Bed Occupancy Optimization:

Combining Wards to Gain Performance

Author:	Stephen Kil
Academic Supervisor:	A.P.M. Wagelmans
External Supervisor:	J.M. van Oostrum

Erasmus School of Economics
Operations Research and Quantitative Logistics
in cooperation with,
Erasmus Medical Center

Master's Thesis 2011
Rotterdam, 26th August 2011

Keywords: *Healthcare, Ward, Occupancy, Inventory Management*

Abstract

Nowadays university hospitals become more and more interested in operations research. Within a hospital all medical departments are connected by some process. One of those processes is the care wards provide to patients. While providing this care, a patient occupies a hospital bed; those beds are scarce. There is a clear trade-off between the occupancy level and ward availability. The more beds, the lower the occupancy and the higher the availability. We describe the idea of increasing the occupancy while maintaining the same availability, by combining wards. To estimate the occupancy and ward availability we developed a model that not only uses the patient arrival rate, but also includes the patient bed requirements (i.e. a patient requiring multiple beds).

Contents

1 Introduction

1.1 Hospitals

One of the main objectives of an university hospital, besides providing education and doing research, is to provide care to those who need it. Part of this care is provided in the wards of the hospital. A ward is a care unit that provides care to patients during treatments and is, in general, a scarce resource within a hospital[1]. Furthermore, not only is this a scarce resource, most individual wards are controlled by different medical department rather than the wards being one shared resource.

While wards are essential to hospital care, they are also a huge cost factor as a medical departments Nowadays, the health care sector is becoming more and more interested in using operations research to optimize the available resources, enhance patient care and minimize cost. However, in case of wards, current solutions only go so far as to more accurately estimate the arrivals and target a given occupancy level (Harper, 2002; Green, 2002). Although these solutions do benefit the hospital, they have negative impact on patient service (Green & Nguyen, 2001).

1.2 The scope of this research

The main goal of this thesis is to find a way to,

> Optimize the bed occupancy level by combining ward locations, while keeping the current level of ward availability.

The literature suggests several definitions for the *bed occupancy level*, but the most used is

$$occupancy\ level = \frac{average\ number\ of\ occupied\ beds}{total\ operational\ beds}. \tag{1.1}$$

Using Equation 1.1 we can easily show that we can increase the occupancy level by reducing the total operational beds, but this inadvertently will also lower the ward availability. The *ward availability* is usually defined as,

$$ward\ availability = \frac{admitted\ patients}{total\ arrivals}. \tag{1.2}$$

As a result of lowering the operational beds, fewer patients can be admitted and thus the ward availability will decrease. Therefore we have to find an alternative way to increase the occupancy level and maintain the service level, for example combining *ward locations*. Throughout this thesis we answer a series of questions, which help reaching our intended goal.

1. *How do wards operate and what characteristics can we exploit in our models?* Section 2 is used to introduce wards, as well as their general behaviour. Furthermore we will describe the situation at Erasmus MC, which provided us with the patient data; the Erasmus MC is trying to restructure the organisation and increase the occupancy level, without lowering the service level.

[1] In Section 2 we will explain wards and ward locations (WLs) in more detail.

2. *What solution methods exist in the currently available literature?*
Within the operations research field there already exist various models and solutions related to health care. Generally these methods can be classified in four different levels; strategic, tactical, off-line and on-line operational control. In Section 3 we will present some of the existing ideas or methods, as well their usual operational level.

3. *Which model is best to describe the patient flow in the wards?*
The first step is to analyse the available data, in Section 4, so that we can use that in our model. Thereafter we derive our theoretical model in Section 5, which we will evaluate using the simulation described in Section 6. Section 7 will show results for two different divisions, as well as a series of different theoretical situations.

4. *Can managerial decisions further optimize bed occupancy?*
Some aspects of wards that affect the occupancy or service level are by design and can only be changed by managerial decisions. We use Section 8 to elaborate on some ideas which might further increase occupancy or service levels.

This research is done for and in cooperation with the Erasmus MC, which is the largest university hospital in the Netherlands.

2 Characterizing Wards

2.1 Wards in general

A ward is a care unit that provides care to patients during treatments. While wards are an essential part of the hospital, they are also expensive. Historically wards are categorised by their speciality, e.g., general surgery or orthopaedics. Recently other classifications are used in extension to the specialities, such as average length of stay (LOS) and level of care. The advantage of these classifications is that each ward only has one type of patient. However, they might also lead to low occupancy levels as arrival rates for some specialities are quite low.

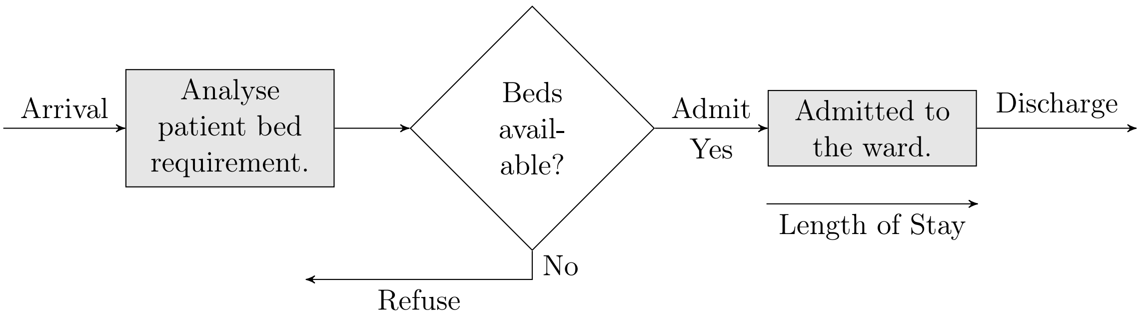


Figure 1: Patient flow through a ward.

Figure 1 shows general patient flow through a hospital ward[2]. At patient arrival, the hospital estimates the patient's bed requirement – e.g. 2 beds – and if these beds are available the patient is admitted. If not, the patient is refused and most likely will find

[2]This flow diagram is inspired on the flow diagram we found in (Bruin, Bekker, Zanten, & Koole, 2010)

care elsewhere. The patient stays in the hospital ward and occupies a bed until the current treatment has been completed. After completing the treatment, the patient is discharged and the bed available again.

2.2 Wards in Erasmus MC

The Erasmus MC has 115 wards of which the majority is categorised by their speciality and the length of stay (LOS). As the term 'ward' is both used for a physical location in the Erasmus MC as well as a hierarchical term, we will refer to one of these 115 locations as ward location (WL). As such in our case a *ward* can consist of multiple locations, i.e., WLs. Throughout the Erasmus MC each WL is owned by one medical departments, as shown in Figure 2.

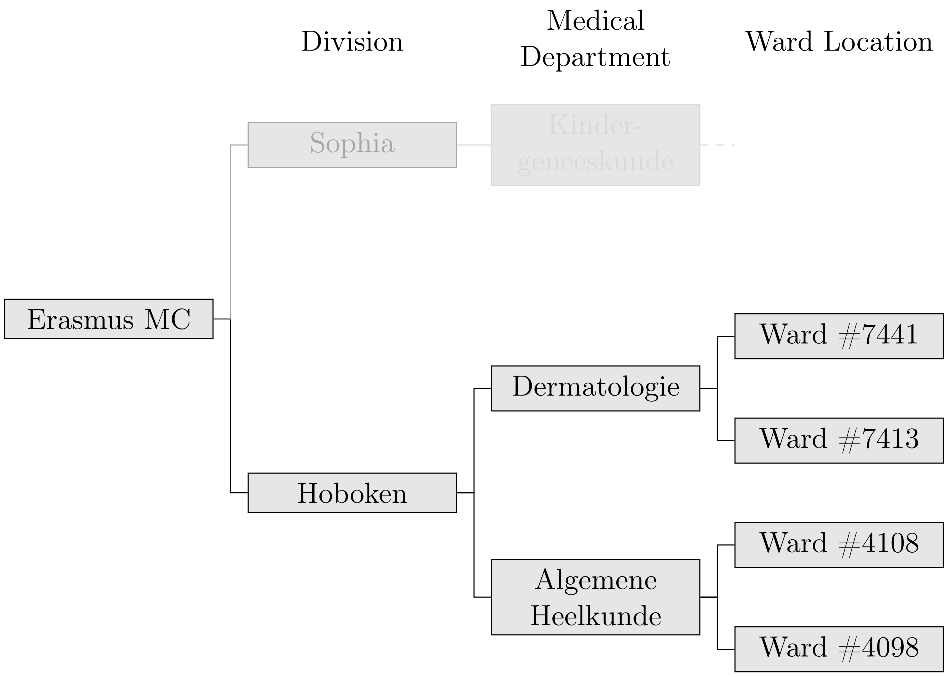


Figure 2: Part of the current situation within the Erasmus MC.
This organisational chart only shows a small part of the Erasmus MC. In fact *Algemene Heelkunde* has 6 WLs.

Therefore, a WL only provides care to patients of that medical department.

2.3 Case Study

2.3.1 Introduction

The general idea for this thesis originated from a project the Erasmus MC is working on. The Erasmus MC in Rotterdam currently has 33 medical departments across 7 divisions in 3 different locations. As mentioned above, currently each medical department is responsible for a series of WLs; these only provide care for patients from that medical department.

In the near future the Erasmus MC will restructure the divisions and medical departments to reduce cost. One of the proposed changes is to reposition the WLs within the organisation.

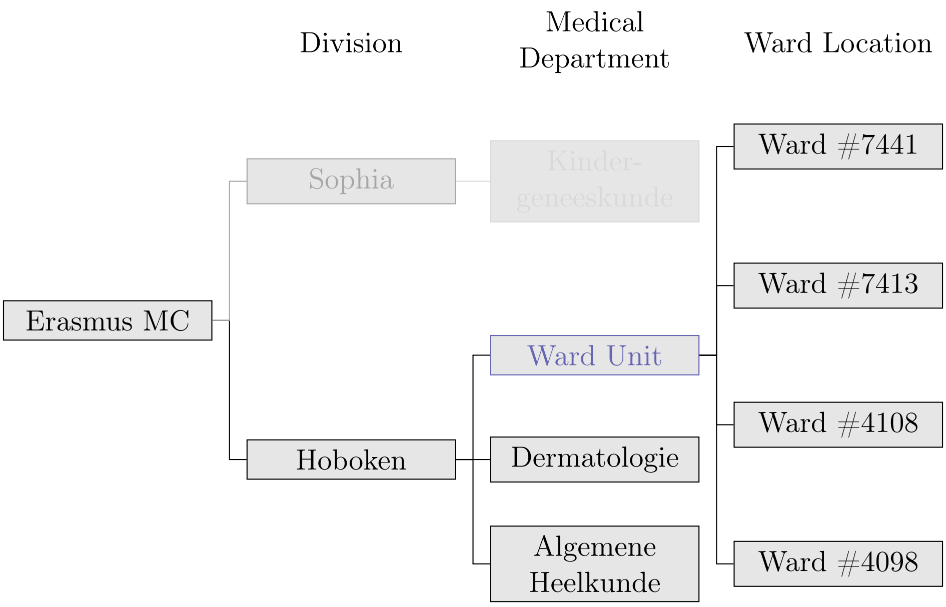


Figure 3: The proposed situation by the Erasmus MC.

A new medical department will be created, for each division, and has as sole purpose to provide (ward) care for patients of the medical departments within that division. There has not yet been a decision for a precise layout of the individual WLs this new medical department is in charge of, but the goals are to

- reduce cost;
- increase the occupancy level;
- maintaining at least the same availability[3].

The first goal by itself is easy. The majority of the cost of a ward comes from the operational beds, even if there are no patients assigned to them. For this reason it seems only fair to decrease the number of operational beds, which will also increase the occupancy level due to relation 1.1. However, as we mentioned before, this will negatively influence the ward availability, i.e., service level – see Equation 1.2.

2.3.2 Study Design

As this study has a clear practical application, we employ a classical 3-step approach: (theoretical) design, (empirical) validation and implementation. In this thesis we address the first two phases, i.e. design and validation, of this approach.

1. **Design**
   Sections: 4, 5
   During this phase we analyse the available data and identify the key processes within wards. We then use these processes to design a theoretical model that represents reality. When processes are uncertain, no clear representation possible, we have to make assumptions and as such the represented reality may change.

[3]As we will use inventory management, this is also referred to as the *service level*.

2. **Validation**
   Sections: 6, 7
   We validate our theoretical model by use of simulation. Using the actual data we designed a simulation environment that supports a series of testing scenarios. This phase is usually as close to reality as the data allows, but can also cover extreme cases.

The third and final phase, i.e. the implementation, is done by the hospital management in a later stadium. This phase requires some more research into some soft-aspects of this model. For example, this model might show that combining wards has a clear financial benefit, but planning might be so complex the result can never be implemented. The actual choice for implementation depends on several factors, ranging from the actual benefit, the perceived complexity by employees to the implementation cost.

3 Literature Overview

3.1 Background

Within the field of healthcare management, a field that has relatively small overlap with the operations research community, there are several popular subjects (Carter, 2002). For example, as approximately 60% of all inpatient admissions consist of a visit to the operating room (OR) department, the OR department is an interesting subject. However none of these subjects can be viewed as stand-alone, because they are all connected through various resources within the hospital (Van Berkel & Blake, 2007). Some of these resources are scarce and impose constraints on the performance of other medical departments. One such a resource are the beds wards provide to patients. Again considering the OR department example, the ward imposes constraints on the OR department's schedule since after surgery a bed has to be available for recovery. Assuming we target a ward availability of 95 per cent and if the ward is functioning sub-optimal, at the point where it has too few beds, the OR department can never attain the best possible throughput.

Historically, many decisions within a hospital, including the ward size, are based on basic statistics, e.g., averages and proportions. More recent, many authors considered the patient flow and bed requirement to be like queueing models, which vary greatly in complexity (Harper & Shahani, 2002). Other authors used integer programming (Ruth, 1981) and simulation approaches (Dumas, 1985; Van Berkel & Blake, 2007). These models share a similar goal, to optimize the bed allocation throughout the hospital to reduce cost.

3.2 Planning and Ward Occupancy

This section gives an overview of ward resource planning and the proposed solution methods in the literature. We will decompose the planning process in four classic hierarchical levels: strategic, tactical, off-line and on-line operational control (Vissers, Adam, & Bekkers, 2002).

