LEIDEN UNIVERSITY MEDICAL CENTER

Workload leveling of nursing wards in Leiden University Medical Center

JURJEN TJOONK

13 DECEMBER 2010

Workload leveling of nursing wards in Leiden University Medical Center

Date
13 December 2010

Author
J. Tjoonk
Industrial Engineering & Management
School of Management & Governance
University of Twente, Enschede

Supervisors
Dr. Ir. E.W. Hans
Operational Methods for Production and Logistics
School of Management & Governance
University of Twente, Enschede

Ir. M.E. Zonderland
Stochastic Operations Research
Department of Applied Mathematics
University of Twente, Enschede

Cover: zorginbeeld.nl / Frank Muller

Management summary

Introduction

In this report, which was written in the period April – December 2010, we study the variability in bed demand at the LUMC Division 1 wards caused by the elective surgery planning. A high variability in bed demand is unfavorable for many reasons, but particularly personnel planning. This study proposes a decision support tool that quantifies the steady-state ward bed demand for a given master surgical schedule - the cyclic OR block plan. We use this tool to generate and evaluate alternative MSSs that level the bed demand.

Approach

We use the model of Vanberkel (2009) to model the expected bed demand resulting from an MSS. We extend the model with a heuristic in order to generate alternative MSSs that improve workload leveling by swapping OR blocks. We introduce the workload level performance indicator which is defined as the sum of the quadratic difference with the mean bed demand for every day in the MSS, to compare the alternatives.

Results

- The heuristic reduces the workload level performance indicator with 46,9% percent, taking into account only the Division 1 ORs, by making four OR swaps
- The maximum bed demand is reduced from 74 (the initial model output) to 71 beds, indicating the possibility of decreasing the number of staffed beds
- An improved workload leveling and reduction of the maximum bed demand is possible when more OR time is available on Monday. The performance indicator of workload leveling then reduces by 65,1% and the maximum bed demand decreases from 74 to 70 beds, but eight swaps are needed to reach this performance

Conclusions

- The best two swaps are to swap empty OR blocks of Monday with Traumatology blocks of Tuesday and Thursday in the second week of the MSS
- The proposed best swaps considers swapping OR blocks that have a high expected value of OR production (the input parameter of expected number of patients that follows from one OR block)
- The importance of higher level of detail of the MSS is invalidated in the LUMC case, since the same decisions are proposed by the heuristic when the level of detail is reduced

Recommendations

- Inform the physicians about the outcome of this study
- Discuss the possibilities of the OR swaps that follow from the proposed best swaps
- In order to improve the workload leveling of the wards, the OR center should carry out more procedures on Monday by moving OR blocks from Tuesday to Thursday in the second week of the cycle to the Mondays
- Discuss the possibilities of exchanging OR time with non-division 1 specialties

Table of contents

Preface

This report is a Master thesis for the study Industrial Engineering and Management with the specialization Production and Logistics Management. The study has been carried out in Leiden UMC and I am very pleased with the result. I would like to thank several people that helped me during the process of this final project.

First, I would like to thank my supervisors Maartje and Erwin for their constructive comments on the report. I experienced the meetings and discussions as very pleasant.

Also, I thank my colleagues from Division 1 for their advice, support and contribution to a very enjoyable working environment.

And last but not least I would like to thank my family and my girlfriend Sharon for their mental support, especially at the start of the project.

Jurjen Tjoonk
Leiden, December 2010

1. Introduction

Patients that undergo surgery at the Leiden University Medical Center (LUMC) Operating Room center (OR-center) need to recover from these procedures. Recovery takes place at the Intensive Care and nursing wards. The wards face high variability in bed occupancy caused by the planning of the OR center. The activities of the OR center are governed by the Master Surgical Schedule (MSS) and it states which patient types receive surgery on which day. Driven by the fact that health expenditures increase, the population is ageing, and efficiency becomes more and more important, the focus in this thesis is on leveling the workload at the nursing wards by quantifying the impact of a certain MSS and propose alternatives. We use a multi-departmental view in this research and include uncertain patient characteristics. This project is part of a larger project that started at the beginning of 2010 focusing on operational excellence of the nursing wards of Division 1. Division 1 consists of most surgical specialties.

This chapter describes the research approach and will provide background information about the hospital and the departments relevant for this study. Paragraph 1.2 discusses the problem definition. In order to fulfill this research successfully its objective followed by the research questions is defined in Paragraph 1.3.

1.1 LUMC

The LUMC is one of the eight University Medical Centers in the Netherlands and employs approximately 7000 professionals. A few general facts of the hospital are provided in Table 1.1. The hospital is divided in five divisions, the directorates, three councils, the executive board and the supervisory board. The divisions 1, 2 and 3 are involved with direct patient care and have a comparable structure. Divisions 4 and 5 focus on the research and education. The structure of Division 1 will be described.

Table 1.1: General information of the LUMC
Source: annual reports LUMC

Patient Health Care	2006	2007	2008
Nursing days	141.128	137.633	139.372
Inpatient	18.908	19.296	20.043
Outpatient	11.957	13.950	15.612
Emergencies	12.451	8.943	8.118
Cancellations	5,3%	4,5%	3,7%

1.1.1 Division 1

Division 1 consists of seven specialty units, two interdivisional centers, the Central Sterilization Service, the Physiotherapy Service and three wards. At the top of this division are the managing director, the health care manager and the division chair (a physician which also is a professor). The next layer contains the Medical and the Nursing heads of the specialties or departments which are respectively a physician and a registered nurse. All specialties and departments have their own managers and they report to the previously mentioned managers of Division 1. The composition of the division is given in Figure 1.1. The figure also shows the subspecialties and the other (shared) departments of Division 1.

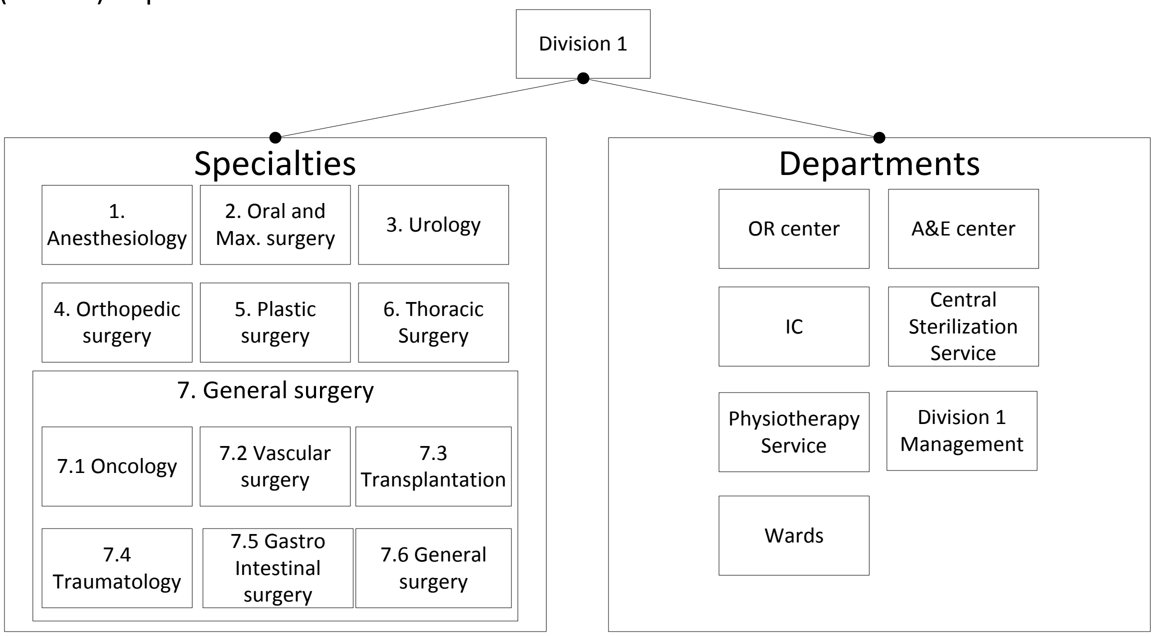

Figure 1.1: Division 1 composition

1.1.2 Nursing wards

All patients that have had surgery and need to recover eventually go to the nursing ward. Patients arrive at the wards via various trajectories. These are shown in Figure 1.2. The total group of admission patients consists of elective and non-elective patients. The elective patients go to the ward when they enter the hospital and will be prepared for their procedure. Non-elective patients arrive at the ward either via the A&E or through an outpatient clinic. It is also possible that patients from the A&E center first go to the Intensive Care (IC) or the Post Anesthesia Care Unit (PACU) after surgery. The PACU is comparable with an IC but the difference is that the patients that go to the PACU need intensive care for just a short period of time. Division 1 has three wards that only serve Division 1-patients. The wards are divided according short versus long stay and the long stay is divided per specialty. More information about the wards is provided in Chapter 2.

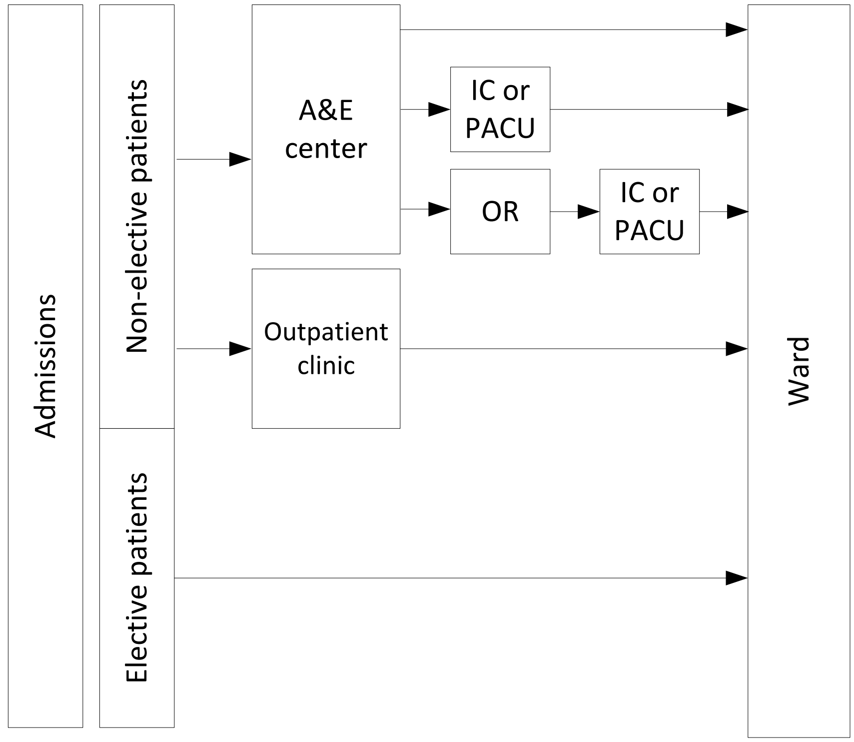

Figure 1.2: Patient flow

1.2 Problem definition

This study is part of a bigger project called LOPEX which stands for LUMC Operational Excellence and started in February 2010. An external consultant was hired to lead this project, with main goal to change procedures at the nursing wards of Division 1, in order to make them more efficient and to increase the quality of care. The processes are analyzed by a problem analysis technique called Brown Paper Analysis (BPA). Together with nursing staff the department's processes are put on a large brown paper. Then the problem and solution areas are pointed out. These areas are prioritized and four cluster problems are defined for further analysis. One of the cluster problems for the LOPEX project is the bed planning of the nursing wards. This evolved into a separate project called LOCAP which stands for LUMC Operational Capacity management. The Division 1 nursing wards have a joint capacity of 88 beds and need to allocate the beds in such a way that the patients receive the care they need. The planning method is elaborately discussed in Chapter 2, but a small summary is given.

The planning of the wards is influenced by the OR-planning of the elective patients and the uncertain arrivals of emergency patients. All specialties have their own OR-time slots and plan patients individually. The specialties fill their time slots with medical procedures. The result is called the Master Surgery Schedule (MSS). From this follows the nursing capacity the specialties need in order to provide a bed for each patient. Because the demand for beds is not coordinated between the specialties, this results in inefficiencies. The head nurses of the wards have indicated the following points:

- Bed planning at the wards takes a lot of time because it is often not clear whether there are any beds available
- Patients are cancelled because there are no beds
- Not enough beds are reserved for emergency patients
- More patients are planned than there are beds available, which results in peak workloads and stress
- The nursing capacity is too low

The above mentioned points are not based on quantitative data but ask for further exploration of the ward bed planning. A way to quantify the problem is to calculate indicators that can support the feelings of the head nurses. An extensive data analysis is presented in Chapter 2, but a first indication of the results is necessary for the remainder of this chapter.

From literature it is known that a constant arrival process is preferable over a highly fluctuating arrival process, since variability will result in peaks and congestion at upstream resources. At Division 1 there are two patient groups, namely elective and non-elective patients. These groups should be viewed and analyzed separately. From the admission pattern in Figure 1.3 and 1.4, we learn that the data shows a leveled load for the emergency patients, but not at all for the planned electives. The latter results in peak workloads and cancellations of patients, but also in empty beds at certain moments. The elective patient arrival is influenced by the MSS, since those patients are planned in advance. The elective patient group covers 80% of all patients, so a focus on the elective patient planning has the largest impact. Smoothing the elective patient arrival streams will likely result in a more leveled bed availability for non-elective patients in the planning, together with better working conditions for the personnel.

