency evaluation for pooling resources in health. *OR Spectrum*, 371–390.

Winston, W. (2004). Modelling arrival and service processes. In W. Winston, *Operations Research* (pp. 1053-1062). Brooks/Cole.

Winston, W. (2004). Queuing Theory. In W. Winston, *Operations Research* (pp. 1115-1119). Brooks/Cole.

# List of abbreviations

In this section, we explain the abbreviations that are used throughout this report.

| | |
|---|---|
| FCFS | First-Come First-Served |
| FTE | Full-time Employee |
| HC | High Care |
| IC | Intensive Care |
| LINAC | Linear Accelerator |
| LP | Linear Programming |
| LUMC | Leids Universitair Medisch Centrum |
| MILP | Mixed-Integer Linear Programming |
| NICU | Neonatal Intensive Care Unit |
| OR | Operation Room |
| PICU | Paediatric Intensive Care Unit |
| PMC | Prinses Maxima Centrum |
| RCU | Respiratory Care Unit |
| RS-virus | Respiratory Syncytial Virus |
| UMC Utrecht | Universitair Medisch Centrum Utrecht |
| WKZ | Wilhelmina Kinderziekenhuis |

# Appendix A: Arrival data

This appendix has been removed due to privacy regulations.

# Appendix B: Statistical distribution fitting

When developing a model, the modeller must decide which statistical distribution is the most appropriate for the input data. If an incorrect distribution is chosen, the output of the model becomes inreliable. In this appendix, we fit statistical distributions to the empirical data we received. Robinson (2014) identifies three stages for the fitting process:

- Select a statistical distribution
- Determine the parameters
- Test the goodness-of-fit

First, we select a statistical distribution for the dataset. This statistical distribution is selected based on the properies of the process. For example, the arrival process at the hospital is assumed to be a Poisson process with interarrival times that are negative exponentially distributed. Then, we determine the parameters that go along with the chosen statistical distribution. For example, the Gamma distribution requires an estimation of the parameters α and β, which represent the shape and scale of the probability density function (PDF). Lastly, we perform a goodness-of-fit test. This test determines how closely a dsitribution fits our empirical data. The frequencies from the cumulative distribution function of the proposed distribution are compared with the observations of the empirical data. This can be done both graphically and statistically. Graphical examples of goodness-of-fit tests are probability-probability (P-P) plots or quantile-quantile (Q-Q) plots. However, we prefer a statistical method of fitting. We select a statistical test called the 'chi-square test' for the fitting process. The formula, stated by Robinson (2014), is as follows:

$$X^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i}$$

$O_i$ represents the observed frequency in the *i*th range, which comes from the empirical distribution. $E_i$ is the expected frequency in the *i*th range, which comes from the proposed distribution. When this is calculated over all *i* ranges, the chi-square value is determined. We select a significance level of 0.05, and the degrees of freedom is: $Number\ of\ cell\ ranges - Number\ of\ estimated\ parameters - 1$. Then, the chi-square value is compared to a critical value. This critical value depends on the degrees of freedom and the level of significance. If the chi-square value is larger than the critical value, our proposed distribution is rejected. Besides, we acknowledge that the empirical data is just a sample and therefore we can never find 'the best statistical distribution'. We aim for a 'best fit', given the available statistical distributions. In the following sections, a summary per fitting process is given. We fit statistical distributions for the arrival process and the service duration.

### Arrival process

- **Selected statistical distribution**: Poisson
- **Parameters**: Arrival rate λ
- **Goodness-of-Fit test**:

For the arrivals, we calculated the number of arriving patients per week. The observed values are compared to the expected values of the Poisson distribution. The figures below summarize our main findings. For the arrival processes on the NICU, Pelikaan and Leeuw, the Poisson distribution is applicable. The chi-square values are smaller than the critical values. Following, the interarrival times are exponentially distributed. *"Interarrival times are exponential with parameter λ if and only if the number of arrivals to occur in an interval of length t follows a Poisson distribution with parameter λt* (Winston, 2004)*."* These interarrival times have an exponential continuous density function (CDF) which decreases as time increases. The 'memoryless property' makes the time until the next arrival independent of the time since the last arrival.

**NICU:**

| #Arrivals/week | Poisson chance with λ=11,8174 | Expected | Observation | (Ob - Ex)^2 | Error |
|---|---|---|---|---|---|
| 0 | 0,0000 | 0,0012 | 0 | 0,0000 | 0,0012 |
| 1 | 0,0001 | 0,0136 | 0 | 0,0002 | 0,0136 |
| 2 | 0,0005 | 0,0803 | 0 | 0,0065 | 0,0803 |
| 3 | 0,0020 | 0,3165 | 0 | 0,1001 | 0,3165 |
| 4 | 0,0060 | 0,9349 | 1 | 0,0042 | 0,0045 |
| 5 | 0,0142 | 2,2096 | 1 | 1,4632 | 0,6622 |
| 6 | 0,0279 | 4,3520 | 3 | 1,8280 | 0,4200 |
| 7 | 0,0471 | 7,3471 | 6 | 1,8147 | 0,2470 |
| 8 | 0,0696 | 10,8530 | 13 | 4,6098 | 0,4248 |
| 9 | 0,0913 | 14,2504 | 22 | 60,0561 | 4,2143 |
| 10 | 0,1080 | 16,8403 | 13 | 14,7478 | 0,8757 |
| 11 | 0,1160 | 18,0917 | 17 | 1,1917 | 0,0659 |
| 12 | 0,1142 | 17,8164 | 16 | 3,2992 | 0,1852 |
| 13 | 0,1038 | 16,1956 | 20 | 14,4732 | 0,8937 |
| 14 | 0,0876 | 13,6707 | 15 | 1,7670 | 0,1293 |
| 15 | 0,0690 | 10,7702 | 4 | 45,8352 | 4,2558 |
| 16 | 0,0510 | 7,9547 | 10 | 4,1832 | 0,5259 |
| 17 | 0,0354 | 5,5296 | 5 | 0,2805 | 0,0507 |
| 18 | 0,0233 | 3,6303 | 6 | 5,6153 | 1,5468 |
| 19 | 0,0145 | 2,2580 | 1 | 1,5824 | 0,7008 |
| 20 | 0,0086 | 1,3342 | 3 | 2,7750 | 2,0800 |

| | |
|---|---|
| Number of weeks | 156 |
| Lambda | 11,8174 |
| DGF | 18 |
| α | 5% |
| Critical value | 28,8693 |
| Chi Square | 17,694 |
| Reject distribution? | No |

