Expectation patterns and planning possibilities of the Post Anaesthesia Care Unit

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Abstract

Patient indication and planning of the Post Anaesthesia Care Unit (PACU) in the Erasmus Medical Centre (EMC) in Rotterdam is found to be complicated. The goal of this research is to verify whether the current capacity of the PACU is sufficient or not. The main objectives we have to consider are minimizing the amount of cancelled surgeries and maintaining an acceptable occupancy level. Using simulation modeling the performance of the PACU for various capacity levels and bed admission policies is obtained. Next to this multiple environmental scenarios are implemented according to specific emergency-patient arriving patterns. An optimal patientmix of elective- and emergency patients is found, restricting the amount of elective arrivals per day, in order to maintain flexibility for unexpected patients. After this we have constructed a mixed-integer program verifying a planning pattern for the after-surgical patients. The planning pattern allows surgical specialisms to secure beds for their elective patients.

Contents

Chapter 1

Introduction

In modern day, operations research becomes more important in various health care aspects. In order to minimize the costs of health care, efficient patient care and effective usage of the available resources are becoming important factors for a hospital.

In this thesis the policy of the Post Anaesthesia Care Unit (PACU) at the Erasmus Medical Centre (EMC) will be researched. The PACU at the EMC started in April 2006. The PACU was established to give extra care to after surgical patients too vigorous to go to the Intencive Care (IC), but in need of higher care for a maximum of twentyfour hours. The main objectives for the establishment of this department were to shorten the patient's length of stay and decrease the amount of post-operative complications, through providing a higher quality and goal specific post-operative care.

Difficulties in various aspects in and around the PACU have been noticed. There are scheduling problems with expected patient arrivals because of a high uncertainty level of these arrivals. The PACU is a relative small department providing low flexibility in patient flow. There has also been an enlargment of the OR since 2006 which indicated that the amount of elective surgeries has grown over the past three years. In the current situation patients arrive on the PACU according to a first-come first-served policy. This will be explained in more detail in chapter 2.2. The question has risen if there are possibilities for planning, and if there is need for extension of the PACU.

The research question of this thesis is stated as follows:

Is the current capacity of the PACU sufficient and how can we optimize efficiency?

Where we define *sufficiency* and *efficiency* as

- Sufficiency: all the arriving patients in need for PACU care can be served at the PACU. There is a mimimal amount of patients that will be rejected.
- Efficiency: Giving a fixed capacity level, how can we use the sources more efficient in order to minimize the occupancy and the amount of surgeries cancelled because of non-availability of a PACU bed.

In order to answer the research question appropriately, we have formulated five related questions that form a guideline through this thesis.

1. *What are the relevant characteristics of the PACU, and what is the present situation of the PACU at the EMC?*
   We will start with an environment sketch. First the aspects of the PACU and related departments in hospitals will be given, whereafter the PACU at the EMC, and the patient's journey to the PACU will be explained. The current situation in the EMC is overviewed giving the reader a clear view of the PACU at the EMC and its difficulties. After this the current situation of the PACU is analysed and the patient flow graphically shown for one month.

2. *Which solution methods exist for operations research health care problems, and how can we apply them in our specific case?*
   Previous research done in health care models will be overviewed. Queueing theory, mathematical programming and simulation modeling are stated, giving the reader a basic idea of modeling types and applications. We will decide which method is most appropriately suited to our problem.

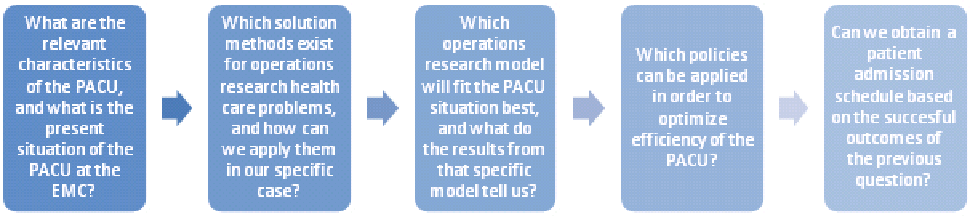

Figure 1.1: *Sub questions*

3. *Which operations research model will fit the PACU situation best, and what do the results from that specific model tell us?*
   Different simulation occupancy models are applied to the PACU problem, each implementing a specific aspect. Thereafter a theoretic model will be applied. Which model is valid, and what can we conclude concerning the PACU problem?

4. *Which policies can be applied in order to optimize efficiency of the PACU?*
   Different applications on the simulation models will be tested, trying to optimize efficiency. These applications indicate various bed policies that can be implemented on the PACU by the staff. Which policy is most succesfull and can improve the current situation at the PACU?

5. *Can we obtain a patient admission schedule based on the succesful outcomes of the previous question?*
   A basic mixed-integer program will be obtained for scheduling a planning pattern. Thereafter we will implement this program on the PACU.

After we have answered the subquestions (shown in figure 1.1) we will form a conclusion concerning the main research question. In the final part the board of the EMC will be advised concerning the most effective solution for planning the PACU.

Chapter 2

Environment sketch

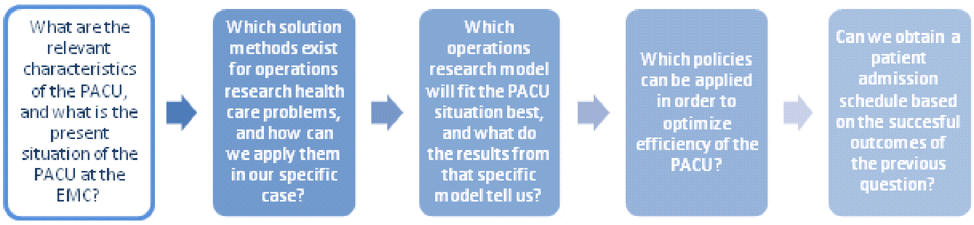

Figure 2.1: *Research question 1*

We start at the first question: what are the relevant characteristics of the PACU, and what is the present situation of the PACU at the EMC? The purpose of this question is to get familiar with the subject of this thesis, and to get an understanding of the difficulties in this area. The next section wil contain an overview of the characteristics of the PACU, and comparable departments in the hospital. Thereafter the aspects of the PACU at the EMC will be summerized. For which patients is the PACU available, and how is an admission request given? After this we will analyse the department for one month in order to get an better understanding of the realistic patient flow. In the last part an overview of problems in the current situation are given, in reference to the small data analysis and interviews with the anaesthetists of the EMC.

2.1 Characteristics of the Post Anaesthesia Care Unit

The PACU provides high care to surgical patients from the OR. In literature research the notification of PACU is not always clear. Many articles refer to PACU as being the recovery next to the OR, where people wake from anaesthesia and have a length of stay between 30 minutes and 3 hours before returning to the ward as described in Marcon et al. (2003). In this report the PACU will be referred to as an independent department, managed by anaesthetists, providing high care to after-surgical patients with an average length of stay of 24 hours. Another term used for the PACU is the Overnight Intensive Recovery (OIR) concept. Unfortunately, there is a paucity of published work on the use of recovery in OIR of PACU in this manner.

The first OIR facility was opened in the general recovery ward at St Thomas' Hosptial, London in 1988. The principles of the OIR are defined in Aps (2004). Overall the concept can be defined as a short duration of stay, with an intensive care level in a recovery unit. The OIR is established as a safe and successful alternative to the ICU for short-term postoperative critical care.

Originally the OIR established in St Thomas was only for cardiadic patients from the OR. Later the OIR developed into a recovery unit available for all after-surgical patients. In the article of Callaghan et al. (2005), the management of elective patients after open aortic surgery was compared using the ICU and the OIR. They concluded that most patients having this surgery can be managed safely using OIR.

2.1.1 Intermediate care units and step-down units

Beside the PACU or OIR other units providing medium care are intermediate care units or step-down units (SDU). Differences with the OIR and the PACU are that these units are not exclusively available for surgical patients and there is no restriction on the length of stay on these units. Research has been done on the effect of a step down unit on the surgical intensive care (IC) population in Eachempati et al. (2004). The step down unit was established because many critical care transfers to the Surgical Intensive Care Units (SICU) were delayed or refused owing to lack of bed availability, and they hypothesized that the SDU would allow treating more patients with high acuity in their own SICU. The results of the study showed that opening an SDU resulted in an increase in the overall severity of the SICU population, and improve outcomes for critically ill surgical patients. The other way around, research was done on the impact of closing an intermediate care unit on the critical care utilization in Byrick et al. (1993). Data showed that more after-surgical admissions were taken to the critical care unit, that there is an increased proportion of critical care admissions with *lower APACHE II*[1] scores, and that the average length of stay on the critical care unit (IC) was decreased. More literature can be found when concentrating on costs. The high costs of providing critical care have provoked a variety of utilization strategies within hospitals to optimize use of these scarce resources. One strategy that many hospitals apply is the provision of graded levels of care.

2.2 Post Anaesthesia Care Unit at the Erasmus Medical Center

A difference between the PACU in the EMC, and the PACU (or OIR) in the literature overview, is that the location is not near the OR and the recovery, which is due to the already full space at the OR. Because of this the PACU has a unit at a different location than the recovery. With the development of a new hospital in 2017 there will be more space at the recovery, where the PACU will be established near the OR.

2.2.1 Difference between IC and PACU

A patient will go to the PACU after surgery if the expectation is that they will need high care for less than twentyfour hours, and there are no vital functions threatened after the operation. The patient will go from the OR to the IC or from the PACU to the IC when vital functions are threatened. The IC at the Erasmus MC has thirtytwo beds, the PACU has only five beds. The PACU is often called little IC, but it is important that it should not be used as an emergency IC when the IC is overloaded. The assessment made by the anaesthesia department is that before the establishment of the PACU, 40 percent of the patients in need for PACU care went immediately to the IC, and 60 percent of these patients went to their original department. The PACU in the Erasmus MC lies next to the OR complex (in the H building). A special aspect of the PACU at the Erasmus MC is the high patients flow with short care contacts (less than twentyfour hours). Therefore it is important that there is a fast feedback from the OR to the PACU. The PACU belongs to the anaesthesia division of the hospital. The reasons why it was important to establish a separate unit for these patients, instead of increasing the bed capacity of the intensive care are primary medical, but also economic. First, adding more beds to the intensive care would be more expensive then adding a bed on the PACU. At the intensive care the rooms are separated and the medical equipment is more expensive, since an IC bed has to be more extended than a PACU bed. This brings us to the next point. The intensive care has other goals with their patients than the PACU. The first one gives priority to the recovery of the vital functions of the patients, while the latter prepares the patients for the ward, and increases the medical condition of the patients after the OR as much as possible in twentyfour hours. Patients in temporary need of more intensive care than can be given at the ward, are helped at the PACU. Doctors on the different units have different education and specialisms.

2.2.2 A patient's course to the PACU

Looking at the whole preoperative course for elective surgery patients, there are certain safety stops during the track. In these safety stops communication between doctors, patients, nurses, various surgical origins, and the OR takes place. Safety stops take place every time before the patient is transported, before every time the patient is delivered to another co-worker, and before the surgery starts. These safety stops are implemented to

[1]APACHE score is a worldwide used number system indicating the health state of a patient. High scores indicate more critical patients, low scores indicate less critical paitents.

decrease the risk of making mistakes. In this course the patient will get a PACU indication if needed at the pre-operative screening. At the pre-operative screening the anaesthetist examines the physical status of the patients given a classification. The classification used is the ASA classification. Apart from the American Society of Anesthetists(ASA)-classification the type of surgery can also play a role in deciding the right destination after the OR. Before explaining this track in more detail I will give some information about the PACU indication that the patients get from the anaesthetist before the operation.

Getting the PACU indication

When the patient meets the anaesthetist, days or even weeks before surgery, an ASA classification is given. The anaesthetist investigates the physical condition of the patient and determines which kind of risk an operation has according to the ASA classification. The ASA classification has 5 levels which represent a decreasing physical health, and is used worldwide, see Keats (1978). A PACU indication can be given in two cases:

1. Dependent upon the ASA classification. The higher this classification is, the higher the risk of surgery. We also call this comorbidity level. This happens for example when the heart-function is not working properly .
2. Dependent on the kind of surgery the patient will get. Surgeries that match these criteria are fixed for every surgical origin, and there will be given a standard PACU indication when these surgeries are planned. These surgeries are standard PACU reservations in the protocol for the anaesthetist. An example of such a surgery is an organ transplantation.

The registration of the ASA-classification and the reservation of a PACU bed is noted down in the patient's medical file. More information about this will be given in the next section.

Course for elective patients

In the following section the journey for surgical patient at the EMC is given.

Preoperative

1. Visiting hour surgeon. The surgeon will confirm the type of surgery.
2. Preoperative anaesthesia research. Here the anaesthetist will give the ASA-classification and assign a post operative treatment (PACU, Ward, IC) in each patient's file. This preoperative screening is valued for a maximum of six months.
3. The surgery is planned.

Peroperative

1. The patient's intake starts a day before, or on the morning of the surgery.

   The patient will be checked in at the ward of its surgical department by the nurse.

   The anaesthetist visits the patient again to see whether the physical situation of the patient is changed compared to the preoperative research. At this moment the anaesthetist can decide to change the ASA classifications and the postoperative destination.

   The surgeon contacts the patient.
2. Just before leaving for the OR, the patient's transport to the OR is prepared and after safety stops and check moments the patient will leave for the OR.
3. OR: Holding - OR

Postoperative
After the surgery is performed the patient can go into different courses:

1. To the recovery room, and thereafter to the ward.
2. Intensive Care Unit, when multiple organs and the vital functions are threatened, the patient needs high care for a time horizon larger than twentyfour hours. After recovery on the IC, the patient will go to the ward.

3. PACU, if the patient is expected to need less than twentyfour hours of extra care. After an operation it becomes clear if the PACU-indicated patient is indeed in need of PACU care. If the patient still needs high care after twentyfour hours, the patient will be taken to the IC. Otherwise the patient will go back to their original department. After these three options, eventually the patient will be fired and can go home.

From: Guideline preoperative process EMC

2.2.3 Capacity and planning of the PACU

Capacity PACU

There are five available beds at the PACU from Monday morning until Saturday afternoon. The workers on this unit are: co-worker region nurse practitioner, nurse practitioner, department assistants, pain consultants and volunteers. The PACU opens on Monday, and the patients come in after their surgeries are done. Patients come in until Friday, and are all fired from the division after Saturday afternoon.

Planning: communication transmission

The information system used on the EMC is Elpado: Electronic Patient Dossier. In this program all the OR planning and extra information (bed reservation on the PACU or IC) are specified.

- Elective patients
  Each department of the surgical groups sets a fixed amount of hours per year on the OR, in which they can perform their surgeries (this time is divided into three months. In blocks of two weeks they schedule their time at the OR). This means that the scheduled time per surgical group differs per day, per schedule cycle. The surgeon first sees the patients, and puts the required information on Elpado. All requests are listed into Elpado's digital waiting lists. The PACU indication given by the anaesthetist will be inserted into the Elpado application, and if the patient is in the right physical condition for the surgery, a green light (permission to operate) is given. The secretary of the surgical group will plan the operations two weeks in advance, choosing the patients on the waiting lists with a green light given by the anaesthetist. The elective dayprogram is known the previous day on the OR. At this moment the coordinator will communicate if a patient can't be operated (for example when there are not enough IC or PACU beds, or when the planning is not possible). Mostly after 24 hours before the OR-day the schedule is made final. The day-coordinator is responsible for a smooth running of the elective program. The emergency surgeries are also admitted to him. He starts the day with studying the scheduled program, and makes sure the first OR will start after he checked whether the required beds on PACU and IC are available or not (this can be changed compared with the status of the previous day). In the latter case, the day-coordinator will contact the surgical group to discuss which patient will be operated and which will not. If the choice is between two patients of different surgical groups, the surgical groups have to decide together which patient will be operated. These decisions are made with the help of a protocol which will give priority to certain operations.

- Emergency patients
  Besides the incoming patients from the elective OR, patients also arrive from the emergency-OR. Every surgical group will reserve some 'emergency time' next to the elective surgery time. The surgical specialism lists their emergency patients and hands them in at the day-coordinator, who will include the added surgeries into the OR-program.

- Substitute elective patients
  Last there is the substitute elective-OR; their surgeries are not planned in advance, but when there is OR time left (because of quicker operations than expected, or because of cancelled operations) these elective surgeries are inserted into the program. The patients are therefore not known at the beginning of the day, but their post-operation destination is known because they have already been to the anaesthetist.

- Other sources
  When there is room available at the PACU, it often happens that patients from the IC or other divisions in need of high care are taken into the PACU.

In figure 2.2, only the patient flows to and from the PACU are given.

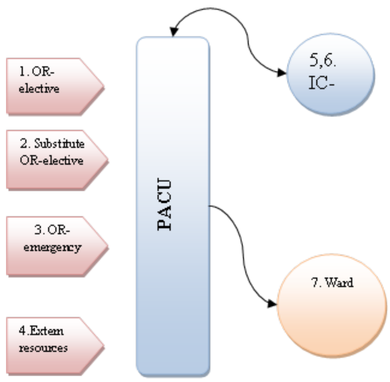

Figure 2.2: *patients flow PACU*

1	OR-elective to PACU
2	Substitute OR-elective to PACU
3	OR-emergency to PACU
4	External sources to PACU
5	ICU to PACU
6	PACU to ICU
7	PACU to Ward

Table 2.1

2.2.4 Information Systems

At the EMC the information registration is done by two large information systems: ZIS[2] and EBS[3]. After registration in ZIS and EBS the data is stored and processed in Oracle. ZIS contains al the information and processes of the patients. EBS contains all the information of finance, human resource management and logistics of the hospital. Two large business intelligence tools provide data visualisation from ZIS and EBS. In Business Objects (from SAP) the data from ZIS can be accessed, and in Oracle Business Intelligence Suite Enterprise Edition (From Oracle) the data from EBS can be accessed.

The surgery bed planning and the patient's intake registration is structured by the program Elpado [4]. Next to this Elpado orders surgery documents, labresults, pre operative screening results, letters from general practitioners and all other information about the patient. The advantage when planning the operation rooms in Elpado is that the patient information is also available.

The gathered information for the research of this thesis is gathered out of Business Objects and Elpado. The information gathered from BO is logistic patient information; how many patients have been on the PACU, the date and time of arrival and departure from the PACU, the specialism resource and the urgency of surgery if there was any. Unfortunately, the results from the pre operative screening was not present in BO. Therefore Elpado was used to gather information about the given post operative destination in the pre operative screening report. Combining the pre-operative screening for each arriving patient of the PACU cost a lot of time. Since BO only registered the arriving patients, we have to check in Elpado each OR day for patients with a post-operative destination PACU on their pre-operative screening report. Studying all the pre operative screenings is necessary in order to find the indicated patients that do not arrive on the PACU.

2.3 Sample data analysis: September 2009

To verify the information gathered in the previous chapters, and to get a better understanding of what is happening at the PACU, one month will be analysed in detail.

[2]Ziekenhuis Informatie Systeem, translated: Hospital Information System
[3]E-Business Suite
[4]Electronic Patient Dossier

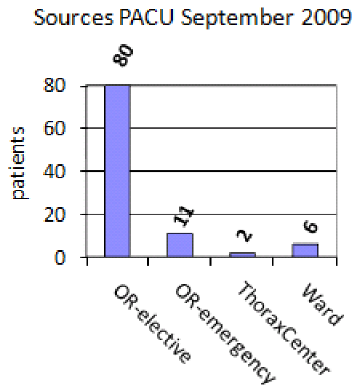

Figure 2.3: *Sources PACU*

2.3.1 Origin of patients

In the previous section the sources of the incoming patients have been discussed. Table 2.2 shows the source sizes of the patients on the PACU. As shown the biggest group of PACU patients come from elective surgeries. These surgeries and the post-operative destination are planned in advance. This outcome makes us question the difficulty of planning possibilities. How can this group be defined in a way that the PACU patients can be planned two weeks in advance? The OR-emergency is the second biggest group. These surgeries are not

OR-Elective	80
OR-emergency	11
Thorax Center	2
Wards (No OR)	6

Table 2.2: *Total sources PACU September 2009*

planned in advance, and did not get a pre-operative screening. At the moment that the surgery is admitted, the expected post-operative destination is known by the anaesthetists, but is not implemented in Elpado. Last we have the patients from the ward (ward, other hospitals and emergency & accidents), and patients who came from the other part of the EMC; the thorax centre OR. The first group did not have an operation the day they came to the PACU. Since this group is so small, the expectation is that it will be difficult to forecast their arrivals. Also these arrivals are less interesting because they are not the target group of the PACU. Note that in September there were no incoming patients from the IC.