3.2.1 Strategic Level

On the strategic level the focal point is on long-term goals and targets. Usually, this involves answering questions like 'what ...?' or 'where ...?', e.g., 'what service level do we target'? To reach these goals, we need to dimension the ward resources (Bruin et al., 2010), such as, the beds and personnel. At this level decisions are made about the physical bed capacity. The ward capacity decisions are not made by the hospital management alone, but are influenced by for example governments imposing a minimum occupancy or service level. Furthermore, agreements are made with the staff concerning their service (Oostrum, 2009). The horizon for strategic planning is usually more than a year and is based on historical data.

3.2.2 Tactical Level

The tactical level is more a mid-term process, anywhere from a couple of weeks up to 1 year (Wullink et al., 2007). Here we focus more on the 'how ...?', e.g., 'how do maintain a certain service level'? The answer to these questions are based on the actual patient demand (Oostrum, 2009). At this stage the operational bed requirements are determined. Historically these operational bed requirements depend on the 'rights' a ward acquired within the organisation (Bruin et al., 2010), but is becoming more and more based on the actual demand (Green & Nguyen, 2001; Green, 2002; Bekker & Bruin, 2010).

3.2.3 Off-line Operational Control

Once both the long-term goals and the mid-term assignments of resources has been completed, it becomes important to create schedules. How many medical personnel has to be assigned to each ward? There already is a fixed operational bed target and the schedule should contain at least enough personnel to main this target. This horizon for planning is usually around 1 week.

3.2.4 On-line Operational Control

On-line operational control involves dealing with the changes in the weekly schedule. Due to, for example, sickness there is a slight fluctuation in available staff, which in terms effects the number of operational beds. This also involves re-scheduling scheduled admissions if there is too little capacity.

3.3 Terminology

In this section we will discuss some commonly used definitions, which might not be evident without a medical or health care management background.

3.3.1 Arrivals versus Admissions

When reviewing hospitals, there is distinct difference between *arrivals* and *admissions*. An arrival is simply a person requiring medical care, who arrives at the hospital. If, upon arrival, there is capacity available he or she is admitted; this capacity can be anything from available beds to the required personnel. Hospitals generally only register admissions, where we require arrivals. To approximate the arrivals we will use a method described in Bruin et al., 2010, which uses the registered admissions, length of stay (LOS) and the number of operational beds.

3.3.2 Scheduled and Unscheduled Arrivals

We can divide all arrivals in two groups, namely scheduled and unscheduled arrivals. The scheduled arrivals usually occur during the day and are known in advance. These arrivals are scheduled anywhere from a couple of days up to several weeks in advance. Unscheduled arrivals on the other hand are not known in advance and usually involve emergency care.

3.3.3 Length of Stay

After a patient is admitted in the hospital, the time he or she spends in a ward is called the length of stay (LOS), abbreviated as LOS. After this time a patient can either be discharged or transferred to another ward[4]. This information can easily be obtained from the hospital administration, as both the time of admission and discharge are registered.

3.3.4 Physical and Operational Beds

We have to classify two different type of beds, namely *physical beds* and *operational beds*. The first one is rather straightforward, but the latter requires some explanation. An operational bed is a management term, which is defined by the available staff for each ward. Usually there is a ratio of operational beds per staff member, i.e., one bed per employee. The amount of operational beds is generally lower than the actual physical beds in a ward. Hence, a patient can only be admitted if there is an *operational bed* available. The number of operational beds is usually evaluated every year, but might vary slightly from week to week (Green, 2002) due to holidays or illness.

4 Quantifying Wards

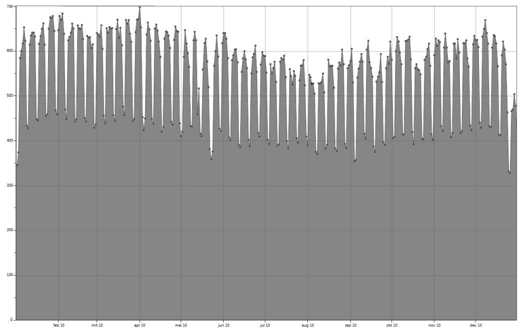
4.1 Overview

The Erasmus MC has provided us with anonymous patient[5] data of 42,431 patients, which were all admitted in 2010. During this year these patients made 91,976 visits to the hospital and stayed 336,605 days in the wards. This comes down to an average of 7.93 days per patient and an average of 3.66 days per visit. Figure 4 shows the number of patients in the hospital per day of each physical location.

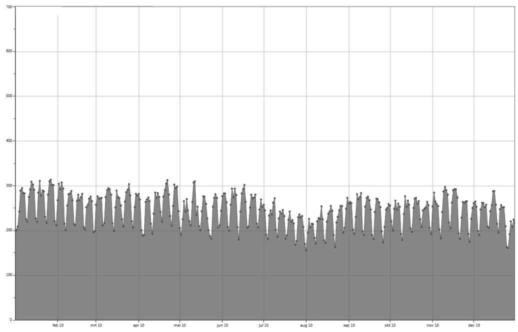
[4] This will be noted as a new admission.

[5] Each patient was assigned a random numeric id and all personal information had been removed.

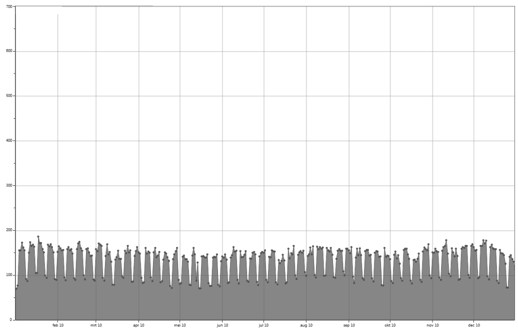
Figure 4: Daily number of patients staying in the hospital.
Throughout the year, there are on average 543 patients in location *Hoboken*, 244 in location *Sophia* and 133 in location *Daniel den Hoed*.



(a) Location: Hoboken



(b) Location: Sophia



(c) Location: Daniel den Hoed

We will use this data to derive the distributions for the arrivals and admissions, Section 4.2, and LOS, Section 4.3. Section 4.4 will be used to explain some assumptions we made about the current number of operational beds per WL.

4.2 Arrivals

4.2.1 Admissions

As we mentioned before, currently the Erasmus MC has 115 WLs, distributed over 7 divisions. As shown in Table 1 the total admission rate (λ) is approximately 321.76 patients per day, but the admission rates per division differs considerably. Due to the length of the table, we refer to Appendix A Table 20 for a full overview of the admission rates.

division	**no. of admissions**	rate [week]	rate [weekend]
Daniel	15,923	58.51	3.13
Diagnostiek	431	1.65	0.00
Hersenen en Zintuigen	10,913	38.50	8.31
Hoboken	22,919	81.39	16.11
Sophia	26,119	87.18	32.36
Spoed en Intensief	6,079	22.18	2.80
Thorax	9592	32.35	11.05
Total	91,976	321.76	73.76

Table 1: Daily admission rate for all 7 divisions in the Erasmus MC.

The provided data does not contain the exact arrival times, merely the dates. However, there is reason to assume that this is not constant during a 24 hour period. For example, most scheduled arrivals occur during office hours and not at night. Therefore there the arrival rate might be considerably lower during the nights. We have no way of confirming this at this time, thus we assume that arrivals occur with the same rate during day and night – Assumption 4.1.

Assumption 4.1 (Admissions) *Patients arrive uniformly over a* 24 *hour period, thus allowing* 1 *arrival rate for a day.*

Table 1 also shows that the admission rate is considerably lower during the weekends. As a result, the occupancy level will also be lower during the weekends.

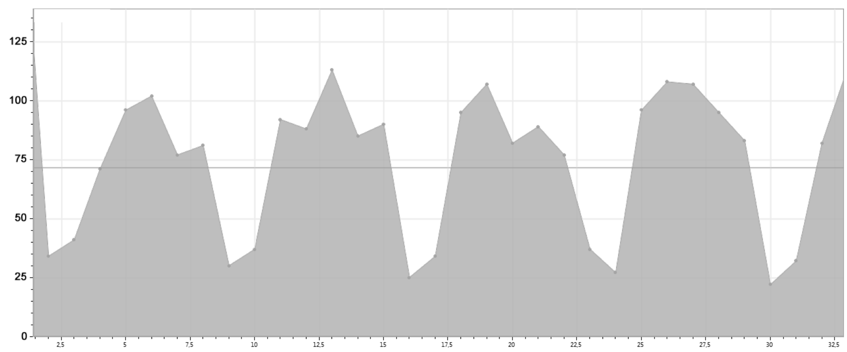


Figure 5: Daily number of admissions for the Sophia division.
Without seperating weekdays and weekends, there are 72.3 admissions per day on average.

4.2.2 Arrival Rate

As we mentioned before, the is no information about the actual arrival rate. Bruin et al., 2010 described a method to derive the actual arrival rate from the LOS and operational beds, using the *Erlang Loss* function. However, the Erlang Loss model requires the arrival rate to be (*pure*) Poisson, which is not necessarily the case. In Section 5 we will adapt their idea to our new situation.

4.3 Length of stay

4.3.1 Deterministic Data

As we mentioned before, there is no information about the actual time of admission, merely the date. Therefore the LOS is deterministic, e.g., either 1 or 2 days, rather than continuous. There are several minor issues with these values, as admissions of a couple of hours are stored as a whole day. As a result, the majority of the WLs have a fairly large amount of patients with LOS of 1 day. Furthermore, a bed can only be used once every day, even though the patient was only in it several hours; hence, it is only freed at the end of a 24 hour period.

4.3.2 Continuous LOS

We assume that this is merely a data issue, rather than the reality. Therefore we assume that the actual LOS is continuous. Some WL only had 1 or even 0 arrivals, we did not include those in the figures in this section as there is too little data to provide an accurate analysis. These WL have so little impact on the overall system, that these are not going to make a difference. We also assume that the LOSs of patients are independent.

Assumption 4.2 (Length of Stay) *The treatment duration of patients are independent; within each ward location they are identically distributed.*

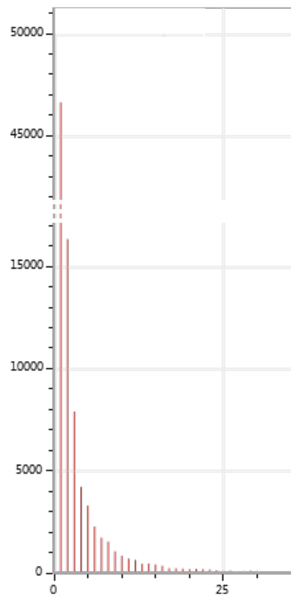


Figure 6: Histogram of the admitted days of all patients.

The average LOS for the entire hospital is 3.66 days, but ranges from less than a day[6] up to 109.77 days. We built a small tool, using *MatLab*, which tries to fit several known distributions over the LOS, e.g., *normal*, *exponential*, *Weibull* and *Gamma* distributions. The majority of the time the LOS can be approximated by an *exponential distribution*, but in some cases a Weibull distribution is a better fit. We found two reasons why Weibull could be a better fit. The first, and most important, reason is that some WL provide treatments that take at least several days, which cannot be approximated by an exponential distribution. These WL have a Weibull shape parameter that is larger than 1, shifting the distribution to the right, i.e., more than 1 day. The second reason is a little less obvious, as the data is rounded upwards to whole days. However, some wards have a relatively large amount of day treatments and thus a relatively large probability of 1 treatment day. This results in a Weibull distribution with a shape parameter less than 1, which looks largely like an exponential distribution but with higher probabilities on the first few days.

During the simulation we use random generated numbers from the appropriate distribution as LOS. While Section 6.2.3 will explain this in more detail, we do want to mention

[6] We cannot be more precise, as we do not have this data.

one thing. As we now draw an arrival from a Poisson distribution and a LOS from either an exponential or a Weibull distribution, the treatment might end in during the night. If we generate an arrival at $10AM$ and draw a LOS of 36 $hours$, the patient is discharged at $2AM$ 2 days later. In reality this will not occur, as these patients will be discharged the next morning. We argue, shown in Section 7.6.1, that this has little impact on the actual performance in reality and thus we assume that patient can also be discharged during the night.

> **Assumption 4.3** (Discharging) *Patients will be discharged immediately after ending their treatment and thus can be discharged at any time during a* 24 *hour period.*

4.4 Beds

4.4.1 Operational Beds

Part of the data we received was a list of operational beds per WL. However, there are some inconsistencies found in this list. While a large part of the data seems accurate, there are a few that stand out. For example, the list states that WL 'Ambulante Zorg Daniel (6951)' has 10 operational beds, but the patient data suggests that on average there are 19.12 beds occupied. Clearly if there are only 10 operational, this cannot happen. There are also a few wards where it is the other way around. WL 'Algemene Heelkunde (4125)' had only 1 arrival last year, but according to the data there were 40 operational beds.

We believe the latter case to be typing mistakes, as usually exchanging 2 subsequent values result in logical combinations – in case of the example we believe that there were 40 operational beds at WL 4126, which had an average of 29.32 occupied beds. However, the first error is harder to correct as these do not seem to be mistakes made when creating this list. We do however notice that in case the data seems to be valid, the occupancy level varies from approximately 40 per cent to 95.4 per cent. This results in a 65 per cent occupancy level on average. As such, in case that the given operational beds is lower than the average occupied beds, we assume that the actual operational beds value should be,

$$total\ operational\ beds = \frac{average\ number\ of\ occupied\ beds}{0.65}. \tag{4.1}$$

This is a little lower than the 85 per cent what some literature suggests (Green & Nguyen, 2001; Bekker & Bruin, 2010), but in line with others (Bruin et al., 2010).

4.4.2 Physical Beds

The data we received contained no information about the physical bed capacity for each WL nor an estimate for the total number of beds the Erasmus MC owns. We do however have information about the number of admitted patients for each day. We also know that, if a patient is admitted, i.e., in our data, he or she has to be assigned to a bed. Thus a WL has to have at least the same amount of beds as the number of patients admitted. Therefore we define the physical bed capacity for a WL as,

$$physical\ beds = \max_i \{occupied\ beds\ on\ day\ i\}. \tag{4.2}$$

This might result in an overestimate of the number of the physical beds, as beds might be borrowed from other wards on peak days, but in general this is not a problem. As we will show in Section 7 we usually require far less beds than this maximum.

4.5 Data Limitations

While the provided data is fairly complete, there are some aspects not covered at the time of writing.