**Pelikaan:**

| #Arrivals/week | Poisson chance with λ=16,4633 | Expected | Observation | (Ob - Ex)^2 | Error |
|---|---|---|---|---|---|
| 0 | 0,0000 | 0,0000 | 0 | 0,0000 | 0,0000 |
| 1 | 0,0000 | 0,0002 | 0 | 0,0000 | 0,0002 |
| 2 | 0,0000 | 0,0015 | 0 | 0,0000 | 0,0015 |
| 3 | 0,0001 | 0,0082 | 0 | 0,0001 | 0,0082 |
| 4 | 0,0002 | 0,0338 | 0 | 0,0011 | 0,0338 |
| 5 | 0,0007 | 0,1113 | 0 | 0,0124 | 0,1113 |
| 6 | 0,0020 | 0,3055 | 0 | 0,0933 | 0,3055 |
| 7 | 0,0046 | 0,7184 | 0 | 0,5162 | 0,7184 |
| 8 | 0,0095 | 1,4785 | 2 | 0,2720 | 0,1840 |
| 9 | 0,0173 | 2,7045 | 3 | 0,0873 | 0,0323 |
| 10 | 0,0285 | 4,4526 | 5 | 0,2997 | 0,0673 |
| 11 | 0,0427 | 6,6640 | 8 | 1,7849 | 0,2678 |
| 12 | 0,0586 | 9,1426 | 9 | 0,0203 | 0,0022 |
| 13 | 0,0742 | 11,5783 | 13 | 2,0213 | 0,1746 |
| 14 | 0,0873 | 13,6155 | 12 | 2,6097 | 0,1917 |
| 15 | 0,0958 | 14,9437 | 15 | 0,0032 | 0,0002 |
| 16 | 0,0986 | 15,3764 | 22 | 43,8720 | 2,8532 |
| 17 | 0,0955 | 14,8910 | 19 | 16,8842 | 1,1339 |
| 18 | 0,0873 | 13,6197 | 9 | 21,3416 | 1,5670 |
| 19 | 0,0756 | 11,8013 | 16 | 17,6289 | 1,4938 |
| 20 | 0,0623 | 9,7144 | 9 | 0,5104 | 0,0525 |
| 21 | 0,0488 | 7,6158 | 7 | 0,3792 | 0,0498 |
| 22 | 0,0365 | 5,6991 | 4 | 2,8871 | 0,5066 |
| 23 | 0,0262 | 4,0794 | 5 | 0,8475 | 0,2077 |
| 24 | 0,0179 | 2,7984 | 5 | 4,8472 | 1,7322 |
| 25 | 0,0118 | 1,8428 | 1 | 0,7103 | 0,3855 |
| 26 | 0,0075 | 1,1669 | 3 | 3,3603 | 2,8798 |
| 27 | 0,0046 | 0,7115 | 1 | 0,0832 | 0,1170 |
| 28 | 0,0027 | 0,4183 | 2 | 2,5016 | 5,9798 |

| | |
|---|---|
| Number of weeks | 156 |
| Lambda | 16,4633 |
| DGF | 26 |
| α | 5% |
| Critical value | 38,8851 |
| Chi Square | 21,0577 |
| Reject distribution? | No |

**Leeuw:**

| #Arrivals/week | Poisson chance with λ=13,1992 | Expected | Observation | (Ob - Ex)^2 | Error |
|---|---|---|---|---|---|
| 0 | 0,0000 | 0,0003 | 0 | 0,0000 | 0,0003 |
| 1 | 0,0000 | 0,0038 | 0 | 0,0000 | 0,0038 |
| 2 | 0,0002 | 0,0252 | 0 | 0,0006 | 0,0252 |
| 3 | 0,0007 | 0,1107 | 0 | 0,0123 | 0,1107 |
| 4 | 0,0023 | 0,3654 | 2 | 2,6719 | 7,3124 |
| 5 | 0,0062 | 0,9646 | 3 | 4,1429 | 4,2950 |
| 6 | 0,0136 | 2,1220 | 3 | 0,7709 | 0,3633 |
| 7 | 0,0256 | 4,0012 | 4 | 0,0000 | 0,0000 |
| 8 | 0,0423 | 6,6015 | 9 | 5,7526 | 0,8714 |
| 9 | 0,0621 | 9,6817 | 8 | 2,8280 | 0,2921 |
| 10 | 0,0819 | 12,7790 | 17 | 17,8166 | 1,3942 |
| 11 | 0,0983 | 15,3339 | 16 | 0,4437 | 0,0289 |
| 12 | 0,1081 | 16,8663 | 20 | 9,8202 | 0,5822 |
| 13 | 0,1098 | 17,1247 | 10 | 50,7616 | 2,9642 |
| 14 | 0,1035 | 16,1452 | 13 | 9,8922 | 0,6127 |
| 15 | 0,0911 | 14,2069 | 14 | 0,0428 | 0,0030 |
| 16 | 0,0751 | 11,7200 | 11 | 0,5184 | 0,0442 |
| 17 | 0,0583 | 9,0997 | 9 | 0,0099 | 0,0011 |
| 18 | 0,0428 | 6,6727 | 12 | 28,3803 | 4,2532 |
| 19 | 0,0297 | 4,6355 | 7 | 5,5909 | 1,2061 |
| 20 | 0,0196 | 3,0592 | 5 | 3,7666 | 1,2312 |
| 21 | 0,0123 | 1,9228 | 2 | 0,0060 | 0,0031 |
| 22 | 0,0074 | 1,1536 | 2 | 0,7163 | 0,6210 |
| 23 | 0,0042 | 0,6620 | 2 | 1,7901 | 2,7040 |
| 24 | 0,0023 | 0,3641 | 0 | 0,1326 | 0,3641 |
| 25 | 0,0012 | 0,1922 | 1 | 0,6525 | 3,3942 |

| | |
|---|---|
| Number of weeks | 156 |
| Lambda | 13,1992 |
| DGF | 23 |
| α | 5% |
| Critical value | 35,1725 |
| Chi Square | 32,6818 |
| Reject distribution? | No |