2.3.2 Surgical groups contributing to PACU

Looking at the amount of patients from elective and emergency OR's at the PACU, we can divide two 'leaders' of surgical groups in terms of the amount of contribution to the PACU. Figure 2.4 shows the different percentages that each group contributes. It is obvious than there are two groups that contribute together almost 60 % of the incoming patients. These groups are CHI and NEC. More that three quarter of the PACU patients are from CHI, NEC, URO and ORT.[5]

2.3.3 OR-elective patients

The amount of elective surgeries performed by each surgical group is shown in table 2.4. Since the OR-elective and OR-substitute elective are all dated as elective in the data, the groups are joined in this section. Note that the OR- substitute elective have been to the pre-operative screening and therefore have an indication, but the surgery was not planned at the start of the day. We see in figure 2.5 that KNO and CHI are the two groups that performed the most elective operations in September. Just a small part of these patients will go to the PACU after the operation. In September this was 14 percent of all the elective surgeries performed.

[5]Explanation of the surgical specialisms can be found in table 2.3.

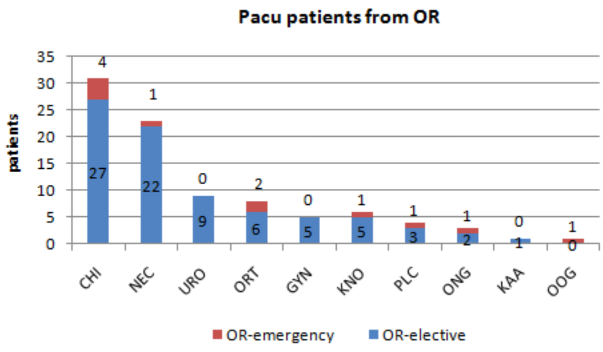

Figure 2.4: *Sources surgical groupes PACU*

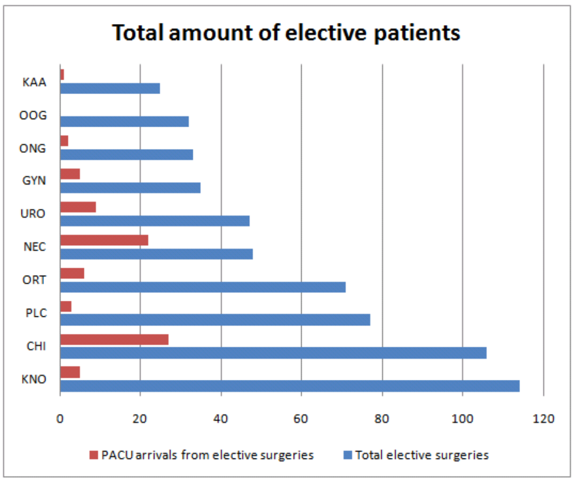

Figure 2.5: *Elective surgeries*

Surgical Group	Description
KNO	Throat, Nose, Ears department
CHI	General surgery department
PLC	Plastic surgery department
ORT	Orthopedic department
NEC	Neuro surgery department
URO	Urology department
GYN	Gynaecology department
ONG	Accidents department
OOG	Eye surgery department
KAA	Oral surgery department

Table 2.3: *Description dutch (afkortingen)*

Surgical Group	**OR-elective**	**PACU**	**Percentage**
KNO patients	114	5	4%
CHI patients	106	27	25%
PLC patients	77	3	4%
ORT patients	71	6	8%
NEC patients	48	22	46%
URO patients	47	9	19%
GYN patients	35	5	14%
ONG patients	33	2	6%
OOG patients	32	0	0%
KAA patients	25	1	4%
Amount of patients	589	80	14%

Table 2.4: *September*

Expected that are realised	51	
Unexpected that are realised	18	
Expectation was ward		16
Expectation was IC		2
Expected that are not realised	26	
Destination ward		16
Operation cancelled; full PACU		2
Operation cancelled: other		8

Table 2.5: *PACU Indications*

In table 2.5 we see that some surgical groups make use of the PACU more often than others. In the table the total amount of elective operations per surgical group is shown in the first row, and the number of patients who went to the PACU is shown in the second row.

Almost half of the patients that are operated by the NEC surgical group will go to the PACU after surgery. For CHI this is a quarter of the performed surgeries. Although these groups contribute the most according to the amount of performed operations, we can compare them with the absolute amount of patients per surgical group that are on the PACU. The four groups that have the most patients lying on the PACU are NEC, CHI, URO and ORT. Only 8% of patients with an elective operation of ORT end up at the PACU, but since the amount of operations performed is much larger than GYN, the absolute amount of patients is also larger.

Indeed, all the elective operations which are not substitutions are known on forehand, but to what extend were they expected at the PACU? All the elective surgeries have a pre-operative screening and have been given an expected post-operation destination. We define the outcome of the pre-operative screening as the expectation of the destination of a patient. In September there were 75 patients that ended up at the PACU, and 73 % of these patients were expected: the PACU indication was correct. There is actually one group that cannot be forgotten; the elective patients with PACU indication that did not get on the PACU after the operation. There are three options.

1. The patients went to another division; ward or IC, because of wrong indication or full occupancy,
2. The operation was cancelled because of full occupancy of the PACU,
3. The operation was cancelled because of other reasons.

Of the 84 expected patients only 58 were realized, and 22 unexpected patients were realized. Also note that the 84 PACU reservations were given in 22 days of September, this means that there are on average 3.8 PACU arrivals from elective surgeries per day. In the following sections the alternating amount of reservations per day will be discussed.

Leaving out the cancelled surgeries (this can happen within 24 hours before the planned OR), it is interesting to see how many patients that actually got surgery, are not going to the postoperative destination as expected, given the expectation was PACU or the destination was PACU. In the morning before the surgeries, around 21 % of the PACU indications shown in Elpado will be incorrect. Another thing that strikes from the data is that

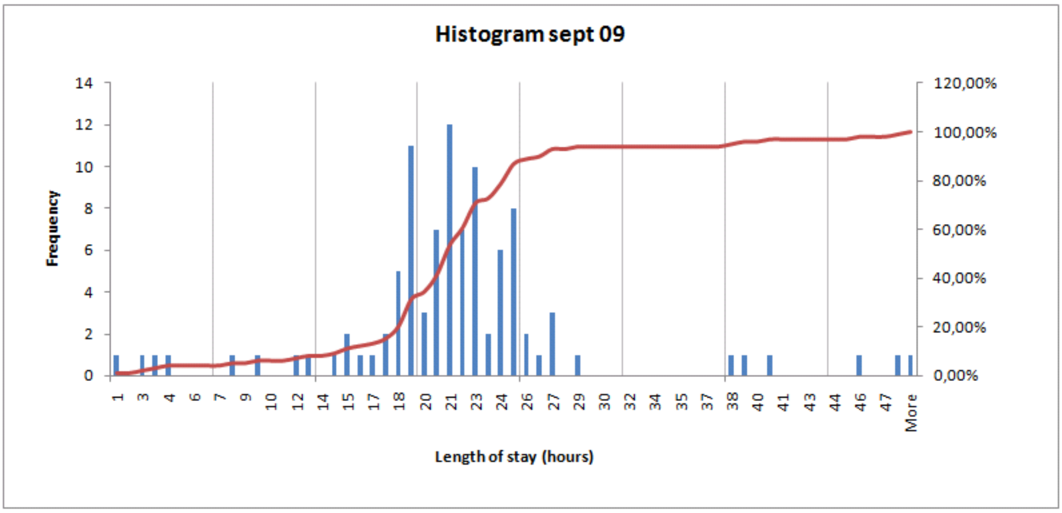

Figure 2.6: *Histogram Length of Stay PACU patients*

of the 40 elective surgeries that were cancelled in September, 10 patients had a PACU bed reservation. Two of these surgeries were cancelled because of full PACU occupancy, but eigth were cancelled for other reasons. This percentage of cancelled surgeries with PACU indication can be higher than the proportion of overall PACU indications on the amount of surgeries because of two reasons. First, PACU patients are in worse physical condition than most patients, operations can be cancelled because of these physical conditions more often when they expect something to go wrong. Second, patients with an PACU indication can be cancelled more often because this gives more relief to the PACU.

2.3.4 OR-emergency patients

Another group to discuss is the incoming patients from OR-emergency. There were 182 emergency surgeries in September, and only 6% of these patients are assigned to the PACU. Of these emergency patients ending op at the PACU, half didn't have a pre-operative screening.

2.3.5 Other sources

Other patients that came to the PACU, but were not indicated are patients with severe health problems in need of extra care. Patients from emergency & accidents belong to this group (these were 3 of the 6 patients). Also unexpected were the patients who came from the thorax OR, while this part of the hospital is in charge of their own IC. Overcapacity is the reason why these patients were placed on the PACU.

2.3.6 Length of stay

It may be clear that patients on the PACU are expected to stay less than 24 hours. In order to verify this, the histogram 2.6 will give us a view of reality. It shows that indeed most patients stay around 24 hours on the PACU. To be exact, 79% of the patients in September 2009 stayed less than 24 hours on the PACU. There are a few outliers. The shorter stays are mostly patients that didn't have a surgery, and came from external sources. Patients that were in worse condition, and stayed longer than 24 hours are emergency patients, or elective patients with longer operations than expected and more than four procedures in a operation.

2.3.7 Occupancy

Figure 2.7 shows us the in- and outflows of the patients, requests for entering and cancelled operations in September 2009. Looking closer, we see that the stars (that represent patients with PACU reservation, who went to the ward) can indicate that the indication (pre-operative screening) may be right, but the requests could be rejected due to full beds. It is shown that is happens often that patients with an PACU indication are rejected, even when not all the beds at the PACU are full. The reason for this will be investigated following chapters.

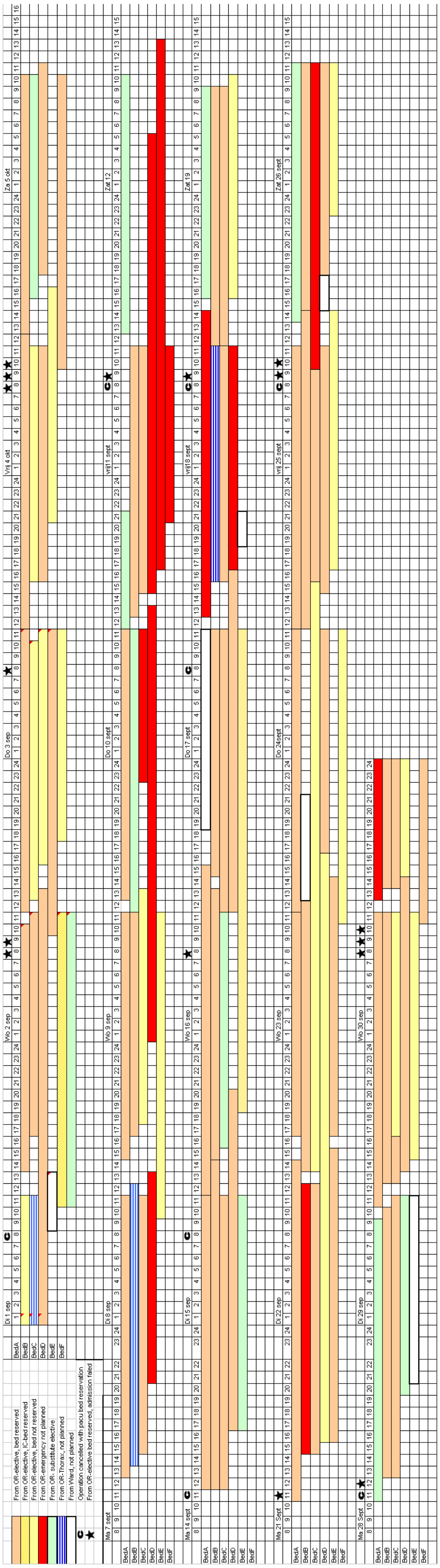

Figure 2.7

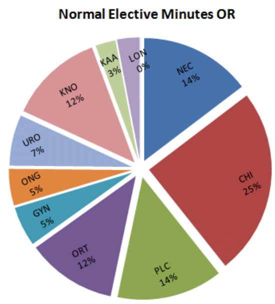

Figure 2.8: *OR time elective surgical groups*

After an average of x minutes, one patient arrives at the PACU			
	Elective	**Emergency**	**Total**
	Arrival rate	**Arrival rate**	**Arrival Rate**
NEC	**650,6**	4580,0	**821,5**
CHI	**894,8**	**1882,0**	**1022,2**
PLC	4549,7	4575,0	4556,0
ORT	1925,8	1406,0	1795,9
GYN	**1025,0**		**1141,2**
ONG	2360,0	3741,0	2820,3
URO	**731,8**		**774,4**
KNO	2437,0	**349,0**	2089,0
KAA	2604,0		3332,0
OOG		**644,0**	3528,0
Total	1222,7	1733,9	1360,7

Table 2.6: *Arrival rates dependent on OR time*

2.3.8 PACU occupancy with relation to OR-time

In pie 2.8 the total available elective OR time divided by the surgical specialisms are stated. CHI has the most elective time at the OR followed by NEC, PLC and ORT. In table 2.6 below the arrival rates are given, this means that there is one arrival at the PACU after an average amount of x minutes OR-time. Because the emergency surgeries bring in just a few PACU patients, given the amount of OR time, considering only the elective OR-time for known seems to be more realistic. This also explains the big difference between the two. The bold statistics in the table are the three surgical groups that contribute the most to the PACU per OR-time. If the expected PACU arrivals (which will be tested in further chapter) are stable, this table can help us determining the PACU arrivals given the amount of OR time for each specialism. At this point the conclusion we can draw from the table is that there are probably more severe surgeries where patients are in need for PACU care at the specialisms with the fastest arrival rates.

2.4 Problems occuring in the current situation

In the previous sections the current policies concerning the PACU are given. In this section the problems with the current policy will be shown, and the problems according to the co-workers of the PACU are stated. After interviewing three aneastetist working at the PACU, the department manager of the PACU, the department manager of anaesthesia and the manager of the OR and anaesthesia department(see section A), the following problems became clear. In the italic text the subsequent research that needs to be done is formulated.

1. The PACU also receives non-surgical patients.
   The data of incoming patients will have to give a clear profile where the PACU patients are from.

2. Uncertain of availability PACU beds.
   Research has to be done to find significant factors for estimation of patient's length of stay, in order to be able to forecast the lengths of stay.

3. The PACU indication given by the anaesthetist gives several problems. Three subproblems can be stated:

1. Not all anaesthetists give the right indication. Sometimes the patient's condition is underestimated.
The problem lies in subjectivity of the anaesthetist. Make a notification on the protocol for the anaesthetist to fill in the expected condition of the patient after surgery, in a mandatory field.

2. A lot of patients with a PACU indication, are not coming to the PACU after the OR.
Research also has to be done to find out whether the origin of this problem lies in the wrong given PACU indication by the anaesthetist, or in bed occupancy.

3. A day before the operation a PACU indication can be changed.

4. There is no restriction in the OR planning concerning the amount of PACU indications allowed [6].
Give the specialisms a restriction on the amount of PACU indications they can plan.

5. Emergency patients will not appear in Elpado with PACU indication [7] .
Find estimation factors for OR-emergency patients: how often do they arrive?

6. Because each surgical department plans its own operations and is not aware of the PACU indications of the other divisions, the planning can go wrong.
Why aren't there restrictions on planning, will this be useful and can this be implemented?

7. Not all surgical departments submit the PACU bed reservations to Elpado.
The planner of the surgical group doesn't fill in the field in Elpado: can the PACU reservations submitted by the anaesthetist always be used?

8. High pressure on PACU and IC, overload of incoming patients.
How can we lower or equalize the occupancy without losing patients?

9. There is no planning for the PACU, three sub problems can be formulated.
Explore the possibilities of planning.

There are no known expectations in advance, not considering the amount of OR time a specialism gets on a day.
Is the arriving rate of PACU patients dependent on the different types of surgical department and their OR time?

Incoming patients are not only from the elective-OR which are known in the morning, but also come from emergency operations and other sources.
To get a view of the arriving patterns besides the OR the data must be analyzed. An arrival pattern of incoming emergency-OR's has to be made and their contribution to the PACU.

A surgery can be cancelled twenty-four hours in advance when there are no available beds at the PACU.
Find possibilities to minimize the amount of operations rejected because of full occupancy. Can the OR-planning be known earlier?

2.5 Conclusion

In this chapter we have seen the capabilities and the characteristics of the PACU. We have seen that the different aspects around the PACU influencing the patients flow are complex. From the data sample we have seen that there is indeed a large group of elective patients on the PACU. We think that if the arrivals are known in advance, there are options for planning, and hopefully optimizing efficiency with a certain capacity. The problem is that because of unexpected PACU indications (from OR-elective patients without the correct indication, and OR-emergency patients), the planned patients from elective surgeries can't always go to the PACU and get the care they need. The occupancy of the PACU is not the problem; there are always enough patients in need of high care, mostly not noticed in advance. Scheduling the PACU is a difficult task, and may not be doable, but we should be able to predict the minimum amount of beds needed at the PACU given arrivals of patients at the OR, elective and emergency.

[6] The surgical departments make their planning independent of each other
[7] These are OR-emergency patients and bad screened OR-elective patients

Chapter 3

Methodology

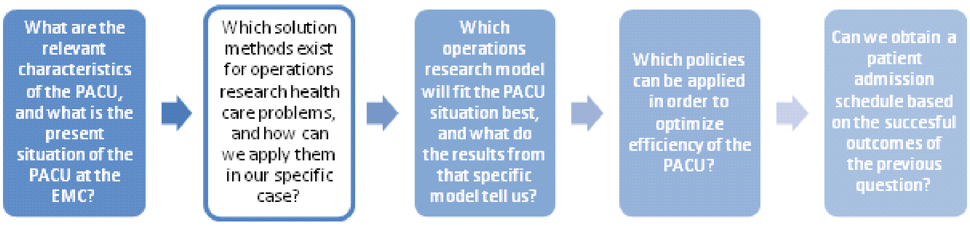

Figure 3.1: *Research question 2*

In the previous part we have explored the environment in which the PACU problem is situated. The PACU situation can be described as a small post-surgery unit. The arriving patients are mostly from elective surgeries, but the arriving process of these patients is too uncertain to obtain a specific planning in the current situation. The next question we will try to anwer is: 'which operations research solution methods exist for health care problems, and how can we apply them in our specific case?'. First we have to summarize the existing modelin methods in health care. Which solution methods are used, how do they work and are they applied in literature before? We will distinguish three solution methods and try to characterize them as described above. Next we have to decide which methods we will use on the PACU problem. First we have to obtain goals and characteristics to decide which method could be used best. After this parameters, variables and definitions are given to give a clear view of the used information (gathered in section 2.2.4). After this the methodology of each solution method we will use will be given.