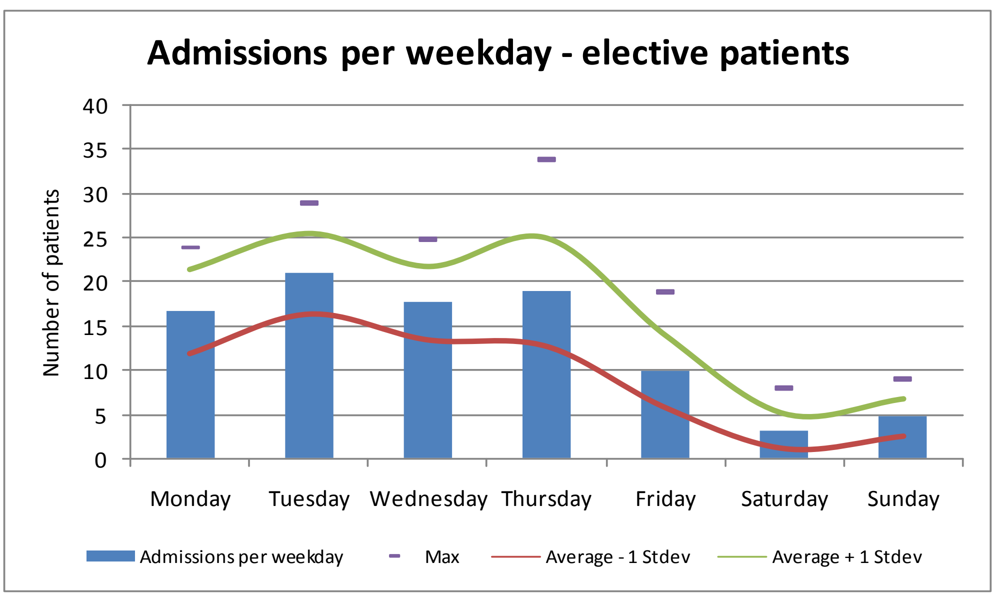

Figure 1.3: elective admissions per weekday
Source: MIS, 2008, n=4880

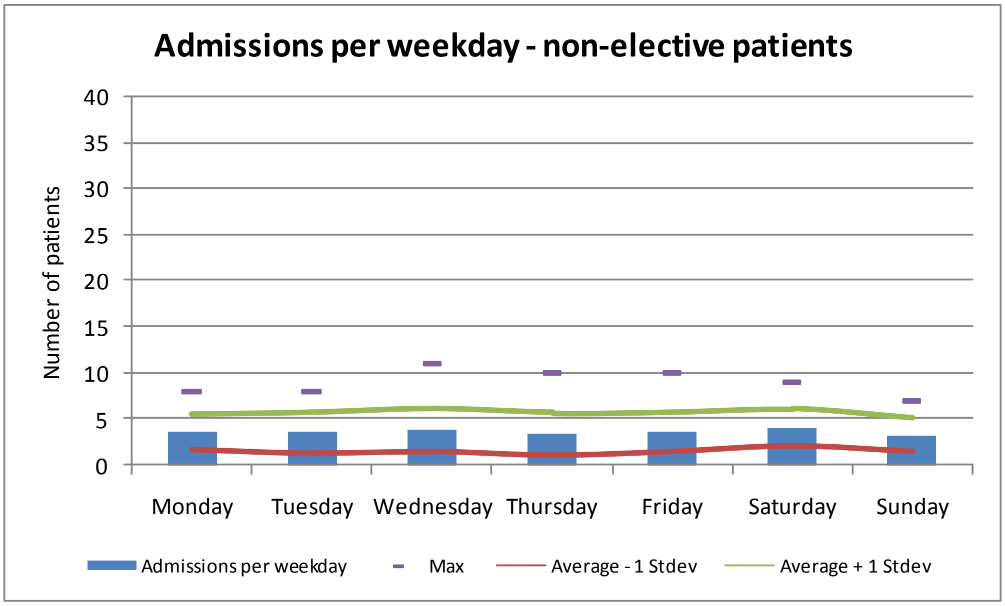

Figure 1.4: Non-elective admissions per weekday
Source: MIS, 2008, n=1336

1.3 Research objective

It is clear that capacity management of the nursing wards should be investigated since there is a lack of insight in the available bed capacity on the wards. Furthermore independent surgery planning of the specialties results in peak workloads at the wards and cancellation of patients. Therefore the first phase of the LOCAP project is about obtaining more insight in the management of bed capacity and the regulations that play a role. The second phase of the LOCAP project, described in this thesis, concerns the relationship of the MSS with the workload at the wards. The research objective is defined as follows:

Propose a decision support tool that models the workload of the nursing wards as a function of the MSS in order to level the workload and decrease peak workloads.

1.3.1 Research questions

To reach the objective, and to structure this research, we define the following sub questions:

1. *What are the current processes and planning methodology?*
   [Process analysis]

This first question will provide information about the nursing wards and the processes for elective patients, and is discussed in the first and second paragraph of Chapter 2.

2. *Which indicators express the workload at the wards resulting from elective surgeries carried out at the OR-center?*
   [Data analysis]

With answering this question quantitative evidence for the workload variability in the current situation at the wards is provided. Data of the year 2008 is analyzed to define patterns in the data (Paragraph 2.3).

3. *What models are useful in workload leveling at nursing wards and take into account the relationship between the OR-center and the wards?*
   [Literature review]

This third question concerns a literature review. It will focus on models that level the workload of the succeeding departments of the OR center (Chapter 3).

4. *In what way can the MSS block planning be adapted, taking into account the same procedure demand, in order to level the workload at the wards?*
   a. *How is the demand for ward beds modeled?*
   b. *How can the model be used to come up with an alternative MSS?*
   c. *What is the performance of the alternatives?*

   [Model + Results]

In Chapter 4 we present the model that we use to model the demand for beds. Also the model is extended in order to serve as a decision support tool. The outcome and further implications of the model are presented in Chapter 5.

5. *What are the implications for practice?*
   [Conclusions and recommendations]

At last we question how to make the theory useful in order to level workload at the wards. Finally, Chapter 6 draws the conclusions and recommendations of this thesis.

2 Process analysis

This chapter describes processes that are relevant for this study. Paragraph 2.1 concerns the patient flows. Paragraph 2.2 handles patient planning for the specialties. The OR-planning as well as the hospitalization planning is discussed. In Paragraph 2.3 the nursing ward performance is discussed.

2.1 Nursing ward process

There are two patient groups of which only the elective patients are important in this study, since the focus lies on this group. This is the reason why the non-elective patient process will not be discussed. Elective patients can be divided per specialty and every specialty has their own nursing team and beds on the ward.

2.1.1 Elective patient process

Patients scheduled for surgery first undergo a pre-operative screening at the Anesthesiology department. This takes place during a separate visit to the hospital. The outcome will determine whether the patient is ready for surgery. A surgery has a large impact on the patient so the physical condition of the patient should be sufficient. If so, the patient is approved for surgery and returns at the specific surgery date. The pre-operative screening is not included in the research.

The elective patients that check in for surgery will first visit the nursing ward to be prepared. The check in can be at the day of surgery but also the day before. After preparation they are transported to the OR and undergo surgery. Depending on the type and outcome of the surgery the patient can be transferred directly to the nursing ward or first visit the IC or PACU.

2.1.2 Ward configuration

Division 1 has three wards where various teams operate. An overview is provided in Table 2.1. In the current situation, the beds of the three nursing wards are dedicated to specialty teams. Table 2.1 shows that this means team orthopedic surgery has fifteen beds to hospitalize patients. In practice it happens that the beds are used in a flexible manner, so that patients can recover at another ward if there is no place at their ‘home ward’. The hospital strives to move these patients as soon as possible to the ward they belong to. In case all wards are full, other divisions are asked for empty beds. Patients are transferred to other hospitals if there are no empty beds. In practice this last point is only relevant for non-elective patients.

Table 2.1: Nursing wards Division 1 LUMC, 2010

Ward	Operational capacity (# beds)	Physical capacity (# beds)	Teams (# beds)
J-09-Q	32	34	– Team Orthopedic surgery(15) – Team Plastic surgery (1) – Team Urology } see Team Traumatology – Team Traumatology } 16 flexibly used with Urology
J-10-P	20	28	– Team Transplantation surgery (10) – Team Vascular surgery (9) – Oral and maxillofacial surgery (1)
J-10-Q	36	40	– Team Oncology (10) – Team Gastrointestinal surgery (10) – Short stay (16)
Total	**88**	**102**	

Source: LUMC intranet, May 2010
Operational capacity: official nurse/bed ratio
Physical capacity: maximum number of beds that fit on the ward

2.2 Planning methodology

Patients, in most cases, need to visit more than one department in a hospital on multiple occasions. In this study about hospitalization, patients visit the OR or A&E combined with the nursing wards. The planning of patients for the specific departments is done independently. This means that the OR-planning does not take into account the number of available beds at the wards which happens in reality. In the following subparagraphs we discuss the OR- and hospitalization planning.

2.2.1 OR-planning & surgery planning

At LUMC the OR-planning is leading since the OR center is considered as the most valuable asset. The planning consists of three stages. The process of the patient planning is graphically shown in Figure 2.1 (based on Van Houdenhoven (2007)). The first stage is the case mix planning. The available OR-time is divided by the OR-manager in cooperation with the heads of the specialties. The result is a schedule with time slots (OR-time) for every specialty. These decisions belong to the strategic level. In stage two each specialty fills the time slots with a subspecialty or surgery type with corresponding surgeons. The result is a Master Surgical Schedule (MSS). Stage three is the actual planning of the patient and belongs to the operational level. This is divided in an offline (for elective patients) and online (for non-elective patients) planning. A more formal description of OR-planning is provided in the literature review in Chapter 3.1.

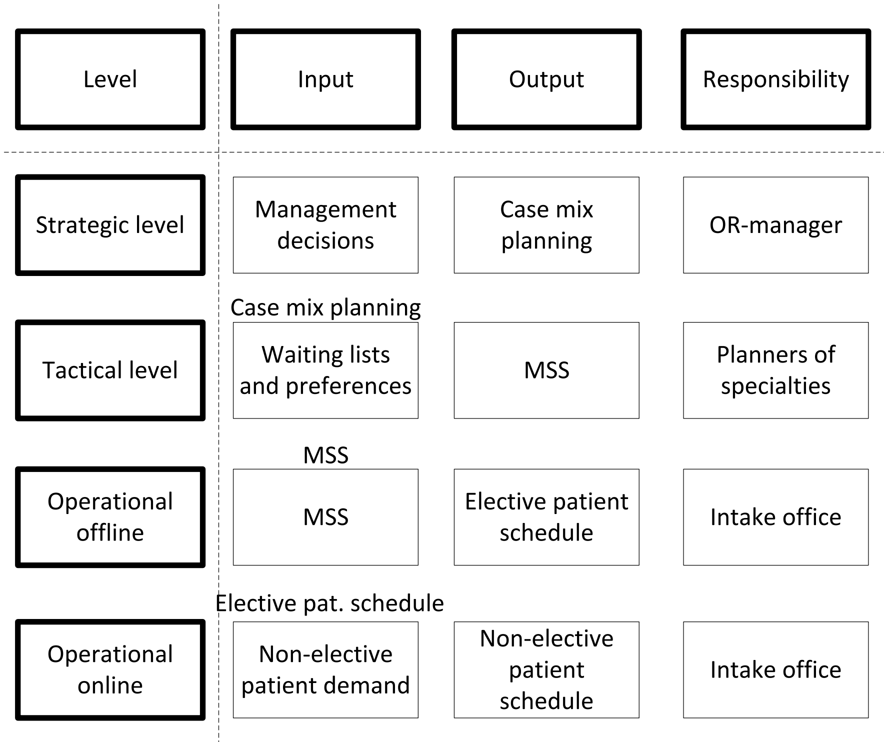

Figure 2.1: Planning framework OR center
(Based on Van Houdenhoven, 2007)

2.2.2 Hospitalization planning

After the surgeries are planned, the intake office then will insert the appointments in the agenda and inform the patient about the procedure. This office then collects all procedures and defines the total demand for the wards. As a result, the ward planning follows directly from the elective surgery planning. The wards inform the office about their actual capacity in the number of staffed beds. This capacity can vary for example because of illness of nurses. If demand is larger than the ward capacity the bureau tries to switch patients, or if this is not possible, inform the head of the nursing wards about the lack of capacity. The head will then find another solution. This takes a lot of time and effort. No beds are reserved for non-elective patients.

2.3 Restrictions for the MSS

This paragraph discusses the restrictions for the MSS. Subparagraph 2.3.1 the level of control for a MSS. Subparagraph 2.3.2 the performance for a MSS and Subparagraph 2.3.3 the optimization constraints for a MSS.

2.3.1 Level of control

The MSS is a cyclic OR schedule; in most hospitals one MSS cycle represents two weeks. The construction of the MSS takes place at the tactical level of control and is constructed by the OR manager. The process of constructing a MSS is complex because there are many factors that play a role. The total OR-time is shared by various specialties. For these specialties, several physicians perform the procedures. But physicians have many other tasks next to operating, such as outpatient consultations, conferences, staff meetings, lecturing, and sometimes work at other hospitals too. Next to the physicians, ORs also have limited capacity or are dedicated to specific specialties.

2.3.2 Performance of a MSS

There is no clear definition of the performance of a MSS. In the previous paragraph we mention the complexity of constructing a MSS and this is mainly focused on the availability of personnel and resources of the OR center. Overcoming these constraints makes the MSS feasible. In the current situation the performance of the LUMC MSS is not evaluated with respect to quantitative outcomes. This research quantifies the performance of a MSS using the performance indicator of workload leveling. We present the definition of this indicator in Chapter 5. The model for the calculations of expected bed demand is presented in Chapter 4.

2.3.3 Optimization constraints

In this study, we present a model to calculate the expected bed demand derived from a MSS. This makes it possible to compare alternative MSSs, and to find a better MSS. Many different schedules are possible in constructing an alternative MSS. For a two week cycle with ten work days (weekends are excluded) and ten ORs, (10x10)! unique alternatives (OR-block swaps) can be constructed. This tremendous amount of alternatives is impossible to calculate in polynomial time and therefore it takes mathematical programming to calculate the optimal MSS. But not all alternative MSSs are feasible. The planning of some procedures can sometimes not be changed. The most common reasons are summarized below; these are the constraints in the model.

- Some ORs are dedicated to specific specialties or procedures
- Physicians have other responsibilities

An important constraint is the limitation in the number of changes in the MSS. As said before, changing a MSS is difficult for various reasons and therefore it is desirable that an alternative MSS only has little changes. The proposition of alternative MSSs is discussed in Chapter 5.

2.4 Workload at the nursing wards

This section will elaborate on the current workload variability at the nursing wards. In the problem description the feelings of the nurses are already discussed. In short, planning of the wards takes a lot of time and discussion. Also there is no clearance about the available capacity at a given moment and the differences of workload vary a lot. In this section data from the Management Information System (MIS) is used to generate quantitative evidence for these arguments. To analyze the workload, a query was defined to collect the useful data. Table 2.2 shows the variables. Also a clear definition of workload variability is necessary to avoid misunderstandings:

The definition of workload variability is in this study the sum of all variances of the expected bed occupancy minus the average bed occupancy over the steady-state MSS cycle for every day

The definition of bed occupancy and bed demand in this study is the exact number of beds occupied on a specific time of the day

In this chapter only the existence of workload variability is justified. Performance measures concerning workload variability are presented in Chapter 5, because in this chapter steady-state MSSs are presented.

Table 2.2: Query

Group	Variable	Group	Variable	Group	Variable
Hospital	Department code	*Patient*	ZIS number	*Time*	Year
	Admission type		Contact number		Start day/time
	Specialty		Urgence		End day/time

Table 2.3 gives an overview of nursing ward admissions, with the number of patient per year, ward ID and patient type. The numbers are used to obtain a feeling for the scale of the patient groups. The subparagraphs discuss three performance indicators that are used to conclude on the workload at the nursing wards. Respectively the admissions and discharges, the ward occupancy and the patient Length of Stay (LOS) are discussed.

Table 2.3: Number of nursing ward admissions in 2008 (source: MIS)

Year	**2008**					
Ward	**Elective**	**Percentage**	**Non-elective**	**Percentage**	**Total**	**Percentage**
General surgery 1	864	17,2%	348	26,0%	1212	19,1%
General surgery 2	696	13,9%	248	18,6%	944	14,9%
Orthopedic surgery	666	13,3%	192	14,4%	858	13,5%
Urology	539	10,8%	410	30,7%	949	15,0%
Short stay	2244	44,8%	138	10,3%	2382	37,5%
Total	5009	100,0%	1336	100,0%	6345	100,0%

2.4.1 Admission and discharge of patients

Figures 1.3 and 2.2 show a high variability for the admissions per weekday for elective patients, but the arrival of emergency patients showed a smooth line.