## Service duration

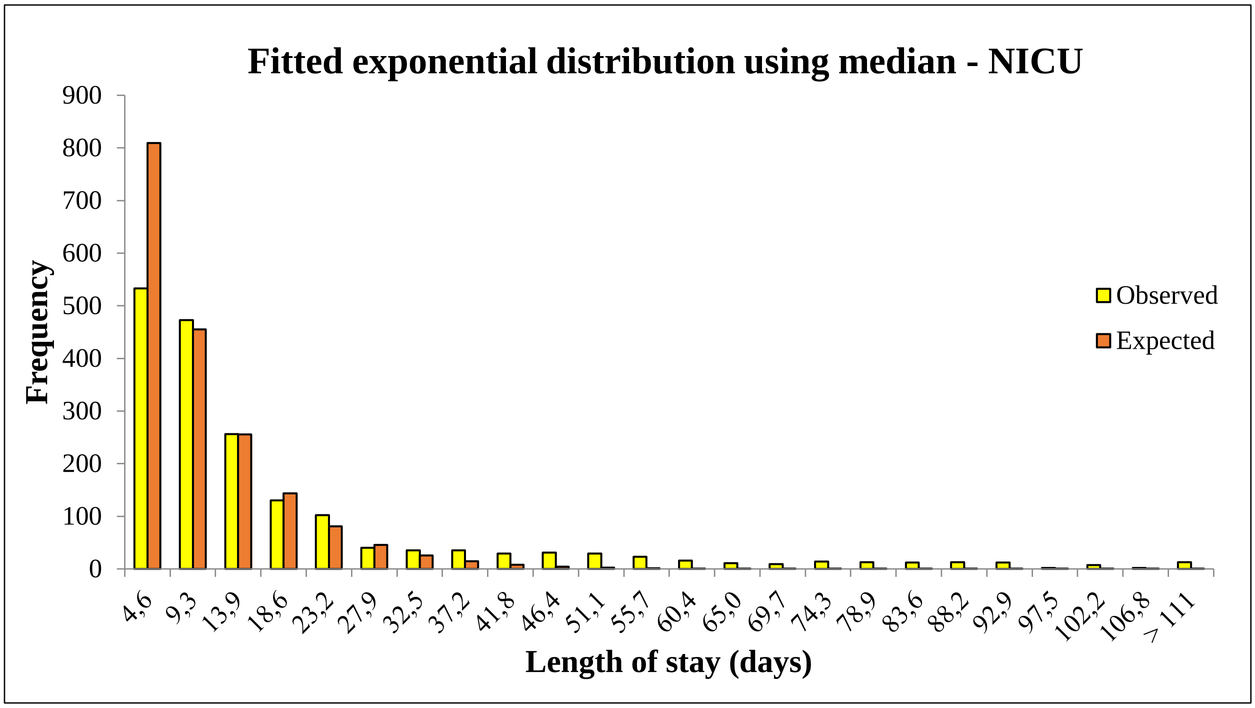
- **Selected statistical distribution**: Exponential
- **Parameters**: Mean time to complete service μ
- **Goodness-of-Fit test**:

Below, we visualise the goodness-of-fit test for the service duration on the NICU. For each range, the expected value is determined via the exponential distribution. In the first range, the expected value is the highest. Meaning, most patients are expected to leave within 4.64 days. The expectations per range continue to decrease from here on. After this, we compared the observed values with these expected values. The figure shows that the chi-square value is ten times as large as the critical value. Therefore, we must reject the exponential distribution as statistical distribution for the service duration. For the Pelikaan and Leeuw, the goodness-of-fit test provided identical results. Even when clustering the last ranges, due to a low number of observations, the chi-square values remained larger than the critical values.

| Bin | Exponential chance with μ=0,0593 | Difference | Expected | Observation | (Ob - Ex)^2 | Error |
|---|---|---|---|---|---|---|
| 4,6439 | 0,2407 | 0,2407 | 444,8587 | 533 | 7768,8964 | 17,4637 |
| 9,2879 | 0,4235 | 0,1828 | 337,7703 | 473 | 18287,0631 | 54,1405 |
| 13,9318 | 0,5623 | 0,1388 | 256,4608 | 256 | 0,2123 | 0,0008 |
| 18,5758 | 0,6676 | 0,1054 | 194,7244 | 130 | 4189,2500 | 21,5137 |
| 23,2197 | 0,7477 | 0,0800 | 147,8495 | 102 | 2102,1768 | 14,2184 |
| 27,8636 | 0,8084 | 0,0607 | 112,2585 | 40 | 5221,2939 | 46,5113 |
| 32,5076 | 0,8545 | 0,0461 | 85,2352 | 35 | 2523,5711 | 29,6072 |
| 37,1515 | 0,8895 | 0,0350 | 64,7170 | 35 | 883,0988 | 13,6456 |
| 41,7954 | 0,9161 | 0,0266 | 49,1380 | 29 | 405,5400 | 8,2531 |
| 46,4394 | 0,9363 | 0,0202 | 37,3093 | 31 | 39,8073 | 1,0670 |
| 51,0833 | 0,9517 | 0,0153 | 28,3280 | 29 | 0,4515 | 0,0159 |
| 55,7273 | 0,9633 | 0,0116 | 21,5088 | 23 | 2,2237 | 0,1034 |
| 60,3712 | 0,9721 | 0,0088 | 16,3311 | 16 | 0,1096 | 0,0067 |
| 65,0151 | 0,9788 | 0,0067 | 12,3998 | 11 | 1,9595 | 0,1580 |
| 69,6591 | 0,9839 | 0,0051 | 9,4149 | 9 | 0,1721 | 0,0183 |
| 74,3030 | 0,9878 | 0,0039 | 7,1485 | 14 | 46,9433 | 6,5669 |
| 78,9469 | 0,9907 | 0,0029 | 5,4277 | 13 | 57,3402 | 10,5644 |
| 83,5909 | 0,9930 | 0,0022 | 4,1211 | 12 | 62,0771 | 15,0633 |
| 88,2348 | 0,9947 | 0,0017 | 3,1290 | 13 | 97,4357 | 31,1391 |
| 92,8788 | 0,9959 | 0,0013 | 2,3758 | 12 | 92,6250 | 38,9867 |
| 97,5227 | 0,9969 | 0,0010 | 1,8039 | 2 | 0,0385 | 0,0213 |
| 102,1666 | 0,9977 | 0,0007 | 1,3697 | 7 | 31,7008 | 23,1451 |
| 106,8106 | 0,9982 | 0,0006 | 1,0399 | 2 | 0,9217 | 0,8863 |
| 111,4545 | 0,9987 | 0,0004 | 0,7896 | 6 | 27,1482 | 34,3821 |
| 116,0984 | 0,9990 | 0,0003 | 0,5995 | 1 | 0,1604 | 0,2675 |
| 120,7424 | 0,9992 | 0,0002 | 0,4552 | 2 | 2,3864 | 5,2424 |
| 125,3863 | 0,9994 | 0,0002 | 0,3456 | 4 | 13,3544 | 38,6383 |
| 130,0303 | 0,9996 | 0,0001 | 0,2624 | 2 | 3,0192 | 11,5048 |
| 134,6742 | 0,9997 | 0,0001 | 0,1993 | 0 | 0,0397 | 0,1993 |
| 139,3181 | 0,9997 | 0,0001 | 0,1513 | 2 | 3,4177 | 22,5908 |
| 143,9621 | 0,9998 | 0,0001 | 0,1149 | 0 | 0,0132 | 0,1149 |
| 148,6060 | 0,9999 | 0,0000 | 0,0872 | 1 | 0,8332 | 9,5528 |
| 153,2499 | 0,9999 | 0,0000 | 0,0662 | 0 | 0,0044 | 0,0662 |
| 157,8939 | 0,9999 | 0,0000 | 0,0503 | 0 | 0,0025 | 0,0503 |
| 162,5378 | 0,9999 | 0,0000 | 0,0382 | 1 | 0,9251 | 24,2319 |
| 167,1818 | 1,0000 | 0,0000 | 0,0290 | 0 | 0,0008 | 0,0290 |
| 171,8257 | 1,0000 | 0,0000 | 0,0220 | 0 | 0,0005 | 0,0220 |
| 176,4696 | 1,0000 | 0,0000 | 0,0167 | 0 | 0,0003 | 0,0167 |
| 181,1136 | 1,0000 | 0,0000 | 0,0127 | 1 | 0,9748 | 76,8258 |
| 185,7575 | 1,0000 | 0,0000 | 0,0096 | 0 | 0,0001 | 0,0096 |
| 190,4014 | 1,0000 | 0,0000 | 0,0073 | 0 | 0,0001 | 0,0073 |
| 195,0454 | 1,0000 | 0,0000 | 0,0056 | 0 | 0,0000 | 0,0056 |