3.1 Overview: use of Operations Research in health care

In order to find efficient ways of planning in health care, operations research and health care modeling is becoming a more often used and investigated instrument. After performing a global research using *scholar.google.com* we found that there are three models which are often used in health care modeling: discete event simulation, queueing modeling and mathematical programming. An important aspect of health care models is the area in which we situate the problem. The articele of Jacobson et al. (2006) defines two areas on which health care modeling can be applied: (1) optimization and analusis of patent flow and (2) allocation of assets to improve the delivery of services. When looking at the scheduling, which has an significant impact on patient flow we can distingous outpatient scheduling and inpatient scheduling. Inpatient scheduling and admissions concerns scheduling patients within a hospital. The article of Jacobson et al. (2006) concluded that patients scheduling and admission rules within patient appointment timing van have a significan impact on physician utilization and patient waiting. The studies represented in the article have all recognize the important aspect of smoothing patients arrival rates and service time (decrease the variablility), and in most articles this leads to performace improvement. When looking at the health care asset allocation, bed sizing and planning has significant influence on the health care delivery. When determining the amount of beds needed to meet demand, scheduled and emergency demand have to be taken into account. In the article of Vanberkel et al. (2009) the authors studied health care models for multiple departments. In their literature research they distinguish four approaches of health care modeling; Mathematical programming, Simulation, Queueing theory and System dynamics. Problems from particular areas mostly prefer the same approach type. They found that in a survey of 88 articles, simulation and mathematical modeling are the two most used solution approaches. In this thesis we have chosen to explore only the three first approaches, because the use of System Dynamics was not often used as a solution approach in problems comparable with our PACU problem.

3.1.1 Discrete event simulation

Discrete event simulation is a approach which have been developed for modeling over time and determine significant factors. Because the model evolves over time there is mostly a complex structure involved. This complex structure forbids the user to determine significant factors without following the model over time Ross (2006). The article of Jacobson et al. (2006) provides an overview of discrete event simulation modelling applications to health care clinics and integrated health care systems from 1965 untill 2006. Dicrete event simulation is an operations research modeling and analysis methodology that permits end-users to evaluate the efficiency of existing health care delivery system, and to design new health care delivery systems. There are lots of articles that have researched the bed requirements in critical care areas(operating room, recovery room, intensive care unit and intermediate care units. In the article of Lowery (1992) a hospital suit and critical care areas are modeled using simulation. The objective was to simulate the patient's flow through critical care areas, and to determine the critical care bed requirements. We have noticed a lot of differences with our problem area. First of all, our area is only about the PACU, and simulating the bed requirements of the PACU. In this article the whole course from OR to various critical departments is simulated in order to verify the bed requirements of all the departments the patient comes through. With the help of interviews of the staff of the hospital the publishers distinguished different flow patterns for specific types of patients. In our research we are acknowledge the expertise and the need for information of the staff of the hospital, since they are the main users of the model. When looking at input distributions they have referred to previous research to state a distribution of the LOS and inter arrival times. Since the PACU has specific aspects according to the LOS and arrival of patients, we will chose to test our own distributions instead of referring to previous literature. The article of Cahill and Render (1999) simulated the patient flow on a ICU. The problem is stated that the ICU is full for one-third on the time, which is unacceptable. In section 2 we have shown that our problem is similar. The solution approach is however different, as they differentiate the ICU unit in three types of care. In the simulation approach the patients, are diverted into this three types, and the ideal bed requirement for each type is simulated with the same patient flow. They conluded that the differentiation of care was not efficient, and that the model was not satisfactory.

3.1.2 Queueing models

A common theory which can be applied to various health care modeling issues is queueing model theory. In the article of Fomundam and Herrmann (2007) a survey is presented summarizing the use of queueing theory in the past decades. Also articles of queueing theory used in the ICU and intermediate care unit were available. Using the parameters arrival rate, service rate, and amount of servers, the probability that a patient has to wait and that a patient gets blocked can be formulated. Also the whole cycle an arriving customer will make through the queueing system can be determined and verified in detail. In this section some basic knowledge about queueing theory will be explained.

The basics of queueing theory were founded by A.K. Erlang in the early 1900s. Queueing theory describes a class of models in which customers arrive at a random order at a service facility. Upon arrival the customers have to wait in a queue until it is their turn to be served. When the customers are served they are generally assumed to leave the system. This is also called a service system design. In this model it is possible to determine the amount of customers in the system, or in the queue and the average time they will spend in the system. The shorthand notation for the different queueing models can be explained as follow:

$M/G/C$

- M: Distribution of the arrival times (M=Markovian, or Poisson distribution, G= general distribution)
- G: Distribution of the service times
- C: Amount of servers

The regular known queueing system is the $M/M/1$ system, in this case, the arrivals are Poisson distributed, the service times are exponentially distributed and there is one server available. In queueing systems we often assume that the customers arrive in accordance with a Poisson process having rate λ. This means that the interarrival times between customers are independent exponential random variables having mean $1/\lambda$. Also note the memoryless property of the exponential interarrival times.

The relations by which quantities can be determined are given by P_n, the long-run probability that there will be exactly n customers in the system.

Erlang loss model

A form of queueing modeling is the Erlang Loss models. Because of its characteristics this model is used in health care problems. First we will explain the general theory, and thereafter some literature will be reviewed.

In this section the books of Ross (1997) and Tijms (2003) are cited. The Erlang loss system is a specific loss system which considers Poisson distributed arrivals. If a customer arrives and finds all c servers busy, the customer is lost and has no further influence on the system. The service times are independent and identically distributed random variables. We are interested in determining the long term fraction of customers that are lost. The Erlang loss system can be described as a $M/G/c/c$ queue.
In the early 1900s Erlang studied this model in the framework of a telephone switch which can handle only c calls. Erlang (1917) was able to find a formula for the fraction of calls that are lost. He established this formula first for the particular case of exponentially distributed service times. Also he conjectured that the formula for the loss probability remains valid for generally distributed service times. Therefore in this summary we will first assume that the service times have an exponentional distribution with mean $\frac{1}{\mu}$.

For any $t >= 0$,

$X(t) \ = \ the \ number \ of \ busy \ channels \ at \ time \ t.$

The stochastic process $(t), t >= 0$ is a continuous time Markov chain with state space $I = 0, 1, \ldots, c$. The time average probability p_i gives the long-run fraction of time that I channels are occupied. Since for each state I the transition rate $q_{ij} = 0$ for $j \leq i - 2$, the equilibrium probabilities p_i can be recursively computed. Equating the rate out of the set of stated $I, i+1, \ldots, c$ to the rate into this set, we obtain

$i\mu p_i = \lambda p_{i-1}$ for $i = 1 \ldots c$.

This equation can be solved explicitly. Iterating the equation gives

$p_i - \frac{(\lambda/\mu)^i p_o}{i!}$ for $i = 1, \ldots, c$.

Using the normalizing equation $\sum_{i=o}^{c} p_i = 1$, we obtain

$P_i = \frac{(\lambda/\mu)^i/i!}{\sum(\lambda/\mu)^k/k!}$

Note that the distribution is a truncated Poisson distribution (multiply both the numerator and the denominator by $exp(-\lambda/\mu)$. Denote by the customer-average probability $p_i(i)$ the longrun fraction of arriving customers that find i other customers present upon arrival. Then, by the PASTA property,

$\pi(i) = p_i$

And the fraction of arrivals that are lost, p_{loss} is

$P_c = \frac{(\lambda/\mu)^c/c!}{\sum(\lambda/\mu)^k/k!}$

This formula is called the Erlang loss formula. As said before, the formula for the time-average probabilities p_j and the formula for the loss probability remain valid when the service time has a general distribution with mean $E(S)$. In this case we replace the exponential service times with mean $\frac{1}{\mu}$ by mean $E(S)$. The state probabilities p_j are insensitive to the form of the probability distribution of the service time and require only the mean service time.

In the article of de Bruin et al. (2009) the relation between the number of refused admissions and the target occupancy rate for all wards in the hospital is investigated. Using this research the goal is to show that using the same target occupancy rate of 85% for all wards isn't a valid assumption. The Erlang loss model and queueing theory are used to verify this assumption. In this research scheduled and unscheduled admissions are regarded (just as we can define with the PACU problem), leaving out wards with specific characteristics as the emergency department, first cardiac aid and short stay unit. First the scheduled and the unscheduled admissions are proven to be Poisson distributed. The length of stay is distributed with the help of the Lorenz curves and Gini-coefficient. The occupancy rate is determined using Little's formula Little (1961).

$$Occupancy = \frac{Average\ number\ of\ occupied\ beds}{Number\ of\ operational\ beds}$$

$$Occupancy = \frac{Admissions(per\ time\ unit) * ALOS(time\ unit)}{Number\ of\ operational\ beds}$$

Next the Erlang loss model is applied. Since there is no waiting area the Erlang model gives us a formula for the fraction of patients which is blocked, which is applied because information is only available for the number of admitted patients and not the number of arrived patients (just as in the PACU problem). The former formulas can be used to determine the blocking percentage, and after substitution also the arrival rate. Very uncertain are the distribution fits needed to apply the Erlang distribution. In the results they showed economies of scale are good for declining the blocking rate. We think that this result is logical, and is not due to the goodness of the model.

3.1.3 Mathematical programming

Mathematical programming is an optimization method for real life problems. In mathematical programming the problem is formulated according to an objective function and constraints. The optimal variables are determined in the objective function. The values of the parameters must be fixed. Mathematical programming in health care is often used when costs-efficiency is envolved, determining costs of resourses in hospitals. Characteristics of mathematical programming in health care is that the problem must be framed, and that the resources, or amount of competing programmes must be fixed with deterministic variables.

A wide variety of practical problems can be formulated and solved using integer programming. An integer program has the form $max\ cx : Ax \leq, x \geq 0$ Whereby A is a m by n matrix, c an n-dimensional row vector, b an m-dimensional column vector, and x an n-dimensional column vector of variables or unknowns. We add in the restrictions that certain variables must take integer values, in case of a (Linear) Integer Program this al all the x variables. Another type of integer program is a binary program, whereby al the variables can only take values zero or one. Below we will formulate two well-known integer programming problems The formulations for the problems and the explanations are cited from Wolsey (1989).

Knapsack problem

The Knapsack problem is one of the commonly used problems using integer programming, it is a NP-hard problem. This means that it is a non-deterministic polynomial time hard problem. The problem starts with a knapsack, which can be filled by items. The knapsack has limited capacity, and the amount of items which can be fitted in, giving a certain amount of satisfaction, must be optimized. The problem can be formulated as below:

The $0-1$*, or Binary, Knapsack Probles (KP) is:*
given a set of n items and a knapsack, with

p_j =profit of item j,
w_j =weigth of item j,
c = capacity of the knapsack,

maximize $z = \sum_{j=1}^{n} p_j x_j$
s.t. $\sum_{j=1}^{n} w_j x_j \leq c$,
$x_j 0\ or\ 1, j \in N = 1, ..., n.$

$x_j = 1$ if item j is selected; 0 otherwise. The goal is to choose a set of items so that the profit is maximized, and the capacity of the knapsack is not exceeded. This problem is one of the easyest examples of a maximization problem, and therefore has been studied since 1897 Kellerer et al. (2004).

The question we want to ask ourselves is: can we relate the knapsack problem to the PACU problem? We intuitively feel that a PACU day can be seen as a 'knapsack' that needs to be filled with patients. We have the capacity of beds on a day, and the amount of patients that can be implemented. The amount of 'profit' we get for each patient can exist out of the preference of a specialism for a specific day.

Set Covering problem

Given a certain number if regions, the problem is to decide where to intall a set of emergency service centers. For each possible center the cost of installing a service center, and which regions it can sercice are known. If the centers are fire stations, a station can service those regions for which can be reached within a certain amount of time. The goal is to choose a minimum cost set of service centers so that each region is covered. The problem can be formulated as an abstract combinatorial formulation problem. We can define:

$M = 1, ..., m$ the set of regions,
$N = 1, ..., n$ the set of potential centers,
$S_j \subseteq M$ the regions that can be serviced by a center at $j \in N$,
c_J the installation costs,

We can formulate the problem as a binary integer problem. Therefore we have to define matrix A such that
$a_{ij} = 1$ if $i \in S_j$, and
$a_{ij} = 0$ otherwise

minimize$\sum_j^n c_j x_j$
s.t. $\sum_{j=1}^n a_{ij} x_j \geq 1$ for $i = 1, ..., m$
$x_j \in 0, 1$ for $j = 1, ..., n$

$x_j = 1$ if center$j$ is selected; 0 otherwise.

3.2 Methodology of modeling the PACU

In the first chapter we have described the characteristics of the PACU. In order to find a model that will fit our problem we have to compare this characteristics with the theory given in the previous section. An important aspect of the PACU is that the arrivals are uncertain. Therefore, we must use a model that can describe the arrivals as good as possible. With simulation, we can use the historic arrival pattern. Also, we will try to fit the arrivals according to a distribution pattern. If we can find a proper fit, or can make realistic assumptions concerning the arrivals we can also apply queueing theory. We think that the arrival pattern is stochastic, and therefore it will not be possible to program the PACU patient flow with mathematical programming. Therefore for obtaining the PACU model, and determining the proper capacity level we will use simulation and queueing modeling. After this, the next research question involves policies which must be applied to optimize the efficiency in term of decreasing the rejected number of patients and occupancy level. Using simulation, we can implement these policies in the model, and compare them with previous results. We will try to find an optimal schedule in the last chapter.

3.2.1 Definitions

In this part the scientific methods that used in the formulation, simulations and determination of parameters will be given.

First we will define the variables which are most important in modeling the PACU

- **PACU Arrivals** This are all the patients that will arrive on the PACU, and will ask for admission

  We can divide the PACU arrivals into two groups:

  PACU Admissions; arrivals that are admitted a bed at the PACU.

  PACU Rejections after operation; arrivals that are rejected.

Another group are the

- PACU rejections before operation; this group is shown in historic data.
  A last definition that will be used often is

- Length of stay (LOS) or Service time; this is the time a patient spend on the PACU.

Occupancy

A definition for the occupancy rate has to be stated. There are three definitions that are used in the hospital to define the occupancy.

1. The amount of hospital day. This is in the contracts of the EMC, and the production is measured by this method. We can define a hospital day as a day the patient is on the PACU after 17.00 hours. We will determine this amount as follow: Amount of patients on the PACU after 17.00 per day * amount of days / bed capacity

2. The amount of hospital days and treatment days. In the first definition patients are not takes into account who are discharged before 17.00 hours. We will determine this amount as follows:
   Amount of patients on the PACU during one day * amount of days / bed capacity

3. Total time a PACU bed is occupied * amount of beds * amount of days / total bed capacity

It is obvious that these definitions differ a lot. In this report, for the sake of clarity, we will use one definition for the occupancy rate. All the occupancy rates in the following report will be determined as definition 3:
$\frac{\sum_i^N LOS_i}{cap*T}$

Whereby

$i,..,N \ = \ patient\ i \ \in \ N$
$LOS \ = \ length\ of\ stay$
$cap \ = \ total\ capacity\ available$
$T \ = \ time\ horizon$

Blocking rate

The blocking rate is defined concerning the amount of arrivals which are rejected by the PACU. The blocking rate can be stated:

$$\frac{amount\ of\ patients\ rejected}{total\ amount\ of\ patients\ requested\ PACU\ stay^1} \tag{3.1}$$

3.2.2 Simulation occupancy models

Model 1: Historic Overview model; exact replication

This model is based on historic data of September, October and November 2009. In this model the aim is to simulate the historic events and obtain statistics. We use the admission rates from the historic data and the service rates from the historic data. The model will show the patient flow into the PACU. A large difficulty in the simulation is the uncertainty of rejections. First, the emergency OR patients mostly don't have a pre-operative screening. This means that we are uninformed about the incoming arrivals from OR-emergency that were rejected from the PACU. Second, we have the elective patients which arrive having an indication or not. With simulating the PACU it is important to get a correct view of the incoming arrivals, the percentage that is rejected (because of capacity) and the percentage that is admitted. Because the rejected arrivals are not noted, we don't have this information and we will work with elective patients with PACU indication that did not arrive at the PACU. There are three ways which we can use considering rejected PACU indications in history.

1. Find out the reason because of the PACU indication rejection.

2. Look at the availability of the PACU at the time of admission (time that the operation ended).

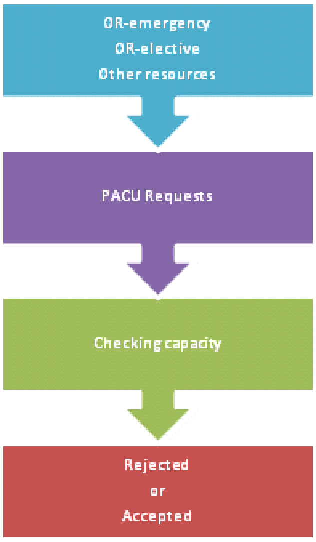

Figure 3.2: *Arriving PACU Requests*

3. Model all the indications that were not realized as blocked.

In this model we will explore the first two manners and their differences in outcome.

The following input and output will be used for this model:

- Input

  PACU Arrivals:

  PACU Historic admissions

  PACU Historic rejections: rejections after operation, rejections before operation

- System

  Apply historic capacity = 5 beds (but, in extreme cases an extra PACU bed is permitted)

- Output

  Occupancy rate

  Blocking rate

Model 2: Simulation including elective indications

The objective of the simulation models is to find the optimal capacity for the PACU. Therefore we would like to observe the changes in behavior of the PACU patients with respect to different capacity levels. Changes in behavior can be patients that will get admitted on the PACU, which in the previous model did not, and the other way around. This model is made using only the information available of the historic arrivals, and the historic rejections. We encounter all the elective indications that were cancelled after and before surgery as PACU arrivals, instead of rejecting them immiddiately. The following input and output will be used for this model:

- Input

  PACU Arrivals: historic PACU admissions and historic PACU rejections

- Model

  Vary in capacity

- Output

  Occupancy rate

  Blocking rate

In figure 3.2 the process of rejecting or admitting a patient is shown. The first block shows the sources of all patients. In the next block, a selection of these patients will be in need for PACU care, and request admission. After a PACU request, the occupation of the unit is checked. If the unit is fully occupied, a patient gets blocked (rejected). A patient can't arrive after Saturday afternoon, before Monday and after the limited time horizon.

Tests
We are informed about the day that a rejected request in history arrived. In case of historic rejection after surgery, also the time of the day is known when the patient requested PACU care. In case of historic rejection before surgery, we are informed about the day the patient arrived, but the arrival time will be generated, as if the patient had a surgery. Also the service time is an unknown parameter. With the help of tests, the arrival times and service times will be generated according to a best fitting distribution. We have used a Excel AddIn program DataFit for fitting these distributions.

Arrival time during the day
We also must perform tests to generate the arrival times as if the historic rejected patients before surgery, actually had surgery. We have to fit a distribution on the arrival times, and perform goodness of fit tests to conclude which distribution can be used best.

Service times
The service times of the new requests are unknown, and will be determined using tests. First we would like to find out if the distribution of the elective, emergency and other arrivals differ from each other. Next we will try to find a distribution for the elective service times (in case the distribution differs per group), or the overall service times (in case they don't differ). The test we will use for the first part is called the ANOVA (Analysis of Variance) test. This test verifies if the distribution, and the variances of the three groups are the same.

The nulhypothesis of ANOVA is thus:

Ho: the groups are drawn from the same distribution

and the alternative hypothesis is:

Ha: the groups are not drawn from the same distribution

After this multiple distributions will be fitted on the available data. De best fitting distribution can be found using goodness-of-fit tests (see B).

3.2.3 Finding lost patients

In the previous simulation occupancy models, we remained unaware about the missing emergency arrivals. This chapter verifies how the blocking rate should be in case we were informed about the missing emergency requests. We can distinguish two 'emergency' cases:

1. The actual emergency arrivals, characterized by an emergency surgery.
2. Unexpected elective arrivals, these elective patients did not get an indication in advance of the elective surgery, and can therefore be described as 'unexpected'.