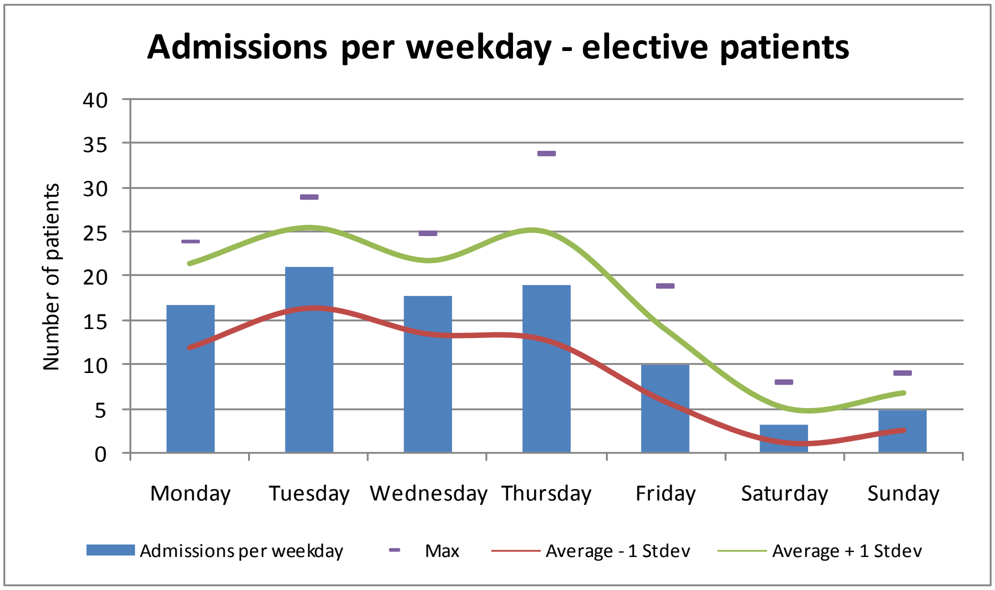

Figure 2.2: elective admissions per weekday
Source: MIS, 2008, n=4880

Figure 2.2 shows that on average the number of admissions on Tuesdays is higher than on any other weekday and that the variability is highest on Thursdays. Since OR-time slot are defined for a whole year this could indicated that on Tuesdays Division 1 has more time slots. It could also mean that on Tuesday shorter surgeries and thus more patients are planned than other days resulting in increased admissions. To confirm this, further investigation of the surgery schedule is needed, but the fact is that the number of admissions significantly differs per weekday. The confidence intervals in Table 2.4 and Figure 2.7 validate this. To illustrate the variability of the arrivals of the elective patients, we use April 2008 as an example. For every day in April 2008 the admissions are counted in displayed in Figure 2.3. We see that the variability of elective patients seems quite high, especially comparing it to the non-elective admissions.

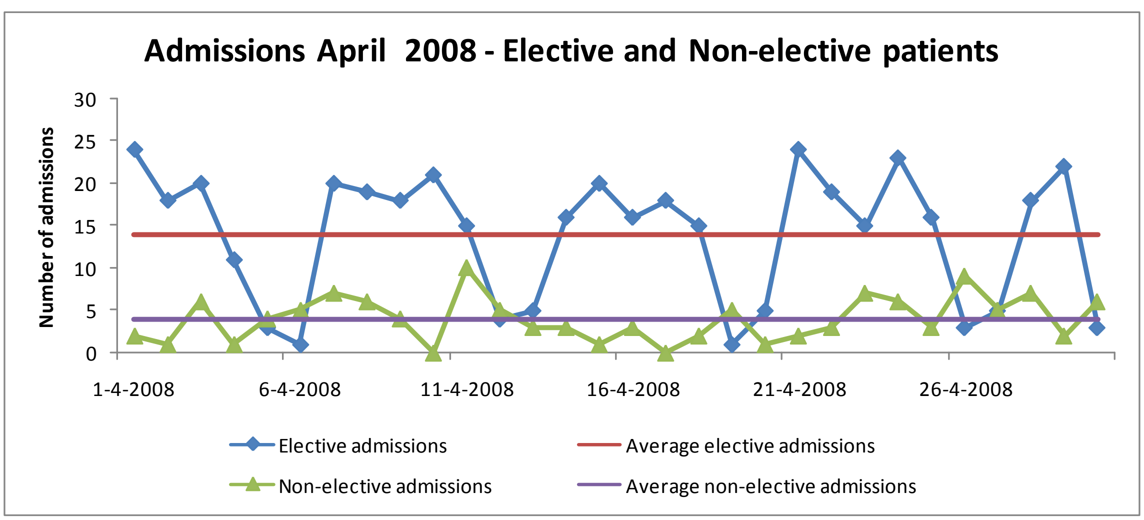

Figure 2.3: Admissions April 2008
Source: MIS, 2008, n=418

To further study the variability of admissions between the weekdays confidence intervals in Figure 2.4 are used to analyze the differences. The weekdays are significantly different if their confidence intervals do not overlap. The formula used for calculating the confidence intervals is $x \pm Z * (s/sqrt(n))$, where x is the mean, Z represents the confidence level, s the standard deviation, and n the number of data points.

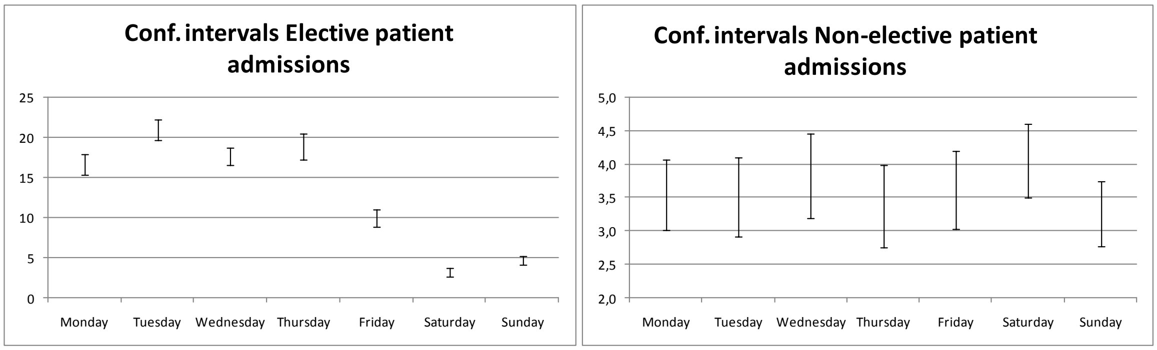

Figure 2.4: Confidence intervals patient admissions
95% (Z=1.96) confidence interval

Table 2.4 summarizes the confidence intervals of Figure 2.4. For the elective patients there are many significant differences indicating variability in the admissions. The admissions of non-elective patients show no significant differences indicating low variability.

Table 2.4: Significant differences of admissions between weekdays

Elective admissions	Significant difference						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday		yes	no	no	yes	yes	yes
Tuesday	yes		yes	no	yes	yes	yes
Wednesday	no	yes		no	yes	yes	yes
Thursday	no	no	no		yes	yes	yes
Friday	yes	yes	yes	yes		yes	yes
Saturday	yes	yes	yes	yes	yes		yes
Sunday	yes	yes	yes	yes	yes	yes	

Non-elective admissions	Significant difference						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday		no	no	no	no	no	no
Tuesday	no		no	no	no	no	no
Wednesday	no	no		no	no	no	no
Thursday	no	no	no		no	no	no
Friday	no	no	no	no		no	no
Saturday	no	no	no	no	no		no
Sunday	no	no	no	no	no	no	

The same procedure is executed for the discharge of patients. In this part we only show the confidence intervals of the patient discharges per weekday. The figures and tables can be found in Appendix A. Figure 2.5 shows the significant differences at the long and short stay wards. For the long stay wards most patients are discharged at Friday, before the weekend. For the short stay wards the figure is as expected. Since this ward is closed in the weekend, the discharges on Sunday are zero and low on Mondays. The other days show comparable numbers.

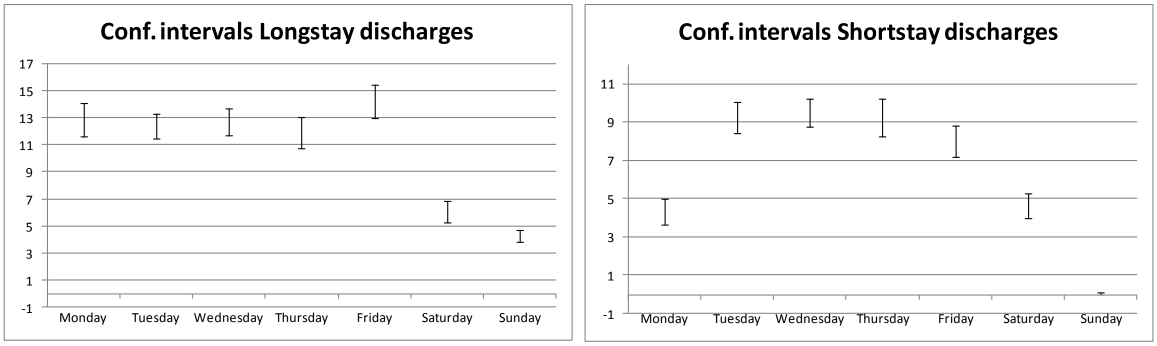

Figure 2.5: Confidence intervals patient discharges
95% (Z=1.96) confidence interval

For the long stay patient the difference of Friday is only significant with Saturday and Sunday. For the short stay facility the difference of Monday is confirmed.

2.4.2 Bed occupancy

An important indicator for the workload at the wards is the bed occupancy. In this paragraph the bed occupancy for various patient groups are presented and discussed. The definition of bed occupancy in this case is the exact number of beds occupied on a specific time of the day.

Figure 2.6 shows the total occupancy for the year 2008. During summer there is a lower occupancy and also during Christmas and New Year there are fewer patients. This is due to closure of ORs in these weeks.

The capacity line at 88 beds is the joint ward capacity of Division 1. The figure shows two days that pass the capacity of 88 beds but in reality it is common that the capacity is lower due to personnel shortage which causes closure of beds. Because of this fact there are more days with over occupancy. Also patients are registered as cancelation if their appointment is canceled more than 24 hours in advance. Because of this fact, in reality the number of days that demand exceeds capacity is higher. Table 2.5 provides some general conclusions of the total occupancy.

Table 2.5: General facts of total occupancy

	Number of beds
Minimum	39
Maximum	92
Average	69,6

Capacity used	Percentage of days per year
<85%	61.2%
85% - 90%	18.9%
>95%	9.3%

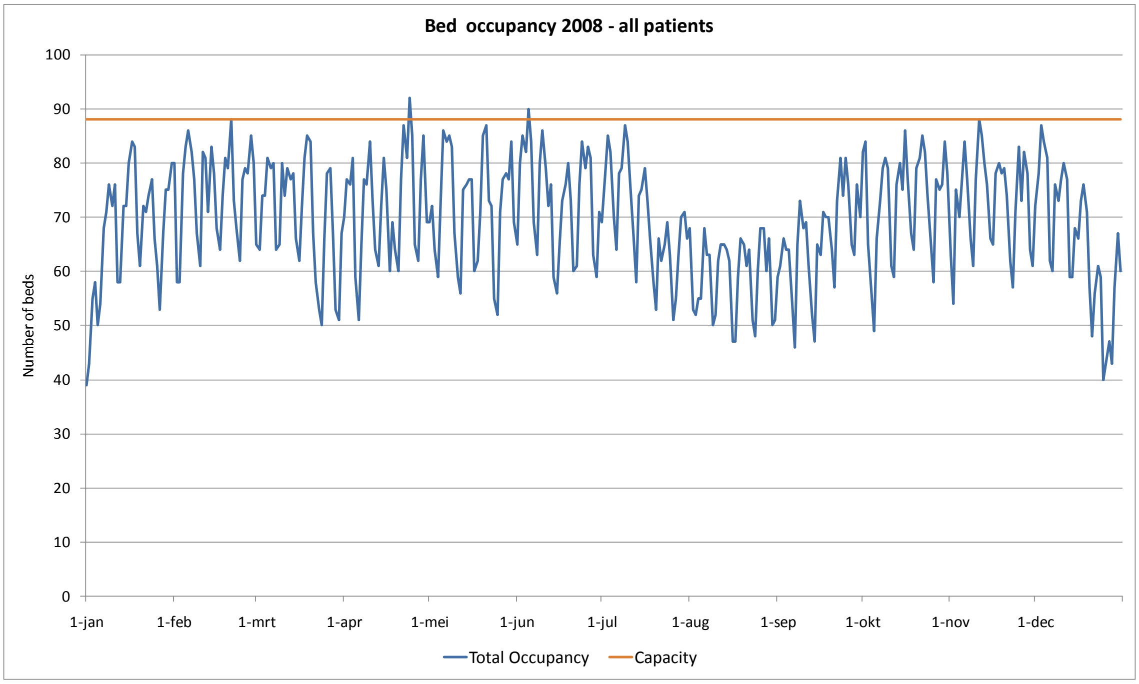

Figure 2.6: Bed occupancy for 2008
Source: MIS, 2008, N=6300

Figure 2.7 shows the bed demand for the elective and non-elective patients. The figure shows high variability of the occupancy of the elective patients and a smoother line for the non-elective patients.

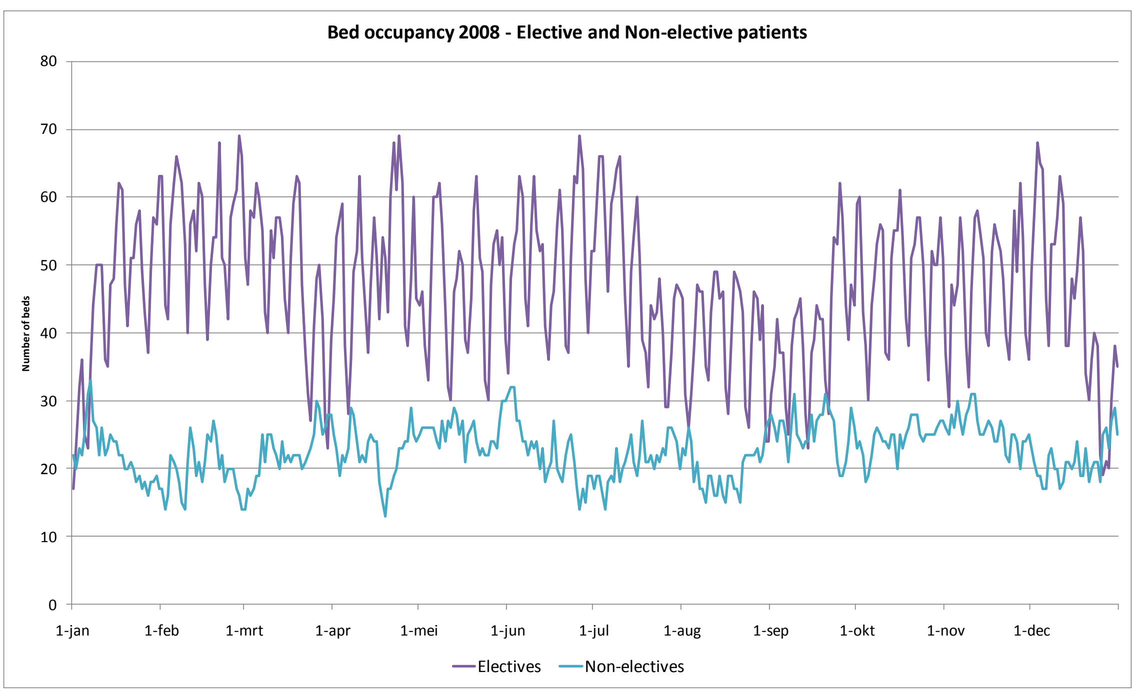

Figure 2.7: Bed occupancy elective and non-elective patients
Source: MIS, 2008, N=6300

Figure 2.8 shows the bed demand for the month May. The non-elective patient group shows a steady occupancy. The elective patient group shows many up and downs. This is probably due to weekends, when the short stay facility is closed. Therefore the total patient group is also split in long and short stay admission. This is the difference between VA02 (short stay facility) and the other ward admissions. Still the long stay patient group shows up and downs.