| | |
|---|---|
| Number of patients | 1848 |
| Mu | 16,8631 |
| DGF | 40 |
| α | 5% |
| Critical value | 55,7585 |
| Chi Square | 556,8539543 |
| Reject distribution? | Yes |

The parameter that we used for this goodness-of-fit test was the average service time μ. However, we notice that the mean value is for both departments much larger than the median. For example, where the average for the NICU is 16.86, the median is 8.06. This discrepancy is caused by many short service durations against neonates with long lengths of stay. The rejection of the exponential distribution may have been caused by this discrepancy. Therefore, we perform a chi-square test using the median as parameter. Again, we use a range size of 4.64 days. The figure below compares the empirical data of the NICU (in yellow), with the exponential distribution (in orange) using the median as parameter. In the first range, the observed values are much lower than the expected values. This causes a large chi-square value, which results in the exponential distribution again being rejected. Chi-square tests for the Pelikaan and Leeuw provide identical results. Also, when taking smaller range sizes, the exponential distribution cannot be accepted for the lengths of stay.




Now that we completely reject the exponential distribution, we use distribution fitting software to find the best fit. This process saves us much time, and the fitting software is also less prone to errors. Besides, the fitting software provides much visual support, such as P-P plots, Q-Q plots, box plots and more. The programs we use for distribution fitting are JMP Statistical Software and EasyFit. We use two programs, to substantiate the best fit. Below, we show the JMP goodness-of-fit tests for respectively the NICU, Leeuw and Pelikaan.

Compare Distributions

| Show | Distribution | Number of Parameters | -2*LogLikelihood | AICc |
|---|---|---|---|---|
| | Johnson Sl | 3 | 13898,7393 | 13904,7523 |
| | Johnson Su | 4 | 13898,7393 | 13906,761 |
| | Weibull | 2 | 14028,2059 | 14032,2124 |
| | Extreme Value | 2 | 14028,2059 | 14032,2124 |
| | LogNormal | 2 | 14052,7026 | 14056,7092 |
| | GLog | 3 | 14052,7026 | 14058,7157 |
| | Normal 3 Mixture | 8 | 14058,0221 | 14074,1004 |
| | Gamma | 2 | 14079,0282 | 14083,0347 |
| | Exponential | 1 | 14137,6733 | 14139,6755 |
| | Normal 2 Mixture | 5 | 14393,6853 | 14403,7178 |
| | Normal | 2 | 16836,9875 | 16840,994 |

Compare Distributions

| Show | Distribution | Number of Parameters | -2*LogLikelihood | AICc |
|---|---|---|---|---|
| | Johnson Sl | 3 | 9207,5651 | 9213,57674 |
| | Johnson Su | 4 | 9207,5651 | 9215,58451 |
| | LogNormal | 2 | 9348,30338 | 9352,3092 |
| | GLog | 3 | 9348,30338 | 9354,31502 |
| | Normal 3 Mixture | 8 | 9369,59298 | 9385,66298 |
| | Weibull | 2 | 9544,11126 | 9548,11708 |
| | Extreme Value | 2 | 9544,11126 | 9548,11708 |
| | Gamma | 2 | 9707,00946 | 9711,01527 |
| | Exponential | 1 | 9812,1796 | 9814,18153 |
| | Normal 2 Mixture | 5 | 10004,4683 | 10014,4974 |
| | Normal | 2 | 14764,5637 | 14768,5695 |

Compare Distributions

| Show | Distribution | Number of Parameters | -2*LogLikelihood | AICc |
|---|---|---|---|---|
| | Johnson Su | 4 | 11494,4687 | 11502,4842 |
| | Johnson Sl | 3 | 11760,7914 | 11766,8008 |
| | LogNormal | 2 | 11845,6811 | 11849,6858 |
| | GLog | 3 | 11845,6811 | 11851,6904 |
| | Normal 3 Mixture | 8 | 12012,1555 | 12028,2115 |
| | Weibull | 2 | 12447,1556 | 12451,1602 |
| | Extreme Value | 2 | 12447,1556 | 12451,1602 |
| | Gamma | 2 | 12704,9931 | 12708,9977 |
| | Exponential | 1 | 12888,5721 | 12890,5736 |
| | Normal 2 Mixture | 5 | 13504,1335 | 13514,1568 |
| | Normal | 2 | 19194,0249 | 19198,0295 |

Smaller values of the negative log-likelihood indicate better model fits (JMP Statistical Software, 2017). The Akaike's Information Criterion (AICc) is another form of fit assessment. The three figures above present the Johnson, Weibull and lognormal distribution as the best fits. The exponential distribution seems for all three datasets not an appropriate distribution. Now, we present the three goodness-of-fit tests from EasyFit to substantiate our findings.