Statistics about the bed availability in time is needed. This can be determined using the results of the historic model, giving us a realistic view of the occupation of the beds in the time horizon. The next step is determination of the amount occupied beds before emergency patients, and unexpected elective patients are admitted. We assume that there actually is a demand for PACU beds from the emergency and unexpected elective patients, when the PACU is already full. We are able to determine the amount of patients that would have requested for PACU care, but were rejected because lack of capacity. The surplus of arrivals generated by both the emergency patients and unexpected elective patient will be generated in the simulation occupancy models 3 and 4 of chapter 'Simulation emergency patients' and 'Simulation unexpected elective patients'.

Model 3: Simulation with generated emergency arrivals

In this model a simulation is made using historic arrivals and the expected missed emergency arrivals will be generated to make the simulation model more realistic according to emergency patients. We encounter all the elective indications that were cancelled after and before surgery as PACU requests, use historic arrivals, and generate new emergency arrivals. The changes in behavior of the PACU patients are simulated with respect to different capacity levels. The following input and output will be used for this model:

- Input

  PACU Arrivals: historic PACU arrivals and historic PACU Rejections

  PACU Arrivals: generated PACU emergency arrivals

- Model

  Vary in capacity

- Output

  Occupancy rate

  Blocking rate

Tests
We have to obtain the distribution of the number of arrivals during a time horizon, the arrival time on a day (given that a patient arrives) and the service times for the emergency patients. The historic emergency patients will be used to verify the statistics and distributions for these arrivals.

Arrivals on a day
The surplus of the amount of arrivals that will be generated will be determined using 3.2.3. The distribution that fit the emergency arrivals the best, might be the Poisson distribution. We will use the dataFit program to verify if this is indeed the best distribution for the emergency arrivals.

Arrival time on a day
For the distribution of the arrival time on a day for emergency patients we will use the DataFit program to fit various distributions on the historic arrival times of emergency patients.

Service times
If the service times of the different resources group differ from each other, we have to find the distribution for the emergency service times. This will be done using the DataFit program, and applying goodness-of-fit tests.

Model 4: Simulation with generated unexpected elective arrivals

In this model we will generate the missed unexpected elective arrivals. Instead of simulating the historic arrivals and the missing emergency arrivals, we will also generate the missing unexpected elective arrivals and implement them in this model. The changes in behavior of all the PACU patients are simulated with respect to different capacity levels. The following input and output will be used for this model:

- Input

  PACU Arrivals: historic PACU arrivals and historic PACU Rejections

  PACU Arrivals: generated PACU emergency arrivals and unexpected elective arrivals

- Model

  Vary in capacity

- Output

  Occupancy rate

  Blocking rate

Tests
We have to obtain the distribution of the number of arrivals during a time horizon, the arrival time on a random day (given a patient's arrival) and the service times for the unexpected elective patients. The historic unexpected elective patients will be used to verify the statistics and distributions for this arrivals.

Arrivals on a day
The surplus of the amount of arrivals that will be generated will be determined using 3.2.3. The distribution

that fit the unexpected elective arrivals the best, might be the Poisson distribution. We will use the dataFit program to verify if this is indeed the best distribution for the emergency arrivals.

Arrival time during the day
The distribution of arrival time during the day will be the same as used in model 2.

Service times
If the service times of the different resources group differ from each other, we have to find the distribution for the elective service times. The same distribution can be used as used in model 2.

3.2.4 Queueing model

In our case we think the theoretical model Erlang loss model could be an appropriate model for the PACU situation. We can use the $M/G/c/c$ (3.1.2) in order to use the Erlang model. We know the admissions of the PACU, not the arrivals. The admissions have to be fitted into the Poisson distribution, after this, a Pearson's Chi-Square goodness of fit method, or a Poisson index of dispersion can be used to verify the goodness of the empirical distribution fitting the data. The service times may have a general distribution,with mean μ. From the information of the hospital, we are able to find the occupancy rate.

$Occupancy\ rate\ = \frac{Admissions\ per\ time\ unit\ *\ Average\ Length\ of\ Stay}{Number\ of\ operational\ beds}$

In the Erlang loss model we can find a formula for the blocking percentage:

$P_c = \frac{(\lambda E(S))^c/c!}{\sum(\lambda E(S))^k/k!}$

With the help of this blocking percentage and the formula of occupancy:

$Occupancy\ rate = \frac{(1-P_c)\lambda E(S)}{c}$

We can substitute these formulas in a manner that only the λ (arrival rate) is the unknown variable. After determination a solution is given for λ and the percentage of blocking.

3.3 Conclusion

In this chapter we have defined three main operations research solution methods used in health care problems: simulation, queueing modeling and mathematical modeling. Looking at the characteristics of our PACU problem we have concluded that the first two methods can be implemented. After this decision, we have distinguished three simulation models and one queueing model. The methodology, needed tests, definitions and parameters of each model is given. The models will be implemented and verified in the next chapter.

Chapter 4

Modeling the PACU situation

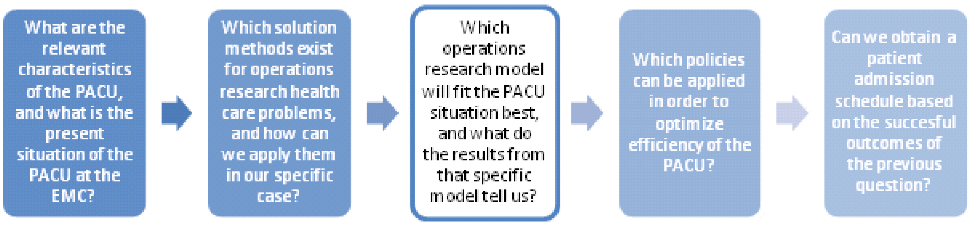

Figure 4.1: *Research question 3*

In the previous sections we have explored the environment of our problem, and learned how the PACU is currently situated in the EMC. Thereafter modelling techniques were summarized. Two modeling approaches were choosen to apply on our case. The operations research solution approaches choosen are simulation modeling, and queueing theory using the Erlang Loss model. In this chapter we will determine the test results and implement the final models, in order to verify which model fits the PACU situation best. In the first section we will investigate the historical statistics in a exact replicated model. This model can be used for comparison with the current situation. After this four simulation models and a queueing model are obtained, where after these models will be compared. Ending this chapter a model validation and verification will be given, before giving the final conclusion. All the simulation occupancy models will be implemented in Matlab.

4.1 Model 1: Historic Overview model; exact replication

This model is made for a historic view of the service rates in order to get a realistic comparison for furder models. The exact same PACU situation as in history is evalueated. Also the reasons for patient rejection are explored. The methods used can be found in 3.2.2.

Arrivals

Since we are using the historic arrivals, all historic admitted patients arrivals on the PACU, the historic rejected patients are blocked. In table 4.1, the sources of the arriving patients are shown. Available information about an arriving patient at the PACU are:

- Their source (OR-elective, OR-emergency, Other sources) and surgical specialism.
- If available, the pre-operative screening, which means the PACU indication according to the doctors and the anaesthetists.

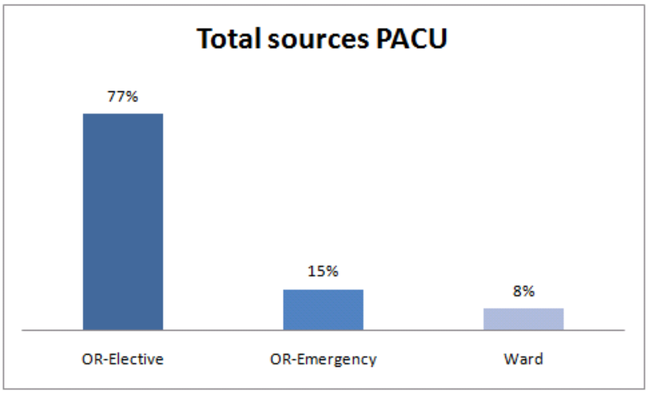

Figure 4.2: *Sources PACU Sept-Oct-Nov 09*

OR-Elective	230	77%
OR-Emergency	44	15%
Ward	14	5%
Thorax/Sophia	5	2%
Accidents & Emergency	3	1%
Pre-operative	1	0%
Total	297	100%

Table 4.1: *Total resources PACU Sept/Okt/Nov 2009*

- Time of operation, type of surgery
- Time of arrival, and time of discharge from the PACU.

At figure 4.2, the sources of the arriving patients are given.

Rejections after operation

There were 71 elective patients that were identified as PACU patients in their pre-operative screening, but did not end up at the PACU. There are three approaches on determining the amount of patients that got rejected by the PACU after the operation, which are stated below.

- The reasons why patients with an indication did not enter the OR can be found in table 4.2. The tree 4.3 includes the rejection before the OR, these were thirdteen rejections. In total the tree gives all the options for PACU patients that did not go to the PACU. This information is gathered with the help of experts A opinions.
- The availability of the PACU at the time of admission of a patient (time that the operation ended) is given in table 4.3. We have counted the amount of beds that were available at the PACU at the arrival times of the admitted and rejected patients. The 71 rejected patients can be divided into groups according to the amount of beds that are occupied at their admission request. Of the arriving patients that are rejected,

PACU indications that did not come to PACU	71		
NO PACU BED Available		9	*12,676%*
IC			2
Longer Recovery			7
Other reasons		62	*87,32%*
Indication withdrawn before OR			18
Uncertain indication, dependent on operation			29
Other operation performed than expected, post destination PACU unneccesary			13
Complications during operation, post destination IC			2

Table 4.2: *Reasons no PACU indication after OR*

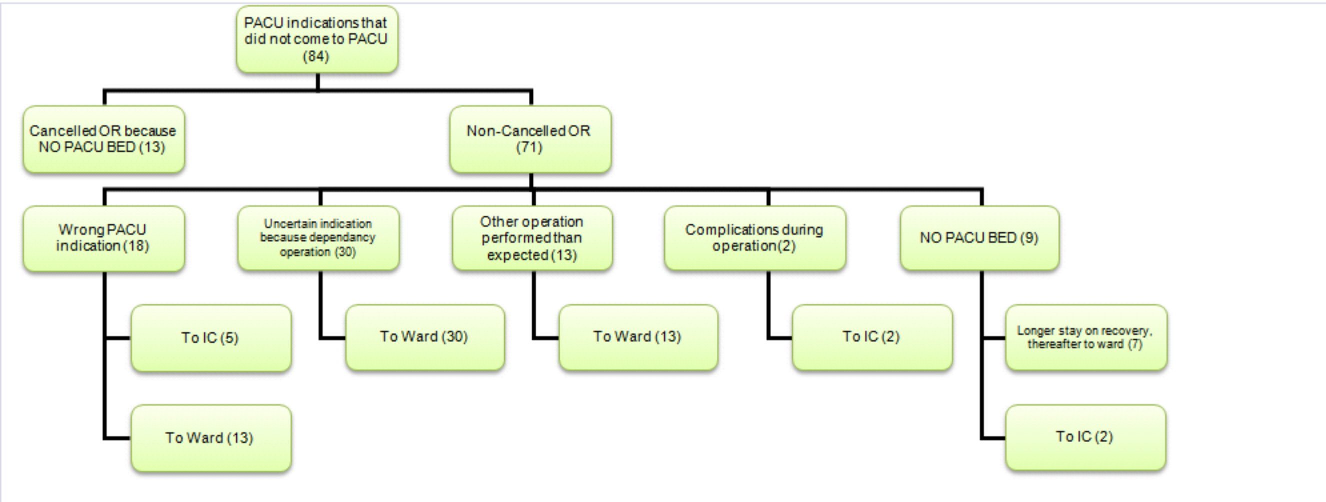

Figure 4.3: *What happened to the PACU indication?*

Occupied beds at arrival					
Available beds		*Rejected patient*		*Admitted patient*	
5		26,76%		4,71%	
4		25,35%		23,91%	
3		16,90%		27,95%	
2		18,31%		24,24%	
1		11,27%		13,47%	
0		1,41%		5,72%	

Table 4.3: *Occupied beds per group arrival*

26.27% found five beds occupied. It is shown in the table that the mean has shifted upwards towards more people finding occupied beds when in the rejected patient group, compared with the case that they were admidded. The reason why 4,71% of the admitted patients found already five availble beds is because in these cases the sixth bed was used.

The information about the rejections of the PACU patient is subjective, and we should note that in case of multiple PACU indications, the patients with highest need for high care will enter the PACU. The downside is that many patients, who are initially in need would have to make room for more urgent cases. These patients are not noted, there is no information available we can use considering this situation. Also the patients who had a longer stay on the recovery room because more urgent patients are prefered are not noted. This is why in the further simulations, we will encounter all the patients with an indication in need of a PACU bed.

Rejections before operation

On the day of surgery, surgeries are cancelled frequently (elective surgeries). The reasons of the cancelled surgeries are indicated. In the historic dataset 13 patients were not operated because of to many indications on that day.

Modeling

In the model of this historic data, the characteristics of serving the arrived patients are stated. There are no preferences in patients groups between elective and emergency patients. It is stated that there are no admitted patients from other sources in case the PACU is full. There is also no differentiation between requests from different surgical groups. The capacity of the PACU is five beds.

Blocking Rate	0.2188
Occupancy Rate	0.7744

Table 4.4: *Service rates history*

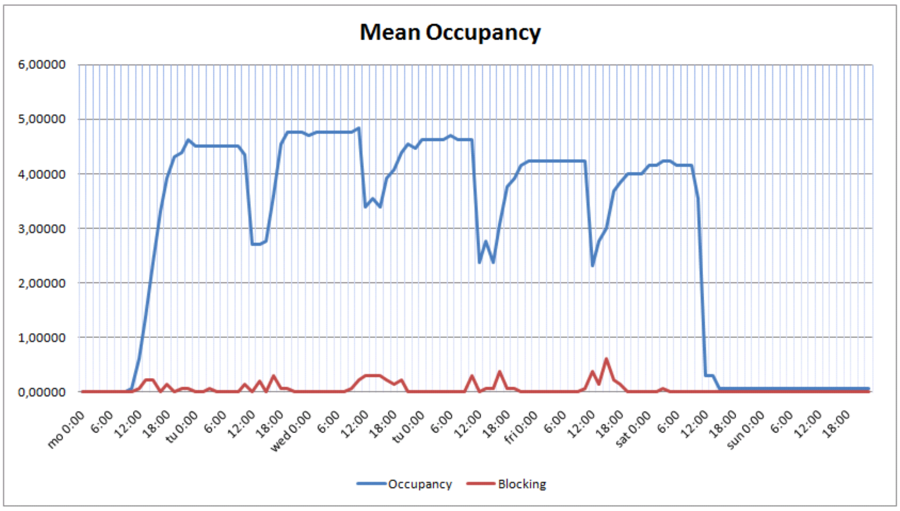

Figure 4.4: *Mean occupancy during the week*

4.1.1 Analysis

In the analysis we will look at the output, and analyse the performance of the model. In this case we will see what happened in the past, and how we can describe the current policy. This model will be used in order to compare other models and optimizing solution approaches.

Service levels

The occupancy is determined using the formula stated in the methodology. The time horizon at the PACU are 66 weekdays, and 13 Saturday's. The following results are given in table 4.4. The occupancy rate and blocking rate are both high. The aim is to find a balance between the two, verifying a minimal blocking percentage given the occupancy rate as high as possible.

In figure 4.4 the mean occupancy rate and blocking rate per weekday is given. Note the long time before start at Monday. The bed changes are at noon, which is shown by the temporary gap in the graph each weekday between 12.00 hours and 18.00 hours. Looking at the days that the most beds are occupied, Monday, Tuesday and Wednesday have slightly fuller occupation than Thursday and Friday.

Overcapacity

Although not possible in future simulation models, there was some overcapacity in history. Extra beds were included at the PACU for extra patients. Table 4.3 verfies that in 4,71% there were already 5 beds occupied when a new patient arrives. In this case there are actually 6 beds full, while the capacity is only 5. Table 4.5 states if this happens in the morning, afternoon or evening. (In the morning most patients get off the PACU, so beds come free earlier. Also the time that the PACU is occupied a 120% is given(time before next patients leaves). In the model the patients using the 6th bed in the morning, are in 90 % of the cases elective patients. In the evening this percentage is 100 % emergency patients. Note that if the capacity would be strictly 5, the verified blocking rate as in 4.4 would higher. The occupancy rate would be lower.

Time Of Day	Amount of patients	Mean between time before 6th bed is empty
Morning	71,43%	0:16:54
Afternoon	21,43%	0:57:00
Evening	7,14%	0:14:00

Table 4.5: *Patients using a 6th bed*

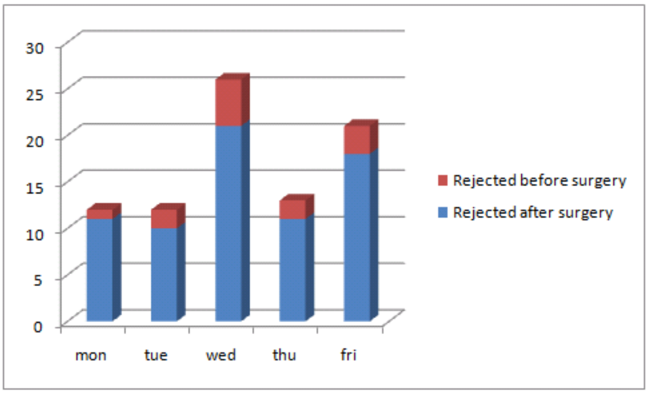

Figure 4.5: *Rejection day of the week*

Rejections

Another interesting feature is looking at the rejections on the day of the week. We would expect that the day of the week would make no difference in the amount of rejections. However, in the histogram 4.5 it is shown that on wednesday and friday, the amount of rejections is significantly higher than on other days. Reasons for this can be the difficulty of the operations performed by a surgical group on that day, or the length of OR time a specific surgical group has on these days.

4.1.2 Conclusion

We can conclude that the current blocking rate is lower than originally thought, although we have to remember that the rejections from emergency OR, could not be fitted into this model. Since the occupancy rate is high, we can state that it would be difficult to obtain bed flexibility in the current situation. Since we are interested in the optimal capacity of the PACU, giving a low blocking percentage and high occupancy rate, we have to simulate the PACU with different capacity rates. An important feature of simulation are the requests for the PACU, or the arrival of patients who are admitted or rejected. Since information about these rejections is not available or uncertain, a couple of models will be presented giving different scenarios of patient arrivals.

4.2 Model 2: Simulation including elective indications

In this model we would like to observe the changes in behaviour of the PACU patients with respect to different capacity levels. The arrival times and service times are obtained from the historic data. The difference compared to the last model is that we include all the elective patients with a known PACU destination which did not arrived at the PACU in history. We therefore expect an enlargement of the occupancy rate and the blocking rate. The unknown parameters are determined in the next section.

4.2.1 Tests

Arrival time during the day

In this section we use tests to generate the arrival times as if the historic rejected patients before surgery, actually had surgery. We have tested multiple theoratical distributions on the sample data of the elective patients that arrived in history. Because the elective patients arrive in the middle of the day, during working hours, we see that the variance is relatively low. Because it was impossible to fit an theoratical distribution to significant fit we have chosen to fit this variable according to the normal distribution.

The arrivals are generated having a normal distribution with mean 0.65 days and standard deviation 0.13 days, and the parameters of the normal distribution used to generate random arrival times drawn from the normal distribution are stated in table 4.6. With the normal distribution we capture the nessecary variance of arrival times on a day, including the high probability that a patient arrives between elective surgery hours.