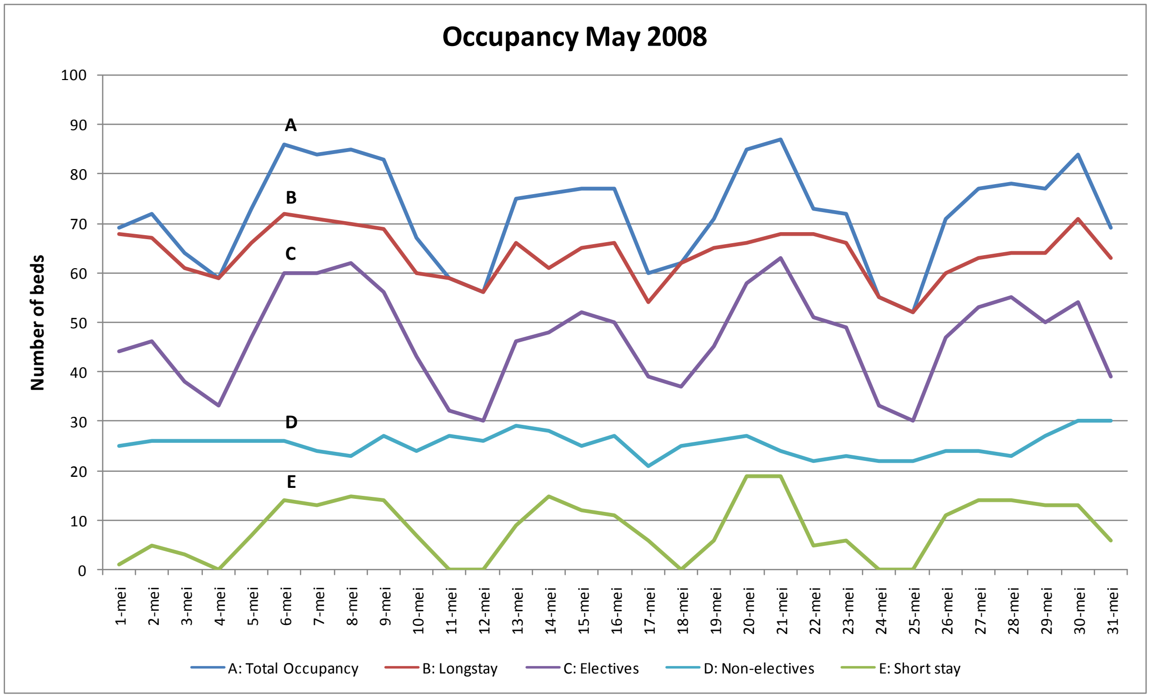

Figure 2.8: Occupancy May 2008
Source: MIS, 2008

For the remainder of this study it is useful to see which months of the year can be used to validate the model presented in Chapter 4. Some months probably should be excluded because they cannot be compared to the others. Again confidence intervals are used to see which months are likely comparable and which months should be excluded.

Figure 2.9 shows the confidence intervals for the patient groups. The figure of the elective patients shows that the intervals of February, August and September do not overlap with most other months. Removing the three months and use the other nine as input should be considered to improve the correctness of the model results.

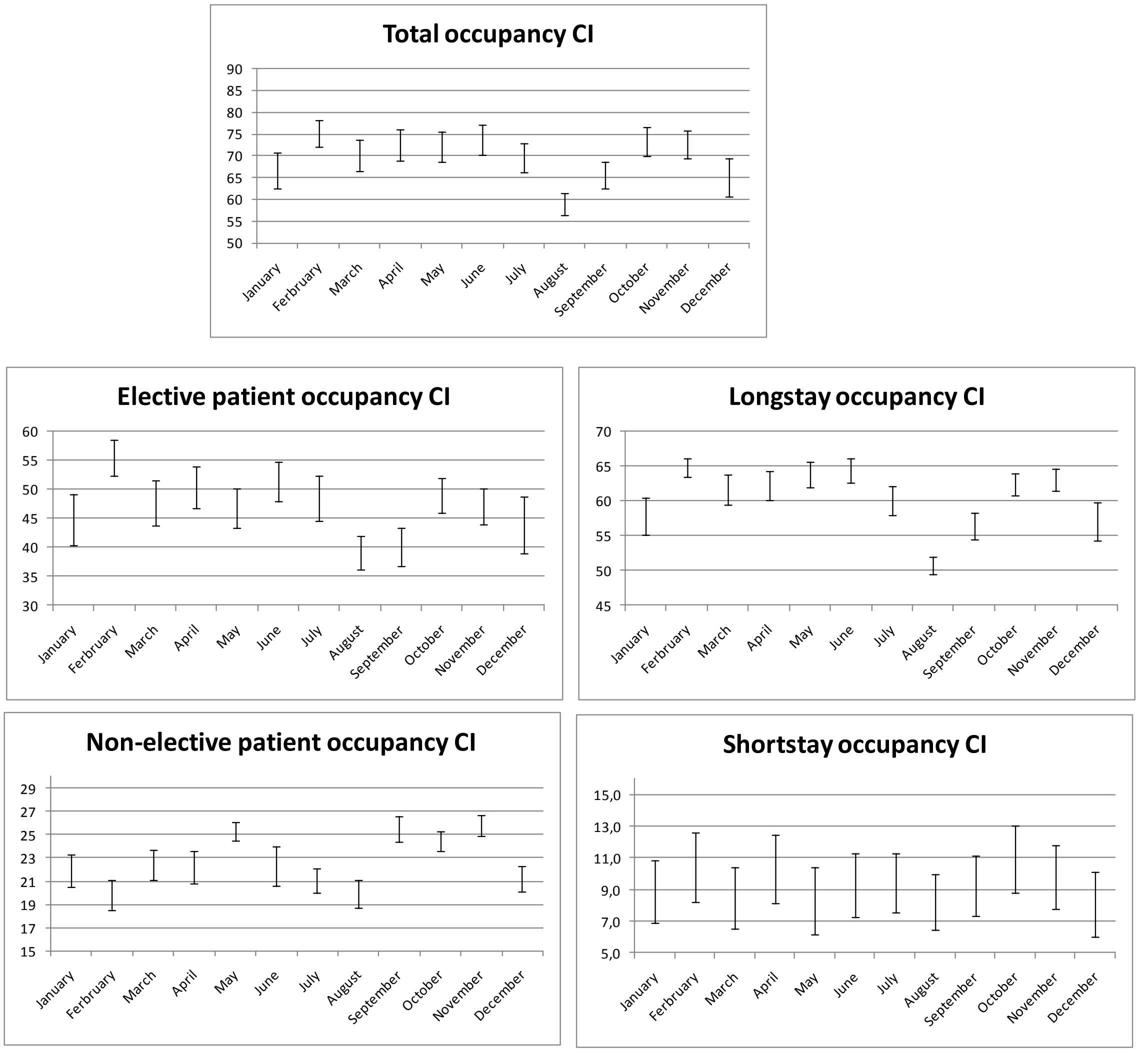

Figure 2.9: Confidence intervals bed occupancy
95% (Z=1.96) confidence interval

2.4.3 Length of stay

This paragraph concerns the Length of Stay (LOS) of the patients. Table 2.6 shows the average LOS of the specific patient group. Taking not only the average but the total distribution, the figures show a lognormal distribution. These can be found in Appendix B. The lognormal distribution is often mentioned in literature (Strum, 2010).

Table 2.6: Average Length of Stay
Source: MIS, 2008

Length of Stay (days)	2008
All patients	3.8
Elective patients	3.2
Non-elective patients	6.0
Long stay ward	5.6
Short stay ward	0.9

Summary

- Around eighty percent of all admissions consist of elective patients
- Elective admissions show high variability
- Non-elective admissions show low variability
- Short stay discharges of Mondays are significant different from the other weekdays
- Long stay discharges per weekday are not significant different
- The bed occupancy per day of elective patients shows high variability
- The bed occupancy is low during summer and Christmas
- The LOS of the patient groups show a lognormal distribution and this matches the literature
- This thesis focuses on the elective patient group because,
    - Elective patients account for eighty percent of the total patient population and therefore has the biggest impact on the bed occupancy and workload
    - The planning of elective patients can be influenced
    - In the near future there probably will be an emergency ward
- Changing the MSS is difficult, because physicians have many other tasks
- Based on the paragraphs of the patient admissions and the bed occupancy, we conclude that the feelings of the nurses about the capacity shortages and peak workloads, as discussed in Paragraph 1.2, are quantified

3 Literature review

As stated in the problem analysis, the OR-planning has a strong influence on the variability at the wards. Therefore the literature review focuses on papers with quantitative models that account for interdepartmental relationships. Among others, two recent literature reviews are of valuable input. The first review (Vanberkel et al., 2010) is about health care models that encompass multiple departments and the second review (Cardoen et al., 2009) focuses on operating room planning and scheduling. The latter paper evaluates the literature on multiple fields that are related to either the problem setting (e.g., performance measures or patient classes) or the technical features (e.g., solution technique or uncertainty incorporation) (Cardoen et al., 2009). It provides a useful classification of the papers that for example include the wards in their model and also incorporate uncertainty. Vanberkel et al., (2010) highlight the extent to which operational research models account for interdepartmental relationships. They conclude that often researchers overlook the complex relationships that exist in health care and take an atomistic view of hospitals. Also they plead for elimination of artificial variability (variability caused by the system) and better protocols or work practices and a clear understanding of patient care trajectories.

This chapter is organized as follows. Paragraph 3.1 covers the realization of the OR-planning that is used in most hospitals and discusses the planning objectives of the stages. Paragraph 3.2 is the literature review about quantitative multi-department models that can contribute to this thesis. The chapter closes with a summary on the literature and gives direction to the remainder of this study.

3.1 OR-planning definitions and terminology

The ward planning follows directly on the OR-planning made by the OR-planners of the specific specialties. Since the OR center of a hospital is the most expensive asset (van Oostrum et al., 2008), hospitals strive for high utilization of their rooms. The OR-planning not only influences the capacity of the wards but also other departments such as rehabilitation and physiotherapy, departments that have a relationship with the recovery process of a patient. Since the demand at the aforementioned departments is a direct derivative of the OR-planning it is useful to first elaborate on the realization of an OR-planning.

In most hospitals, and also at LUMC, the planning of the OR center has three stages. These are briefly explained below.

1. *Case mix planning*
   The first stage is called case mix planning and consists of strategic decisions made by the hospital management about how to divide the available OR-time over the specialties. The result of this planning is an overview of how much time each specialty or surgeon will get. This is a strategic decision because the OR-time is divided for at least a year.

2. *Master surgery schedule (MSS)*
   The master surgery schedule is a cyclic schedule that defines the number and type of operating rooms available, the hours that rooms will be open, and the surgeons who are to be given priority for the operating room time (Blake et al. 2002). In short, it is decided which specialty/surgeon will operate where (OR) and when (OR-time slot). The MSS is at the tactical level.
3. *Elective patient planning*
   The third stage is the planning of the patients at the operational level. This stage is the daily routine of the intake bureau.

3.2 Operating room planning and scheduling literature

OR planning and scheduling has a strong increasing interest in the literature and cost reduction for hospitals is one of the major causes of this trend (Cardoen et al., 2009).
Most literature about optimizing the OR-planning and scheduling focuses on the elective patient planning because of the high uncertainty involved with emergency patients. Also most research use deterministic arrival rates and procedures durations, but in reality these variables are stochastic. Again the main reason for this is the increased computational complexity (Cardoen et al., 2009). Vanberkel et al., (2009) conclude that interdepartmental relationships in health care are overlooked because of the high complexity and variability. As another cause it indicates the absence of standard patient care trajectories. The following subparagraphs will discuss the single and multi-department optimization.

3.2.1 Single department optimization

When building surgery schedules several objectives can be taken into account. Mostly hospitals strive for high utilization of their ORs, since the OR center of a hospital is the most expensive asset. Beliën and Demeulemeester (2007) performed a literature review and discovered other frequently used optimization goals are minimization of OR staffing costs and the management of uncertainty. These goals all optimize just one department in the chain, namely the OR center. By limiting the scope, the complexity and uncertainty becomes more manageable, but leads to sub-optimal solutions (Vanberkel et al., 2009). The departments have conflicting goals and surgeons tend to plan their procedures independently which results in peak demands at for example the wards (van Oostrum et al., 2008).

3.2.2 Multi-department optimization

The effect of the MSS on ward occupancy is studied by several authors but in just a few cases the solution is looked for at the OR-planning. De Bruin et al., (2009) take the MSS as given and give insight in how many bed to allocate to a specific ward to meet production targets. Using the Erlang loss model with among others Poisson arrivals the paper offers a decision support tool to evaluate the current size of a nursing unit. Also the effects of merging wards are quantified. It tries to deal with the variability caused by the OR-planning and it does not solve the problem at the root.

Van Oostrum et al., (2008) optimizes room utilization at the OR center and in addition it levels the workload at the downstream departments like the IC and the nursing wards. The model generates cyclic MSSs within acceptable time bounds. In their two stage model they assume stochastic duration for surgery procedures but not for the length of bed request. Also only frequent elective procedures that account for around eighty percent of the patients are incorporated in the model.

Cochran and Bharti (2006) model multiple departments to balance the inpatient bed unit utilization in an entire hospital. They propose a multi-stage stochastic methodology which consist of queuing network analysis combined with discrete event simulation. The queuing network analysis is used to achieve balanced targets and the discrete event simulation to maximize flow. Simulation is used because queuing network analysis cannot handle time dependent arrivals, blocking of patients and nonexponential length of stays. They conclude queuing networks used in preparation of simulation models is a superior way to model whole hospitals (Cochran J.K., and Bharti A., 2006).

Beliën and Demeulemeester (2007) propose a two stage model to solve the problem at the tactical level and levels the ward workload by adapting the MSS. Next to other authors like Litvak and Long (2000), Harrison et al. (2005) and Vanberkel et al. (2009) they point out artificial variation in the utilization of resources introduced by surgery schedules used in operating theatres that can be avoided by taking into account the dependencies between these resources when developing master schedules. Artificial variability has a very negative impact on productivity and reducing it is one of the major concerns of health care management (Beliën and Demeulemeester, 2007). The model uses stochastic arrival rates and stochastic procedure durations, but only includes inpatients.

Adan, I. and Vissers, J. (2002) consider both inpatients and outpatients. They formulate a mixed integer programming model to identify the cyclic number and mix of patients that have to be admitted to the hospital in order to obtain the target utilization of several resources such as the operating theater or the IC. They demonstrate that taking into account these departments results in an overall better performance of the system instead of maximize OR center utilization. These evidences are based on deterministic arrivals and durations and outpatients are modeled as inpatients with a length of stay of one day.

Another paper that accounts for the dependencies of the departments is Vanberkel et al., (2009). In contrary of other papers, Vanberkel et al., (2009) describes an analytical approach to project the workload for downstream departments and provides a decision support tool. Simulation models have the disadvantages of being inexact and take a lot of development time. Analytical models have distinct advantages in terms of precision and development time. A disadvantage of an analytical model is that the problem cannot be too complex otherwise it becomes hard to solve and not useful anymore. The reason that Vanberkel et al., (2009) uses it is that the model can be used to quickly evaluate proposed MSS solutions for additional factors and that it uses actual data input. The application is appropriate for both tactical and operational level decisions something that is not the case with most other models. Furthermore, inpatient as well as outpatients can be included.