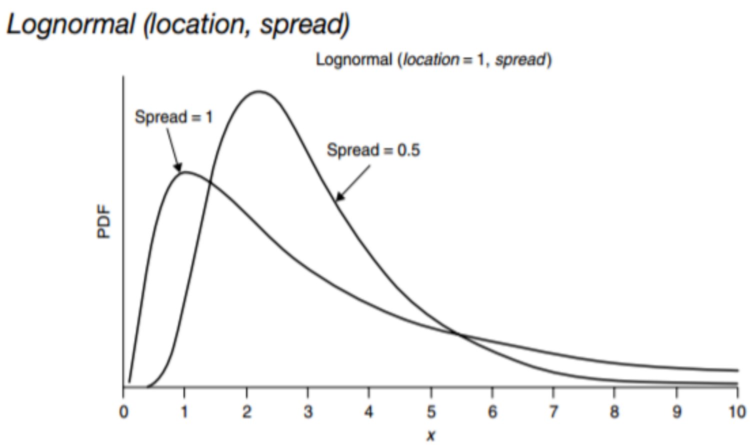
| Distribution | Kolmogorov Smirnov | | Anderson Darling | | Chi-Squared | |
|---|---|---|---|---|---|---|
| | Statistic | Rank | Statistic | Rank | Statistic | Rank |
| Frechet (3P) | 0,0274 | 1 | 2,1173 | 2 | 30,028 | 1 |
| Log-Logistic (3P) | 0,02756 | 2 | 2,0462 | 1 | 34,719 | 2 |
| Log-Logistic | 0,03689 | 10 | 4,3284 | 10 | 36,044 | 3 |
| Dagum (4P) | 0,03163 | 5 | 2,6947 | 3 | 49,852 | 4 |
| Lognormal (3P) | 0,03227 | 8 | 3,2776 | 6 | 51,431 | 5 |
| Burr (4P) | 0,03171 | 6 | 3,1364 | 5 | 53,523 | 6 |
| Dagum | 0,03196 | 7 | 3,0231 | 4 | 54,605 | 7 |
| Pearson 6 (4P) | 0,03051 | 3 | 3,3007 | 7 | 56,345 | 8 |
| Burr | 0,03123 | 4 | 3,6408 | 8 | 61,269 | 9 |
| Lognormal | 0,05232 | 13 | 8,645 | 12 | 63,998 | 10 |

| Distribution | Kolmogorov Smirnov | | Anderson Darling | | Chi-Squared | |
|---|---|---|---|---|---|---|
| | Statistic | Rank | Statistic | Rank | Statistic | Rank |
| Log-Logistic | 0,09932 | 12 | 25,619 | 10 | 295,12 | 1 |
| Gen. Extreme Value | 0,07304 | 7 | 13,699 | 5 | 322,35 | 2 |
| Pareto 2 | 0,11589 | 16 | 34,812 | 12 | 340,17 | 3 |
| Lognormal | 0,11314 | 15 | 37,688 | 13 | 378,42 | 4 |
| Log-Logistic (3P) | 0,06493 | 1 | 11,332 | 1 | 395,55 | 5 |
| Pearson 6 | 0,08227 | 9 | 20,327 | 9 | 400,07 | 6 |
| Burr (4P) | 0,06598 | 4 | 12,147 | 2 | 404,35 | 7 |
| Dagum | 0,06554 | 3 | 12,447 | 4 | 434,91 | 8 |
| Dagum (4P) | 0,06549 | 2 | 12,422 | 3 | 437,51 | 9 |
| Burr | 0,07066 | 5 | 15,417 | 6 | 441,07 | 10 |

| Distribution | Kolmogorov Smirnov | | Anderson Darling | | Chi-Squared | |
|---|---|---|---|---|---|---|
| | Statistic | Rank | Statistic | Rank | Statistic | Rank |
| Pearson 5 | 0,08051 | 1 | 51,906 | 15 | 496,22 | 1 |
| Burr (4P) | 0,09794 | 4 | 16,159 | 1 | 550,57 | 2 |
| Burr | 0,09776 | 3 | 19,709 | 2 | 678,33 | 3 |
| Dagum (4P) | 0,10467 | 9 | 20,882 | 3 | 706,27 | 4 |
| Pearson 6 (4P) | 0,10462 | 8 | 21,641 | 4 | 712,03 | 5 |
| Pearson 5 (3P) | 0,11694 | 15 | 54,592 | 16 | 740,1 | 6 |
| Pearson 6 | 0,10424 | 6 | 24,99 | 6 | 765,28 | 7 |
| Gen. Extreme Value | 0,1232 | 18 | 32,183 | 9 | 772,46 | 8 |
| Dagum | 0,10429 | 7 | 23,331 | 5 | 772,46 | 9 |
| Pareto 2 | 0,13118 | 19 | 56,199 | 17 | 788,21 | 10 |
| Log-Logistic (3P) | 0,10838 | 11 | 29,272 | 7 | 858,39 | 11 |
| Log-Logistic | 0,11845 | 16 | 30,7 | 8 | 881,16 | 12 |
| Lognormal | 0,10412 | 5 | 33,301 | 10 | 910,46 | 13 |
| Lognormal (3P) | 0,11527 | 14 | 34,171 | 11 | 921,41 | 14 |

The three figures above show the goodness-of-fit test for respectively the NICU, Leeuw and Pelikaan. We rank the outcomes based on the chi-square test. Again, we identify that the lognormal distribution seems a good fit. EasyFit does not state the lognormal distribution as the best fit, but this distribution does appear within the ten best distributions for the three datasets.

Robinson (2004) discusses the potential application of a lognormal distribution as "*time to complete a task*". Therefore, this distribution seems applicable for service times. Besides, the median and mode of all three datasets are close to each other. Since the mode is a small value, the 'hump' of the PDFs are close to the Y-axis. The figure below shows the PDF of the lognormal distribution, visualised by Robison (2004).