As we explained in Section 2, each patient is assigned to a bed (or refused) when arriving at the hospital. However for various reasons the hospital can decide to deviate from this protocol. For example when a patient is highly contagious he or she can be assigned to multiple beds to avoid infection of other patients[7]. As we have little to no information about the frequency of this happening, we do include it in our theoretical model, but not in our results. Therefore, we assume that all patients will only require 1 bed.

Assumption 4.4 (Beds) *All patients are provided with* 1 *bed, no more, no less.*

5 Theoretical Approach

5.1 Relation to Warehousing and Inventory Management

The easiest analogy to a ward is a service environment, i.e., queueing theory. Such an environment usually involves a series of employees, called servers, who serve customers for a certain time-frame, the service time. To complete the analogy, the server in this case would be a bed and the service time would be the LOS. However, in this context, literature assumes that each customer occupies only 1 server. Therefore we use different analogy, namely inventory management in warehousing.

While a ward is not necessarily the same as a warehouse, there are quite a few similarities we can exploit to model the resource flow.

A warehouse is part of a supply chain (Ghiani, Laporte, & Musmanno, 2004) and usually stores a product – which we will refer to as a 'unit'. When a customer buys an unit, this unit is withdrawn from the stock. Re-supplying the warehouse can be done by employing one of several strategies. The most used are continuous review polices; once the amount of units in stock hits a certain lower bound value, an order is placed to re-supply the warehouse. If the re-supply order is not fulfilled immediately the warehouse has to have a number of units in stock to meet the demand during this time, i.e., the safety stock.

The connection with the hospital wards might not be exactly evident, but lets assume the stored units are in fact the hospital beds. Also assume that the lead-time of a 'new bed' is equal to the LOS of a patient. We can then compare the ward unit as a warehouse that 'sells' beds and places a re-supply order for each sold bed. This type of warehousing policy is called the $(S-1, S)$-policy, or more general S-policy, where S is the number of 'units' or beds the warehouse has in stock.

[7] The patient is assigned to one bed, but the beds directly next to him or her remain empty to avoid infection.

5.2 (R,Q)-Policy

The $(S-1,S)$-policy is a classic inventory management model based on the (R,Q)-policy. The (R,Q)-policy has a fixed re-order size Q at a fixed re-order point R, which in case of $(S-1,S)$ are 1 and $S-1$ respectively.

Using the (R,Q) policy's properties we can determine *when* to place a re-supply order. This decision should be based on the current stock situation, the anticipated demand, and different cost factors Axsäter, 2006. While it is easy to base the decisions solely on the physical stock on hand, it is important to also include the *outstanding re-supply orders* and *back-orders*[8]. Therefore (Axsäter, 2006) defines two different characterizations of the stock situation, namely the inventory position (IP) (Definition 5.1) and inventory level (IL) (Definition 5.2).

Definition 5.1 (Inventory Position[9]) *The inventory position is the sum of the stock on hand and the outstanding re-supply orders, minus the back-orders.*

Definition 5.2 (Inventory Level) *The inventory level is the difference between the stock on hand and the back-orders.*

When we consider a hospital ward, there is a vague area concerning the back-orders. While it is widely known that there are waiting lists for certain medical procedures, these delays are not necessarily caused by the hospital wards. As a result there is reason to assume that a patient will get treatment elsewhere, e.g., a less preferable ward, if the current ward has insufficient capacity. Therefore we assume that insufficient capacity results in a *lost sale* or *blocking*.

5.2.1 Palm's Theorem

Palm, 1938 decribed a well-known queuing theorem, which can be applied to inventory control systems. Assume we have a pure Poisson[10] demand process with an arrival rate λ per time unit. Also assume that the re-supply time has distribution $\psi(t)$ with mean $\bar{t}$ and that we do not allow back-orders. (Palm, 1938) then states that,

Theorem 5.1 (Palm's Theorem) *During the steady state, the probability of x units in re-supply R at any given time are equal to the normalized values of the Poisson distribution with rate $\lambda{\cdot}\bar{t}$, i.e.,*

$$P[R=x] = \frac{\frac{(\lambda\bar{t})^x}{x!}e^{-\lambda\bar{t}}}{\sum_{k=0}^{S}\frac{(\lambda\bar{t})}{k!}e^{-\lambda\bar{t}}}. \quad 0 \leq x \leq S \tag{5.1}$$

A proof of Theorem 5.1 is complicated due to a finite value for S. Nonetheless several proofs are found in the literature, including in Palm, 1938 where the theorem originated.

[8] A backorder is an unfulfilled customer order due to insufficient stock on hand; this order has to be fulfilled in the future, when a re-supply order arrives.

[9] Note that in our case, the IP has a constant value of S, due to the fact we place a re-supply order for each 'sold' unit; hence, S-policy.

[10] A poisson distribution where each customer will buy one unit.

Theorem 5.1 is closely related to the *Erlang Loss* model, which descibes the probability a customer's order is not accepted. Assume we use $(S-1, S)$-policy and we accept no back-orders. Then the order is accepted if we have less than S units in re-supply; hence, if there are S units in re-supply there are no units in stock. We can thus rewrite the probability of a customer being accepted as,

$$P\left[R < S\right] = \sum_{i=0}^{S-1} P\left[R = i\right] = \sum_{i=0}^{S-1} \frac{\frac{(\lambda\bar{t})^{x}}{x!}e^{-\lambda\bar{t}}}{\sum_{k=0}^{S}\frac{(\lambda\bar{t})}{k!}e^{-\lambda\bar{t}}}.$$

Similarly we can define the probability an order is rejected as,

$$P\left[R \geq S\right] = \frac{\frac{(\lambda\bar{t})^{S}}{S!}e^{-\lambda\bar{t}}}{\sum_{k=0}^{S}\frac{(\lambda\bar{t})}{k!}e^{-\lambda\bar{t}}}, \tag{5.2}$$

the Erlang Loss function.

5.2.2 Compound Poisson Demand

A common assumption in inventory management is that the cumulative demand is not pure Poisson, but can be represented as a limit of an appropriate compound Poisson processes (Feller, 2002). This means the customers arrive according to a Poisson process with given intensity λ and that the size of their demand is also a stochastic variable. We can define the probability of k customers arriving in time interval t as

$$P\left(k\right) = \frac{(\lambda t)^{k}}{k!}e^{-\lambda t}, \quad k = 0, 1, 2, \ldots \tag{5.3}$$

with mean, as well as variance, λt.

The the demand size, or *compounding distribution*, is not required to be a single type of distribution as long as it is independent and identically distributed (I.I.D.) and independent of the customer arrivals. Therefore we define the demand size as

$$f_j = probability\ of\ demand\ size\ j (j = 1, 2, \ldots). \tag{5.4}$$

Note that due to Assumption 4.4 we get $f_1 = 1$, thus the cumulative demand can be described by a *pure Poisson process* as in Equation 5.3. However, throughout this section we will consider the more general case where the demand size can vary; this will allow future implementation of this idea in situations where patients might require multiple beds.

We can extend Equation 5.4 by assuming that there are no demands of size zero, i.e., $f_0 = 0$ and that not all demands are multiples of some integer larger than one. We can assume this without loss of generality, since we can always rewrite the process to a situation where the previous holds; for example, in the situation where the demand size *is* a multiple of some integer, we can assume that one *new unit* is in fact several *old units*.

If we define $D(t)$ as the stochastic demand during time interval t and extend f_j by the number of customers that generated demand j to f_j^k, we can denote the distribution of $D(t)$ as

$$P\left(D\left(t\right)=j\right)=\sum_{k=0}^{\infty}\frac{\left(\lambda t\right)^{k}}{k!}e^{-\lambda t}f_{j}^{k}, \tag{5.5}$$

where

$$f_{j}^{k}=\sum_{i=k-1}^{j-1}f_{i}^{k-1}f_{j-i}. \tag{5.6}$$

The *pure Poisson process* has mean and variance λt, which is the average number of customers in time interval t. The mean (μ) and variance (σ^2) of the *compound Poisson process* is a little different as it includes the demand size. If we define K as the stochastic number of customers during one time unit and J as the stochastic demand size of one customer, we can write the mean of the *compound Poisson process* as

$$Z=P\left(D\left(t\right)=j\right) \tag{5.7}$$

$$\mu=E\left[Z\right]=\underset{k}{E}\left[E\left\{Z|K\right\}\right]=\underset{k}{E}\left[KE\left(J\right)\right]=E\left(K\right)E\left(J\right)\overset{5.3,5.4}{=}\lambda\sum_{j=1}^{\infty}jf_{j}. \tag{5.8}$$

Similarly the variance can be written as

$$\begin{aligned}E\left[Z^{2}\right]-\mu^{2}&=\underset{k}{E}\left[E\left\{Z^{2}|K\right\}\right]-\mu^{2}\\&=\underset{k}{E}\left[var\left\{Z|K\right\}+\left(E\left(Z|K\right)\right)\right]-\mu^{2}\\&=\underset{k}{E}\left[Kvar\left(J\right)+K^{2}\left(E\left(J\right)\right)^{2}\right]-\mu^{2}\\&=\lambda var\left(J\right)+\left(\lambda+\lambda^{2}\right)\left(E\left(J\right)\right)^{2}\\&=\lambda\left[var\left(J\right)+\left(E\left(K\right)\right)^{2}\right]\\&=\lambda E\left(J^{2}\right)=\lambda\sum_{j=1}^{\infty}j^{2}f_{j}.\end{aligned} \tag{5.9}$$

Notice that 5.8 and 5.9 degenerate to λ if $f_1=1$. This proves that a pure Poisson process can be modelled as compound Poisson process without further consequences; thus allowing us to continue with compound Poisson and apply Assumption 4.4 in the final stage.

5.2.3 Generalized Palm's Theorem

The theorem Palm proposed in Palm, 1938, now known Palm's theorem, is only valid for the pure Poisson distribution and thus we cannot use this directly. Therefore we have to use a more generalized version of Palm's theorem as described in Feeney & Sherbrooke, 1966.

Theorem 5.2 (Generalized Palm's Theorem) *During the steady state, the probability of x units in re-supply R at any given time are equal to the* *normalized values of the compound Poisson distribution with rate $\lambda \cdot \bar{t}$, i.e.,*

$$P\left[R = x\right] = \frac{p\left(x|\lambda\bar{t}\right)}{\sum_{k=0}^{S} p\left(k|\lambda\bar{t}\right)}, \qquad 0 \leq x \leq S \tag{5.10}$$

where,

$$p\left(x|\lambda\bar{t}\right) = \sum_{k=0}^{x} \frac{\left(\lambda\bar{t}\right)^k}{k!} e^{-\lambda\bar{t}} f_x^k.$$

As the proof of Theorem 5.2 is rather lengthy, we refer to Feeney & Sherbrooke, 1966 for the actual proof. We will however state the most important assumptions and results of this proof.

The first assumption is that there are no *partial fills*, thus an order is accepted or rejected as a whole. This means that if a customer requires, for example, 3 units and there are only 2 left, this customer order is rejected and we remain with 2 units in stock. We argue that this close to reality, as hospital procedures and rules prevent sub-standard solutions, e.g., too little beds for a patient.

The second assumption is that, per customer, there is a single re-supply order with a single lead-time; thus all units in the same re-supply order have the same lead-time. Surely if we only look at bed occupancy, i.e., a patient is occupying a bed, this is true; when a patient is discharged, all beds are 'available' at the same time. However, a bed might not be available immediately after a patient is discharged. Normal procedure includes cleaning the beds and the bedding. Depending on the size of the cleaning crew, the beds a patient occupied might or might not be ready simultaneously. We do however assume that the cleaning time is relatively short compared to the LOS and thus can be ignored[11].

5.2.4 Service Level

There are many definitions for the service level of a warehouse or queueing system. Axsäter, 2006 defines three, namely the *probability of no stockout per cycle*, the *fraction of the demands that can be satisfied with stock on hand* and the *fraction of time without back-orders*. While many systems use the first definition, it is flawed and should be avoided if possible. If the re-order point R is high compared to the order quantity Q, the *probability of no stockout* can be relatively high, while the actual service is low. Also, as we do not allow back-orders – see Definition 5.2 –, the *fraction of time without back-orders* is flawed as well. This leaves us with the second definition for the service level, usually refered to as the *fill rate*, which is the most accurate of the 3 mentioned as well as the most difficult to calculate.

Throughout the literature there exist 2 definitions for the *fill rate*, which are very similar to read, but different nonetheless. The first definiton, the one we mentioned before, is used to calculate the number of customers that were accepted; the second, the *fraction of demand that can be satistied with stock on hand*, also includes the order size and can be seen as a weighted average of customers. As we are interested in the number of patients we accept, disregarding their bed requirement, we will use the first definition.

[11] An alternative would be to include the average cleaning time in the LOS, however we have no such information available.

Definition 5.3 (Fill Rate (F_s)) *The fill rate is the faction of the demands that can be filled immediately from stock on hand.*

Feeney & Sherbrooke, 1966 derived an equation for the expected fills[12] F_c, using the steady state properties and Theorem 5.2. Assume we have S units in stock, and that the arrival rate λ during the leadtime $\bar{t}$ can be written as $\lambda\bar{t}$, the expected number of fills can then be written as,

$$F_c(S) = \lambda \left\{ f_1 \sum_{x=0}^{S-1} P\left[R = x\right] + 2f_2 \sum_{x=0}^{S-2} P\left[R = x\right] + \ldots + S f_s P\left[R = 0\right] \right\}. \tag{5.11}$$

We can easily rewrite Equation 5.11 to the fill rate F_s, by dividing by λ. Furthermore to reduce the number of summations in Equation 5.11 we can use the fact that $P\left[R = x\right]$ can be written as Equation 5.10. This results in,

$$F_s(S) = \frac{f_1 \sum_{x=0}^{S-1} p\left(x|\lambda\bar{t}\right) + 2f_2 \sum_{x=0}^{S-2} p\left(x|\lambda\bar{t}\right) + \ldots + S f_s p\left(0|\lambda\bar{t}\right)}{\sum_{k=0}^{S} p\left(k|\lambda\bar{t}\right)} \tag{5.12}$$

Equation 5.12 can be used to evaluate a ward's performance as well as estimate the unobserved arrival rate.

5.3 Combining What We Know

We have shown that you can use inventory management to model the flow of beds in hospital wards, but the main goal was to optimize the bed occupancy by combining WLs.