Summary

- Literature offers many single department models that provide suboptimal solutions
- Artificial variability in health care processes recognized as main problem
- Only a few papers on multi department optimization
- To reduce complexity deterministic or partially stochastic data is used
- The literature offers many simulation studies and little analytical models
- Most papers use mathematical programming in combination with simulation study
- Vanberkel et al. (2009) propose a model that can be used to quickly evaluate proposed MSS solutions and is appropriate for both tactical (MSS) and operational level. In contrast to other models, it uses stochastic and actual data instead of deterministic

4 Proposed model for OR and ward synchronization

This chapter describes the mathematical model that we use to calculate the influence of the MSS on the workload at the nursing wards. Paragraph 4.1 justifies the model choice. Paragraph 4.2 is a short description of the model, Paragraph 4.3 discusses the programming issues, and in Paragraph 4.4 we discuss the model assumptions that are required.

4.1 Model choice

We use the analytical model described by Vanberkel et al., (2009) to analyze the LUMC Division 1 case at LUMC. The model is intended to serve as a tool to quickly evaluate proposed MSS solutions. It is appropriate for various levels of planning. The impact on the wards from small changes in the MSS is directly visible, which is valuable for hospital management in order to make decisions with respect to desired occupancy rates. Furthermore, the model is chosen because it incorporates the OR-center as well as the nursing wards, where the focus is on synchronizing these departments. Also, contrary to other models, it uses stochastic data. This is useful because the model reflects the fluctuations of the bed occupancy which in practice is caused by unpredictable factors. The model calculates the steady-state distributions for the bed occupancy and is therefore best used as a static model to influence long term ward occupancy. The steady-state distributions of the bed occupancy the model can serve as a decision support tool to support the management in taking decisions involving the MSS as well as the wards.

4.2 Model description

The model description is based on the article of Vanberkel et al., (2009). For the extensive and formal model description we refer to the article which is available online[1]. Table 4.1 provides the notations for all steps and the remainder of this paragraph describes these steps.

[1] Vanberkel, P.T. and Boucherie, R.J. and Hans, E.W. and Hurink, J.L. and van Lent, W.A.M. and van Harten, W.H. An exact approach for relating recovering surgical patient workload to the master surgical schedule. November 2009, Internal Report, http://doc.utwente.nl/68493/

Table 4.1: Notation of the model

Step	Model input and output
Step 1	**Input:** $c^j(x)$: probability distribution of specialty j completing x surgeries in one OR block d_n^j: the probability that a patient, who is still in the ward on day n, is to be discharged that day. **Output:** $h_n^j(x)$: probability distribution of x patients of a single OR block of specialty j still in recovery, n days after surgery $h_n^j(x) = \begin{cases} c^j(x) & when\ n = 0 \\ \sum_{k=x}^{c^j} \binom{k}{x} (d_{n-1}^j)^{k-x} (1-d_{n-1}^j)^x h_{n-1}^j(k) & otherwise \end{cases}$
Step 2	**Input:** $h_n^j(x)$: from Step 1 A single MSS: defines which day *q* specialty *j* operates in OR *i* **Output:** $\bar{h}_m^{i,q}(x)$: probability distribution of x patients of the MSS still in recovery on day m. $\bar{h}_m^{i,q} = \begin{cases} \mathbf{0} & if\ m < q \\ h_{m-q}^j & if\ m \geq q \end{cases}$ where **0** means $\bar{h}_m^{i,q}(0) = 1$ $H_m(x)$: probability distribution of *x* patients still in recovery on day *m* (result for a single MSS in isolation). Let * indicate a convolution then, $H_m(x) = \bar{h}_m^{1,1} * \bar{h}_m^{1,2} * \cdots * \bar{h}_m^{1,Q} * \bar{h}_m^{2,1} * \cdots * \bar{h}_m^{I,Q}$
Step 3	**Input:** $H_m(x)$: From Step 2 Repeating MSSs **Output:** $H^{SS}_q(x)$: the steady-state probability distribution of recovering patients on day *q*. $H_q^{SS}(x) = H_q * H_{q+Q} * H_{q+2Q} * \ldots * H_{q+roundup(M/Q)*Q}$

In brief, the goal of the model is to determine the workload placed on hospital departments by recovering surgical patients. The input of the model consists of:

- The probability distributions of the number of procedures in a single OR block for each specialty
- The probability distributions that a patient, who is still in the ward on day *n*, is to be discharged that day

The distributions can be derived from the Management Information System (MIS) of the hospital. Using these distributions as model inputs, for a given MSS the probability distribution of the number of recovering patients on each day of the MSS cycle can be computed. Three steps are used for the calculation of these distributions. Step 1 calculates the distribution for a single OR block, Step 2 calculates the impact of a single MSS cycle and Step 3 calculates the steady-state of the distribution, since it is possible that patients with a long LOS cover multiple MSS cycles, so also should be accounted for in multiple cycles. The three steps are shortly discussed below.

Step 1: Distribution of recovering patients from specialty j following from a single OR block

The kernel of the model is a single OR block and its expected impact on the arrival rate of patients to the nursing wards. Table 4.2 and 4.3 give examples of a MSS. The MSS is split up in OR blocks $b_{i,q}$ with $i \in \{1,2, \ldots, I\}$ and $q \in \{1,2,\ldots,Q\}$ where I is the maximum of ORs and Q is the cycle length of the MSS. Every OR block is assigned to specialty j, or left empty. Step 1 of the model calculates the distribution hjn(x) for every OR block, that is the distribution for the number of recovering patients on day n, which is the day of recovery. N days after carrying out a block of specialty j, x patients of the block are still in recovery. The input for these steps consists of two probability distributions. $c^j(x)$ is probability distribution of specialty j completing x surgeries in one OR block and d_n^j is the probability that a patient, who is still in the ward on day n, is to be discharged that day. Note that n ∈ {0,1,…,Lj}, where Lj is the maximum LOS) and x ∈ {0,1,…,Cj} (Cj is maximum number of patients in one OR block, and that, for example, $h^j_3(5)= 0.25$ means that 3 days after surgery there is a 25% probability that 5 patients are still recovering in the hospital. For the probabilities h^j_n we have $\Sigma^{Cj}_{x=0} h^j_n(x) = 1$, for all $n \in \{0,1,\ldots,L^j\}$.

Table 4.2: an empty MSS

Days in MSS →

Available ORs ↓

	q=1	q=2	q=3		q=Q
OR i=1	b1,1	b1,2	b1,3	…	b1,Q
OR i=2	b2,1	b2,2	b2,3	…	b2,Q
OR i=3	b3,1	b3,2	b3,3	…	b3,Q
	…	…	…		…
OR i=I	bI,1	bI,2	bI,3	…	bI,Q

Table 4.3: MSS example

MSS for the even weeks					
OR/DAY	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
1	ORT	ORT	ORT	ORT	
2	ORT	HLK	ORT	ORT	
3	HLK	URO	URO	URO	URO
4					
5	HLK	HLK		HLK	ORT
6	HLK	HLK	HLK	HLK	HLK
7	URO			HLK	HLK
8	HLK		HLK	HLK	HLK
9		HLK	HLK		
10	PLA	MHK	PLA	MHK	PLA

Step 2: Aggregate distribution of recovering patients following from a single MSS cycle

The second step in the model calculates the demand for ward beds for every single day in one MSS cycle. The previously computed probability distribution h^j_n and a single MSS are used as input. To calculate the overall distribution of recovering patients, we first have to identify for each block $b_{i,q}$ the impact this block has on the number of recovering patients in the hospital on days (q, q+1, ...). In other words, the distribution needs to be shifted to the right day. If j denotes the specialty assigned to block $b_{i,q}$, then the distribution $\bar{h}_m^{i,q}$ for the number of recovering patients of block $b_{i,q}$ on day m ($m \in \{1,2,\ldots,Q, Q+1, Q+2,\ldots\}$) is given by:

$$\bar{h}_m^{i,q} = \begin{cases} \mathbf{0} & if\ m < q \\ h_{m-q}^{j} & if\ m \geq q \end{cases}$$

In this equation **0** means $\bar{h}_m^{i,q}(0) = 1$ and all other probabilities $\bar{h}_m^{i,q}(l)$, $l > 0$ are 0. Let H_m be a discrete distribution for the total number of recovering patients on day m resulting from a single MSS cycle. Since recovering patients do not interfere with each other we can simply iteratively add the distributions of all the blocks corresponding to the day m to get H_m. Discrete convolutions are used to compute the total patients in recovery by adding up the distributions per OR and per day. The result is a matrix size the length of the MSS cycle by x, the number of expected patients (i.e. beds needed). The formula for these matrix calculations is given by:

$$H_m(x) = \bar{h}_m^{1,1} * \bar{h}_m^{1,2} * \cdots * \bar{h}_m^{1,Q} * \bar{h}_m^{2,1} * \cdots * \bar{h}_m^{I,Q}$$

Step 3: Steady state distribution of recovering patients

The final step calculates the effect of multiple MSS-cycles. One patient can be present in several MSS-cycles. Since the MSS is cyclical, the cumulative number of patients from recurring MSS cycles can be computed. A finite LOS is required to ensure convergence to a steady-state result. In Step 2 we have computed H_m for a single MSS in isolation. Let M be the last day where there is still a positive probability that a recovering patient is present in H_m. This M indicates the range of the MSS. To calculate the overall distribution of recovering patients when the MSS is repeatedly executed we must take into account $\lceil M/Q \rceil$ consecutive MSSs. Figure 4.1 shows an example of overlapping recovering patients. Let H_q^{SS} denote the probability distribution of recovering patients on day q of the MSS cycle, resulting from roundup[M/Q] consecutive MSS.

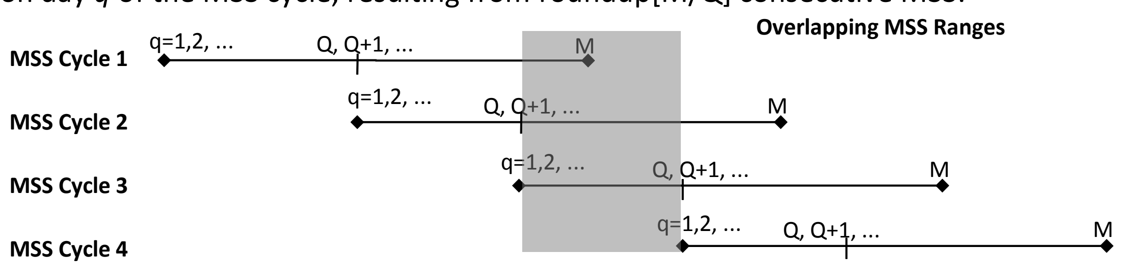

Figure 4.1: Consecutive MSSs illustrating overlapping recovering patients

Since the MSS does not change from cycle to cycle, H_q^{SS} is the same for all MSS cycles. Such a result, where the probabilities of various states remain constant overtime, is referred to as a steady state result. Using discrete convolutions, H_q^{SS} is computed by:

$$H_q^{SS}(x) = H_q * H_{q+Q} * H_{q+2Q} * \dots * H_{q+\,roundup(M/Q)\,*Q}$$

The result of this formula is the steady-state distribution with the probability of x patients/beds for day q of the MSS-cycle.

Output

The main output of the model is the distribution for the number of patients present in the system on each day of the MSS. This distribution can now be used to calculate performance measures. Vanberkel et al., (2009) describes calculations for ward occupancy, admission and discharge rate, and the number of patients in day *n* of their recovery.

4.3 Programming issues

This paragraph discusses some programming issues that came up while programming the model in Matlab. Matlab is chosen because of the possibilities to program a generic version of the model and a second reason is that Matlab is easy to learn for less experienced programmers. We use the Matlab model in Chapter 5 both to evaluate the current demand for beds as well as to come up with alternative solutions.

The calculation of Step 3 after Step 1 and move Step 2 to the end makes the programming of the model easier. The result after the three steps remains unchanged: the steady state probability distribution with the chance of *x* recovering patients at day *q* of the cycle. The Matlab code is presented in Appendix C.

Another programming issue is the calculation time for one run. This issue is not to be underestimated. In a later stage, when the original MSS is changed to find an alternative schedule, the model has to calculate various new versions of the MSS. When a swap heuristic is used to come up with an alternative, it is likely that we need to perform a lot of model runs demanding short running time in order to give a solution within a reasonable time. The Matlab model in this research calculates ward projections for any specific MSS within two to three seconds. For recalculating small changes in the MSS it is only necessary to calculate Step 2. This takes just a third of a second.

4.4 Modeling assumptions

The model of Vanberkel et al., (2009) uses a couple of assumptions in order to calculate the probability distributions. These assumptions, together with the motivation, are summarized below.

- At the ward, each patient directly occupies a bed for a certain period of time and occupies it the whole day

- In the queuing model, the ward is seen as an infinite server system where the patients occupy a server (ward bed) without delay
- The MSS is cyclical in order to calculate a steady-state result
- A finite LOS is required to ensure convergence to a steady-state result

Summary

- The model of Vanberkel et al., (2009) is chosen because it incorporates the OR-center as well as the nursing wards and the focus is on synchronize these departments
- The model is also chosen because it uses stochastic and actual data and it therefore better reflects reality
- The model is programmed in Matlab and the steps 2 and 3 are swapped, because of programming convenience
- The most important assumptions of the model are a finite LOS and a cyclic MSS

5 Practical application of the model

In this chapter, we use the Matlab model to evaluate the MSS of LUMC. Paragraph 5.1 discusses the computer implementation issues. In paragraph 5.2, we present the application of the model for the current MSS and compare the results to the occupancy data from the data analysis in Chapter 2.3.2. Paragraph 5.3 discusses the possibilities of improving the workload level of the wards by swapping OR blocks in the MSS. In this paragraph we present a heuristic that proposes alternative MSSs. In paragraph 5.4 we run the heuristic for various instances in order to come up with alternative MSSs. Paragraph 5.5 presents a sensitivity analysis on the model output and Paragraph 5.6 discusses the issue of granularity of the model input.

To perform a practical application of the model first we present a plan, which is shown in Table 5.1.

Table 5.1: Plan for the practical application

Paragraph	Subject
5.1	Issues that influence the determination of the input parameters
5.2	Application to the current MSS • Input generation • Run the model with the current MSS • Discuss and validate the computer output
5.3	Propose alternative MSSs • Introduction of a performance indicator to compare solutions • Introduction of a heuristic to find alternative MSSs
5.4	Results • Execution of the heuristic and output generation • Discussion on the model output • Presentation of best swaps
5.5	Sensitivity analysis • Model runs for various percentiles of demand • General surgery subspecialties are split up in various classes to discuss the importance of the level of detail of the model input

5.1 Model input issues

This paragraph is a critical appraisal on the model input. The calculations of the input distributions as well as the layout of the MSS for the LUMC case study are not as straightforward as described in Vanberkel, (2009). The reason for this is the different environment where the model is used. The model is validated in the NKI (Dutch Cancer Institute) in Amsterdam which has a limited number of specialties and small differences in procedure length within these specialties. Patients can be aggregated in limited groups. Calculation of the distributions for LUMC is less straightforward since there are many (sub)specialties and also various procedure types per specialty. It takes a lot of effort to differentiate the data but also to put it in the right OR-block. The MSS of LUMC only provides the specialty IDs and is not subspecialty specific. This makes it harder to put a corresponding distribution to the right OR-block. This makes patient aggregation much harder. A recommendation that follows from this research is that a correct and unambiguous registration of procedures is necessary in order to provide the model input. To see whether this recommendation is valid, the importance of the level of granularity of the input is tested in paragraph 5.6.

Paragraph 5.2 provides the calculations of the distributions for all specialties and compares the initial model output with real data from the MIS.