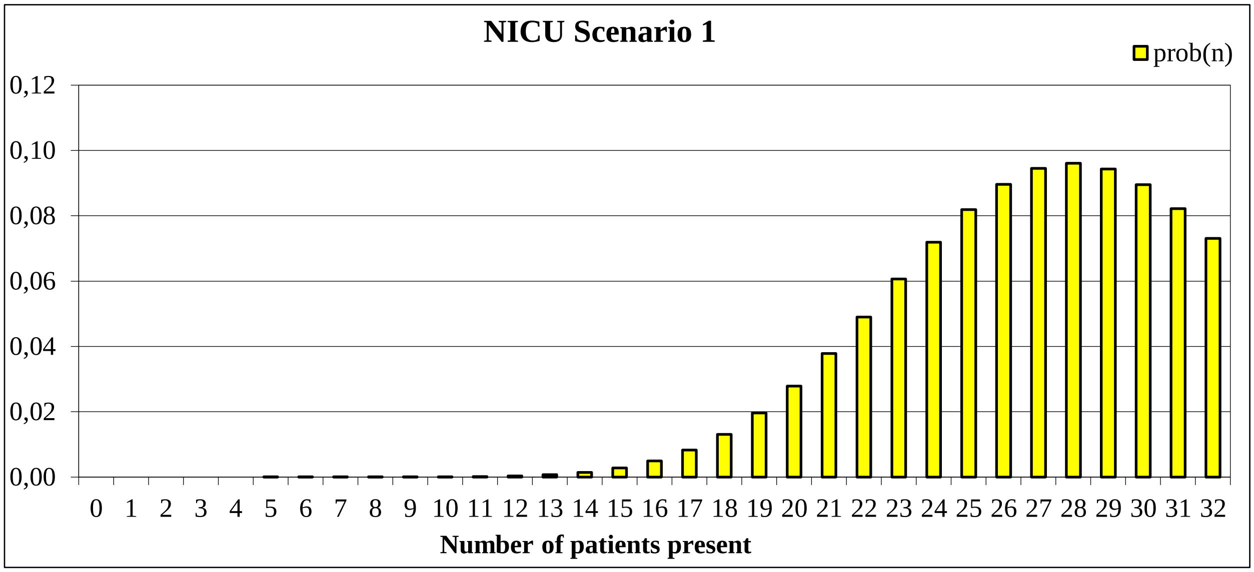

We conclude by saying that our queueing model is a M/G/c/c-model. The *M* stands for a Poisson arrival process with interarrival times that are exponentially distributed. The *G* states that service times have a general distribution. We rejected the hypothesis of an exponential distribution. Then, by using fitting software, we selected the lognormal distribution as most appropriate. However, QtsPlus does not make a distinction between the other distributions when rejecting the exponential distribution. The first *c* stands for the number of servers that are operational, while the second *c* indicates that no queueing for hospital beds is allowed, as the maximum number of customers in the system is equal to the number of servers operational. This appendix serves as substantiation of Section 4.1.

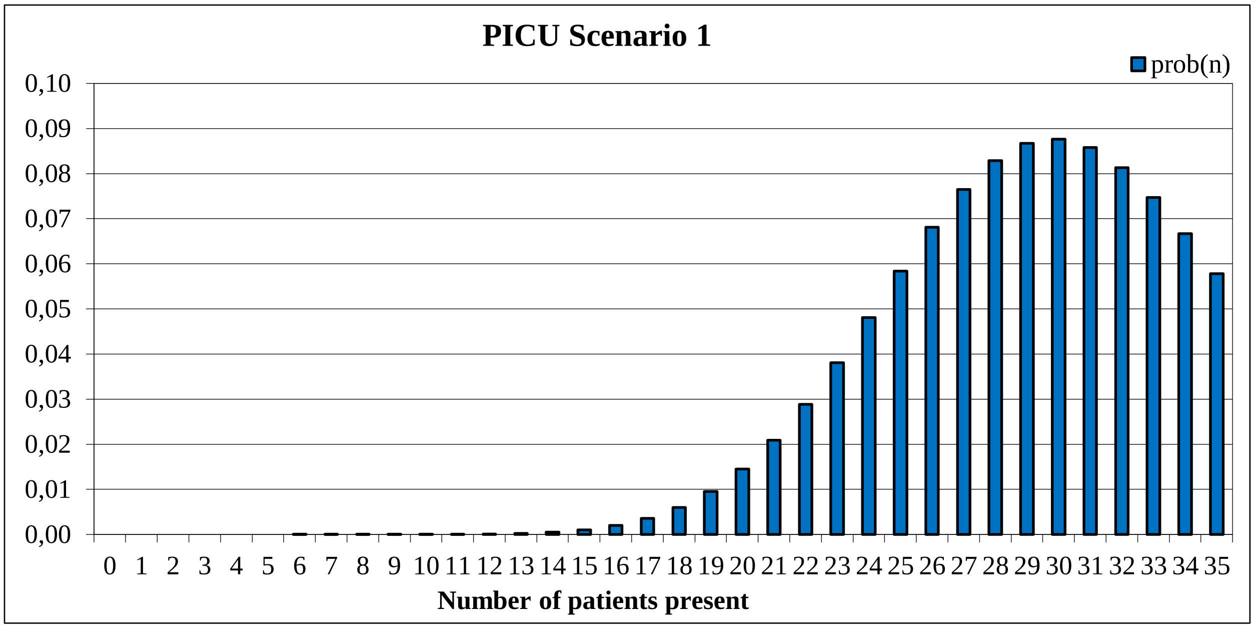
# Appendix C: Probability distributions

In this appendix, we present the probability distribution of present patients in the queueing system. For the four scenarios, we visualise the probability for the number of patients present. We do this because each scenario has impact on the rejection probability, the number of patients present and the corresponding occupancy rate. This appendix is meant to substantiate the evaluation of scenarios described in Section 4.4.