The literature suggests that most WL have exponentially distributed LOS with an arbitrary parameter λ. Assuming we are combining two or more wards, the combined LOS distribution can be written as *hyper-exponential*, i.e.,

$$f_X\left(x\right) = \sum_{i=1}^{n} f_{Y_i}\left(x\right) p_i, \quad 0 < p_i < 1, \quad \sum_{i=1}^{n} p_i = 1, \tag{5.13}$$

$$\textit{where}$$
$$Y_i \sim exp\left(\lambda_i\right),$$
$$p_i = P\left[\textit{patient arrives at } \text{WL } i\right].$$

The hyper-exponential is closely related to the generalized Erlang distribution, where $p_i = 1$ for all i. Nonetheless in Section 4.3 we showed that not all WLs have exponentially distributed LOS, e.g., some have Weibull distributed LOS. Similar to the hyper-exponential distribution, there is the *mixed-Weibull* distribution. In case of mixed-Weibull Equation 5.13 remains unchanged, except for Y_i which now is Weibull distributed with parameters α_i and β_i for shape and scale respectively (Kao, 1959). Both hyper-expontential and mixed-Weibull have similar statistical properties, e.g., the expected value is given by

[12] The expected number of demands that can be filled immediately from stock on hand; equal to $\lambda * F_s$.

$$E[X] = \sum_{i=1}^{n} E[Y_i] \cdot p_i, \quad (5.14)$$
$$where$$
$$Y_i \sim exp(\lambda_i) \vee weib(\alpha_i, \beta_i).$$

More important, the exponential and Weibull distribution are closely related; an exponential distribution with parameter λ is equal to a Weibull distribution with parameter(s) $\alpha = \lambda$ and $\beta = 1$. Due to this relation we can actually sum over different type of distributions, e.g., where $Y_1 \sim weib(\alpha_1, \beta_1)$ and $Y_2 \sim exp(\lambda_2)$.

Besides the expected lead-time, we also require the unobserved arrival rate. Bruin et al., 2010 suggested to use the Erlang Loss model to approximate the arrival rate λ, but this result is only valid for *pure Poisson* processes. Therefore we use the *fill rate*, which has similar properties. Due to the fact that we refuse all patients that whose bed requirement we cannot meet, this is also the percentage of patients that is admitted. If know the average LOS, $\bar{t}$, we can then use,

$$average\ number\ of\ occupied\ beds = \lambda \cdot \bar{t} \cdot \frac{f_1 \sum_{x=0}^{S-1} p(x|\lambda\bar{t}) + \ldots + sf_s p(x|\lambda\bar{t})}{\sum_{k=0}^{S} p(k|\lambda\bar{t})} \quad (5.15)$$

Now, assume that we combine n wards with arrival rates $\lambda_i, \ldots, \lambda_n$. The combined arrival rate can then be expressed as,

$$\Lambda = \sum_{i=1}^{n} \lambda_i. \quad (5.16)$$

Using Equation 5.16 we can rewrite the *probability a patient has LOS distribution* i as,

$$p_i = \frac{\lambda_i}{\sum_{j=1}^{n} \lambda_j} \qquad for\ i = 1, \ldots, n. \quad (5.17)$$

Combining this definition of p_i with Equation 5.14, we get

$$E[X] = \frac{\sum_{i=1}^{n} E[Y_i] \cdot \lambda_i}{\sum_{j=1}^{n} \lambda_j}, \quad (5.18)$$

which we can use as expected lead-time $\bar{t}$ in Theorem 5.2.

Using the expected lead-time we can estimate the required number of beds[13] to reach a target *fill rate*. This process can only be done by enumerating all the possible values for S, the number of beds, untill we hit the target fill rate, as the values for $F_s(S)$ change each iteration – see Section 5.2.4. Luckily todays computers are fast enough to go through

[13] Physical as well as operational.

these values in mere seconds.

Input: $\lambda > 0$ /* Arrival Rate */
Input: $\bar{t} > 0$ /* Expected Lead-Time */
Input: $M > 0$ /* Physical Beds */
Input: $0 < F_s^{target} < 1$ /* Target Fill Rate */
Input: $0 < f_i < 1$ /* Probability for i items */
Output: S /* Required Beds */

$beds := -1$;
$f_{calculated} := 0$;
while $F_s^{calculated} < F_s^{target}$ *and* $S \leq M$ **do**
  $S := S + 1$;
  $p_{sum} := 0$; $numerator := 0$;
  for $x := 0$ *to* S **do**
    $p_{partial} := 0$;
    for $k := 0$ *to* x **do**
      $p_{partial} := p_{partial} + \frac{(\lambda\bar{t})^k}{k!} e^{-\lambda\bar{t}} f_x^k$;
    end
    if $k < S$ **then**
      $numerator := (S - x) \cdot f_{S-x} \cdot p_{partial}$;
    end
    $p_{sum} := p_{sum} + p_{partial}$;
  end
  $F_s^{calculated} := \frac{numerator}{p_{sum}}$;
end

Algorithm 1: Required amount of beds to get to a target fill rate.
This method can be used to estimate both the physical as well as the operational beds, the only difference is the planning horizon. As we have written in Section 3, acquiring physical beds is on a strategic level, a horizon of a year or more, where operational beds is on an tactical level, a horizon of a few weeks to a year.

Algorithm 1 is the method we used to estimate the bed requirements for the new wards. *Note* that the expected lead-time for Weibull depends on the *Gamma distribution*, which is hard to approximate numerically. Therefore we use *Stirling's Formula* (Feller, 1967) as approximation.

6 Modelling the Ward(s)

6.1 Introduction

This section will describe the simulation model we designed to test our theoretical model under several different circumstances. The model as described in this section is generic and can be adapted to several different situations we describe in Section 7.

Throughout the literature there are several different types of simulations, e.g., *Monte-Carlo simulation*, *system dynamics* and *discrete event modelling*. As we are interested in how the system evolves over time, we can either do system dynamics or discrete event modelling (Ross, 2006). System dynamics, the most complex of the two, has support for *feed-back loops*[14], but requires the simulation to keep track of time. Discrete event modelling is a more direct method, where order events by their due time and jump through them in order; thus the simulation will skip proportions of time until the next event, see Figure 7. While both are a valid option, clearly discrete event modelling is the better choice, as we do not require feed-back loops.

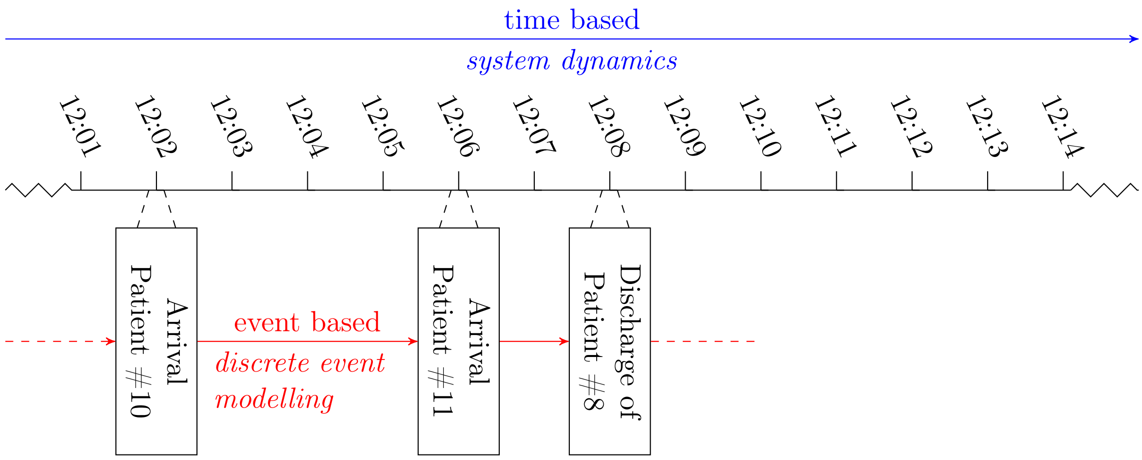


Figure 7: Discrete event modelling versus System Dynamics.

Our model will be based on the data characteristics described in Section 4 and thus fall in the 'stochastic modelling' category. Using the methods described in Section 6.2 we generate 2 types of events, namely *arrival* and *discharge* events.

- *Arrivals* At each arrival event, we check the current simulation and ward state. If there are beds available in the intended ward, we generate a discharge event in the future, using the method in Section 6.2.3. Furthermore, we draw a new inter-arrival time until the next arrival occurs and generate an arrival event at that time.
- *Discharge* A discharge event is considerably easier, as it is only used to release a bed. While no new events are generated, we do store the realised LOS for this patient, as we need this later on.

We will continue generating events up to a fixed horizon, e.g., 10 years. The hospital's, division's[15] or ward's *service level* and *occupancy level* will be based on the successful arrivals, i.e., those which spawned a discharge event.

6.2 Implementation

6.2.1 Pseudo-Random Number(s)

As Marsaglia, 1986 showed, many programming languages generate pseudo-random numbers (PRNs) which fail the randomness tests, i.e., no randomness, not efficient or not homogeneous. We designed a PRN-algorithm which generated PRNs which are uniformly

[14]Usually an equation that characterizes a variable based on the system's state, e.g., decreasing the inflow if the system is full.

[15]The weighted average fill rate of all wards in a division of the hospital.

distributed between 0 and 1, based on the algorithm proposed in Marsaglia, Zaman, & Tsang, 1990 which does not suffer from these limitations. More important, unlike the built-in PRN, the algorithm produces the same output when seeded with the same initial values; it passes the repeatability test proposed in Marsaglia et al., 1990. As we also require exponential and Weibull distributed random numbers, we implemented Equation 6.1 and Equation 6.2 to generate these random numbers.

$$\begin{aligned} X &= \frac{1}{\mu} \cdot -log\left(U\right) \\ where& \\ X &\sim exp\left(\mu\right) \\ U &\sim uniform\left[0,1\right] \end{aligned} \tag{6.1}$$

$$\begin{aligned} Y &= \alpha \cdot \left(\frac{1}{k}\right)^{-log(U)} \\ where& \\ Y &\sim weibull\left(\alpha,k\right) \\ U &\sim uniform\left[0,1\right] \end{aligned} \tag{6.2}$$

6.2.2 Arrival Rate

As shown in Section 4.2.1 the LOS and operational beds vary per WL. Therefore we estimate the arrival rate per WL before combining them to one ward. We then use the Poisson distribution properties, which say that the sum of independent Poisson variables rate λ_i is also Poisson with rate $\Lambda = \sum_i \lambda_i$, to combine these arrival processes to one. During the simulation we use another Poisson property, which says that the *inter-arrival times* between two consecutive arrivals is exponentially distributed with rate $\frac{1}{\Lambda}$.

6.2.3 Length of Stay

The LOS is implemented as a two-step random process. Prior to running the simulation we calculated p_i (Equation 5.17), which can be used as the *probability an arrival occurred at ward i*.

```
Input: P = P_1, P_2, ..., P_n        /* Cumulative Probability Values of p_i */
Output: LOS
u := uniform random value;
while u ≤ p_i do
    i := i + 1;
end
los := random value from LOS in WL i;
```

Algorithm 2: Generate a random LOS.

Upon an arrival event, we draw a random uniform value u between 0 and 1. We compare this value, using Algorithm 2, to the cumulative probabilities P_i. If u is between 0 and P_1 we choose ward 1, if u is between P_1 and P_2 we choose ward 2, and so forth – see Figure 8.

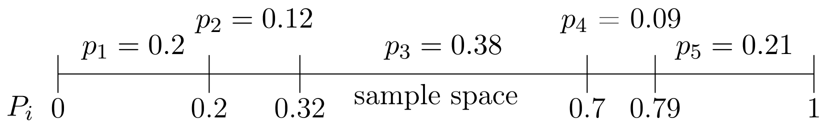


Figure 8: Sample space of P_i.

Once we identified the WL the patient would have originally arrived at we generate a random LOS from the distribution we fitted over that WL's LOS. This will result in the most accurate LOS distribution for all patients at the combined ward, as we make no further assumptions for the combined LOS.

6.3 Performance Indicators

After the simulation is finished we are interested in two different performance indicators, namely the *service level* and *occupancy level.* The first one is easy to calculate, as we know which arrival events spawned two new events, i.e., a new arrival and a discharge event. We assume that these arrival events are 'successful' and all other arrival event have 'failed'. We can then write the service level as,

$$service\ level = \frac{successful\ arrival\ events}{total\ arrival\ events}. \tag{6.3}$$

Where the *total arrival events* is the sum of all successful and failed arrival events.

The occupancy level is a little more complex, as we might skip several days due to our choice in simulation set-up; we cannot keep track of the number of occupied beds on each day. Therefore we use a variant of the formula presented in Bruin et al., 2010. They define the occupancy level using Little's formula (Little, 1961) as,

$$occupancy = \frac{admissions\,(per\ time\ unit)\cdot average\ LOS\,(timeunit)}{number\ of\ operational\ beds}. \tag{6.4}$$

At the end of our simulation we do know the total number of admissions; the number of 'successful' arrivals. We also know the number of operational beds, as this is a given and fixed value. If we alter a successful arrival event to not only spawn a discharge event, but also store the generated LOS in a list, we can then write the occupancy as,

$$occupancy = \frac{\frac{total\ number\ of\ arrivals}{simulated\ days}\cdot\frac{\sum_{admissions} LOS}{total\ number\ of\ arrivals}}{number\ of\ operational\ beds}. \tag{6.5}$$

Equation 6.6 can be simplified to,

$$occupancy = \frac{\sum_{admissions} LOS}{number\ of\ operational\ beds\cdot simulated\ days}. \tag{6.6}$$

7 Results

This section contains some of the results of both the theoretical model and the simulation model. As the Erasmus MC currently has 7 divisions, 33 medical departments and 115 wards, we will not show all results in this section; more specific we will focus on two divisions, which show the most interesting results, namely 'Daniel' and 'Hoboken'. Furthermore, if unspecified, a target service level of 95% is used. The complete results are available in Appendix B and Appendix Appendix C.

7.1 The Erasmus MC

Before we alter operational beds or combine wards, we have to get an indication of the current situation within the hospital. Therefore we ran both the theoretical and simulated model as is, without any modifications to the data. As the table is too large to include in the text, the complete result can be found in Appendix B. Table 2 shows a summary of these results for each division.