5.2 Application to the current MSS

As mentioned in Chapter 4, the model is intended to evaluate a proposed MSS. This subparagraph runs the model for the LUMC with the input gathered from the MIS. From Chapter 4 it follows that there are three inputs for the model. The two probability distributions are calculated with data from the MIS, and the OR-center provides the MSS. The calculations of the c^j-distribution, which is the number of procedures carried out in one OR-block (note that one OR-block is the same as one OR day at LUMC), are not straightforward since in the MSS general IDs for the OR-blocks are used. For example, the General Surgery-blocks in the MSS account for all subspecialties that cover the General Surgery specialty. These blocks are divided over all subspecialties by the head of the surgery department of that specific specialty. For all (sub)specialties it happens that procedures from other (sub)specialties are planned in those blocks or that the block content differs slightly from week to week. In the remainder of this paragraph we describe the calculation steps for generation of the cj-distributions. An assumption of the calculation of the probability distributions is the following. Since this project considers tactical planning and we therefore need a certain level of patient aggregation, we assume that patients are identically distributed within a specialty type. We check the model output against real data to ensure the aggregate results are valid.

Calculation of cj-distribution
To calculate the distributions of the number patients per OR block, OR data from the MIS is used. The advantage of this data is that next to the date the procedure is performed, also the OR number is stored. With this information, the output of a specific OR block and day combination is calculated. Before this is done, some data should be removed from the data set.

- Emergency patients are removed because only elective patients are considered
- Children (<18 year) are removed, because they recover at a the children's ward which is not part of Division 1
- Some patients have multiple procedures during the same surgery, but should be counted as one admission for the ward

The next step in the calculation is to order patients according to specialty, week, weekday and OR number. We use pivot tables to do this. The result is the number of patients of a specialty that had surgery in a specific week, weekday and OR. This data is compared with the initial MSS. Only the patients operated in the OR blocks dedicated to the specialty are used for the calculation of the cj-distribution.

Table 5.2: Example Plastic surgery patients in OR 10

Plastic surgery patients in 2008 in OR 10						
Number of patients	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Total**
1	4	5	6	0	3	18
2	24	0	14	0	13	51
3	11	0	13	0	13	37
4	0	0	2	0	4	6
5	0	0	0	0	1	1
Total surgery days	39	5	35	0	34	113

In the example in Table 5.2, for the Plastic surgery patients, the summary of the number of patients per weekday in OR 10 is given. This table is compared to the MSS, which has a full Plastic surgery block scheduled on the Mondays and the first Friday in the cycle. The specialty has half OR-blocks on Wednesdays and on Fridays in the second week of the cycle. Table 5.2 is used to calculate a cj-distribution for these OR-blocks. This is done by dividing the numbers of occurrences by the total number of occurrences. The probability distribution is given in Table 5.3. Since it is not favorable to have a unique distribution for every Plastic surgery OR block, we take the total number of patients from all Plastic surgery block to derive the distribution. We differentiate between whole and half OR blocks. There are two reasons for this. First, too many distributions increase the computation time. The second reason is that we need to base the distribution on a significant number of patients. We assume that the patient types from the different Plastic surgery blocks are identically distributed since we need to aggregate on patient groups.

Table 5.3: cj-distribution Plastic surgery patients in OR 10

Number of patients	Monday	Wednesday	Friday
1	0,1026	0,1714	0,0882
2	0,6154	0,4000	0,3824
3	0,2820	0,3714	0,3824
4	0,0000	0,0571	0,1176
5	0,0000	0,0000	0,0294
Total	1	1	1

As mentioned before, it is not useful to use a specific distribution for every OR-block, because this takes too much calculation time. For every specialty a consideration is made which distribution to use. Some OR blocks are divided between specialties or only half OR day is filled. In these cases an alternative distribution is calculated. The various distributions used are summarized in Table 5.4.

Table 5.4: cj-distribution (N is sample size)

Specialty	Spec ID	N	0	1	2	3	4	5	6	7	8
Oral and Maxillofacial surgery	1	84	0,00	0,54	0,41	0,05	0,00	0,00	0,00	0,00	0,00
Plastic surgery 1 OR	2	74	0,00	0,17	0,45	0,32	0,05	0,01	0,00	0,00	0,00
Plastic surgery half OR	3	36	0,00	0,42	0,27	0,27	0,04	0,00	0,00	0,00	0,00
Orthopedic	4	310	0,00	0,21	0,36	0,31	0,12	0,00	0,00	0,00	0,00
Urology 1 OR	5	152	0,00	0,29	0,32	0,19	0,11	0,07	0,01	0,00	0,00
Urology half OR	6	42	0,00	0,07	0,90	0,02	0,00	0,00	0,00	0,00	0,00
General surgery	7	167	0,00	0,35	0,28	0,17	0,09	0,02	0,06	0,02	0,01
Oncology and Gastro	8	187	0,00	0,10	0,40	0,30	0,10	0,10	0,00	0,00	0,00
Transplantation	9	117	0,00	0,11	0,63	0,21	0,05	0,00	0,00	0,00	0,00
Traumatology	10	68	0,00	0,05	0,27	0,55	0,09	0,05	0,00	0,00	0,00
Vascular surgery	11	100	0,00	0,32	0,63	0,05	0,00	0,00	0,00	0,00	0,00
Mixed general surgery	12	360	0,00	0,26	0,45	0,24	0,03	0,03	0,00	0,00	0,00

For General Surgery, calculations are a little different. This specialty has five subspecialties and the General Surgery blocks in the MSS are divided over these subspecialties. Note that the General surgery specialty also has a subspecialty called General surgery. In practice it happens that blocks are not dedicated to a specific subspecialty. Therefore the specialty Mixed general surgery is introduced. The calculation of the probability is based on all subspecialties.

Calculation of dj-distribution

For the calculation of the dj-parameter, the probability distribution that a patient, who is still in the ward on day *n*, is to be discharged that day, ward data from the MIS is used. The LOS is easy to calculate by taking the difference between the day and time of admission minus the day and time of discharge. With this data, the probability of discharge is calculated and for the calculation of the parameter this value is divided by the total chance of discharge of proceeding days. The same comment as with the other distribution is present. The LOS of patients within a certain specialty tends to vary a lot for the various procedures that exist. To give an example, within Orthopedic surgery hip and knee patients have a different LOS, but are planned in the same OR block. Also for other specialties it is quite common that OR blocks consist of a mixed patient groups. A solution would be to split the OR blocks in the same as proposed for the cj-distribution. Again the same problems arise: distributions based on small patient groups and too many different groups require a lot of calculation time. Also, patients are planned disorderly in the MSS. In this research we choose to use the LOS of the total (sub)specialty group. This means that for example the LOS of all Orthopedic surgery patients is used while calculating the dj-distribution. For convergence, we use a maximum LOS of 50 days. Patients that stayed longer are given a LOS of 50. Some specialties have no patients that stayed for 50 days or longer. Therefore the numbers at day 50 in Table 5.5 can also be zero.

Table 5.5: dj-distribution (N is sample size)

Specialty	Spec ID	N	0	1	2	3	4	…	50
Oral and Maxillofacial surgery	1	156	0,03	0,34	0,47	0,51	0,54	…	0,00
Plastic surgery 1 OR	2	333	0,03	0,56	0,74	0,46	0,30	…	1,00
Plastic surgery shared OR	3	333	0,03	0,56	0,74	0,46	0,30	…	1,00
Orthopedic	4	1028	0,03	0,35	0,36	0,15	0,12	…	1,00
Urology 1 OR	5	821	0,06	0,33	0,54	0,43	0,37	…	0,00
Urology shared OR	6	821	0,06	0,33	0,54	0,43	0,37	…	0,00
General surgery	7	364	0,13	0,44	0,21	0,13	0,13	…	1,00
Oncology and Gastro	8	740	0,14	0,38	0,18	0,10	0,12	…	1,00
Transplantation	9	149	0,09	0,08	0,07	0,18	0,32	…	0,00
Traumatology	10	132	0,07	0,57	0,32	0,19	0,24	…	0,00
Vascular surgery	11	251	0,21	0,34	0,17	0,16	0,26	…	0,00
Mixed general surgery	12	1636	0,35	0,43	0,23	0,16	0,19	…	1,00

The next step is to fill in a more detailed version of the MSS as shown in Table 5.6. The difference with the original one is that the General surgery blocks are now divided over the subspecialties.

Table 5.6: Initial MSS for Division 1 OR-blocks

OR/Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	4	4	4	4	0	0	0	4	4	4	4	0	0	0
2	4	10	4	4	0	0	0	4	10	4	4	12	0	0
3	8	5	5	5	6	0	0	8	5	5	5	6	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	11	8	11	7	4	0	0	11	8	11	10	4	0	0
6	8	8	8	12	9	0	0	8	8	9	12	8	0	0
7	5	0	0	7	12	0	0	5	0	0	7	12	0	0
8	7	8	8	7	12	0	0	8	8	8	7	12	0	0
9	0	2	0	0	0	0	0	0	8	12	0	0	0	0
10	2	1	3	1	2	0	0	2	1	3	1	3	0	0

The three wards of Division 1 are considered as one in the model for complexity reasons, because patients from all specialties can end up in one of the three wards.

Conclusion on distribution calculations

There are many specialty and procedure types at Division 1 of LUMC compared to the hospital where the model was validated. It takes effort to make subclasses and define separate distributions. As the number of classes increase, the distributions are based on fewer procedures, which make them less reliable. Also, in the situation of many subclasses, it is complex to dedicate the distributions to an OR block. This is caused by procedures within a specialty and subspecialties of General Surgery are planned disorderly, with different Length of Stay durations. As a solution, the output for a specific OR block is matched to the specialty ID in the MSS and the probability distributions are based on these patient output. Using this input, the model is useful on the tactical planning's level to show how variability in the total steady-state bed occupancy can be reduced by small changes in the OR center.

A straightforward recommendation then would be to better organize planning and storage of data and to provide a more detailed MSS. This would probably improve the exactness of the model output. In Paragraph 5.5, the granularity of the input is discussed. The importance of the level of detail for the General Surgery specialty is discussed in order to say something about the quality of the overall results.

Output of the initial MSS

The calculated distributions together with the original MSS serve as input for the initial model run. The output is given in Figure 5.1 the form of a bar chart.

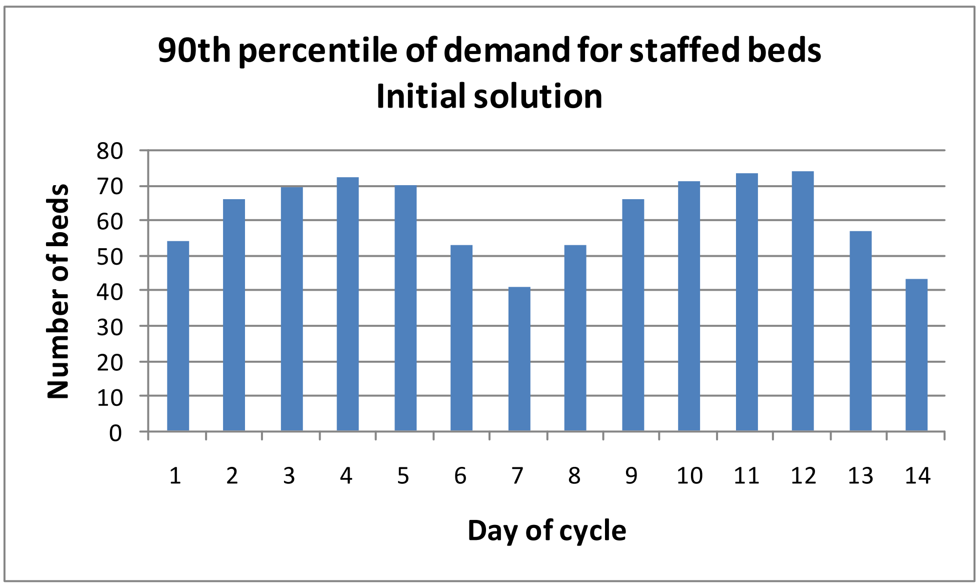

Figure 5.1: Result for initial MSS

Figure 5.1 shows the steady-state for the 90th percentile of demand staffed beds and shows that the variability during the cycle length is considerably high. The percentile of demand indicates that for ninety percent of the days there is sufficient coverage. The difference of the demand between the first Monday and first Thursday of the cycle is almost twenty beds. The maximum bed demand is on the second Thursday, when 74 beds are needed. Table 5.7 gives the outcomes of the model with the initial MSS. The model results are calculated for different percentiles of demand. These values are also calculated for the bed occupancy in Chapter 2. This is done by ordering the occupancy levels for all days in a year and taking the corresponding percentage of data compared to the coverage percentile. The percentage reflects the chance that the expected number of beds in sufficient. For example, using the 95th percentile indicates that there is a chance of 1/20 that the number of beds is not sufficient. For the 85th, 90th, and 95th percentile of demand the model and data analysis show comparable values.

Table 5.7: Initial MSS results with different percentiles

Percentage staffed beds	Average bed demand based on model	Maximum beds needed	Bed demand based on data analysis	Maximum beds needed in data analysis
70%	58,9	71	55	69
75%	59,5	72	56	69
80%	60.1	72	57	69
85%	61,0	73	59	69
90%	61.6	74	61	69
95%	62,4	75	63	69
99%	63,1	76	68	69

The model can be used to compare the effects in variability for various MSS. In paragraph 5.3, we present a heuristic to come up with an alternative MSS that reduces the variability in the demand for staffed beds.

5.3 Alternative MSS proposal

Subparagraph 5.3.1 introduces the performance indicator that we use to evaluate alternative MSSs and proposes an alternative MSS with less variability in bed occupancy during the cycle length. Subparagraph 5.3.2 gives a description of the heuristic that we use to generate alternative output.

5.3.1 Performance indicator and generation of alternatives

In paragraph 2.3 we discussed the restrictions for alternative MSSs. The conclusion was that there are many alternative MSSs possible, making it hard to define the optimal MSS. A technique such as mathematical programming is needed to find an optimum, but this is beyond the scope of this research. Therefore in this subparagraph we present a heuristic to come up with a satisfying alternative. Important issues in defining a heuristic are the risk of ending up in a local minimum instead of the preferred global minimum and the calculation time. We choose a local search approach in order to find an acceptable alternative solution, because we only review part of the solution space. The essence of local search heuristics is that neighborhood solutions (in this study these are swaps of OR-blocks) are compared to find better solutions. The local search stops when all allowed swaps are considered, a maximum of swaps is reached or when a certain time limit has passed. The starting solution is of influence on the performance of the heuristic. Clever rules to pick a neighborhood solution, will improve the solution.

There are many local search methods all having their (dis)advantages. Also existing heuristics can be adapted to better fit the environment. In our situation, it is hard to evaluate all solutions; therefore a good starting solution is important. Also it is very likely to end up in a local minimum. To explain this last point: when evaluating swaps and only accept improvements, one can end up in a local minimum because at a certain point, no better solutions are found. This method is called iterative local search. To escape from a local minimum, we can choose a heuristic that also accepts worse solutions or recalls already reviewed solutions and make these forbidden forcing alternative neighborhood solutions. The first one is called the Simulated Annealing approach and the other one Tabu Search. In the following paragraph, the proposed heuristic is described.

The goal of the heuristic defined in this subparagraph is to find a better workload level for the wards. This means we would like to minimize the variation between the days of the cycle taking into account that for the weekend it is not preferred that the occupancy increases. This is due to personnel constraints. We define the performance indicator to compare alternative MSSs using the occupancy of day *q* in the MSS cycle compared to the average of the weekdays and of the weekend days.