### Scenario 1: Current situation

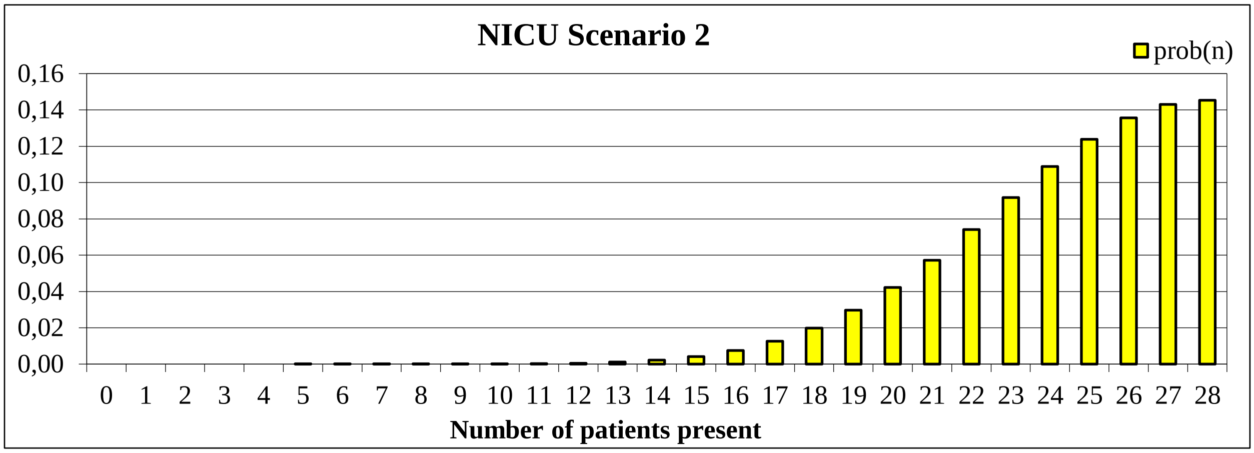
In the first scenario, the capacity is allocated based on the current situation. We do this to validate our queueing model. In this scenario, 32 rooms are assigned to the NICU and 35 to the PICU. The first scenario shows that the NICU most likely treats 28 patients, while the PICU most likely has 30 patients present. After the peak, the probabilities decline which result in a rejection probability of 7.3% on the NICU and 5.8% on the PICU. At these moments, the system is fully occupied and any arriving patients will be rejected. There is no probability that less than five patients are present on either department.

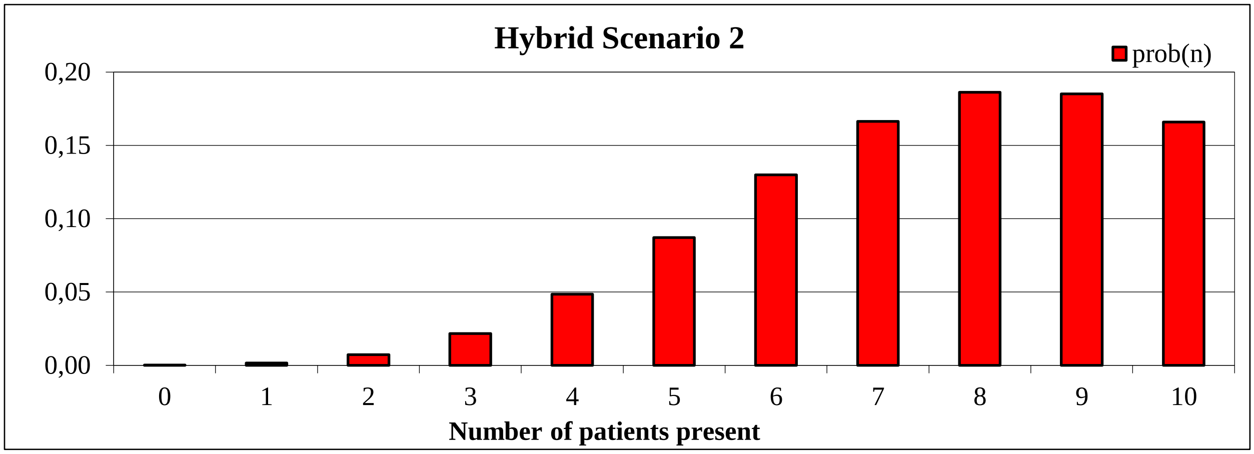


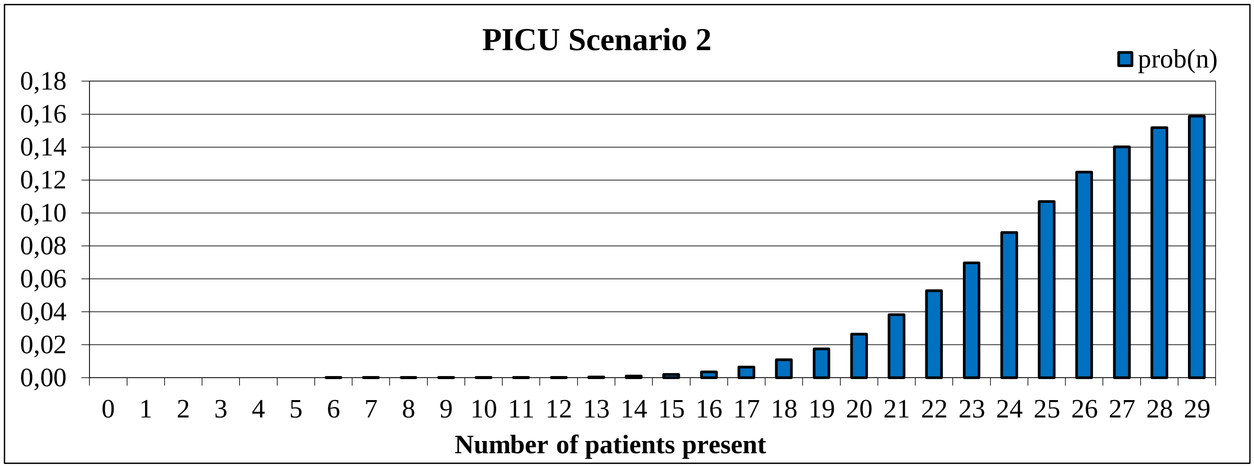



### Scenario 2: Occupancy to capacity

The second scenario allocates the capacity based on the current occupancy rates. This means that 28 rooms are assigned to the NICU, 29 rooms to the PICU and the resulting 10 rooms to the hybrid. In contrast with the first scenario, the following three graphs have a different shape. The peaks in probability of the PICU and NICU are at the right end of the X-axis. Meaning, it is most likely that the systems are fully occupied. For the hybrid, it is most likely that 8 patients are present. The rejection probabilities are respectively 14.5%, 16.6% and 15.9%. The figures of the NICU and PICU are shortened versions of the graphs shown in the first scenario. This is because the parameters of the NICU and PICU remain constant over the four scenarios.