		Theoretical		Simulated	
division	**beds**	**occupancy**	**service**	**occupancy**	**service**
Daniel	219	0.733	**0.753**	0.732	**0.753**
Diagnostiek	4	0.843	*0.442*	0.840	*0.444*
Hersenen en Zintuigen	282	0.620	0.927	0.618	0.928
Hoboken	522	**0.607**	0.965	**0.610**	0.965
Sophia	432	0.683	0.891	0.683	0.891
Spoed en Intensief	86	0.630	0.970	0.632	0.970
Thorax	173	0.669	0.902	0.666	0.906
Erasmus MC	1680	0.666	0.884	0.666	0.884

Table 2: Simulation results for the Erasmus MC without any changes.

The occupancy level for the entire Erasmus MC is 66.6%, which is relatively low considering there the service level is 88.4%. This suggests that there is enough capacity, just not in the right place. These initial results also gives us two great sample cases to evaluate further, namely *Daniel* and *Hoboken*. Of all divisions which have more than one WL[16], Daniel has the lowest service level. Similarly Hoboken has the lowest occupancy level. Therefore, in case of Daniel, we focus on increasing the service level, while keeping at least the same occupancy level, and in case of Hoboken we will do it the other way around.

7.2 Daniel

Where most medical departments are performing on average, large part of Daniel's poor service level is due to the WLs of medical department *SOG Daniel*. These WLs currently have a combined service and occupancy level of 37.3% and 88.9% respectively. Table 3 shows in detail which WLs in medical department SOG Daniel are performing poorly, namely (6961) and (6973). The high occupancy levels at these WLs indicates there is too little operational capacity at these locations. In direct opposite to WLs (6961) and (6973), locations (6960) and (6978) have a high service level and low occupancy levels.

[16] All divisions with exception of *Diagnostiek*.

medical department	wards	**opr. beds**	Theoretical **occupancy**	**service**	Simulated **occupancy**	**service level**
SOG Daniel		**42**	**0.889**	**0.373**	**0.889**	**0.374**
	(6960)	20	0.573	0.993	0.569	0.994
	(6961)	14	0.978	0.244	0.978	0.247
	(6973)	4	0.930	0.235	0.931	0.234
	(6978)	4	0.085	1.000	0.082	1.000

Table 3: Baseline results for medical department *SOG Daniel*.

Therefore the first step we take is to combine these 4 WLs to one new ward. Similarly we will do this for all medical departments in division Daniel.

medical department	**opr. beds**	Theoretical **occupancy**	**service**	Simulated **occupancy**	**service**
Ambulante Zorg Daniel [6941, 6951, 6953]	25	0.752	0.954	0.758	0.952
Haematologie [5428, 5444, 5445, 6630, 6971, 6972]	60	0.855	0.957	0.862	0.953
Interne Oncologie [5353, 6966, 6968, 6969]	54	0.845	0.956	0.841	0.959
Radiotherapie [6963, 6964, 6965]	18	*0.739*	0.931	*0.740*	0.935
SOG Daniel [6960, 6961, 6973, 6978]	42	0.978	**0.490**	0.979	**0.488**
Division: Daniel	199	0.861	0.799	0.862	0.798

Table 4: Theoretical and Simulated results for division *Daniel*.
We set the maximum capacity to the sum of the operational beds of the individual wards. As a result divisions *Radiotherapie* and *SOG Daniel* are still below our service level target of 95 per cent.

As a result of the changes to the organisational structure the overall service level has increased by 4% while the operational beds decreased by 9%, i.e., 20 beds. We do note however that the operational bed decrement is merely due to a fixed maximum capacity to the combined wards, as SOG Daniel still has a poor performance. Nonetheless, both the service level as the occupancy level increased, which cannot be done without combining WLs.

While the service level certainly increased, it is still approximately 9% below average. Another option we have is not to set a capacity constraint on the individual wards, but rather the division as a whole. Previously we had 219 operational beds over all WL, which leaves us with 20 (operational) beds for which we have manpower. If we ignore the physical bed constraints and run Algorithm 1 for each ward, we get an estimate of the operational bed requirements.

	beds	service level 90%	service level 95%
medical department	**physical**	**operational beds**	**operational beds**
Ambulante Zorg Daniel [6941, 6951, 6953]	40	23	25
Haematologie [5428, 5444, 5445, 6630, 6971, 6972]	65	54	60
Interne Oncologie [5353, 6966, 6968, 6969]	85	49	54
Radiotherapie [6963, 6964, 6965]	26	17	19
SOG Daniel [6960, 6961, 6973, 6978]	54	**82**	**89**
Division: Daniel	270	205	247

Table 5: Operational bed requirement for division *Daniel*.
We ran the algorithm for each ward with an infinite physical capacity, i.e., $M = \infty$.

Clearly, in both cases, the overall operational bed requirement is below the physical capacity of 270 physical beds – see Table 5. However medical department SOG Daniel requires 80+ operational beds to maintain the target service level(s), which is notably higher than the 54 beds it currently has. So if we cap the maximum operational beds by the number of physical beds, medical department SOG Daniel can only use these 54 beds. As a result the total operational beds decreases by 35 from the 247 mentioned in the last column of Table 5.

	opr.	Theoretical		Simulated	
medical department	**beds**	**occupancy**	**service**	**occupancy**	**service**
SOG Daniel [6960, 6961, 6973, 6978]	54	0.971	**0.626**	0.972	**0.626**
Division: Daniel	212	0.857	0.845	0.855	0.846

Table 6: Theoretical and Simulated results for medical department *SOG Daniel*.
The operational beds is capped at the available physical beds the medical department currently has. The total operational beds lower than the 247 in Table 5 due to the restriction on medical department SOG Daniel.

Therefore, even in the new situation, SOG Daniel can only attain a service level of 62.6% at a maximum 54 operational beds. Not to mention, by increasing the maximum operational beds in medical department SOG Daniel, the overall service level goes up to 84.5%; only 3.9% lower than the original average service level. Nonetheless, we are still only using 212 of the 270 available beds. This implies that the service level can increase more if we increase the physical bed capacity, e.g., in medical department SOG Daniel. A way to increase the physical bed capacity in SOG Daniel is to merge it with *Interne Oncologie*, which has 36 unused beds. These 36 beds are more than enough to increase SOG Daniel's service level to 95%.

	opr.	Theoretical		Simulated	
medical department	**beds**	**occupancy**	**service**	**occupancy**	**service**
Ambulante Zorg Daniel [6941, 6951, 6953]	25	0.752	0.954	0.750	0.955
Haematologie [5428, 5444, 5445, 6630, 6971, 6972]	60	0.855	0.957	0.858	0.957
Interne Oncologie & SOG Daniel [5353, 6966, 6968, 6969, 6960, 6961, 697	136	0.921	0.953	0.922	0.954
Radiotherapie [6963, 6964, 6965]	19	0.715	0.950	0.707	0.959
Division: Daniel	240	0.862	0.953	0.862	0.955

Table 7: Theoretical and Simulated results for division *Daniel* after combining *Interne Oncologie* and *SOG Daniel*.

Table 7 clearly shows we now have an overall service level of 95.3%, as well as a service level of at least 95% in each ward. Not only the service level is above average[17], the occupancy level is with 86.2% also 20% above average. The only problem we foresee with the proposed structure, is that the operational bed requirement is now 240 beds. This is significantly higher than the 219 in the baseline solution. However, if we continue to combine WLs we can further decrease this requirement.

	opr.	Theoretical		Simulated	
medical department	**beds**	**occupancy**	**service**	**occupancy**	**service**
Division: Daniel	220	0.947	0.950	0.947	0.952

Table 8: Theoretical and Simulated results for division *Daniel*.
The individual WLs are combined to one ward, which provides care for patients from all medical departments in division Daniel.

If all medical departments in division Daniel are all sharing the same ward, the operational bed requirement drops to 220. This is, compared to the baseline solution, only 1 more than before. We do note that one of the goals mentioned in Section 2.3 was to reduce cost. Clearly increasing the operational beds is not in line with this, but we argue that we increased the occupancy and service levels such that the increased cost justifiable.

7.3 Hoboken

Combined division Hoboken currently has an occupancy level of 60.7%, which is about 6% below average. Though, while the occupancy level is fairly low, the service level is second highest of the entire Erasmus MC. Therefore we have to find a way to increase the occupancy level without sacrificing service. Note that we, to keep in line with previous results, will target a service level of 95%, which is a little below the current 96.5%.

[17] Compared to the baseline in Section 7.1.

medical department	wards	opr. beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service level
Algemene Heelkunde						
	(4125)	2	0.000	1.000	0.000	1.000
Inwendige Geneeskunde						
	(3194)	1	0.115	0.885	0.121	0.857
	(5118)	5	0.191	0.997	0.180	0.999
	(5126)	36	0.002	1.000	0.002	1.000
	(5226)	10	0.000	1.000	0.001	1.000
	(7616)	5	0.116	1.000	0.120	0.999
MDL						
	(5243)	1	0.172	0.828	0.169	0.823

Table 9: Baseline results for low occupancy WLs in division *Hoboken*.

Large part of the low occupancy and high service level can be explained by a series of WLs that have a relatively low arrival rate, but a large number of operational beds. Table 9 shows the WLs with less than 20% occupancy. Most interesting are WLs (3194) and (5243), which have a service level lower than the target of 95%. Assuming we value service over occupancy, we should increase the operational beds to 2 for each ward. However, the occupancy level would decrease to 0.064 and 0.102 respectively. As shown in Table 10 we can increase the occupancy level, in for some WL, by lowering the amount of operational beds, but only very little. Therefore we continue, same as with division Daniel, and combine the WLs per medical department.

medical department	wards	opr. beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service level
Algemene Heelkunde						
	(4125)	1	0.015	0.985	0.028	1.000
Inwendige Geneeskunde						
	(3194)	2	0.064	0.993	0.064	0.991
	(5118)	4	0.236	0.987	0.240	0.988
	(5126)	3	0.038	0.997	0.045	1.000
	(5226)	1	0.004	0.996	0.002	1.000
	(7616)	3	0.189	0.982	0.184	0.985
MDL						
	(5243)	2	0.102	0.982	0.105	0.988

Table 10: Optimized theoretical and simulated results for low occupancy WLs in division *Hoboken*.

By combining the WLs per medical department we increased the occupancy level to 82.1%, which is a short over of 15% above average. Due to this combination, the operational bed requirement dropped by 41.2% from 522 to 307 beds.

medical department	opr. beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service
Algemene Heelkunde [4098, 4108, 4125, 4126, 4127, 4221]	89	0.894	0.953	0.895	0.951
Dermatologie [7413, 7441]	18	0.690	0.958	0.687	0.959
Inwendige Geneeskunde [3194, 5118, 5124, 5126, 5138, 5142, 522	93	0.898	0.952	0.900	0.954
MDL [5241, 5243, 5277, 5278]	49	0.839	0.953	0.838	0.954
Orthopedie [4427]	28	0.768	0.954	0.761	0.957
Plastische Chirurgie [4525]	22	0.711	0.964	0.719	0.962
Reumatologie [5957, 5958]	8	**0.482**	0.970	**0.486**	0.967
Division: Hoboken	307	0.821	0.955	0.821	0.955

Table 11: Theoretical and simulated results for division *Hoboken*.

While we clearly succeeded in all 3 of the goals mentioned in Section 2.3, there is still one ward that has a relatively low occupancy level, namely *Reumatologie*. This is due to patients, in this ward, having a low arrival rate – less than 1 patient a day – and relatively high LOS – more than 4 days. Therefore we can combine it with a ward that has more arrivals and a lower LOS, like *Dermatologie*; the arrival rate is about 13 patients a day, which have LOS of less than 1 day.

medical department	opr. beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service
Algemene Heelkunde [4098, 4108, 4125, 4126, 4127, 4221]	89	0.894	0.953	0.895	0.951
Dermatologie & Reumatologie [5957, 5958, 7413, 7441]	22	0.734	0.953	0.734	0.952
Inwendige Geneeskunde [3194, 5118, 5124, 5126, 5138, 5142, 522	93	0.898	0.952	0.900	0.954
MDL [5241, 5243, 5277, 5278]	49	0.839	0.953	0.838	0.954
Orthopedie [4427]	28	0.768	0.954	0.761	0.957
Plastische Chirurgie [4525]	22	0.711	0.964	0.719	0.962
Division: Hoboken	303	0.834	0.953	0.833	0.954

Table 12: Theoretical and simulated results for division *Hoboken*.

The combined ward *Dermatologie & Reumatologie* now have a occupancy level of 73.4%, which is an increase over when they were both separate. As a result the overall occupancy level also increased a little, by 1%. This is not that much, but this can be explained by the fact that medical departments *Orthopedie* and *Plastische Chirurgie* now have increased influence on the overall occupancy. We can continue this process until we combined all wards in this division, which is shown in Table 13.

medical department	opr. beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service
Division: Hoboken	269	0.954	0.950	0.956	0.948

Table 13: Theoretical and simulated results for division *Hoboken*.
The WLs in division Hoboken are now a completely shared resource, which results in a overall occupancy and service levels.

7.4 The Erasmus MC as one

We showed that both the service level as well as the occupancy can be increased by combining wards. Furthermore, due to the relation between occupancy level and operational beds, the operational bed requirement decreased if more medical departments share the same ward resource. Therefore a theoretical, but nevertheless interesting, case is to see how far we can increase the occupancy and decrease the operational beds, by combining all the wards within the Erasmus MC to one resource.

medical department	opr. beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service
Erasmus Medical Center	1109	0.986	0.950	0.986	0.952

Table 14: Theoretical and simulated results for entire Erasmus MC.
The WLs in the Erasmus MC are now one shared resource.

While the results in Table 14 show that we can decrease the operational beds by 34% and increase the occupancy level to 98.6%, we have to note that will always be a purely theoretical case, as there are too many challenges to overcome. Of these challenges the most obvious is that the Erasmus MC has 3 different locations and it is not always possible[18] to transfer a patient to a ward on the other side of town.