Week

- Performance indicator for Weekdays = Σ (Occupancy of Weekday q – Average Occupancy of Weekdays)^2

Weekend

- Performance indicator for Weekend days = Σ (Occupancy of Weekend day q – Average Occupancy of Weekend days)^2

We use the quadratic difference, because then larger absolute differences get a higher weight. To obtain the weighed performance we calculate the workload level performance of an alternative MSS as:

Workload level performance = ((10****week***) + (4****weekend***))/14

With the aforementioned performance indicator we are able to compare alternatives. It is not possible to review all alternatives, so we need to evaluate those that represent an improvement. We use a heuristic to select OR blocks, swap them, calculate the performance, and eventually choose an OR block swap that gives a better solution. In the previous part we mentioned two techniques to escape from a local minimum. These are Simulated Annealing and Tabu Search but both cause many changes in the MSS, since also worse swaps are allowed. This is not a preferable situation, since the focus is on a good result in combination with limited swaps. Limited swaps resemble three to five changes in the MSS. It might be the case that only three changes in the MSS already give a good solution. But which swaps should we choose?

Example

We use trial and error to come up with an alternative solution. In the original MSS, OR blocks from the days where demand is highest are moved to empty blocks at days demand is lower. Moving four blocks reduces the maximum of beds from 74 in the original to 72 in the alternative MSS. The workload performance indicator drops from 412.29 to 258.79. This is a decrease of 37.2 percent. Figures 5.2 shows the results.

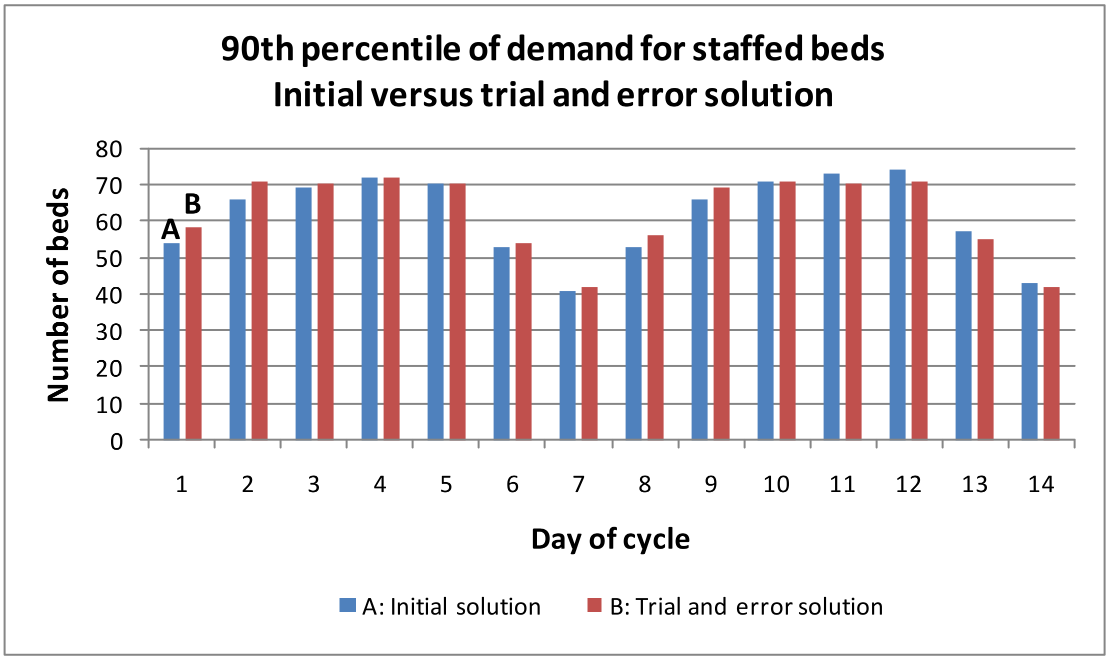

Figure 5.2: Comparison initial MSS with trial and error bed demand

The figure shows a more leveled demand for staffed beds. Changing more OR blocks with a trial and error strategy results in worse solutions, probably because the weekdays Tuesday to Friday have a comparable level. This trial and error method suggests that only limited block changes are needed to come to an interesting alternative solution. Decreasing the peak from 74 to 72 implies that two beds could be closed, cutting costs considerably. We propose a heuristic that focuses on attacking the peak demand days, taking into account limited OR block swaps. We use the performance indicator defined in this paragraph for evaluation.

5.3.2 Heuristic

In short, the proposed heuristic compares the initial solution with alternative solutions. The alternative solutions are compared to the current solution based on the performance indicator as defined in this paragraph. The plan is to replace an OR block from the day that generates the highest bed demand with a block on a day that the least beds are needed (weekends excluded). All ORs of the two selected OR blocks are evaluated. This results in 10x10=100 swaps and also hundred times the execution of the model. It is likely that the best performance of those hundred first swaps is not the overall best swap. We therefore choose to also evaluate other days with a high bed demand. From the initial solution it is given that demand is highest between Tuesday and Friday in both weeks. This makes sense since there are no procedures planned during the weekends. These are eight days of a cycle and we choose these days to swap with the day that the least beds are needed. It takes less than four minutes to calculate this. The best proposed swap is chosen and we return to step 3 and run the heuristic with the adapted MSS. The heuristic stops when a predefined number of swaps is executed or when there are no better solutions found. The heuristic is, just as the model, implemented in Matlab.

A more formal description of this heuristic in pseudo code:

```
1. Define the initial solution (current demand for beds for
   every day in the cycle for the initial MSS)
2. Calculate the workload level performance for this MSS and
   store it as CurrentBest
3. Take the current MSS and put the days in descending order
   for the number of beds needed
4. Start of swap procedure
     a. Select the day with the highest bed demand (DayMax)
     b. Select the day with lowest bed demand (not a weekend
        day)(DayMin)
     c. For all OR swap combinations, swap OR n from DayMax
        with OR n from DayMin, resulting in n*n swaps
          i. For every separate swap, run step 2 of the model
             (output of step 1 and 3 do not change)
         ii. Calculate and store workload level performance
     d. Repeat point 4 for the second until the eight day from
        the list of highest demand days
5. Pick best performance out of 8*n*n runs
6. Compare the best performance with the CurrentBest
   performance
     a. If the performance is better, accept the proposed swap
     b. Adapt the MSS and set as current MSS
     c. Stop heuristic when no better performance is found
7. Return to point 2
8. Stop after a predefined number of swaps
9. Provide end results (swap + performances)
```

Speed up the process
For the execution of this heuristic it is not necessary to run the total model for every step. Since Step 1 and 3 are only specialty specific, the results for these steps do not change. Step 2 puts every probability distribution on the right day of the MSS and therefore must be recalculated after swapping. This modification reduces the run time from two seconds to a third of a second per model run.

Validation of the heuristic
Test data and step-by-step debugging programming analysis is used to verify the correct implementation in Matlab. The code that we use for generating the outcomes of the

initial MSS helps to verify the correctness of the heuristic. This is simply done by adapting the input manually and run the model.

5.4 Results

This paragraph describes the results of the model runs with different parameter input. We compare the initial output with the results after applying the heuristic. We apply the heuristic on two situations and discuss on the new performance output. Since nine ORs in the hospital are dedicated to Division 1 we allow swaps between these ORs. A small number of OR days is filled by specialties of other divisions. The model assumes that it is possible to swap these OR blocks and we define these blocks as empty OR blocks in the model input. In the second situation we increase the OR availability with one OR. The LUMC has twenty ORs in total of which OR 4 and 12 are dedicated to emergency patients. In this second situation we assume that one more OR is available for Division 1 on every day of the cycle. We run the heuristic for both situations and elaborate on the model output. Next we provide the best and best alternative swaps together with their implications.

5.4.1 Workload leveling performance

As illustrated in paragraph 5.2, the ward occupancy for the initial model fluctuates throughout the working week. The occupancy was relatively low on Mondays and relatively high on Tuesday to Friday. Four of the ten working days required more than seventy beds with a maximum of 74 beds on Friday in the second week of the MSS cycle. In Table 5.8 we show the improvements after applying the heuristic. We use a 90^{th} percentile of demand for staffed beds and run the heuristic. When only 9 ORs are available, the heuristic stops after four swaps, because there are no better solutions found for a next swap. The maximum occupancy level is now reduced with 3 beds from 74 to 71 beds. Furthermore there is only one day that the expected demand is more than seventy beds. Table 5.8 also shows the output when 10 ORs are available. The model run stops after eight swaps. The maximum occupancy is reduced from 74 to seventy beds so there are no more days that demand is higher than seventy beds. Figure 5.3 shows the two experiments together with the initial solution.

Table 5.8: Initial MSS results

Experiment	9 ORs			10 ORs		
Swap	Maximum number of beds	Workload level performance	Cum. % of decrease	Maximum number of beds	Workload level performance	Cum. % of decrease
0	74	412,3	0,0	74	412,3	0,0
1	74	341,9	37,2	74	341,9	26,2
2	72	274,0	73,1	72	274,0	51,5
3	71	244,5	88,7	72	229,7	68,0
4	71	223,1	100,0	71	182,5	85,5
5				71	164,9	92,1
6				71	154,0	96,1
7				71	150,5	97,4
8				70	143,6	100,0
Decrease	**189,2 = 46,9%**			**268,6 = 65,1%**		

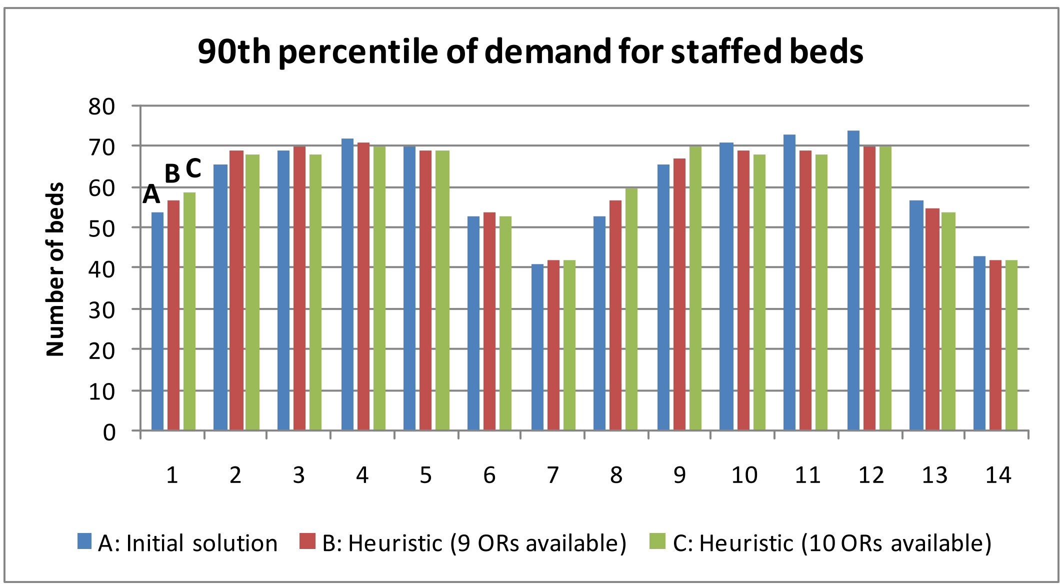

Figure 5.3: Demand for staffed beds

The decrease in workload for every swap is shown in Figure 5.4. For the situation where 9 ORs are available, we see that after two swaps the slope of the line decreases, indicating less reduction in workload compared to the first two swaps. The workload level performance after the fourth swap is reduced with 45,9 percent compared to the initial solution. If we take the reduction in workload of both the first two swaps, we see that this represents already 75 percent of the total reduction. This means the benefit of swap 3 and 4 is relatively small. The question that rises is whether the benefit of executing these swaps is higher than the work of realizing them.

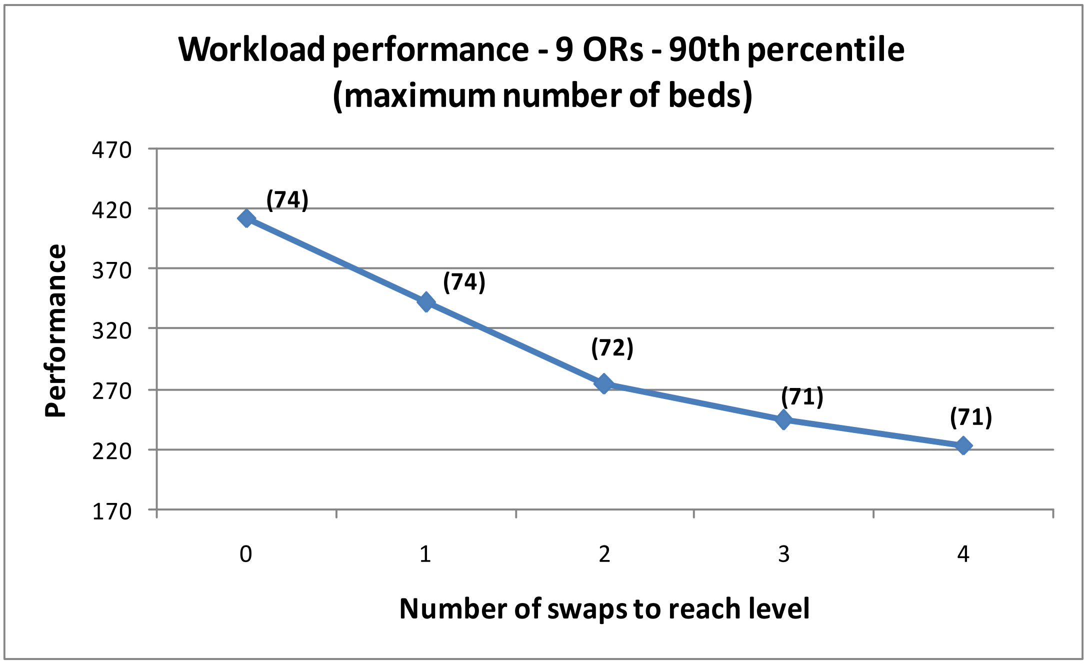

Figure 5.4: Workload performance (9 ORs) with the maximum number of beds needed

For the second situation showed in Figure 5.5, where 10 ORs are available, we see that after four swaps the slope of the line decreases, indicating less reduction in workload compared to the first four swaps. The workload performance after the eight swap is reduced with 65,2 percent. If we take the reduction in workload of both the first four swaps, we see that this represents already 86 percent of the total reduction. See Appendix D for more detailed data. Swaps 5, 6, 7, and 8 only have a small improvement. Subparagraph 5.4.2 discusses this issue and suggests the most interesting swaps.