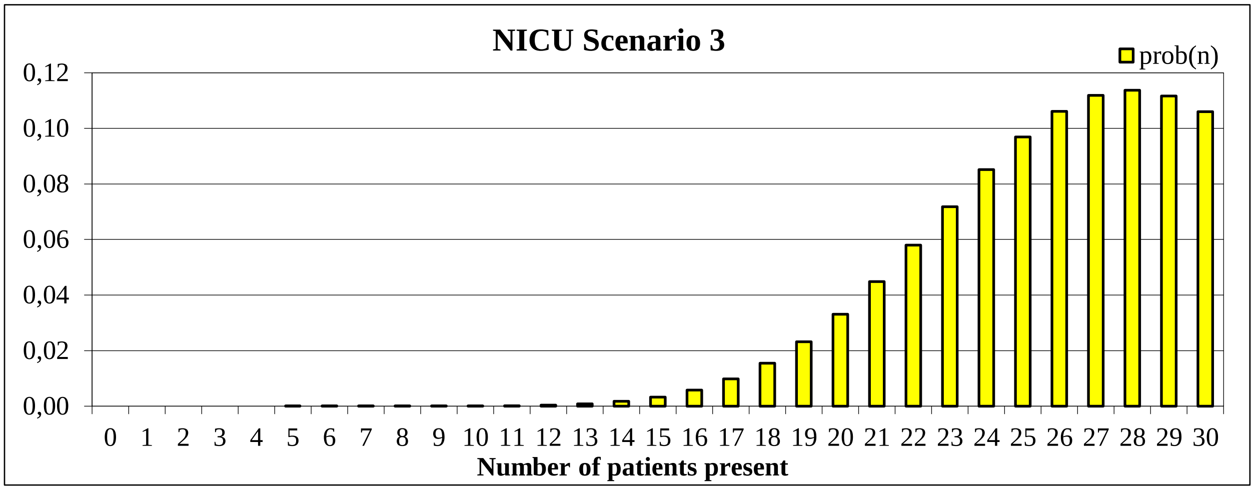


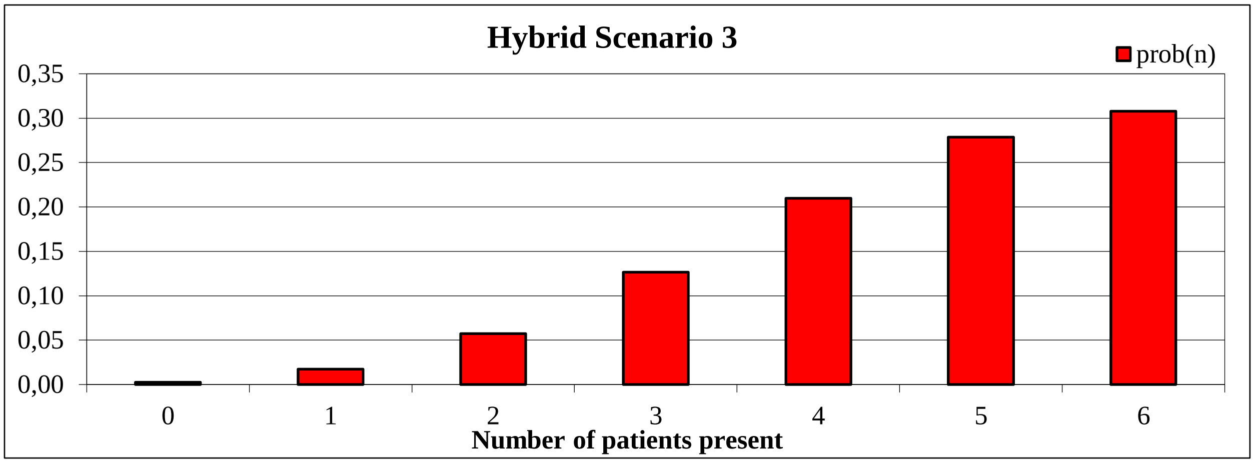



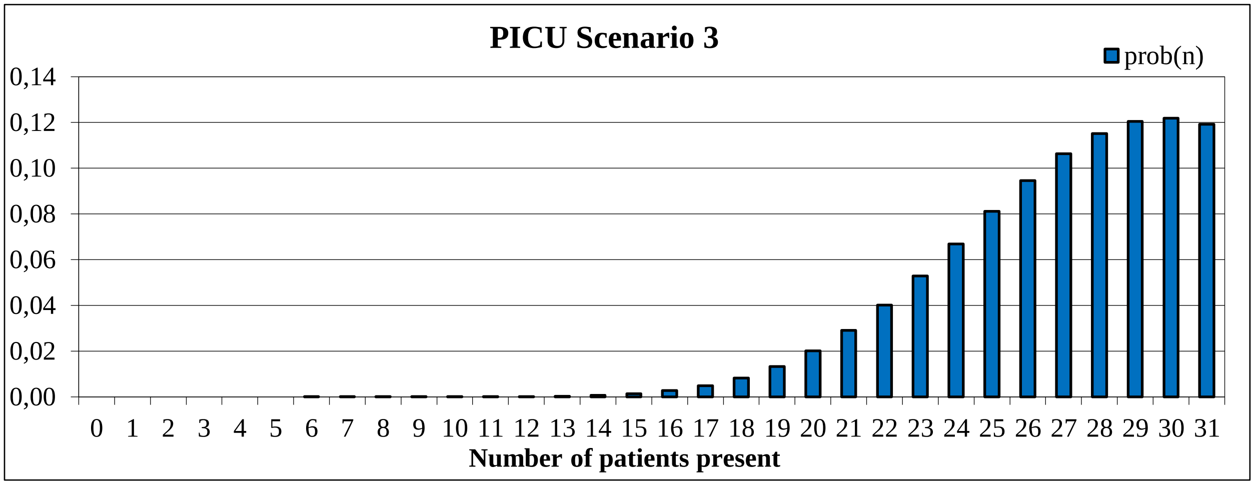



### Scenario 3: Safety stock

The third scenario includes a buffer in capacity. Compared to the second scenario, this scenario allocates extra rooms to the NICU and PICU based on the standard deviation. Therefore, since this capacity is meant to accommodate high demand, we call this 'safety stock'. In the three graphs below, we identify that when the NICU have 30 rooms assigned, the rejection probability is 10.6%. For the hybrid this probability is 30.8%, while 11.9% of the time the PICU is fully occupied. When six rooms are assigned, is most likely that the hybrid is fully occupied.



### Scenario 4: Two of each

This scenario allocates four single-person rooms to the Harmonica, based on stakeholder preferences. Each department allocates two rooms to the hybrid to accommodate high peaks in demand. The three graphs below visualise the impact of this scenario. As in the third scenario, the NICU has 30 rooms assigned. Therefore, the NICU graph is identical. The hybrid has a 44.3% chance of rejecting patients, which is considerably larger than in the other scenarios. Furthermore, the NICU rejection probability is 10.6% and for the PICU this number is 8.5%.