Service times

We have tested with the ANOVA test if the distribution of the elective, emergency and other arrivals differ from each other. As shown in table 4.2.1 we have rejected the nulhypotheses that the groups are drawn from the

Normal distribution	
Mean	0,616
Standard Error	0,008
Median	0,619
Mode	0,551
Standard Deviation	0,133
Sample Variance	0,018

Table 4.6: *Parameters of normal distribution of the arrival time during the day*

ANOVA

Variation	*Squared Sum*	*Degrees of Freedom*	*Mean Squares*	*F*	*P-value*	*Critical bound of F-value*
Between groups	2,99	2	1,50	15,47	0,00	3,03
Within groups	28,44	294	0,10			
Total	31,44	296				

Table 4.7: *ANOVA service times*

same distribution. Second, a distribution for the elective service times must be found. When using the DataFit program, it is shown that the elective service times do not follow a particular distribution well. This is mostly because some large outliers, the cases when a patient is only there for one hour or for more than two days. Also the variation in service times are not regular, since the policy of the PACU attains a service time of 24 hours. Deleting the outliers, the Beta distribution is best for fitting the service time, although is is not significant at a 5% confidence bound. This fit is tested with the regular goodness of fit tests B. In figure 4.6 a histogram of the sample data of the elective service times is shown. The majority of the sample is between 0.7 and 1.2. The Beta function was found to fit the empirical data the best.

Variables Units are in days	Statistic Fit Beta	Data values
Values	'—	214
Base Case	'—	'—
Mean	0,90	0,90
Median	0,89	0,90
Mode	0,88	0,77
Standard Deviation	0,10	0,10
Variance	0,01	0,01
Skewness	0,24	0,24
Kurtosis	2,80	2,77
Coeff. of Variability	0,11	0,11
Minimum	0,56	0,62
Maximum	1,49	1,19
Mean Std. Error	'—	0,01

Table 4.8: *Fit Beta distribution to service times*

Too generate the unknown service times for elective patients, a beta distribution will be used. The data values and the comparison with this empirical distribution are shown in table 4.8. The used parameters for generation are given in table 4.9.

In the simulation model, the unknown service times for requests are randomly drawn from a Beta distribution.

4.2.2 Analysis

After running the simulation 100 times for the different capacity levels, the following results can be given. The blocking rate and the occupancy rate are given in table 4.2.2. A capacity of 4, 5 or 6 is preferable considering the preferable blocking and occupancy rates as stated below.

In graph 4.7 a graphical specification is given of table 4.2.2. The table shows us that the blocking rate drops less as the capacity grows. Moreover, the occupancy rate drops more when the capacity grows. The relations between the service rates and capacity level is transparant. The next relations can be stated:

$For\ occupancy\ > 0.65 \ \ \Rightarrow\ capacity\ \leq 5$

Beta distribution with parameters:	
Minimum	0,56
Maximum	1,49
Alpha	6,64
Beta	11,52

Table 4.9: *Parameters of Beta distribution of service time*

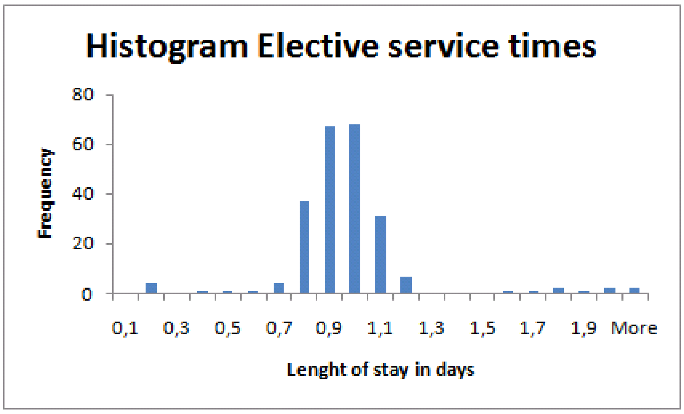

Figure 4.6: *Elective service times*

Capacity	1	2	3	4	5	6	7	8
Blocking	0,817	0,635	0,472	0,319	0,178	0,075	0,034	0,019
Occupancy	0,817	0,812	0,789	0,770	0,730	0,671	0,596	0,527

Table 4.10: *Blocking and occupancy per capacity*

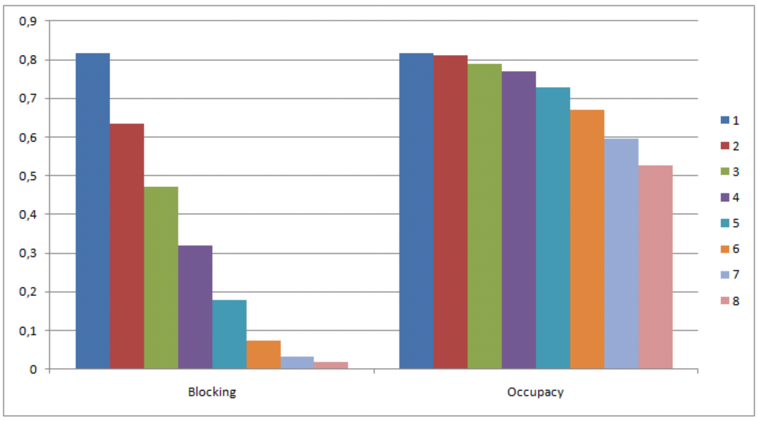

Figure 4.7: *Blocking and occupancy rates*

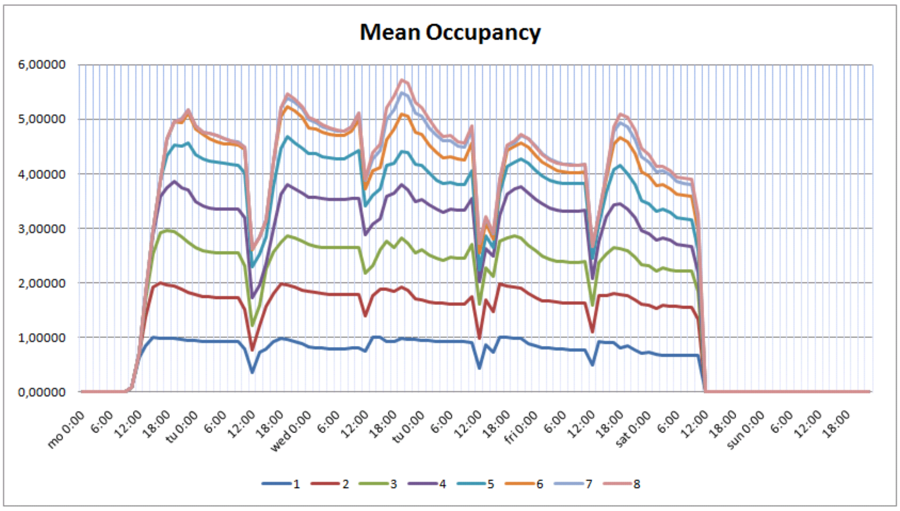

Figure 4.8: *Occupancy rate*

Capacity	1	2	3	4	5	6	7	8
Admitted: Emergency	15,2%	26,1%	42,6%	58,3%	76,1%	86,0%	90,0%	91,8%
Admitted: Elective	17,9%	37,5%	54,1%	69,2%	82,8%	93,4%	97,6%	99,2%
Admitted: Other	29,6%	42,0%	54,2%	71,3%	85,8%	93,2%	95,8%	95,8%

Table 4.11: *Admitted patients per source*

For blocking $< 0.20 \Rightarrow$ *capacity* ≥ 5

At first sight a capacity of 5 or 6 will be preferable. In figure 4.8 the mean occupancy of the PACU per weekday is shown, in the various cases of capacity levels. Note that the surplus of occupied beds gets smaller at higher levels of capacity. Explanation for this is that all the arrivals are scheduled at high capacity, and there are no blocked patients left.

Finally in table 4.11 the total percentage of admission per source patients is shown. It is clear that the overall arrival of emergency patients is less than the overall arrival of elective patients. It tells us that more emergency patients are blocked, in relation to the elective patients. This can be explained by the fact that the arrival of emergency patients is unexpected, and the PACU will be mostly filled with elective (indicated) patients. Another reason is that the arrival time of emergency patient is more variable than the arrival times of elective patients. Emergency patients are more likely to come in the evening compared with elective patients. By this time the PACU wil already be full. In graph 4.9 the total blocking during the week of this simulation, and the

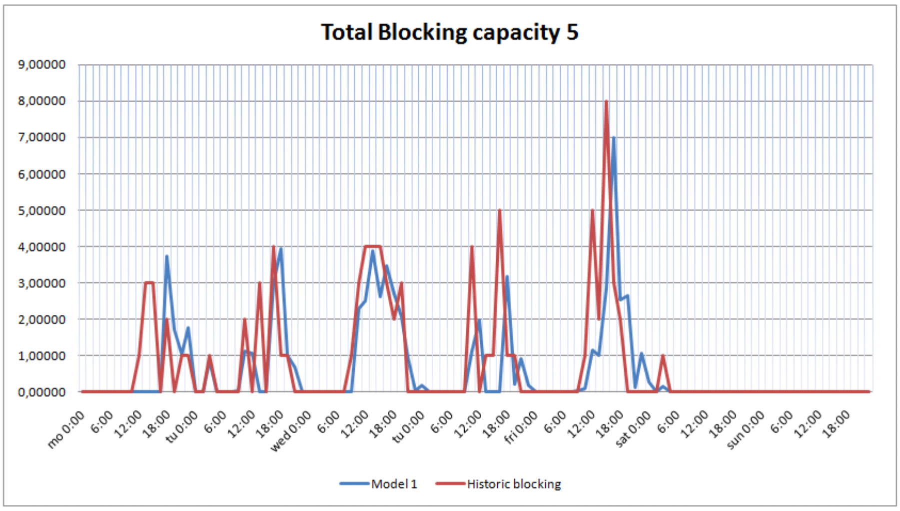

Figure 4.9: *Total blocking in simulation*

Beds occupied (X)	Emergency
0	2,3%
1	9,1%
2	13,6%
3	29,5%
4	40,9%
5	4,5%
Total	100%

Table 4.12: *Percentage of arriving patients that find X beds occupied at admission*

Beds occupied	Percentage Time
0	6,0%
1	5,3%
2	6,8%
3	14,7%
4	27,8%
5	39,4%

Table 4.13: *Occupation in percentage of total time*

previous historic model are shown. Most patients get blocked during the day, when most patients arrive. The highest peek is shown on Friday, at this point patients get blocked because of the closure on Saterday.

4.2.3 Conclusion

Running the simulation occupancy model, the results verify that a capacity of 5 or 6 gives us reasonable outcomes according to our preferences. In future models, we will try to optimize the service levels with this capacity by applying bed reservations and a limit of Elpado restrictions on this model.

4.3 Model 3: Simulation with generated emergency arrivals

In this model we will encounter the expected missed emergency arrivals, enlarging the arriving rate of the patients. The arrival rates of the elective patients will not change compared to the previous model. This model will be able to simulate all the arrivals which can't be captured in the current hospital databases.

4.3.1 Tests

Arrivals on a day

Unfortunateley, the empirical Poisson ditribution does not fit the data on a 5% significant level. However, we will assume that the emergency arrivals are Poisson distributed, since the characteristics of emergency arrivals are in line with the Poisson distribution. The arrivals are not influenced by surgery time, but are completely random arrivals. The reasons why the data does not fit the distribution can be the small amount of emergency arrivals that arrived on the PACU in the past. Since the PACU is mostly fully occupied, the amount of arrivals we see are not completely random distributed because at some days, and certain moments on a day, the PACU is already filled with elective patients (shown in model 1). This influences the randomness of the emergency arrivals at the historic data.

Amount of emergency patients

First we have determined the occupation of PACU beds in time, using the first simulation occupancy model. This is shown in 4.13. The next step was (3.2.3) to verify the amount of emergency patients that are admitted at each capacity level. This is shown in 4.12. If there could be admissions when the occupation is five, which is in 39,44% of the total arrival time of the emergency patient, there would be 65% more emergency arrivals than there are now. The blocking percentage would theoratically increase from 21,8% to 27,8%. With the help of this information concerning the actual emergency arrivals, we can generate the extra blocked arrivals.

Comparison Chart		
Statistic	Fit 1: Beta	Data values
Mean	0,71	0,71
Median	0,71	0,69
Standard Deviation	0,15	0,16
Variance	0,02	0,02
Skewness	0,01	0,01
Kurtosis	2,21	2,11
Coeff. of Variability	0,22	0,22
Minimum	0,34	0,41
Maximum	1,08	0,97

Table 4.14: *Fit Beta distribution to arrival times*

Service times emergency patients	
Statistic	Lognormal distribution
Base Case	0
Mean	0,8
Median	0,76
Mode	0,68
Standard Deviation	0,46
Variance	0,21
Skewness	0,56
Kurtosis	3,57
Coeff. of Variability	0,57

Table 4.15: *Parameters from Lognormal distribution of emergency service times*

Using the Poisson distribution for the generation of PACU arrivals on a day, we have determined that the amount of emergency arrivals over the time horion will grow with 65%. We consider the historic emergency arrivals to be Poisson distributed with λ_1, and we have assumed that the overall process of emergency arrivals will be Poissin distributed with λ_3, given 65% growth:
$\lambda_3 = \lambda_1 * 1.65$

From the summation property ([1]), we consider that the missed emergency arrivals, are Poisson distributed with $\lambda_2 = \lambda_3 - \lambda_1$.

The missed emergency arrivals will be randomly drawn from the Poisson distribution to generate new arrivals in the time horizon.

Arrival time during the day

Also the time of arrival on a day differ from the elective arrivals. We have fitted the sample of the historic emergency arrivals on different theoretical distributions using the goodness-of-fit tests. This sample has little data points. We have found that the Beta distribution fitted the data best, although not on the 5% significant level. In table 4.14 the Beta distribution is compared to the sample data.

Service times

We already have determined in model 2 that the service times of the different resources group differ from each other, using the ANOCA test. We therefore have to fit multiple theoratical distributions on the sample data of the length of stay of the emergency arrivals in history that are known.

The Lognormal distribution fitted the service times of the emergency patients best. The service times of emergency patients are mostly around the overall mean of 22 hours, but there are more outliers shown compared with the elective patients. The distribution therefore shows a large tail on the right, confirming a more frequent

[1] To verify the total amount of emergency arrivals, without generating the historic arrivals again, we consider the property of Poisson distribution:If X and Y are two independent Poisson random variables with parameters respecitively λ_1 and λ_2, then $Z = X + Y$ is also Poisson distributed with parameter $\lambda_1 + \lambda_2$.

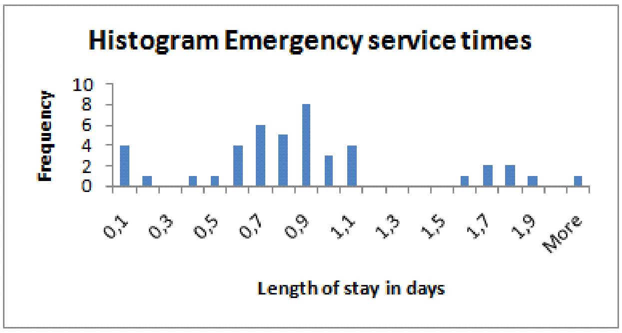

Figure 4.10: *Emergency service times*

Capacity	1	2	3	4	5	6	7	8
Blocking rate	0,838	0,674	0,526	0,388	0,256	0,154	0,088	0,056
Occupacy rate	0,865	0,855	0,833	0,814	0,784	0,742	0,683	0,622

Table 4.16: *Blocking and occupancy rates*

surplus than the average length of stay. he service times are considered to have a lognormal distribution with the data values from table 4.15. Unfortunately the Lognormal distribution did not fitted the sample data to a 5% significance level. Actually, because of the few data points available in this group there was no theoretical distribution found. In figure 4.10 a histogram of the sample data is shown. Because of the reasons described above we have chosen to use this distribution to generated the service times for generated emergency arrivals in the simululation occupancy model.

4.3.2 Analysis

After running the simulation 100 times per different capacity level, the following results can be given. From the results of table 4.16 it is shown that the occupancy rate drops more rapidly for a capacity level bigger than five. A capacity level of at least six is preferable looking at the blocking rate. Since more arrivals are generated in this simulation, more patients will be blocked having a same capacity level compared with the previous models. Therefore we must consider a larger capacity level in order to keep the service level for the patients high.

If all the generated data in this model immiddiately gets blocked, as in history, the blocking rate would be 0.278. This percentage is in line with the outcomes of the blocking rate in these results, only giving a higher occupancy rate. Noting the mean occupancy per weekday in graph 4.11, the overall picture has not changed enormously. Adding an extra bed to the PACU slowly decreases the size of the extra occupancy level. Untill a capacity level of 7, the effect is still significant. In table 4.17 it is shown that the rate of elective patients

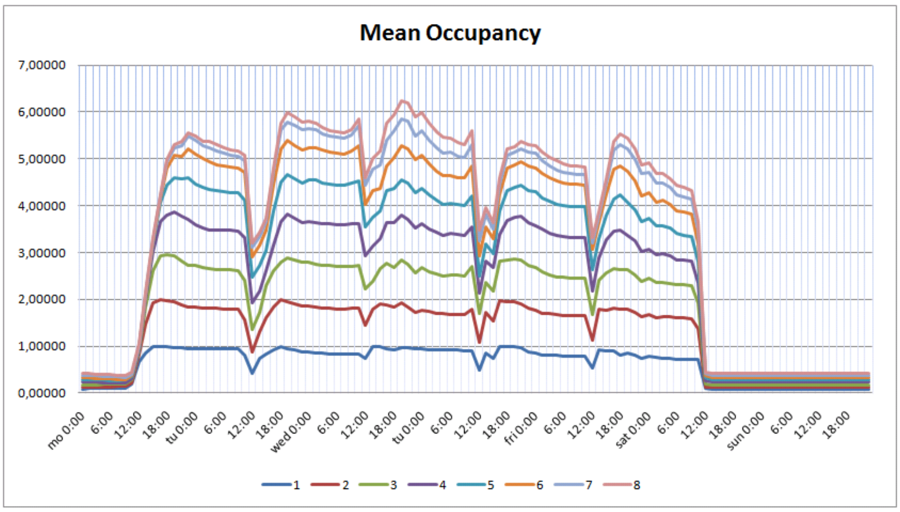

Figure 4.11: *Occupancy rate*

Capacity	1	2	3	4	5	6	7	8
Admitted: Emergency	13,1%	21,4%	32,6%	44,1%	58,4%	69,6%	77,1%	81,3%
Admitted: Elective	16,4%	34,9%	50,8%	65,0%	77,8%	87,8%	94,4%	97,5%
Admitted: Other	25,0%	38,0%	50,2%	65,5%	80,0%	90,5%	93,2%	95,2%

Table 4.17: *Admitted patients per resource group*

Beds occupied (X)	Unexpected elective
0	11,1%
1	20,0%
2	17,8%
3	20,0%
4	26,7%
5	4,4%
Total	100%

Table 4.18: *Percentage of arriving patients that find X beds occupied at admission*

admitted to the PACU is larger than the rate for emergency patients. Since the emergency arrival rate is made more realistic, we see in the statistics that it is hard to admit all these patients to the PACU, and they are blocked more often. Also the elective patients got blocked more often, making room for the emergency patients. We would prefer a situation with a high admission rate for elective patients, and a slightly lower admission rate for emergency patients. This means that we aim for no cancelled surgeries for elective patients, and a large availability for uncertain emrgency arrivals.

4.3.3 Conclusion

From the results of this simulation model, we can conclude that a larger capacity than the current level is preferable. A capacity level $\geq$ 6 gives us a satisfactory blocking rate, and a capacity level $\leq$ 7 gives a satisfactory occupancy rate. The amount of blocked elective patients should be lowered. More available beds have to be reserved for uncertain emergency arrivals, in a manner that they won't block the elective patients. In the next part some solution methods for these problems will be investigated.