7.5 Sensitivity Analysis

7.5.1 Changing the Arrival Rate

An interesting question is how sensitive these new wards are to changes in the arrival rate(s) or LOS distribution of the individual WLs. In Section 5.3 we showed that we can use Equation 5.16 to calculate the combined arrival rate of a new ward, which consists of n WLs. Assume that the arrival rate of an arbitrary WL j increases by 10 per cent. We can then write the combined arrival rate as,

$$\Lambda_{new} = \sum_{i=1}^{n} \lambda_i + 0.1\lambda_j, \tag{7.1}$$

where λ_j is the previous arrival rate of WL j. We can then write the total per cent change as,

[18] Probably never.

$$\begin{aligned}\frac{\Lambda_{new} - \Lambda}{\Lambda} &= \frac{\sum_{i=1}^{n} \lambda_i + 0.1\lambda_j - \sum_{i=1}^{n} \lambda_i}{\sum_{i=1}^{n} \lambda_i} \\ &= \frac{0.1\lambda_j}{\sum_{i=1}^{n} \lambda_i}. \end{aligned} \tag{7.2}$$

From Equation 7.2 it is clear that Λ_{new} will increase by at most 10 per cent. In fact, there will only be a 10 per cent increase if λ_j is the only arrival rate, i.e., $\lambda_i = 0 \; \forall \; i \; \neq j$. As Equation 5.12 is non-linear and depends on the number of WLs we are combining, there is no one-on-one translation to the change in service level. However, we find that generally the service level decreases by 5 to 15 per cent if we increase an arbitrary λ_i by 10 per cent; the larger the overall change in Λ is, given by Equation 7.2, the lower the service level becomes.

When the arrival rate of an individual ward increases, it also has impact on the combined LOS distribution. In Section 5.3 we defined the combined LOS as a mixed-Weibull distribution, with $p_i = \frac{\lambda_i}{\sum_{j=1}^{n} \lambda_j}$ – Equation 5.18. Therefore, an increase in λ_j will increase the chance a patient has LOS distribution j. Depending on the actual LOS, the expected combined LOS may either increase or decrease. We noticed that generally the change in LOS is neglectably small compared to the change in Λ.

7.5.2 Changing the LOS distribution

Similar to the change in arrival rate, we can write the change in LOS $E[Y_j]$ as,

$$\begin{aligned}\frac{\bar{t}_{new} - \bar{t}}{\bar{t}} &= \frac{\sum_{i=1}^{n} E[Y_i] \cdot p_i + 0.1 \cdot E[Y_j] \cdot p_j - \sum_{i=1}^{n} E[Y_i] \cdot p_i}{\sum_{i=1}^{n} E[Y_i] \cdot p_i} \\ &= \frac{0.1 \cdot E[Y_j] \cdot p_j}{\sum_{i=1}^{n} E[Y_j] \cdot p_i}. \end{aligned} \tag{7.3}$$

The actual change in the overall LOS is a little more complex, as it depends on p_j, which in turn depends on λ_j and Λ. However, from Equation 7.3 we can derive that the change to $\bar{t}$ will be less than 10 per cent if the new ward exists of more than one WL; $p_j < 1$ for WL j.

Simulations showed that a 10% increase in LOS yields the exact same results as a 10% increase in arrival rate. This can be explained by analysing Equation 5.6 in Section 5. The equation depends on Λ multiplied by $\bar{t}$, like,

$$\Lambda \cdot \bar{t} = \sum_{i=1}^{n} \lambda_i \cdot \sum_{j=0}^{n} E[Y_j] \cdot p_j. \tag{7.4}$$

We also showed that p_i can be written as the fraction of the total arrivals that occurred at WL i, i.e., $\frac{\lambda_i}{\Lambda}$. Therefore we can rewrite $\Lambda \cdot \bar{t}$ as,

$$
\begin{aligned}
\Lambda \cdot \bar{t} &= \sum_{i=1}^{n} \lambda_i \cdot \sum_{j=0}^{n} E\left[Y_j\right] \cdot p_j \\
&= \sum_{i=1}^{n} \lambda_i \cdot \frac{\sum_{i=0}^{n} E\left[Y_j\right] \cdot \lambda_j}{\sum_{i=1}^{n} \lambda_i} \\
&= \sum_{i=0}^{n} E\left[Y_j\right] \cdot \lambda_j. \qquad (7.5)
\end{aligned}
$$

As a result, any increase to either λ_j or $E\left[Y_j\right]$ will result in the same change to $\Lambda \cdot \bar{t}$ and thus yield the same decrease in service level. Accordingly, we can assume that a 10% increase to $E\left[Y_j\right]$ will also result in a 5 to 10% decrease in service level.

7.6 Non-Stationary Arrival Rate

Up until now we assumed that arrival rate to be stationary and discharged patients immediately after finishing the treatment. We made these assumptions due to the data limitations, as described in Section 4. While the results of our theoretical model seems to be accurate under these assumptions, we are interested in different – more realistic – scenarios too. Throughout this section we will test our theoretical model using the data from division '*Hersenen en Zintuigen*'[19] in 3 different, hypothetical scenarios.

7.6.1 No patient discharges during the night

Assume that we drop Assumption 4.3 and replace it with the assumption that patients can only be discharged between $8AM$ and $10PM$. Then any patient that has a LOS that results in an end of treatment after $10PM$ today, will be discharged tomorrow at $8AM$ exactly. Note that the theoretical results have not changed as we did not change the input; we still use the same arrival rate and the same LOS distribution. See Section 7.6.3 for results after changing the input of the theoretical model.

[19] This division is not limited by the number of physical beds and as such our algorithm has no constraints which might affect the results.

medical department	opr. beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service
KNO [7310, 7328]	23	0.730	0.959	0.741	0.949
Mondziekten, Kaak en Aangezichtschirurgie & Bijzondere Tandheelkunde[4625]	7	0.499	0.954	0.508	0.943
Neurochirurgie [6216, 6225]	28	0.770	0.953	0.784	0.941
Neurologie [3613, 6116, 6124, 6125, 6128]	46	0.830	0.955	0.827	0.932
Oogheelkunde [7710, 7727, 7792]	21	0.728	0.952	0.738	0.900
Psychiatrie [7294, 7295, 7296, 7297, 7298, 7299, 756	74	0.882	0.951	0.891	0.953
Division: Hersenen en Zintuigen	199	0.767	0.954	0.773	0.927

Table 15: Theoretical and simulated results for division *Hersenen en Zintuigen*. Scenario: a patient can only be discharged between $8AM$ and $10PM$.

As a result our theoretical model has a slight over-estimate of the service level, as shown in Table 15. This can easily be explained by the fact that, during the nights, no patients are discharged and there is no change in arrival rate. Therefore, if at some point during the night all beds are taken, no additional patients can be admitted until $8AM$ the next morning. This is in contradiction with our theoretical model, which assumes discharges occur right after the end of the treatment.

7.6.2 Low arrival rate during the night

Throughout this thesis we ignored the fact that the arrival rate might fluctuate during the day, even though we did mention it in Section 4.2.1. We mentioned the idea that the arrival right might be significantly lower during the nights, due to scheduled appointments only occuring during office hours. In this scenario, an extension of the one above, we will lower the arrival rate during the night by 90 per cent and discharge only between $8AM$ and $10PM$.

medical department	opr. beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service
KNO [7310, 7328]	23	0.730	0.959	0.729	0.974
Mondziekten, Kaak en Aangezichtschirurgie & Bijzondere Tandheelkunde[4625]	7	0.499	0.954	0.612	0.903
Neurochirurgie [6216, 6225]	28	0.770	0.953	0.810	0.947
Neurologie [3613, 6116, 6124, 6125, 6128]	46	0.830	0.955	0.736	0.997
Oogheelkunde [7710, 7727, 7792]	21	0.728	0.952	0.659	0.984
Psychiatrie [7294, 7295, 7296, 7297, 7298, 7299, 756	74	0.882	0.951	0.976	0.913
Division: Hersenen en Zintuigen	199	0.767	0.954	0.736	0.971

Table 16: Theoretical and simulated results for division *Hersenen en Zintuigen*. Scenario: A patient can only be discharged between $8AM$ and $10PM$, and the arrival rate during the night is 90 per cent lower than by day.

Due to its setup, the results in this scenario are affected in two different ways. The lower arrival rate during the night will increase the service level and decrease the occupancy level, while the longer LOS will increase the occupancy level and lower the overall service. The end result depends on both the original arrival rate and LOS distribution. For example, the higher the original arrival rate is, the more effect the low nightly rate has. In this situation, without changing the input parameters, on average our theoretical model under-estimates the service level and over-estimates the occupancy.

7.6.3 Higher arrival rate during office hours

In this scenario we increase the arrival rate during office hours to counter-act the lower arrival rate during the night. By lowering the arrival rate between $10PM$ and $8AM$, the daily arrival rate is also affected. For example, assuming we originally had a ward that has 19 arrivals a day and we lower the nightly arrivals by 90 per cent, then this ward will now only have 11.9 arrivals a day. As the daily arrival rate is a given parameter, we have to increase the arrivals during office hours by about 64 per cent.

medical department	opr. beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service
KNO [7310, 7328]	23	0.730	0.959	0.877	0.844
Mondziekten, Kaak en Aangezichtschirurgie & Bijzondere Tandheelkunde[4625]	7	0.499	0.954	0.752	0.787
Neurochirurgie [6216, 6225]	28	0.770	0.953	0.909	0.807
Neurologie [3613, 6116, 6124, 6125, 6128]	46	0.830	0.955	0.904	0.886
Oogheelkunde [7710, 7727, 7792]	21	0.728	0.952	0.824	0.887
Psychiatrie [7294, 7295, 7296, 7297, 7298, 7299, 756	74	0.882	0.951	0.986	0.671
Division: Hersenen en Zintuigen	199	0.767	0.954	0.876	0.846

Table 17: Theoretical and simulated results for division *Hersenen en Zintuigen*. Scenario: A patient can only be discharged between $8AM$ and $10PM$, 90 per cent of the patients arrive during the day and the other 10 by night.

Without changing the input parameters, the theoretical model both under-estimates the occupancy level and over-estimates the service level by around 11 per cent – see Table 17. Where a 2 or 3 per cent offset could be disregarded as acceptable, a 11 per cent offset cannot. This shows that, the larger the difference between day and night arrivals, the harder it is to predict both the occupancy and service level and the larger the bias is.

8 Managerial Decisions

In this section we will describe some management decisions that might further increase the bed occupancy. Note that some of these measures do not increase the service level – i.e. fill rate – per se; merely the occupancy level.

8.1 Weekend-Ward(s)

As we have shown in Table 20 – Appendix A – there is a significant difference in admissions during the week versus the weekends. The method in Section 5 combines existing wards, which either increases the fill rate or reduces the required operational beds. However, even after combining several wards, during the weekends the arrival rate is still relatively low. This is due to the fact that scheduled arrivals generally do not occur during the weekends, thus resulting in only unscheduled arrivals. Furthermore admitted patients might be allowed to go home during the weekends, which decreases the operational bed requirement for these wards.

		Theoretical		Simulated	
medical department	**beds**	**occupancy**	**service**	**occupancy**	**service**
Ambulante Zorg Daniel [6941, 6951, 6953]	1	0.010	0.990	0.008	1.000
Haematologie [5428, 5444, 5445, 6630, 6971, 6972]	53	0.845	0.955	0.837	0.958
Interne Oncologie [5353, 6966, 6968, 6969]	28	0.757	0.960	0.753	0.963
Radiotherapie [6963, 6964, 6965]	12	*0.586*	0.967	*0.602*	0.962
SOG Daniel [6960, 6961, 6973, 6978]	25	0.746	0.957	0.743	0.958
Division: Daniel	119	0.756	0.959	0.753	0.960

Table 18: Operational bed requirement during the weekend for division *Daniel*.
The beds requirement is acquired by use of the method described in Section 5 with a target fill rate of 0.95.

Looking at Table 18, we find that there are approximately 15 unscheduled arrivals each weekend for division Daniel – 7952 arrivals in a 10 year simulation. Maintaining a service level of 95% during the weekends, requires at least 119 beds divided over 5 wards.

		Theoretical		Simulated	
medical department	**beds**	**occupancy**	**service**	**occupancy**	**service**
Weekend-Ward	101	0.903	0.953	0.899	0.956

Table 19: Operation bed requirement for the ‘weekend-ward’ in division *Daniel*.
Beds are estimated with a fill rate of 0.95 and the simulation ran 10 years.

If we create a new ‘weekend-ward’, which is the combination of all wards in Table 18, we notice the bed requirement dropped by 15% to 101 operational beds – see Table 19. Furthermore, the occupancy level increased to 90.3% and the simulated service level is 95.3%, only 0.6% less than the separate wards and still over the required target of 95%. This shows that a ‘weekend-ward’ is a viable alternative to keeping the wards separate during the weekends. However, it does add additional complexity in organizational structure of the hospital, as well as the planning process. There now is a special ward only available during the weekends and these patients might still require care during the week.

8.2 Service Level Differentiation

Service level differentiation is a relatively new concept in call centres (Gurvich, Armony, & Mandelbaum, 2008; Gurvich & Whitt, 2009) and spare part inventory management (Kranenburg & Houtum, 2007). The key idea is to divide the customers in two different groups, e.g., ‘good’ and ‘normal’ customers. Then both these groups will get a different service level, e.g., 95 per cent for ‘good’ customers and 85 per cent for ‘normal’ customers. Compared to an overall service level of 95 per cent, the required servers, in case of service systems, or units, in case of inventories, decrease. This allows for lower inventories while keeping a high service level for certain customers.

As we have seen in Section 5 and Section 7, there is a trade-off between operational beds and the service level. For example *Haematologie 5444* had a service level of 79.8%

and an occupancy level of 39.9%, which increases if we combine wards. However we can only do so much as there are physical beds available, some wards might still have not that high service levels; see SOG Daniel in Section 7.2. Further increasing the service level requires additional operational beds, but lowers the occupancy level. We cannot change this trade-off, but we can shift in service levels. For example, by setting a service level of 95 per cent for emergency, unexpected, patients and 85 per cent for expected patients, we can maintain the current operational bed requirements, while increasing the service level for the 'good' customer group, i.e., emergency patients.

We believe that in reality this is already the case, as most hospitals cancel scheduled admissions if there are to many emergency, unexpected, arrivals, but it has never been described.

9 Conclusion

In this paper we have shown a way to increase the occupancy level by combining ward locations (WLs), while maintaining a set ward availability target, i.e., service level target.

We applied inventory management, in particular $(S-1, S)$-policy, to describe the patient flow through hospital wards where patients might be assigned to multiple beds. Using the *mixed-Weibull* distribution as length of stay (LOS) and the generalized Palm's theorem, which seems to accurately estimate the service level in most situations, we could determine the required operational beds per WL or combined WLs.

From the case study we did for the Erasmus MC we learned that this idea can not only be used to increase occupancy level, but also to increase the service level itself. As the results showed combining WLs automatically results in a higher service level. Then, by decreasing the required operational beds, it is possible to increase the occupancy level, while the original service level is maintained. As a result of the lower operational bed requirement, the cost of the wards can also be lowered, which is in line with the 3 goals the Erasmus MC targeted.

10 References

Axsäter, S. (2006). *Inventory control.* Springer.

Bekker, R., & Bruin, A. de. (2010). Time-dependent analysis for refused admissions in clinical wards. *Annals of Operations Research*, *178*, 45-65. Available from http://dx.doi.org/10.1007/s10479-009-0570-z (10.1007/s10479-009-0570-z)

Bruin, A. de, Bekker, R., Zanten, L. van, & Koole, G. (2010). Dimensioning hospital wards using the erlang loss model. *Annals of Operations Research*, *178*, 23-43. Available from http://dx.doi.org/10.1007/s10479-009-0647-8 (10.1007/s10479-009-0647-8)

Carter, M. (2002). Diagnosis: Mismanagement of resources. *OR/MS Today*, *29*(2), 26-32.

Dumas, M. B. (1985). Hospital bed utilization: An implemented simulation approach to adjusting and maintaining appropriate levels. *Health Service Res*, *20*(1), 69-78.

Feeney, G. J., & Sherbrooke, C. C. (1966). The (s - 1, s) inventory policy under compound poisson demand. *Management Science*, *12*(5), pp. 391-411. Available from http://www.jstor.org/stable/2627824

Feller, W. (1967). A direct proof of stirling's formula. *The American Mathematical Monthly*, *74*(10), 1223-1225. Available from http://www.jstor.org/stable/2315671

Feller, W. (2002). *An introduction to probability theory and its applications.* Wiley.

Ghiani, G., Laporte, G., & Musmanno, R. (2004). *Introduction to logistics ssystems planning and control.* Chichester : Wiley.

Green, L. V. (2002). How many hospital beds? *Inquiry - Excellus Health Plan*, *39*(4), 400 - 412. Available from http://search.proquest.com/docview/221000534?accountid=13598

Green, L. V., & Nguyen, V. (2001). Strategies for cutting hospital beds: the impact on patient service. *Health Serv Res.*, *36*(2), 421–442. Available from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1089232/

Gurvich, I., Armony, M., & Mandelbaum, A. (2008). Service-level differentiation in call centers with fully flexible servers. *Management Science*, *54*(2), 279-294.

Gurvich, I., & Whitt, W. (2009). Service-level differentiation in call centers with fully flexible servers. *Operations Research*, *56*(2), 1-13.

Harper, P. R. (2002). A framework for operational modelling of hospital resources. *Health Care Management Science*, *5*, 165-173. Available from http://dx.doi.org/10.1023/A:1019767900627 (10.1023/A:1019767900627)

Harper, P. R., & Shahani, A. K. (2002). Modelling for the planning and management of bed capacities in hospitals. *The Journal of the Operational Research Society*, *53*(1), pp. 11-18. Available from http://www.jstor.org/stable/822874

Kao, J. H. K. (1959). A graphical estimation of mixed weibull parameters in life-testing of electron tubes. *Technometrics*, *1*(4), pp. 389-407. Available from http://www.jstor.org/stable/1266719

Kranenburg, A. A., & Houtum, G. J. van. (2007). Service differentiation in spare parts inventory management. *Operations Research*, *59*(7). Available from http://dx.doi.org/10.1057/palgrave.jors.2602414

Little, J. (1961). A proof of the queueing formula l = λw. *Operations Research*, *9*(1), 383-387.

Marsaglia, G. (1986). A current view of random number generators. *Computer Science and Statistics*, *86*(1), 16.

Marsaglia, G., Zaman, A., & Tsang, W. W. (1990). Toward a universal random number generator. *Statistics & Probability Letters*, *9*(1), 35 - 39. Available from http://www.sciencedirect.com/science/article/pii/016771529090092L

Oostrum, J. van. (2009). *Applying mathematical models to surgical patient planning.* Unpublished doctoral dissertation, Erasmus Research Institue of Management. Available from http://hdl.handle.net/1765/16728

Palm, C. (1938). Analysis of the erlang traffic formula for busy signal assignment. *Ericsson Technics*, *5*(5), 39-58.

Ross, S. (2006). *Simulation.* Elsevier Academic Press. Available from http://books.google.com/books?id=GOxrtYzmixcC

Ruth, R. J. (1981). A mixed integer programming model for regional planning of a hospital inpatient service. *Management Science*, *27*(5), pp. 521-533. Available from http://www.jstor.org/stable/2631117

Van Berkel, P., & Blake, J. (2007). A comprehensive simulation for wait time reduction and capacity planning applied in general surgery. *Health Care Management Science*, *10*, 373-385. Available from http://dx.doi.org/10.1007/s10729-007-9035-6

Vissers, J., Adam, I., & Bekkers, J. (2002). Patient mix optimisation in hospital admission planning: a case study. *International Journal of Operations and Production Managment*, *10*(22), 445-461.

Wullink, G., Van Houdenhoven, M., Hans, E., Oostrum, J. van, Lans, M. van der, & Kazemier, G. (2007). Closing emergency operating rooms improves efficiency. *Journal of Medical Systems*, *31*, 543-546. Available from http://dx.doi.org/10.1007/s10916-007-9096-6 (10.1007/s10916-007-9096-6)

A Admission(s) - Overview

Table 20: Total number of admissions and admission rate for all 7 divisions and 33 medical departments throughout the Erasmus MC.

Hence, the blank rows underneath the medical departments show the individual WL – denoted by the number in the second column. The admission rate for a medical department is the same as the sum of the admission rates for each WL the medical department is in charge off. This is also true for the divisions, where the admission rate is the sum of the individual rates for the medical departments in that division.

medical department	*ward*	**no. of admissions**	**rate [week]**	**rate [weekend]**
Daniel		*15,923*	*58.51*	*3.13*
Ambulante Zorg Daniel		**5077**	**19.45**	**0.01**
	(6941)	1	0.00	0.00
	(6951)	4991	19.12	0.01
	(6953)	85	0.33	0.00
Haematologie		**1196**	**4.72**	**1.71**
	(5428)	349	1.22	0.30
	(5444)	208	0.79	0.02
	(5445)	79	0.30	0.01
	(6630)	16	0.06	0.00
	(6971)	289	0.89	0.54
	(6972)	470	1.46	0.85
Interne Oncologie		**5642**	**20.72**	**2.25**
	(5353)	2941	11.25	0.04
	(6966)	1121	3.64	1.63
	(6968)	1237	4.71	0.07
	(6969)	343	1.11	0.51
Radiotherapie		**815**	**2.95**	**0.43**
	(6963)	365	1.25	0.38
	(6964)	247	0.95	0.00
	(6965)	203	0.76	0.05
SOG Daniel		**2978**	**10.67**	**1.87**
	(6960)	1271	4.75	0.29
	(6961)	1193	4.02	1.38
	(6973)	425	1.55	0.19
	(6978)	89	0.34	0.00
Diagnostiek		*431*	*1.65*	**0.00**
Nucleaire Geneeskunde		**431**	**1.65**	0.00
	(5520)	431	1.65	0.00
Hersenen en Zintuigen		*10,913*	*38.50*	*8.31*
KNO		**1698**	**6.04**	**1.17**
	(7310)	2	0.01	0.00
	(7328)	1696	6.03	1.17

medical department	*ward*	no. of admissions	rate [week]	rate [weekend]
Mondziekten, Kaak en Aangezichtschirurgie & Bijzondere Tandheelkunde		**358**	**1.30**	**0.18**
	(4625)	358	1.30	0.18
Neurochirurgie		**1426**	**4.71**	**1.89**
	(6216)	121	0.46	0.00
	(6225)	1305	4.25	1.89
Neurologie		**3380**	**11.43**	**3.71**
	(3613)	23	0.09	0.00
	(6116)	599	2.30	0.00
	(6124)	136	0.48	0.00
	(6125)	1232	3.56	2.90
	(6128)	1390	5.00	0.81
Oogheelkunde		**3154**	**11.85**	**0.60**
	(7710)	3	0.01	0.00
	(7727)	618	2.13	0.59
	(7792)	2533	9.70	0.01
Psychiatrie		**907**	**3.18**	**0.75**
	(7294)	206	0.67	0.29
	(7295)	182	0.66	0.09
	(7296)	166	0.54	0.23
	(7297)	66	0.25	0.00
	(7298)	128	0.47	0.05
	(7299)	119	0.44	0.03
	(7566)	1	0.00	0.00
	(7569)	39	0.12	0.07
Hoboken		*22,919*	*81.39*	*16.11*
Algemene Heelkunde		**4528**	**14.80**	**6.39**
	(4098)	115	0.44	0.00
	(4108)	76	0.25	0.10
	(4125)	1	0.00	0.01
	(4126)	1508	4.92	2.14
	(4127)	1575	4.99	2.62
	(4221)	1253	4.19	1.53
Dermatologie		**3123**	**11.97**	**0.00**
	(7413)	972	3.72	0.00
	(7441)	2151	8.24	0.00
Inwendige Geneeskunde		**6233**	**21.92**	**4.93**
	(3194)	31	0.11	0.01
	(5118)	222	0.85	0.01
	(5124)	333	1.13	0.37
	(5126)	4	0.01	0.01
	(5138)	884	2.96	1.07
	(5142)	1284	4.10	2.06

medical department	*ward*	no. of admissions	rate [week]	rate [weekend]
	(5226)	1	0.00	0.00
	(5228)	1752	6.71	0.00
	(5323)	1571	5.46	1.41
	(7616)	151	0.58	0.00
MDL		**5903**	**22.08**	**1.36**
	(5241)	2895	11.08	0.04
	(5243)	45	0.17	0.00
	(5277)	1503	5.23	1.32
	(5278)	1460	5.59	0.00
Orthopedie		**1248**	**4.18**	**1.51**
	(4427)	1248	4.18	1.51
Plastische Chirurgie		**1470**	**4.88**	**1.88**
	(4525)	1470	4.88	1.88
Reumatologie		**414**	**1.57**	**0.03**
	(5957)	226	0.85	0.03
	(5958)	188	0.72	0.00
Sophia		*26,119*	*87.18*	*32.36*
Ambulate Zorg Sophia		**3273**	**12.54**	**0.00**
	(3812)	3273	12.54	0.00
ICK		**2097**	**6.82**	**3.05**
	(3920)	497	1.58	0.82
	(3921)	463	1.54	0.60
	(3922)	264	0.85	0.40
	(3923)	482	1.56	0.73
	(3939)	352	1.15	0.49
	(3963)	39	0.15	0.01
KG Neonatologie		**859**	**2.47**	**2.03**
	(3955)	289	0.84	0.66
	(3956)	308	0.86	0.81
	(3957)	259	0.77	0.56
Kinderchirurgische Groep		**3254**	**11.41**	**2.64**
	(3941)	1635	5.78	1.22
	(3943)	1619	5.64	1.42
Kindergeneeskunde		**5049**	**17.53**	**4.56**
	(3529)	123	0.47	0.00
	(3566)	1983	7.18	1.05
	(3567)	1	0.00	0.00
	(3951)	1291	4.34	1.51
	(3952)	823	2.83	0.82
	(3953)	828	2.70	1.18
KJP (incl. Adolescentenkliniek)		**101**	**0.35**	**0.10**
	(3728)	26	0.08	0.04
	(3729)	41	0.16	0.00

medical department	*ward*	no. of admissions	rate [week]	rate [weekend]
	(3738)	9	0.03	0.01
	(3739)	24	0.07	0.05
	(3860)	1	0.00	0.00
Urologie		**2598**	**8.96**	**2.50**
	(4325)	2102	7.06	2.50
	(4329)	496	1.90	0.00
Verloskunde & Vrouwenziekten		**8891**	**27.10**	**17.48**
	(3971)	2177	6.31	5.10
	(3972)	1958	6.05	3.65
	(3973)	962	2.98	1.78
	(3974)	136	0.39	0.32
	(3979)	1920	5.64	4.30
	(7123)	229	0.87	0.01
	(7124)	1509	4.85	2.33
Spoed en Intensief		*6,079*	*22.18*	*2.80*
Anesthesiologie		**903**	**3.45**	**0.03**
	(1509)	900	3.44	0.03
	(7829)	3	0.01	0.00
IC Volwassenen		**2091**	**3.91**	**2.76**
	(4225)	570	1.72	1.17
	(5825)	645	1.99	1.20
	(8326)	876	3.20	0.39
Operatiekamers		**3085**	**11.82**	**0.00**
	(7925)	3085	11.82	0.00
Thorax		*9592*	*32.35*	*11.05*
Longziekten	(5625)	**2246**	**8.12**	**1.21**
	(5625)	1449	5.32	0.58
	(5626)	797	2.80	0.63
Thorax Cardiologie		**5316**	**17.85**	**6.31**
	(8114)	637	2.44	0.00
	(8116)	1229	4.67	0.09
	(8117)	1177	4.04	1.18
	(8126)	1379	3.86	3.57
	(8127)	628	1.97	1.09
	(8328)	266	0.87	0.38
Thorax Chirurgie		**2030**	**6.37**	**3.53**
	(8327)	2030	6.37	3.53
Total		91,976	251.99	0.00

B Service Level(s) - Baseline

Table 21: Simulation results for unaltered wards.
The results in this table are based a 10 year simulation, with the data as presented in Section 4, without combining wards. This can be used as baseline for the other results.