4.4 Model 4: Simulation with generated unexpected elective arrivals

This model will generate the unexpected elective arrivals and the emergency arrivals on top of the historical data. Compared to the previous model this model will also take the unexpected elective arrivals in account. The arrival rate of both the elective and emergency arrivals is highest at this model. We expect that a capacity increase is needed to fulfill the enlarged need of PACU care.

4.4.1 Tests

Arrivals on a random day

For the number of arrivals on a random day, for a time horizon t, the data is fitted on different distributions.

First we have determined the occupation of PACU beds in time, using the first simulation occupancy model. This is shown in 4.13. The next step was (3.2.3) to verify the amount of emergency patients that are admitted at each capacity level. This is shown in 4.18. In this case 57% more requests would occur when there would be no limitation of capacity. Generating this extra arrivals, the blocking percentage in history would theoretically be 31.7%. The extra amount of arrivals to be generated is fitted in the Poisson distribution. This can be explained by the unexpected character. An unindicated arrival can randomly occur and ask PACU admission.

Arrival time during the day

The arrival time during the day will be of elective patients, therefore the same generation method is used as explained in 4.2.1.

Capacity	1	2	3	4	5	6	7	8	9
Blocking rate	0,844	0,686	0,544	0,405	0,276	0,174	0,104	0,064	0,046
Occupacy rate	0,863	0,849	0,832	0,805	0,781	0,743	0,689	0,628	0,569

Table 4.19: *Blocking and occupancy rate*

Capacity	1	2	3	4	5	6	7	8	9
Admitted: Emergency	13,4%	22,3%	33,1%	44,0%	57,7%	67,9%	76,3%	80,3%	83,0%
Admitted: Elective	15,6%	33,7%	48,9%	63,4%	76,0%	86,2%	92,8%	96,8%	98,5%
Admitted: Other	23,7%	36,0%	48,2%	64,0%	77,2%	87,0%	92,0%	94,1%	95,2%

Table 4.20: *Admitted patients per source*

Service times

The service times of these arrivals are from elective patients, therefore we will use the same generation method as explained in 4.2.1.

4.4.2 Analysis

After running the simulation 100 times per different capacity level, the following results can be given. Table 4.19 states the renewed blocking and occupancy rate for this simulation. There are more arrivals, therefore the occupancy and the blocking rates are higher for each capacity level. In the graph of 4.12 the mean occupancy per weekday is shown. After the capacity level of 7, adding an extra bed will not ensure significant more occupancy. A bigger part of elective arrivals is admitted, as shown in 4.20. Note that if all the generated arrivals get blocked, the blocking percentage would be 31.7%. This is in line with the results in 4.19. The occupancy rate is changed, and the blocking rate has dropped because more arriving patients are available at more moments when the PACU is available.

In 4.13 the mean of blocked patients is shown per weekday over the time horizon. Between noon and midnight most patients are getting blocked.

4.4.3 Conclusion

This simulation model has included all the arrivals that are expected to be blocked, but not shown in the available historic information. If we raise the current capacity level from 5 to 6 or 7, they can be admitted to the PACU. It is very important to take this model into account in the final conclusion. Although this model can't be verified by data, it could be the most realistic model. Logically there shouldn't only be blocked elective arrivals,and it is only realistic to assume that emergency and unexpected elective arrivals also will get blocked.

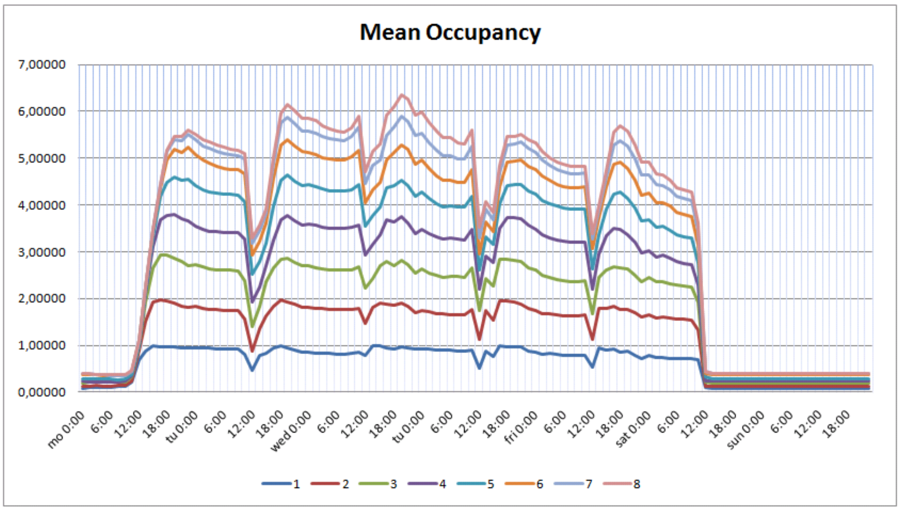

Figure 4.12: *Occupancy rate*

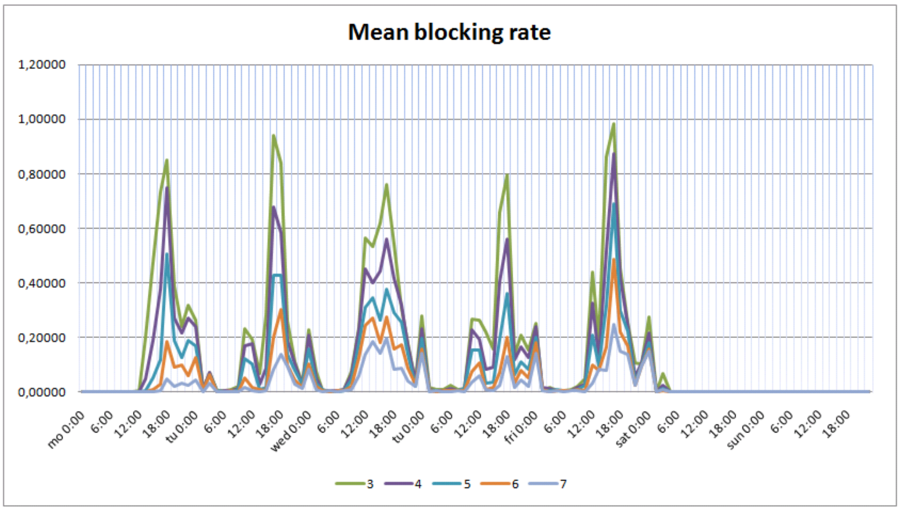

Figure 4.13: *Mean blocked patients*

4.5 Theoretical model: Erlang loss

With the help of the Chi-squared goodness-of-fit test there can be concluded that the admissions between the real observations and the expected values when the observation would be drawn from the empirical ditribution, differ. Reasons for this can be the building up effect of patients who are on the PACU for longer tha a day, which means less admissions the next day. Another reason can be the relationship of elective arrivals with the surgery time, since the elective arrivals are dependend on the surgeries and operation times which a surgical group performs. The known arrivals are in majority elective arrivals, which gives a unrealistic view in the Poisson distribution.
The Poisson index of dispersion can be determined by:

$$((n-1)\ *\ variance\ /\ mean) \tag{4.1}$$

This has a Chi-Square distribution with $n-1$ degrees of freedom (in our case, n is the amount of observations of arrivals per day) The variance-to-mean dispersion ratio was 0.27, meaning that the variance is smaller than the mean, which would not be the case if the admissions were Poisson distributed. Explanation for the small variance lies in the high occupancy, the PACU is practically always full, and there is no room for variation in the number of admissions since this would often be equal to the capacity as it is now (5 available beds). The only variation possible is because of short stay patients (a bed is used multiple times on a day), or at the opposite side when a patient stays longer than a day, in this case less admissions can find place on an average day.

Applying the Erlang loss formula:

$$Occupancy\ rate = \frac{(1-(\frac{(\lambda E(S))^c/c!}{\sum(\lambda E(S))^k/k!}))\lambda E(S)}{c} \tag{4.2}$$

$$0.7744 = \frac{(1-(\frac{(\lambda * 0.90)^5/5!}{\sum_{k=1}^{5}(\lambda * 0.90)^k/k!}))\lambda * 0.90}{5} \tag{4.3}$$

Deciding to determine the blocking percentage with this Erlang loss formula, the formula would determine the real arrivals per day : $\lambda\ =\ 6,906$ with an occupancy rate of $0,774$ (from the historical data) and a blocking percentage of $37,7\%$

4.6 Model validation

In the various models we have seen different problems. The reliability of the models differ because of the variables used. In this chapter the reliability of the variables and the trustworthy of the models will be discussed. The variables used are influenced by the information gathered. A lack of information, or the unreliability of gathered information is a critical point building the models.

PACU Indications All the PACU indications are known, as they are drawn from historic data.
Unreliability in information: Only indications which are wrongly not given, are not noted. We are only aware of the final indications shown in Elpado.
Thrustfactor: Medium

PACU Elective arrivals The PACU Elective arrivals contains the PACU indications, and the elective patients that were not indicated in advance. The PACU elective arrivals without indication: wrongly not given indication, or just unexpected PACU patients.
*Unreliability in information:*Elective arrivals which are rejected and not notified. Out of the elective arrivals without indication there can be patients in need for PACU care, but were rejected because of capacity reasons. These patients are not noted in the hospital.
Thrustfactor: Medium

PACU Emergency arrivals The PACU Emergency arrivals contains patients from the emergency-OR.
*Unreliability in information:*There is no information available about rejected emergency patients, which means that there could be a lot more patients in need for PACU, which are not noted and can't enter the PACU because of full bed occupancy.
Thrustfactor: Low

PACU other arrivals These patients come from other hospitals, general wards or the IC.
*Unreliability in information:*There is no information available about rejected patients, but since the PACU in origin does not admit these patients, we can consider these patients all in emergency need for PACU care.
Thrustfactor: Medium

Variables	Historic	Generated	Validation
Elective arrivals	Yes	No	Good
Emergency arrivals	Yes	No	Medium
Other Arrivals	Yes	No	Good

Table 4.21: *Validation Model 2*

Variables	Historic	Generated	Validation
Elective arrivals	Yes	No	Good
Emergency arrivals	Yes	Yes	Medium
Other Arrivals	Yes	No	Good

Table 4.22: *Validation Model 3*

Variables	Historic	Generated	Validation
Elective arrivals	Yes	Yes	Good
Emergency arrivals	Yes	Yes	Medium
Other Arrivals	Yes	No	Good

Table 4.23: *Validation Model 4*

We have validated the simulation models by comparing them to the exact historic model. This model is verified using graphical representation (section 2.7). Next to this the model statistics are shown to the staff(A). They concluded that the statistics and research outcomes equaled their expectations and experiences on the PACU.

4.7 Conclusion

In graph 4.14 the blocking rate of the Erlang loss model is compared to the blocking outcomes of the three subsimulation for different levels of capacity. The Erlang model continues to have a higher blocking rate for

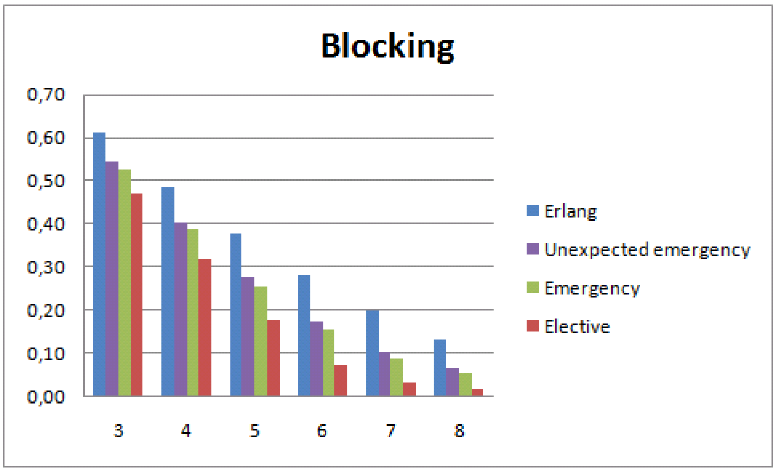

Figure 4.14: *Comparison blocking rates*

Capacity		*3*	*4*	*5*	*6*	*7*	*8*
Blocking	**Erlang**	**0,61**	**0,49**	**0,38**	**0,28**	**0,20**	**0,13**
	Elective	0,47	0,32	0,18	0,07	0,03	0,02
	Emergency	0,53	0,39	0,26	0,15	0,09	0,06
	Unexpected emergency	0,54	0,41	0,28	0,17	0,10	0,06
Occupancy	**Erlang**	**0,81**	**0,80**	**0,77**	**0,74**	**0,71**	**0,67**
	Elective	0,79	0,77	0,73	0,67	0,60	0,53
	Emergency	0,83	0,81	0,78	0,74	0,68	0,62
	Unexpected emergency	0,83	0,81	0,78	0,74	0,69	0,63

Table 4.24: *Comparison service levels*

all the levels of capacity. This can be explained by the relatively high arrival rate compared to the simulation models.

In table 4.24 all the occupancy and blocking rates are determined for the simulation models and the Erlang model. Note that the model which approximates Erlang the most varies per capacity level. Reasons are that the relationship between occupancy rate and blocking rate between the different methods is not linear. In graph 4.14 is shown that the blocking rate is consistently higher for the Erlang model, than the other models. This is not the case for the occupancy rate. The simulation models give higher occupancy rates for the simulation models, which can be explained through the lower blocking percentages of the simulation models, verifying higher occupancy rates.

In graph 4.15 the differences in simulation models over the week are shown.

For practical reasons we are more interested in the simulation models than the Erlang loss model. The arrivals from the simulated data seem to be more realistic since they are drawn from the original data. The assumptions needed for a correct implementation of the Erlang model can't be justified since there are a lot uncertainties. The Erlang model can only be implemented when the arrivals are drawn from a Poisson distribution, which is not the case.

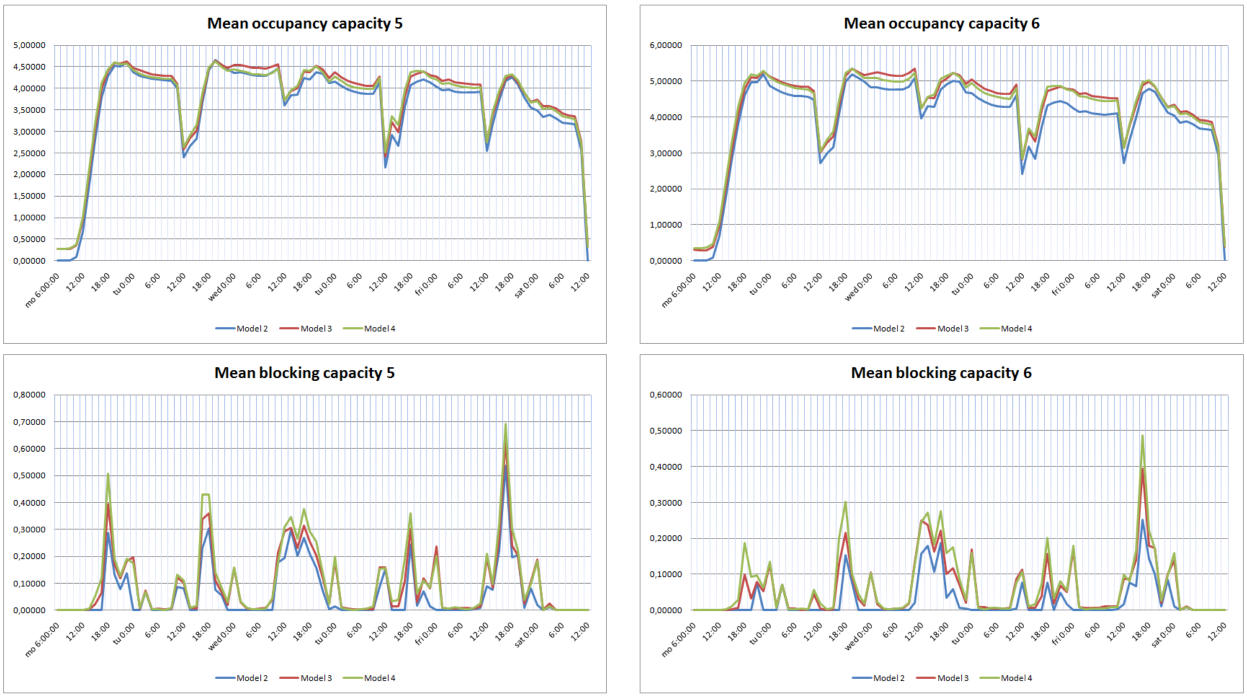

Figure 4.15: *Comparison models*

Chapter 5

Bed admission policies

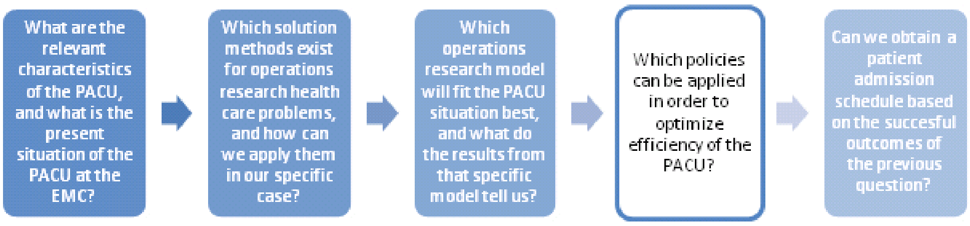

Figure 5.1: *Research question 4*

In the previous chapter we have implemented four models on the PACU problem. Three simulation models identifying different arrival rate cases, and one queueing model. We have concluded that the simulation models fit our problem best. In the following chapters, other solution methods are applied to the existing simulation model, with the objective to improve the service levels for each capacity level. The blocking rate and the occupation rate must be optimal for an efficient PACU. The optimality gives a perfect balance between the blocking percentage and occupancy rate, without changing the input variables of the simulation model.
These solution models change the way of bed admissions, characterized by patient group or source. Also the PACU indication plays an important role. The first policy we will explore is beds reservation, a bed is reserved on a day and only available for specific specialism's. The second policy is indication limitation, this concerns that the amount of patients that can be given on OR with PACU indication is limited. We will try to find out if these policies can improve the service levels, fixing a certain capacity level.

5.1 Bed reservations

In this model the aim is to reserve beds for the PACU for certain surgical groups, or source groups. The three reservation schemes investigated are:

- **Reservation scheme 1:** Elective surgical group CHI, elective surgical group NEC, all patients excluding the two primary groups:

  Statistics have shown that CHI and NEC are the biggest suppliers to the PACU. More than 60% of all the elective patients come from these surgical specialisms. A lot of surgeries in these groups have a protocol indication, obtaining secure arrival of these patients.

  Emergency patients are always uncertain. The arrival can't be planned, and to ensure PACU care for these patients, an extra emergency bed could obtain improval of emergency care.

Capacity 5 CHI:1, NEC:1, Remain: 3			Capacity 6 CHI:1, NEC:1, Remain:4	
Blocking	0,3119		Blocking	0,254
Occupancy	0,596		Occupancy	0,536

Table 5.1: *Reservation scheme 1, Model 2*

Total capacity	5	6
Original simulation	0,730	0,671
Bed reservation	0,596	0,535

Table 5.2: *Comparement occupancy model 2*

- **Reservation scheme 2:** Emergency patients, all patients excluding emergency patients:

  In this case there are no bed reservations for the elective patients, only one emergency bed will be reserved.

- **Reservation scheme 3:** Elective surgical group CHI, elective surgical group NEC, emergency patients, all patients exluding the three primary groups.

For these three reservation schemes, the aim is to obtain the optimal capacity (how many beds should be available?) for each reservation group. The simulation is done for all three subsimulations, in 100 runs for each reservation group.

5.1.1 Reservation scheme 1

This scheme exists out of the following reservation groups: elective surgical group CHI, elective surgical group NEC, and all patients excluding the two primary groups. First the options for the capacity will be given, therafter they will be compared with the original simulations.

Simulation with elective indications

It seems that a single bed reservation for NEC and CHI costs a lot of occupancy, since the flexibility of the reserved beds is gone. Combining one bed reservation for NEC, with one bed reservation for CHI and leaving the empty beds for the other patients, the occupancy and blocking rates are shown in table 5.1.
Increasing the bed reservations for CHI and NEC with 1, the occupancy rate will fall respectively with 19% and 27%. Comparing these results with the occupancy rate for the general simulation(without reservations) it is shown in table 5.2 that the occupancy has dropped considerably using bed reservations. Next we would like to observe the blocking percentage. The blocking percentages of CHI and NEC are very high, which can be explained by the amount of elective patients, arriving at the same moment on a day. Comparing the blocking rates with the original simulation, the differences are still significant.

Observing the individual blocking rates of CHI and NEC compared with the original observation, the original simulation gave more satisfying results. Increasing the bed reservations for CHI and NEC with 1, the blocking rate will fall respectively with 63% and 79%, giving a very satisfying blocking rate. Unfortunately, the occupancy rate will be too low for this combination to be satisfying.

Simulation with emergency patients

Looking at the bed reservations in case of the second original simulation, we notice that there will be no changes in the blocking and occupancy rate for the elective bed reservations for NEC and CHI. We can expect that the occupancy will increase, and the blocking percentage will be higher for the unreserved beds because of the larger arrival rate in this simulation. The results are shown in table 5.3. The occupancy rates are higher for the unscheduled beds, but the occupancy rates of the original simulation are also higher. The blocking rates are increased for the simulation, having a lot of arrivals to reject with relatively few beds. The blocking rates in the original simulation decrease fast when the capacity level goes up. Reservations of CHI and NEC are diminishing for both the blocking and occupancy rates.

Capacity 5 CHI:1, NEC:1, Remain: 3			Capacity 6 CHI:1, NEC:1, Remain:4	
Blocking	0,371		Blocking	0,299
Occupancy	0,654		Occupancy	0,607
Original simulation				
Capacity 5			Capacity 6	
Blocking	0,256		Blocking	0,154
Occupancy	0,784		Occupancy	0,742

Table 5.3: *Reservation scheme 1, Model 3*

Table 5.4: *Reservation scheme 1, Model 4*

Capacity 5 CHI:1, NEC:1, Remain: 3			Capacity 6 CHI:1, NEC:1, Remain:4	
Blocking	0,391		Blocking	0,319
Occupancy	0,658		Occupancy	0,620
Original simulation				
Capacity 5			Capacity 6	
Blocking	0,276		Blocking	0,174
Occupancy	0,781		Occupancy	0,743

Simulation with unexpected elective patients

In table 5.4 a comparement with the original simulation is given for capacity 5 and 6. We can verify that the results are not satifactory.

5.1.2 Reservation scheme 2

This scheme contains the following reservation groups: emergency patients and all patients excluding the emergency patients.

Simulation with elective indications

In this simutalion there are relatively low emergency patients, and we expect that reserving a bed will be inefficient. The results are shown in table 5.1.2. These results are in line with our expextations. A bed reservation for emergency patients will cost too much in service level, and has low occupancy. The amount of beds available for other patients, must be at least as high as normal, because in combinations it will not give an occupancy and blocking rate comparable with the original simulation.

Simulation with emergency patients

In this model the bed reservation is more effective than in the previous simulation. The results are given in table 5.6. Reserving beds for emergency, now gives a higher occupation on that reserved bed, but apparently

Capacity 5	
Em:1, Remain: 4	
Blocking	0,277
Occupancy	0,639
Capacity 6	
Em:1, Remain:5	
Blocking	0,156
Occupancy	0,612

Table 5.5: *Reservation scheme 2, model 2*

Capacity 5	
Em:1, Remain: 4	
Blocking	0,325
Occupancy	0,694
Capacity 6	
Em:1, Remain:5	
Blocking	0,212
Occupancy	0,657

Table 5.6: *Reservation scheme 2, Model 3*

Capacity 5	
Em:1, Remain: 4	
Blocking	0,341
Occupancy	0,689
Capacity 6	
Em:1, Remain:5	
Blocking	0,228
Occupancy	0,654

Table 5.7: *Reservation scheme 2, Model 4*

there is not enough flexibility because a lot of emergency patients will get blocked. This part makes the rates incomparable with the results for the original simulation.

Simulation with unexpected elective patients

We have considered the comparison of a total capacity of 5 and 6. As shown the results for the bed reservations are not better compared with the results from the original simulation. The results for this model can be found in table 5.7.

Overall we can conclude that reserving one emergency bed gives better results than reserving beds for elective CHI and NEC. The blocking is less per capacity level and the occupancy higher. The results don't live up to our standards.

5.1.3 Reservation scheme 3

This scheme contains the following reservation groupes: elective surgical group CHI, elective surgical group NEC, emergency patients, all patients exluding the three primarly groups.

From the results of the former reservation schemes, we can conclude that the results for both schemes were not good. This scheme is a combination of the two schemes above. Although some rates will differ, it still is obvious that the blocking rate and occupancy rate will not improve by reserving beds for all reservation groups. The blocking rate will exceed the previous results, and the occupancy rate will decrease because of less arrivals for the vacant beds.

5.1.4 Conclusion

From the results of the simulations, we can conlcude that in no simulation case it is optimal to use bed reservations. The demand for PACU beds of the reservation groups is too small to realise fully occupied beds. Because the flexibility of beds is limited when reserving beds for only the reservation groups, the demand is more often rejected.
The idea of bed reservations for the PACU is clear at the other hand, the objective is that the elective patients from the biggest surgical groups are secured with one bed on a day, and the emergency arrivals are always sure of one bed, which can't be taken by elective patients. Continuing we are searching for a more flexibal way of bed reservations and, on the other hand, obtaining a security level for bed availability for the elective patients.

Figure 5.2: *Ordinary arrival process*

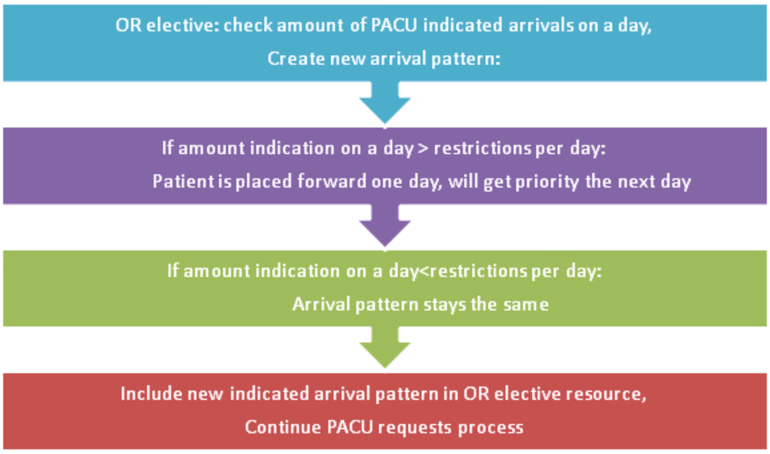

Figure 5.3: *Limiting indication arrivals*

5.2 Limiting bed reservations

In our search for a more flexibel way of reserving beds and obtaining a security level for bed availability for the elective patients, we will try to limit the amount of bed reservations one or more surgical groups can get on a day, anticipating their PACU patients on this limit. The first goal is to obtain more flexibiliy for the beds. In the previous chapter we have seen that reserving beds for specific patient's groups diminished the flexibility. Therefore, in this simulation we consider all beds available for all incoming patients. The second goal is to obtain a security level for the surgical elective patients, confirming the availability of beds after surgery. We are doing this using the available information about the elective patients: the PACU indication. To obtain certainty for the elective patients we are searching for a limited amount of PACU restrictions each day that minimizes the probability of getting blocked. The flexibility is an important characteristic for the incoming emergency patients, while the indication restriction must decrease the blocking rate for elective patients. For all tree submodels, the optimal amount of PACU indications per day of elective arrivals will be obtained.

Processing Elective arrivals according to restriction limits

The original models were generated in the manner of 5.2. We will change the OR-elective arrivals. Restrictions per day wil be given, and surgical groups will have to spread their PACU patients over the week (lower quantity per day and increase the frequency over the week). In the model we use the PACU indications in history: this is the amount of elective patients that were actually indicated going to the PACU. This amount of PACU indications per day will be restricted. We change the arrivals of the OR-elective, as in 5.3, and then continue the process as in 5.2.

5.2.1 Restriction model on simulation occupancy model 2

We will focus on the three levels of capacity: 4, 5, and 6. We will try to beat the blocking and occupancy rates of the original simulation by including restrictions.

Capacity 4

If the capacity level is equal to 4, the service rates of the original simulation can be improved by limiting the indication restrictions. In table 5.8 we see that the blocking percentages can be improved by setting a restriction of at least 4. The bold values give the optimal service rates found. When giving indication restrictions, we can

Capacity : 4				
	Restriction: 0	**3**	4	5
Blocking	0,32	**0,25**	0,31	0,32
Occupancy	0,77	**0,68**	0,74	0,75

Capacity : 5				
	Restriction: 0	4	5	6
Blocking	0,18	0,17	0,18	0,18
Occupancy	0,73	0,70	0,71	0,72

Capacity : 6				
	Restriction: 0	5	6	7
Blocking	0,07	0,08	0,07	0,07
Occupancy	0,67	0,66	0,67	0,67

Table 5.8: *Indication restrictions, model 2*

Capacity 5	Res 0	Res 4	Res 5	Res 6
Admitted: Emergency	76,1%	78,1%	74,6%	75,2%
Admitted: Elective	82,8%	83,0%	82,8%	82,2%

Table 5.9: *Admitted patients, model 2*

assume that the surgical specialism planning the patients, will prefer to reschedule the patient within a week instead of highering the probability that the patient will be rejected.
Overall these indication restrictions on a capacity of 4 don't give a blocking rate lower than 0.20. We can conclude that a capacity of 4 is not optimal.

If we look at the capacity level 5, it is hard to improve the blocking and occupancy rate by setting up indication restrictions. The restrictions done improve the original service levels as shown in table 5.8. If we look at the source of patients that got admitted, with a restriction indication limit of 4 we see that the emergency patients that are admitted has grown from 76% to 78%. The elective demand has spread more, and therefore more room for emergency arrivals has become available.
At the capacity level of 5 we can conclude that a restriction level of 4 PACU indicated patients each day would be preferable. In graph 5.4 the mean occupancy level during a week is shown for the historic model, model 1, and model 1 with restriction 4. Every day but Wednesday, the simulation model with the restriction level shows us a lower mean occupancy level. Also the total sum of blocking is shown for the three models in 5.4. Looking at the peaks it is obvious that the restriction level has encountered less blocked patients at crucial moments.

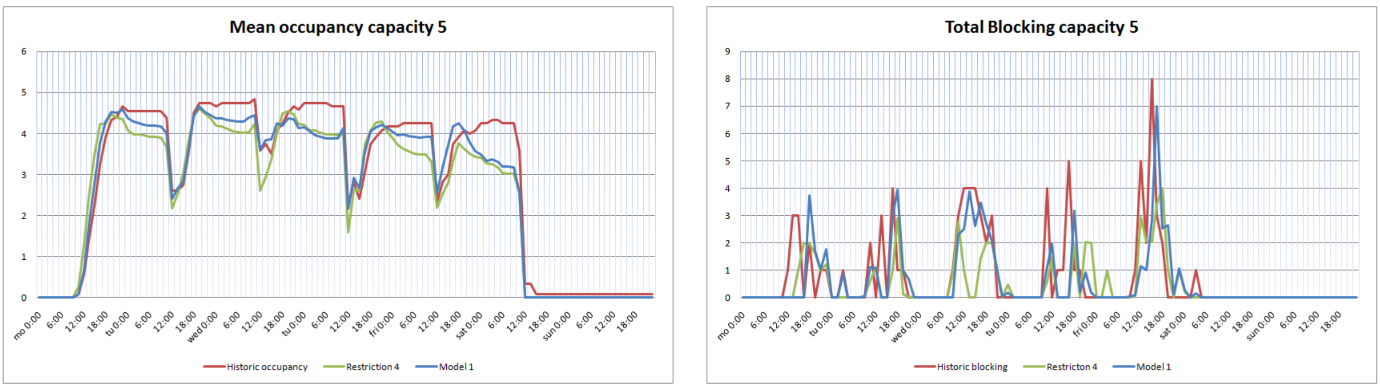

Figure 5.4: *Model 2, capacity level 5 with restriction 4*

Capacity : 5				
	Restriction: 0	4	5	6
Blocking	0,26	0,25	0,26	0,26
Occupancy	0,78	0,76	0,77	0,78
Capacity : 6				
	Restriction: 0	5	6	7
Blocking	0,15	0,15	0,16	0,15
Occupancy	0,74	0,73	0,74	0,74

Table 5.10: *Indication restriction, model 3*

Capacity 6	Res 0	Res 4	Res 5	Res 6
Admitted: Emergency	69,6%	70,4%	69,0%	67,3%
Admitted: Elective	87,8%	86,2%	88,1%	88,2%

Table 5.11: *Admitted patients, model 3*

Capacity 6

Because of the relatively low arrivals in the original model, having indication restriction limits at a capacity of 6 does not encounter any improvements on the service rates of the original model. When the arrival of more emergency patients is prefered, an indication restriction can give the outcome.

5.2.2 Restriction model on simulation occupancy model 3

In this model we are dealing with generated missed emergency arrivals. Setting limiting indications on the elective patients, allowed more admission security for them, while the emergency arrivals are more often refused. Getting restriction does not entail major changes in admission percentages. Overall, there is always one limitation level that will improve the original blocking- and occupancy rate a little. In graphs 5.5 the occupancy and blocking with a capacity level of 6 is compared. In the table only little differences were shown in the service levels. The graph also gives us mixed signs. The occupancy level is often slightly lower, and the big blocking peaks are diminished, giving more frequent blocking in return.

5.2.3 Restriction model on simulation occupancy model 4

In the last model the arrival rate has been brought up. It is shown in table 5.13 that low limitations on the amount of elective arrivals did not work well. Restriction on the amount of indications does not differ a lot, because the generated arrivals in this model are not indicated, there still wil be blocked patients.

5.3 Conclusion

We have obtained that putting up restrictions for the amount of elective indications will give more room for emergency arrivals. Still, it seems hard to lower the blocking percentage below 10%. When the demand is high,

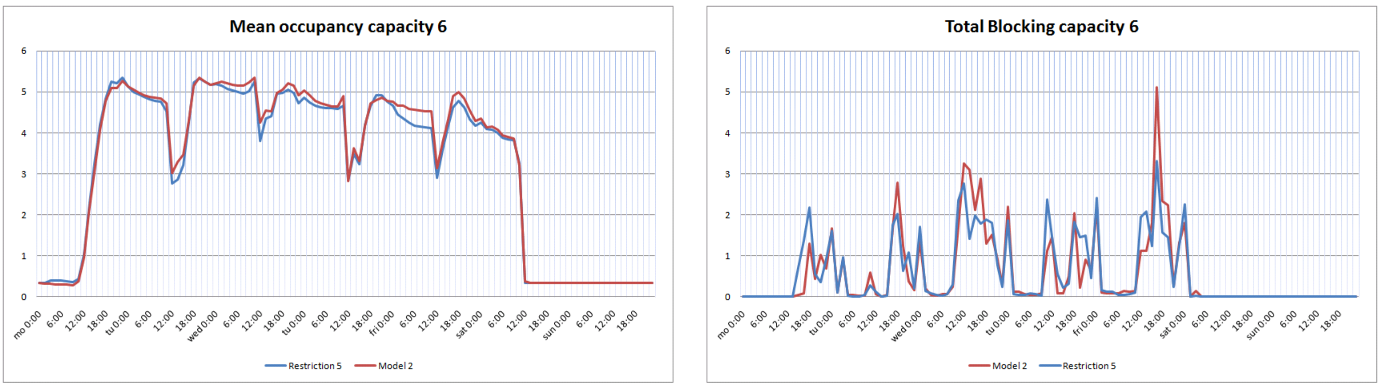

Figure 5.5: *Model 3, capacity level 6 with restriction 5*

	Capacity : 5			
	Restriction: 0	4	5	6
Blocking	0,28	0,27	0,28	0,28
Occupancy	0,78	0,76	0,77	0,78
	Capacity : 6			
	Restriction: 0	5	6	7
Blocking	0,17	0,18	0,17	0,17
Occupancy	0,74	0,73	0,74	0,74
	Capacity : 7			
	Restriction: 0	5	6	7
Blocking	0,10	0,10	0,10	0,10
Occupancy	0,68	0,68	0,67	0,67

Table 5.12: *Indication restriction, model 4*

Capacity 6	Res 0	Res 4	Res 5	Res 6
Admitted: Emergency	67,9%	56,7%	67,3%	75,1%
Admitted: Elective	86,2%	74,9%	85,7%	93,1%

Table 5.13: *Admitted patients, model 4*

or when there are a lot of arriving patients it actually would be wise to include limiting restrictions for the clearity of PACU arrivals on a day. The PACU would have less stress, and more security about the patients that will arrive on a day. The surgical specialisms will spread their demand during the week, since they will not be able to operate all their patients on the same day due to restrictions.

Chapter 6

Scheduling

Figure 6.1: *Research question 5*

From the previous part, we have concluded that for Model 2, a restriction of four PACU indications each day with a total capacity of five is preferable. For practial reasons we will research the scheduling using the results of this model. In chapter 3, we have investigated the use of mathematical programming in health care problems. The conclusion of the previous model has given us opportunity to schedule the amount of indications for each day, for each specialism. In the following sections the scheduling of these elective PACU patients is discussed. First a model for scheduling is obtained, whereafter the model will be applied on the PACU model. The reason why scheduling is nessecary is explained, and the arriving patterns which used for the scheduling are obtained. At least a monthly schedule will be constructed.

6.1 Construction of scheduling model

The restriction on PACU indications must be controlled per surgical group avoiding preferences for the earliest implemented surgical specialism. Thus, we have to obtain a schedule for the PACU indications for each surgical groups on each day. The arriving patterns and OR time must be investigated for the surgical specialismes in order to verify which surgical group will be allowed PACU elective patients on a certain day. With this observation we can obtain the parameters for implementing mathematical programming. There are lots of factors that have to be taken in consideration determining the final schedule. First, the amount of beds are integer. Switches have to be made into the data to define an integer amount of beds. Second, the operating days of the surgical groups have to be in line with the scheduled patients. A surgical group can only deliver patients when they are performing surgeries. Third, we have to encounter the certainty of a delivery from a surgical group.
The parameters needed for the scheduling model are:

1. Limit of PACU indications on a day $= c$. This can be verified by the models in the previous chapter using

the limitation policy in section 5.2.

2. The amount of surgical specialisms that will be placed in the schedule: $i = 1, ...N$.

3. The demand of beds for each specialism per week: d_i. The demand can be verified by researching the specialisms source of the elective PACU patients in history. First we need the percentage of patients each specialisms contributes to the PACU. This can be obtained by historic arrivals in a certain time interval T.
   $percentage_i = \frac{Amount\ of\ elective\ patients\ of\ specialisms\ i\ arrived\ on\ PACU\ in\ T}{Total\ amount\ of\ elective\ patients\ arrived\ on\ PACU\ in\ T}$
   Thereafter we have to obtain integer values for the amount of beds each specialism will demand during a *week*. The formula used is:
   $d_i^{non-integer} = percentage_i \cdot (c \cdot 5)$.
   Next we have obtain integer values for the demand. This can be done by following this algorithm:

   Step 1: For $i\ = 1$ till N, set $d_i^{integer} = \left\lfloor d_i^{non-integer} \right\rfloor$

   Step 2: While $\sum_i^N < (c \cdot 5)$

   Step 3: Find the $max_{i \subset N}$ for $\frac{d_i^{non-integer}}{d_i^{integer}}$, set $d_i^{integer} = d_i^{integer} + 1$.