medical department	*ward*	beds	Theoretical occupancy	Theoretical service	Simulated occupancy	Simulated service
Daniel		*219*	*0.733*	*0.753*	*0.732*	*0.753*
Ambulante Zorg Daniel		**32**	**0.630**	**0.987**	**0.622**	**0.987**
	(6941)	1	0.004	0.996	0.004	1.000
	(6951)	30	0.637	0.994	0.638	0.996
	(6953)	1	0.326	0.674	0.314	0.668
Haematologie		**60**	**0.676**	**0.827**	**0.670**	**0.821**
	(5428)	17	0.858	0.780	0.855	0.780
	(5444)	2	0.395	0.805	0.402	0.806
	(5445)	1	0.299	0.701	0.295	0.710
	(6630)	1	0.061	0.939	0.065	0.949
	(6971)	18	0.643	0.975	0.656	0.971
	(6972)	21	0.853	0.831	0.862	0.810
Interne Oncologie		**67**	**0.675**	**0.956**	**0.675**	**0.954**
	(5353)	18	0.647	0.974	0.645	0.975
	(6966)	18	0.777	0.900	0.781	0.900
	(6968)	16	0.689	0.948	0.688	0.949
	(6969)	15	0.566	0.985	0.565	0.987
Radiotherapie		**18**	**0.649**	**0.802**	**0.644**	**0.816**
	(6963)	10	0.655	0.915	0.655	0.927
	(6964)	4	0.613	0.776	0.610	0.772
	(6965)	4	0.688	0.692	0.681	0.689
SOG Daniel		**42**	**0.889**	**0.373**	**0.889**	**0.374**
	(6960)	20	0.573	0.993	0.569	0.994
	(6961)	14	0.978	0.244	0.978	0.247
	(6973)	4	0.930	0.235	0.931	0.234
	(6978)	4	0.085	1.000	0.082	1.000
Diagnostiek		*4*	*0.843*	*0.442*	*0.840*	*0.444*
Nucleaire Geneeskunde		**4**	**0.843**	**0.442**	**0.840**	**0.444**
	(5520)	4	0.843	0.442	0.840	0.444
Hersenen en Zintuigen		*282*	*0.620*	*0.927*	*0.618*	*0.928*
KNO		**38**	**0.469**	**1.000**	**0.473**	**1.000**
	(7310)	1	0.008	0.992	0.006	1.000
	(7328)	37	0.469	1.000	0.468	1.000
Mondziekten, Kaak en Aangezichtschirurgie & Bijzondere Tandheelkunde		**4**	**0.759**	**0.590**	**0.756**	**0.591**
	(4625)	4	0.759	0.590	0.756	0.591
Neurochirurgie		**39**	**0.578**	**0.997**	**0.569**	**0.997**

medical department	*ward*	beds	occupancy	service	occupancy	service
	(6216)	5	0.093	1.000	0.092	1.000
	(6225)	34	0.638	0.996	0.627	0.997
Neurologie		**55**	**0.642**	**0.907**	**0.640**	**0.907**
	(3613)	1	0.088	0.912	0.094	0.901
	(6116)	5	0.459	0.933	0.455	0.935
	(6124)	1	0.479	0.521	0.484	0.528
	(6125)	28	0.842	0.893	0.847	0.891
	(6128)	20	0.615	0.987	0.617	0.985
Oogheelkunde		**24**	**0.649**	**0.947**	**0.654**	**0.946**
	(7710)	1	0.268	0.732	0.336	0.750
	(7727)	8	0.659	0.878	0.654	0.884
	(7792)	15	0.647	0.962	0.645	0.960
Psychiatrie		**122**	**0.638**	**0.946**	**0.645**	**0.946**
	(7294)	18	0.619	0.982	0.592	0.975
	(7295)	21	0.635	0.985	0.629	0.991
	(7296)	22	0.626	0.988	0.645	0.990
	(7297)	6	0.599	0.875	0.560	0.895
	(7298)	17	0.641	0.973	0.658	0.972
	(7299)	13	0.650	0.948	0.649	0.936
	(7566)	20	0.038	1.000	0.029	1.000
	(7569)	5	0.776	0.626	0.770	0.663
Hoboken		*522*	*0.607*	*0.965*	*0.610*	*0.965*
Algemene Heelkunde		**168**	**0.631**	**0.962**	**0.628**	**0.961**
	(4098)	1	0.441	0.559	0.436	0.551
	(4108)	3	0.617	0.698	0.600	0.718
	(4125)	2	0.000	1.000	0.000	1.000
	(4126)	40	0.736	0.986	0.742	0.984
	(4127)	44	0.550	1.000	0.545	1.000
	(4221)	40	0.648	0.998	0.645	0.999
Dermatologie		**19**	**0.630**	**0.923**	**0.635**	**0.919**
	(7413)	6	0.621	0.858	0.617	0.860
	(7441)	13	0.634	0.955	0.635	0.957
Inwendige Geneeskunde		**191**	**0.599**	**0.986**	**0.600**	**0.987**
	(3194)	1	0.115	0.885	0.121	0.857
	(5118)	5	0.191	0.997	0.180	0.999
	(5124)	12	0.624	0.952	0.625	0.954
	(5126)	36	0.002	1.000	0.002	1.000
	(5138)	23	0.651	0.985	0.640	0.986
	(5142)	40	0.637	0.998	0.633	0.999
	(5226)	10	0.000	1.000	0.001	1.000
	(5228)	18	0.637	0.977	0.637	0.981
	(5323)	41	0.627	0.999	0.627	0.999
	(7616)	5	0.116	1.000	0.120	0.999
MDL		**68**	**0.617**	**0.967**	**0.617**	**0.967**
	(5241)	18	0.615	0.982	0.616	0.983
	(5243)	1	0.172	0.828	0.169	0.823

medical department	*ward*	beds	occupancy	service	occupancy	service
	(5277)	40	0.638	0.998	0.637	0.999
	(5278)	9	0.622	0.922	0.629	0.921
Orthopedie		**35**	**0.642**	**0.996**	**0.642**	**0.998**
	(4427)	35	0.642	0.996	0.642	0.998
Plastische Chirurgie		**34**	**0.477**	**1.000**	**0.482**	**1.000**
	(4525)	34	0.477	1.000	0.482	1.000
Reumatologie		**7**	**0.459**	**0.843**	**0.466**	**0.843**
	(5957)	5	0.532	0.892	0.553	0.889
	(5958)	2	0.398	0.802	0.403	0.788
Sophia		*432*	*0.683*	*0.891*	*0.683*	*0.891*
Ambulate Zorg Sophia		**20**	**0.616**	**0.987**	**0.617**	**0.987**
	(3812)	20	0.616	0.987	0.617	0.987
ICK		**51**	**0.746**	**0.699**	**0.741**	**0.702**
	(3920)	12	0.599	0.962	0.594	0.961
	(3921)	8	0.658	0.879	0.666	0.873
	(3922)	10	0.434	0.991	0.425	0.990
	(3923)	7	0.910	0.419	0.913	0.422
	(3939)	8	0.789	0.729	0.770	0.753
	(3963)	6	0.474	0.948	0.482	0.928
KG Neonatologie		**27**	**0.370**	**0.993**	**0.379**	**0.990**
	(3955)	10	0.327	0.999	0.331	1.000
	(3956)	9	0.367	0.995	0.344	0.997
	(3957)	8	0.421	0.985	0.455	0.986
Kinderchirurgische Groep		**50**	**0.830**	**0.891**	**0.830**	**0.891**
	(3941)	25	0.827	0.894	0.833	0.887
	(3943)	25	0.833	0.888	0.831	0.895
Kindergeneeskunde		**100**	**0.574**	**0.955**	**0.574**	**0.955**
	(3529)	1	0.471	0.529	0.466	0.536
	(3566)	12	0.598	0.963	0.597	0.965
	(3567)	5	0.001	1.000	0.002	1.000
	(3951)	30	0.711	0.981	0.712	0.982
	(3952)	26	0.414	1.000	0.419	1.000
	(3953)	26	0.481	1.000	0.473	1.000
KJP (incl. Adolescentenkliniek)		**58**	**0.599**	**0.942**	**0.603**	**0.932**
	(3728)	9	0.601	0.933	0.543	0.988
	(3729)	12	0.611	0.958	0.674	0.915
	(3738)	5	0.542	0.884	0.531	0.886
	(3739)	11	0.623	0.945	0.575	0.975
	(3860)	21	0.028	1.000	0.017	1.000
Urologie		**38**	**0.692**	**0.950**	**0.696**	**0.950**
	(4325)	34	0.768	0.968	0.768	0.964
	(4329)	4	0.465	0.897	0.458	0.895
Verloskunde & Vrouwenziekten		**88**	**0.725**	**0.846**	**0.726**	**0.846**

medical department	*ward*	beds	occupancy	service	occupancy	service
	(3971)	21	0.694	0.968	0.700	0.965
	(3972)	19	0.630	0.981	0.621	0.983
	(3973)	17	0.797	0.872	0.795	0.871
	(3974)	4	0.361	0.950	0.353	0.954
	(3979)	18	0.732	0.935	0.729	0.936
	(7123)	3	0.629	0.683	0.638	0.685
	(7124)	6	0.817	0.604	0.818	0.603
Spoed en Intensief		*86*	*0.630*	*0.970*	*0.632*	*0.970*
Anesthesiologie		**15**	**0.633**	**0.928**	**0.629**	**0.934**
	(1509)	10	0.635	0.927	0.635	0.927
	(7829)	5	0.002	1.000	0.002	1.000
IC Volwassenen		**52**	**0.642**	**0.966**	**0.649**	**0.964**
	(4225)	18	0.676	0.964	0.691	0.952
	(5825)	21	0.619	0.988	0.629	0.991
	(8326)	13	0.637	0.954	0.629	0.953
Operatiekamers		**19**	**0.622**	**0.983**	**0.623**	**0.984**
	(7925)	19	0.622	0.983	0.623	0.984
Thorax		*173*	*0.669*	*0.902*	*0.666*	*0.906*
Longziekten	(5625)	**60**	**0.546**	**0.998**	**0.546**	**0.997**
	(5625)	32	0.499	1.000	0.491	1.000
	(5626)	28	0.637	0.993	0.638	0.994
Thorax Cardiologie		**83**	**0.679**	**0.853**	**0.678**	**0.851**
	(8114)	5	0.488	0.918	0.494	0.921
	(8116)	14	0.646	0.956	0.646	0.953
	(8117)	15	0.614	0.973	0.615	0.976
	(8126)	18	0.637	0.977	0.645	0.971
	(8127)	16	0.955	0.435	0.956	0.449
	(8328)	15	0.635	0.966	0.646	0.963
Thorax Chirurgie		**30**	**0.777**	**0.955**	**0.772**	**0.954**
	(8327)	30	0.777	0.955	0.772	0.954
Total		1680	0.666	0.884	0.666	0.884

C Service Level(s) - One Ward per Medical Department

Table 22: Simulation results for unaltered wards.
The results in this table are based a 10 year simulation, with the data as presented in Section 4, without combining wards. This can be used as baseline for the other results.

		Theoretical		Simulated	
medical department	**beds**	**occupancy**	**service**	**occupancy**	**service**
Daniel	**212**	**0.857**	**0.845**	**0.855**	**0.846**
Ambulante Zorg Daniel [6941, 6951, 6953]	25	0.752	0.954	0.755	0.955
Haematologie [5428, 5444, 5445, 6630, 6971, 6972]	60	0.855	0.957	0.840	0.967
Interne Oncologie [5353, 6966, 6968, 6969]	54	0.845	0.956	0.843	0.956
Radiotherapie [6963, 6964, 6965]	19	0.715	0.950	0.722	0.948
SOG Daniel [6960, 6961, 6973, 6978]	54	0.971	0.626	0.972	0.626
Diagnostiek	**8**	**0.749**	**0.785**	**0.753**	**0.777**
Nucleaire Geneeskunde [5520]	8	0.749	0.785	0.753	0.777
Hersenen en Zintuigen	**206**	**0.763**	**0.957**	**0.766**	**0.958**
KNO [7310, 7328]	23	0.726	0.961	0.718	0.962
Mondziekten, Kaak- en Aangezichtschirurgie & Bijzondere Tandheelkunde [4625]	9	0.548	0.958	0.560	0.956
Neurochirurgie [6216, 6225]	28	0.761	0.958	0.763	0.958
Neurologie [3613, 6116, 6124, 6125, 6128]	48	0.839	0.952	0.832	0.955
Oogheelkunde [7710, 7727, 7792]	22	0.719	0.961	0.717	0.961
Psychiatrie [7294, 7295, 7296, 7297, 7298, 7299, 756	76	0.879	0.954	0.881	0.957
Hoboken	**307**	**0.821**	**0.955**	**0.821**	**0.955**
Algemene Heelkunde [4098, 4108, 4125, 4126, 4127, 4221]	89	0.894	0.953	0.897	0.947
Dermatologie [7413, 7441]	18	0.690	0.958	0.696	0.956
Inwendige Geneeskunde [3194, 5118, 5124, 5126, 5138, 5142, 522	93	0.898	0.952	0.900	0.950
MDL [5241, 5243, 5277, 5278]	49	0.839	0.953	0.839	0.955
Orthopedie [4427]	28	0.768	0.954	0.762	0.954
Plastische Chirurgie [4525]	22	0.711	0.964	0.716	0.961
Reumatologie [5957, 5958]	8	0.482	0.970	0.482	0.974
Sophia	**336**	**0.824**	**0.956**	**0.824**	**0.955**
Ambulante zorg Sophia [3812]	18	0.670	0.966	0.670	0.968
ICK [3920, 3921, 3922, 3923, 3939, 3963]	51	0.839	0.957	0.842	0.953

medical department	**beds**	**occupancy**	**service**	**occupancy**	**service**
KG Neonatologie [3955, 3956, 3957]	15	0.643	0.963	0.637	0.964
Kinderchirurgische Groep [3941, 3943]	53	0.842	0.958	0.845	0.958
Kindergeneeskunde [3529, 3566, 3567, 3951, 3952, 3953]	59	0.861	0.951	0.861	0.953
KJP incl. Adolescentenkliniek [3728, 3729, 3738, 3739, 3860]	30	0.776	0.956	0.789	0.933
Urologie [4325, 4329]	35	0.794	0.957	0.795	0.957
Verloskunde & Vrouwenziekten [3971, 3972, 3973, 3974, 3979, 7123, 712	75	0.880	0.953	0.882	0.948
Spoed en Intensief	**68**	**0.706**	**0.956**	**0.703**	**0.957**
Anesthesiologie [1509, 7829]	11	0.596	0.956	0.596	0.954
IC Volwassenen [4225, 5825, 8326]	40	0.820	0.951	0.825	0.954
Operatiekamers [7925]	17	0.678	0.959	0.676	0.958
Thorax	**154**	**0.851**	**0.954**	**0.852**	**0.952**
Longziekten [5625, 5626]	40	0.811	0.957	0.820	0.953
Thorax Cardiologie [8114, 8116, 8117, 8126, 8127, 8328]	84	0.889	0.953	0.884	0.957
Thorax Chirurgie [8327]	30	0.777	0.955	0.770	0.956
Total	1291	0.818	0.930	0.818	0.929