   Go back to step 2.

   Now we have obtained the demand for each specialism per week.

4. Preferable weekday rates. By researching the arriving pattern of the elective patients statistics verifying the percentage of arrivals on a day of a specific specialism can be obtained. For each specialism i the percentage of arrivals on each weekday j must be found in matrix a_{ij}. One element a_{ij} can be determined by: $a_{ij} = \frac{Amount\ of\ elective\ patients\ of\ specialisms\ i\ arrived\ on\ PACU\ at\ day\ j\ in\ T}{Total\ amount\ of\ elective\ patients\ of\ specialisms\ i\ arrived\ on\ PACU\ in\ T}$

We can define an integer program for scheduling the amount of beds for each specialism:

$c =$ limit of PACU indications
$j = 1, 2, 3, 4, 5 =$ mon, tu, wed, thu, fri
$d_i =$ demand of specialism i for each week
$i = 1, 2, ..., N =$specialism 1, ..., specialism N
$a_{ij} =$ weekdat rates
x_{ij}= decision variable which indicates the amount of beds for specialism i on day j.

The formulation now becomes:

min $(x_{ij}/d_i - a_{ij})^+ - (x_{ij}/d_i - a_{ij})^-$
s.t. $\sum_i^N x_{ij} \leq c$
$\sum_j^5 x_{ij} = d_i$

6.2 Application of the scheduling model on the PACU

We will implement the PACU situation in the scheduling model. We will use the outcomes of simulation model 2.

We will start by obtaining the parameters for the scheduling model as stated in the previous section.

1. Limit of PACU indications on a day. We aim to a restriction of four PACU indications each weekday with a total PACU capacity of five beds. We can set $c = 4$.

2. The amount of surgical specialisms that will be placed in the schedule: $i = 1, ...N$. In graph 6.2 we have shown on which part of the elective arrivals are from each surgical specialism. We have verified that the amount of arriving patients from GYN, PLC, KAA and ONG is very uncertain. These arriving patients are not indicated by protocol, only for co-morbidity reasons. We decide to implement only the five largest specialisms in the schedule.

3. The demand of beds for each specialism per week: d_i. The demand can be verified by researching the specialisms source of the elective PACU patients in history.

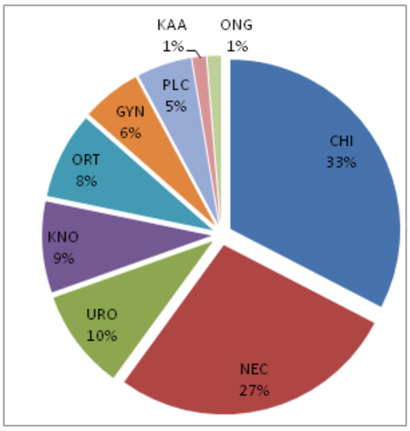

Figure 6.2: *Elective PACU patients*

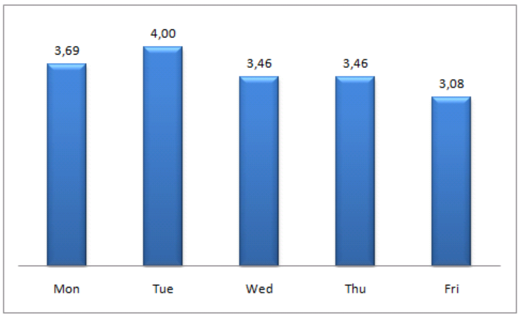

Figure 6.3: *Mean elective patients arrival*

Statistics have shown that 86% of elective patients are from surgical groups CHI, NEC, URO, ORT and KNO. If we look at the total amount of indications, this percentage is 85%. Therefore we will decide only to schedule these surgical group with overall arriving patients 86% of total. The excluded groups can schedule the PACU at on special reserved day. 10% of the schedule is left free for these groups [1]. The expectation is that most people arriving to the PACU from these surgical specialisms will not have an indication and can be encountered by the 5th bed. Using the historic data of the five largest specialisms we first have obtained the percentage of demand of each specialism, in case they are the only five requesting specialisms. This is done in column two and three of 6.1. Because we have chosen to exclude 10% of the beds of the schedule, we will change the formula given in 6.1.Another change is that we will make a pattern of four weeks. Therefore we have modified the formula to
$d_i = percentage_i \cdot (c \cdot 5 \cdot 4 \cdot 0.9)$.

[1]the 10% that will be left free of the schedule in this case is verified by the anaesthetists. This room will be given exclusively by the department.

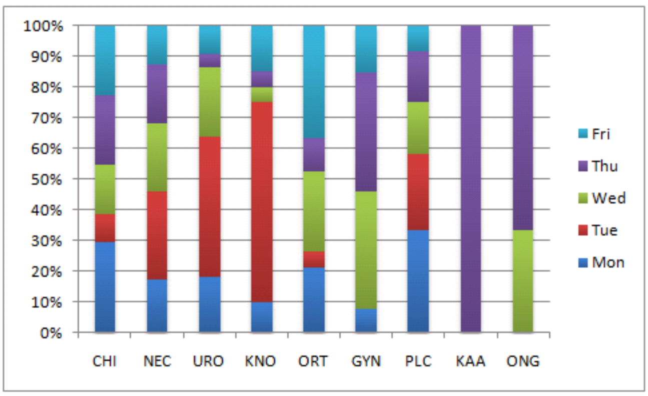

Figure 6.4: *Historic preferences weekday per specialism*

	Real %	New %	# beds to schedule	Integer	# each week	W1	W2	W3	W4
CHI	33%	38%	27,14	27	6,75	6	7	7	7
NEC	27%	32%	22,79	23	5,75	6	6	6	5
URO	10%	11%	7,96	8	2	2	2	2	2
KNO	9%	10%	7,24	7	1,75	2	1	2	2
ORT	8%	10%	6,87	7	1,75	2	2	1	2
	87%	**100%**	**72**	72	18	18	18	18	18

Table 6.1: *Schedule each week*

	(j): Mon	Tue	Wed	Thu	Fri
(i): CHI	0,29	0,09	0,16	0,23	0,23
NEC	0,17	0,29	0,22	0,19	0,13
URO	0,18	0,45	0,23	0,05	0,09
KNO	0,10	0,65	0,05	0,05	0,15
ORT	0,21	0,05	0,26	0,11	0,37

Table 6.2: *Matrix A*

We will apply the rounding algorithm for integer the demands for a total of four weeks (fifth column). Thereafter we decide the integer values for each week which will be implemented in the weekly scheduling model. The d_i for the four weeks can be found in column 7,8,9 and 10 of 6.1.

4. Preferable weekday rates. In graph 6.3 the mean elective arrivals on each weekday are shown. At Tuesday's the most patients arrive from elective surgery. The matrix a_{ij} is determined according to the formula at 6.1, and shown graphically in 6.4. The matrix can be found in 6.2.

We can define the integer program for scheduling the amount of beds for each specialism:

c = limit of PACU indications = 4
$j = 1, 2, 3, 4, 5$ = mon, tu, wed, thu, fri
d_i = demand of specialism i for each week
$i = 1, 2, 3, 4, 5$ =CHI, NEC, URO, KNO, ORT
For week one the d is:
$d_1 = 6$,$d_2 = 6$,$d_3 = 2$,$d_4 = 2$,$d_5 = 2$
a_{ij} = table 6.2
x_{ij}= amount of beds for specialism i on day j.

The formulation now becomes:

min $(x_{ij}/d_i - a_{ij})^+ - (x_{ij}/d_i - a_{ij})^-$
s.t. $\sum_i^5 x_{ij} \leq 4$
$\sum_j^5 x_{ij} = d_i$

6.2.1 Results integer model

If we set the parameters of demand according to 6.1 we can implement the integer programming formulation obtained in the previous section. We will use Excel solver for this. A schedule for 4 weeks will be determined. 80 (4 $beds \cdot 4\ weeks \cdot 5\ days$) beds have to be scheduled, but 10% will be declared unscheduled for the excluded groups.

Week 1	1	2	3	4	5	Tot
1	3	0	1	1	1	6
2	1	2	1	1	1	6
3	0	1	1	0	0	2
4	0	1	0	0	1	2
5	0	0	1	0	1	2

Week 2	1	2	3	4	5	Tot
1	2	1	1	1	1	7
2	1	1	1	2	1	6
3	0	1	1	0	0	2
4	0	1	0	0	0	1
5	0	0	1	0	1	2

Table 6.3: *Solver schedule*

Week 3	1	2	3	4	5	tot
1	2	1	1	2	1	7
2	1	1	1	1	1	5
3	0	1	1	0	0	2
4	0	1	0	0	1	2
5	0	0	1	0	1	2

Week 4	1	2	3	4	5	tot
1	2	0	1	2	2	7
2	1	2	2	1	0	6
3	0	1	1	0	0	2
4	0	1	0	0	1	2
5	0	0	0	0	1	1

Table 6.4: *Solver schedule*

	1					2					3					4				
	M	Tu	W	Th	F	M	Tu	W	Th	F	M	Tu	W	Th	F	M	Tu	W	Th	F
CHI	2	1	1	1	1	2	1	1	2	1	2	1	1	2	1	2	1	1	2	1
NEC	1	1	1	2	1	1	1	1	2	1	1	1	1	1	1	1	1	1	2	1
URO	1	1	0	0	0	0	1	1	0	0	1	1	0	0	0	0	1	1	0	0
KNO	0	1	0	0	1	0	1	0	0	0	0	1	0	0	1	1	1	0	0	0
ORT	0	0	1	0	1	1	0	0	0	1	0	0	1	0	1	0	0	0	0	1
	4	4	3	3	4	4	4	3	4	3	4	4	3	3	4	4	4	3	4	3

Table 6.5: *Final scheduling scheme*

The practical effectiveness of these schedules is doubted. The schedule for 4 weeks should be less alternating and the succesive weeks for each specialism must be more alike, logical and memorizable. With the help of field experts this pattern will be changed to an practical feasible schedule.

6.3 Final adjusted model

Using the percentages in a_{ij}, looking at the amount of operating rooms that will be used in the future, and consulting the experienced staff, the preferences for each specialsism are shown below:

- CHI There are 6 or 7 available beds for CHI each week that have to be scheduled. In history, we see most arrivals on Monday, with a slight decline on Tuesday, and an average rate on Wednesday, Thursday and Friday. Every day the CHI have at least one operating room. The aim is to divide the PACU patients equally for each day.
- NEC There are 5 or 6 available beds for NEC each week that have to be scheduled. Most arrivals are on Tuesday, average arrivals on Monday, Wednesday and Thursday, and a decline of arrivals on Friday. The operating rooms available for NEC are at least one every day of the week. Preferences for scheduling are from high to low: Tuesday, Wednesday, Thursday, Monday and Friday.
- URO There are 2 available beds each week to schedule for URO. Half of the arrivals according to history arrive at Tuesday. Thereafter Monday and Wednesday are preferred. There are almost no arrivals at the other two days. The operating rooms available for URO differ each week.

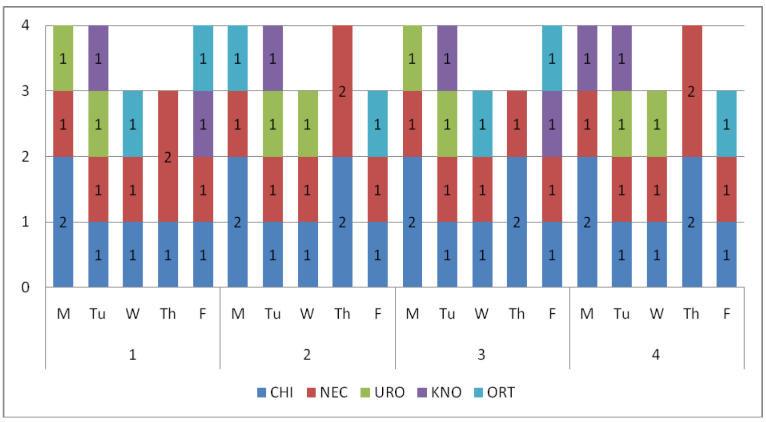

Figure 6.5: *PACU Schedule*

- KNO. There are mostly 2 available beds for KNO each week that have to be scheduled. 65% of the arrivals are on Tuesday's . Only on Thursday there are less operating rooms available for the PACU. On other day's the surgeries are not severe enough to deliver PACU patients. We will have to differentiate the arrivals to equalize them over the week, or two days.
- ORT There are mostly 2 available beds for ORT each week. The arrivals are primary on Monday, Wednesday and Friday. Only on Thursday less operating rooms are available for ORT.

Finally we were able to include all preferences, using the solver solution as starting pattern and change it to an optimal pattern. The pattern is shown in 6.5 and 6.5.

6.4 Conclusion

When taking the amount of bed reservations per day on the PACU as a fixed variable, we are able to obtain a patient admission schedule. Important factors of this scheduling problem are the integrality of the parameters, the preferable day per week and the opening of the OR on that day for each specialism. Optimizing the objective function, which is getting the most PACU admissions for each specialism's on their preferable day, given that they execute surgeries on that day, we have chosen to select the amount of specialism's that are schedules. Only the five biggest specialism's we implemented in the admission schedule, obtaining flexibility for the little specialism's by giving them more choices. Using a mathematical model we were able to obtain a patient admission schedule.

Chapter 7

Conclusion and recommendations

7.1 Conclusion

In this thesis we have answered five subquestions in order to be able to answer the main research question: *Is the current capacity of the PACU sufficient and how can we optimize efficiency?*. After exploring the environment of the PACU and the methodologies used in health are, we found that the simulation occupancy models can accurately approximate the efficiency levels, that is, the occupancy and blocking rate, for multiple capacity levels. Because we are uninformed about the amount of emergency PACU patients and unexpected elective patients which were rejected in history, we developed a method to estimate these patients. After this we implemented these rates in the simulation occupancy models. We would like to decide which model is the most realistic one, which is unfortunately hard to verify.

For all simulation occupancy models we have applied two policies; bed reservations and the limiting indication policy. The occupancy simulation models did not gave satisfactory results for the bed reservations policy. The bed flexibility is missing in this policy which resulted in low occupancy and a high blocking rate. We have seen that the policy of limiting the amount of PACU indicated patients from the OR improves the service levels. For a fixed capacity level, lower occupancy and blocking rates were found. Next to this, other advantages are obtained by this policy. First, the flexibility is large. There is always a bed available for unexpected patients which is preferable. Second, the structure for the staff on the PACU is more regulated. In the morning the OR schedule only shows a restricted amount of PACU indicated patients. Without this policy it often happened that trade-offs between specialisms had to be made, deciding which PACU patient would get to the OR, and which could be canceled.

Because of practical reasons, we have chose to derive a PACU admission schedule for a total capacity of five PACU beds. It is not likely that the capacity of the PACU can be enlarged in the next five years. We think that a patient admission schedule is necessary to avoid a first-come first-serve policy. The patient admission schedule is obtained for the five biggest specialisms using the PACU (derived by statistical research). In this way, the small specialisms have more opportunities to schedule their PACU days, and trade-off with each other. In order for the schedule to be user friendly, we developed a four week pattern. Within this four weeks we tried to be as consequent as possible for the planning within the weeks for each specialism.

There are two advantages of the patient admission schedule. First, implementing the patient admission schedule in the hospital will spread the PACU demand. Specialisms will have to spread their PACU patients over the week, providing less probability that a patient is rejected to the PACU, which means less specific care for the patient. Also the spread of demand diminishes the probability of a canceled surgery. The second advantage is the enlargement of attention for PACU patients. By implementing this schedule, specialisms will become more precise determing the post-operative destination of patients and the importance of it.

7.2 Recommendations and Advise to the board

This research resulted in a couple of solution methods improving the PACU planning and decreasing the amount of blocked patients. Since expending the PACU on short term is not a realistic option, we have focussed on maintaining the capacity level of five, concerning three goals:

- Obtaining more certainty about the arriving patients on a day, implying less PACU bed reservations on a day,
- Lower the amount of surgeries that are cancelled because no PACU bed is available,

- More certainty of bed availability for both emergency- and elective patients.

The solutions obtained in this research are:

- Set up a limit for the amount of PACU bed reservations which may be scheduled in for elective patients in Elpado each day.
- Implement a planning pattern for the biggest surgical specialisms on the OR supplying PACU patients.

Appendix A

Experts

- Drs. M. Feenstra, Anaesthetist, Medical specialist, EMC
- Drs. K. Leendertse-Verloop, Anaesthetist, Medical specialist, EMC
- Ir. Nathan, J.N., Manager clusterbureau 17, EMC
- Prof. dr. R.J. Stolker, Anaesthetist, Chief of anaesthesia department, EMC
- M. Vlasblom-Bosschieter, Anaesthetist, Medical specialist, EMC

Appendix B

Statistical tests

B.1 Goodness of fit tests

We will discuss briefly three goodness-of-fit tests.

1. Anderson-Darling test
   The Anderson-Darling test is a non-parametric test. A data sample is compared to a certain probability distribution. The test can be applied on continuous distributions. The nulhypothesis is:

   Ho: the sample data comes from a specified distribution

   and the alternative hypothesis is:

   Ha: the sample data does not come from a specified distribution

   The test statistic is given by $A^n = -N - S$ whereby $S = \sum_{i=1}^{N} \frac{2i}{N}[lnF(y_i) + ln(1 - F(Y_{N+1-i}))]$. F is the cumulative distribution function of the specified distribution and y_i is the ordened sample data.

2. Kolmogorov-Smirnov test
   This tests is less sensitive at the tails of the distributions compared to the Ansderson-Darling test. It is also a non-parametric test. The test can be applied on continuous distributions. The nulhypothesis is:

   Ho: the sample data comes from a specified distribution

   and the alternative hypothesis is:

   Ha: the sample data does not come from a specified distribution
   The tests statisics are: $D_n^+ = max(F_n(x) - F(x))$ and $D_n^- = max(F(x) - F_n(x))$ Hereby is F the specified distribution and x the data sample.

3. Chi-square test The Chi-square goodness-of-fit test is a parametric test which uses the distance between the histogram of the specified distribution and the histogram of the sample data (empirical distribution). Disadvantage compared to the Kolmogorov-Smirnov is that the Chi-square gives less trustfull results at smaller data samples. The test can be applied on discrete and continuous distributions. The nulhypothesis is:

   Ho: the sample data comes from a specified distribution

   and the alternative hypothesis is:

   Ha: the sample data does not come from a specified distribution

B.1.1 Fitting distribution of elective service times

Distribution	A-D	A-D P-Value	K-S	K-S P-Value	Chi-Square	Chi-Square P-Value
Beta	0,2436	—	0,0349	—	14,6355	0,200
Gamma	0,3112	0,435	0,0384	0,548	14,0374	0,298
Lognormal	0,3114	0,469	0,0380	0,511 14,0374	0,298	
Normal	0,4383	0,302	0,0439	0,428	15,3832	0,284
Logistic	0,6402	0,056	0,0451	0,233	16,4299	0,227
Max Extreme	1,2953	0,000	0,0687	0,013	23,1589	0,040
BetaPERT	2,0682	—	0,0738	—	25,2523	0,014
Weibull	3,0036	0,017	0,0930	0,017	23,0093	0,028
Triangular	3,3778	—	0,0843	—	31,6822	0,002
Min Extreme	3,6580	0,000	0,0927	0,000	42,4486	0,000
Student's t	5,5800	—	0,1298	—	112,4299	0,000
Uniform	17,7663	0,000	0,1906	0,000 126,6355	0,000	
Pareto	45,8490	—	0,3597	—	313,2523	0,000
Exponential	77,4563	0,000	0,5362	0,000	1164,5421	0,000

Table B.1: *Goodness of Fit test Elective Service Times Distribution*

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