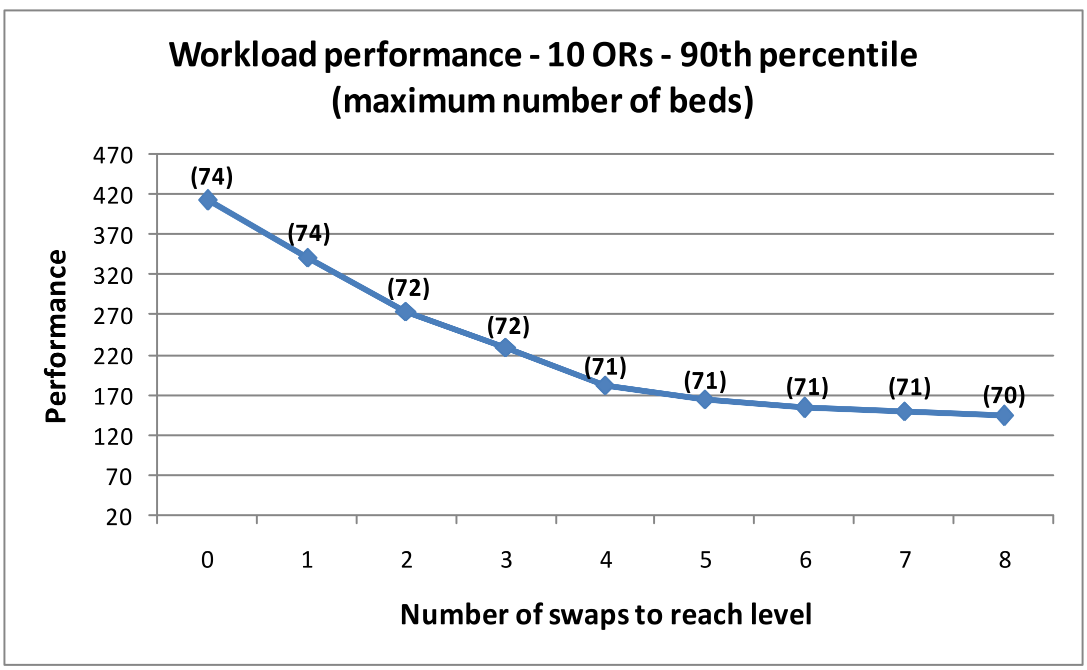

Figure 5.5: Workload performance (10 ORs) with the maximum number of beds needed

5.4.2 Best swaps

To define the best swaps, we first consider the situation in which 9 ORs are available. Since it is hard to change the MSS, the execution of the first two swaps could already give a satisfying solution because the maximum occupancy for the weekdays as well as the weekend days decreases. For weekdays, the number of expected beds decreases with 2 from 74 to 72 accounting for 75 percent of the total benefit. A difference is that after two swaps, not one but two days demand more than seventy beds. We assume that in this situation, the best swaps to perform are the first two swaps. Both swaps demand the replacement of the empty ORs on Mondays by Traumatology blocks of the Tuesday and Thursday in the second week of the cycle. It is reasonable that empty blocks on the days that occupancy is lowest are used to swap. The choice for the Traumatology blocks is validated by calculating the expected values of the model input presented in Table 5.9. Traumatology has the highest expected value for the number of procedures per OR block and a relatively low expected length of stay. The swap of this Traumatology block with the empty OR gives the best solution based on the performance indicator. Other solutions that might be good alternatives, when the swap of Traumatology is not possible, would be other planned specialties from other ORs of this day. Day nine is chosen as best day to swap and recalling the MSS this day has also Orthopedic surgery, Urology, Oncology, and Oral and Maxillofacial surgery blocks. Using these specialties to perform the swap might be good alternatives. The performance of these swaps is given in Table 5.10. The rank of the alternative swaps corresponds to the expected values of the input parameter cj, the expected number of procedures in a block. The table indicates that a good alternative swap is the OR dedicated to Oncology (when for example it is not possible to realize the first swap) since the difference in workload performance is relatively small. Oncology ranks second in Table 5.9 with the expected values. Swapping the OR blocks from the other specialties in Table 5.10 are all improvements but the effect is lower when the specialty ranks lower in Table 5.9. It is possible that now other operating days become more interesting to swap from.

Table 5.9: Expected values of the input distribution for number of patients per block

Specialty	Spec ID	Expected value on number of patients
Traumatology	**10**	**2,818**
Oncology and Gastro	8	2,700
General surgery	7	2,474
Urology (full day)	5	2,397
Orthopedic	4	2,365
Plastic surgery (full day)	2	2,287
Transplantation	9	2,211
Mixed general surgery	12	2,105
Urology (half day)	6	1,951
Plastic surgery (half day)	3	1,923
Vascular surgery	11	1,737
Oral and Maxillofacial surgery	1	1,516

Table 5.10: Expected values of the input distributions

Rank	Specialty ID	Specialty	Workload performance
1	10	Traumatology	341,93
2	8	Oncology	345,71
3	5	Urology	361,93
4	4	Orthopedic surgery	366,57
5	1	Oral and Maxillofacial surgery	383,36

Table 5.11: Best swaps

Swap	90th percentile of demand with 9 ORs available	Max Occupancy
Swap 1	swap OR 9 (empty) of day 8 with OR 2 (Traumatology) of day 9	74
Swap 2	swap OR 9 (empty) of day 1 with OR 5 (Traumatology) of day 11	72
Swap 3	swap OR 5 (Vascular surgery) of day 8 with OR 3 (Urology) of day 3	71
Swap 4	swap OR 5 (Vascular surgery) of day 1 with OR 3 (Urology) of day 10	71

Swap	90th percentile of demand with 10 ORs available	Max Occupancy
Swap 1	swap OR 9 (empty) of day 8 with OR 2 (Traumatology) of day 9	74
Swap 2	swap OR 9 (empty) of day 1 with OR 5 (Traumatology) of day 11	72
Swap 3	swap OR 4 (empty) of day 8 with OR 8 (Oncology) of day 10	72
Swap 4	swap OR 4 (empty) of day 1 with OR 3 (Urology) of day 2	71
Swap 5	swap OR 5 (Vascular surgery) of day 3 with OR 5 (Urology) of day 11	71
Swap 6	swap OR 5 (Vascular surgery) of day 2 with OR 3 (Traumatology) of day 2	71
Swap 7	swap OR 5 (Urology) of day 1 with OR 10 (Plastic surgery) of day 5	71
Swap 8	swap OR 8 (General surgery) of day 1 with OR 1 (Orthopedic surgery) of day 2	70

A first conclusion after so far would be that empty ORs on the Mondays are best used for swapping. The preferable specialty to swap with would be the one with a high expected number of procedures per OR block. The five best blocks for a first swap with day 9 of the cycle are given in Table 5.10. In the following part, we extend the MSS with one more empty OR, available on every day of the cycle.

In case 10 ORs are available, the best swaps to perform are the first four swaps. These swaps account for 85,5 percent of the total benefit. They demand the replacement of the empty ORs on Mondays by Traumatology blocks (first two swaps), Oncology (third swap), and Urology (fourth swap). It is logical that the first two swaps are the same as in the previous setting. Again the question rises if swap numbers 5 to 8 are worth realizing, since the benefit is quite small. The difference in the results between the availability of 9 or 10 ORs is small. The maximum bed demand with the extra OR available is 70 beds, which is only one less than the 9 OR situation. The workload level performance decreases 65.1 instead of 46.9 percent, but we need eight swaps to reach this!

Figure 5.6 gives the workload for the initial solution, the 9 OR situation with two swaps, and the 10 ORs situation with four swaps. As we indicated, the difference in the results between the availability of 9 or 10 ORs is small. The decrease in number of beds and an improved leveling of the workload will not compensate the costs of opening an extra OR.

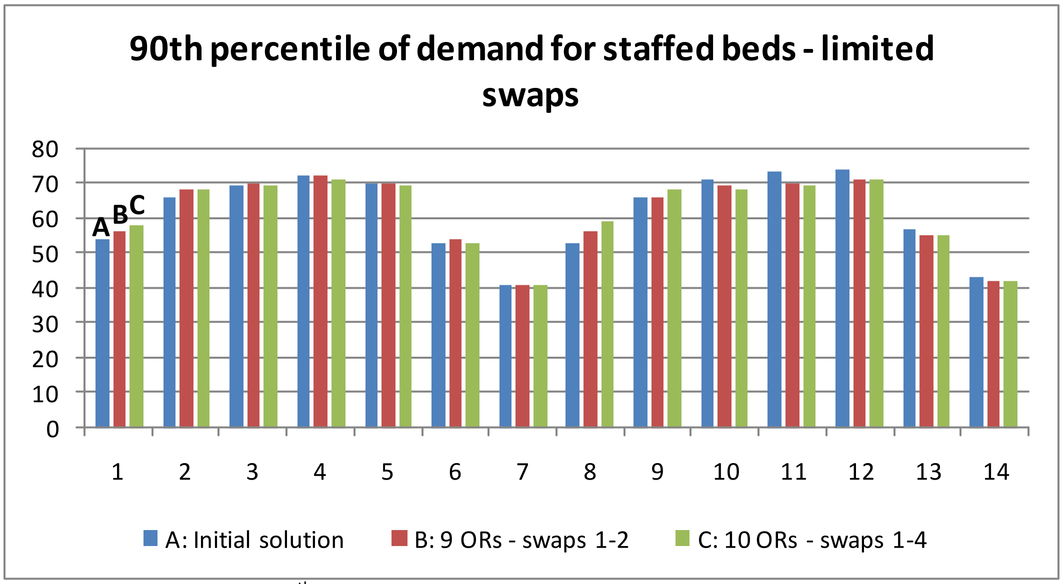

Figure 5.6: 90th percentile demand for staffed beds with limited swaps

5.5 Sensitivity analysis

Sensitivity analysis is used to investigate the robustness of the model. It can be used to test the robustness on among others the model assumptions we discussed, the input data of the model and the use of the model in the future. In this paragraph we run the same experiments (9 and 10 ORs) for various percentiles of demand in Subparagraph 5.5.1. In Subparagraph 5.5.2 we test the importance of the granularity of the MSS and the input variables. The question whether it is beneficial to use more detailed MSS and input distributions is answered.

5.5.1 Percentiles of demand

We choose the 85th and 95th percentile of demand and compare them to the 90th percentile and review the results on number of swaps executed, the reduction in workload and the best swaps. After this, we are able to say something about the robustness of the model and the input. Table 5.12 gives the output of the sensitivity analysis when we consider 9 ORs.

The total decrease in the 9 OR situation ranges between 45,9 and 54,7 percent. For the 10 OR experiment, presented in Appendix E, these percentages are higher ranging between 59 and 67,7 percent, because there is more space to swap OR blocks. The OR swaps to obtain this performance do not change a lot. In all runs, empty ORs on Monday are swapped with ORs from day Tuesday, Wednesday or Thursday from the second week of the cycle. Also for all instances, the most popular specialties to swap with are specialty 10, Traumatology and specialty 5, Urology. These specialties rank high on expected number of procedures and relatively low on the expected length of stay.

Table 5.12: Sensitivity analysis on workload performance with 9 ORs

Workload performance	9 ORs					
Swap	**85th percentile**	**Cum. % of decrease**	**90th percentile**	**Cum. % of decrease**	**95th percentile**	**Cum. % of decrease**
0	422,29	0,0	412,29	0,0	403,71	0,0
1	336,50	37,1	341,93	37,2	350,36	26,2
2	277,36	62,7	274,00	73,1	270,79	65,3
3	254,07	72,8	244,50	88,7	245,07	77,9
4	243,71	77,3	223,07	100,0	223,50	88,5
5	237,43	80,0			220,00	90,2
6	230,64	82,9			216,21	92,0
7	229,71	83,3			206,50	96,8
8	221,79	86,7			200,00	100,0
9	210,36	91,7				
10	191,14	100,0				
Decrease	231,14	54,7%	189,21	45,9%	203,71	50,5%

Figures 5.7 graphically compare the various percentiles of demand. Although there are differences in performances, these are considerably small taking into account the most important swaps (first two for 9 ORs and the first four for 10 ORs). Also the decisions are almost identical: OR blocks are moved from the second week to the Mondays and the most interesting blocks to swap are those of Traumatology and Urology.

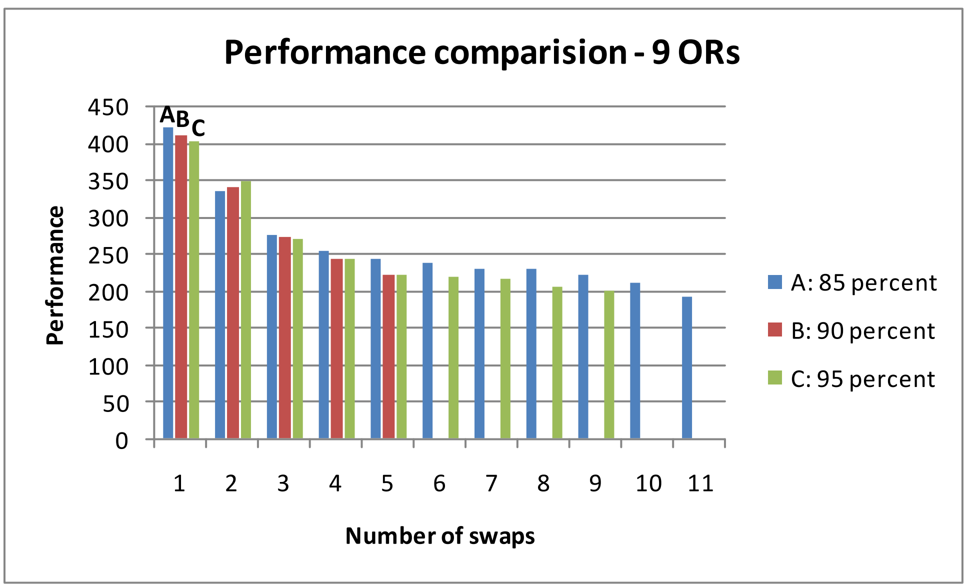

Figure 5.7: Sensitivity analysis 9 ORs

5.5.2 Granularity of the MSS

Granularity concerns the level of detail of the model. In paragraph 5.2 we point out that the MSS of the LUMC states general specialty IDs and that it does not show subspecialty type or procedure type. A more detailed MSS as input improves the accurateness of the model. The issue is that it takes a lot of effort to make classes for every subspecialty or procedure type. Another issue is that these more accurate distributions are hard to dedicate to OR blocks in the MSS, because procedures are planned disorderly. In paragraph 5.2 we also stated that since this project considers tactical planning and we therefore need a certain level of patient aggregation, we assume that patients are identically distributed within a specialty type. This paragraph discusses the necessity of a more detailed MSS.

We choose the General surgery specialty to define the impact of granularity of the model. General surgery consists of six subspecialties and in the previous paragraph six different probability distributions serve as input. We assume this is the high level of detail situation. In this paragraph we review two alternatives. The first one is to take the General surgery specialty as one and define a single probability distribution. We assume this to have the least level of detail. The second alternative is to divide all General surgery OR blocks into three classes based on the expected outcome of the number of procedures in a single OR block. For both situations we also adapt the length of stay distributions according the patient input for the classes. We assume that the situation with General surgery as three classes to be an in-between level of detail.

Calculation of the distributions for the classes

Calculation for the alternative with just one class is straightforward. All output, from the General surgery OR blocks, is considered and both probability distributions (the expected number of patients in a block and length of stay) are based on this data. The calculation for the three class alternative is less straightforward. We use the following steps for calculation:

- For every General surgery OR block separate distributions of the expected number of procedure in one block are calculated
- The expected values of the blocks are compared and divided in three classes
- Class 1: E[X] < 1.75, Class 2: 1.75 =< E[X] < 2, Class 3: E[X] > 2
- For every class a new probability distribution is calculated based on the output of the OR blocks that are in the corresponding class
- For the length of stay distributions we use for class 1 we the length of stay of Oncology, which fits the corresponding input of cj, and for class 2 and 3 we calculate a new distribution based on all General surgery patients

We run the model for these two alternatives and compare the outcome with the data of paragraph 5.4 where 9 ORs are available. We use the 90^{th} percentile of demand for staffed beds. In Table 5.13 we first discuss on the workload level performance of the three runs. Second, we compare the best swaps in order to conclude on the importance of granularity in the MSS.

For the original input, which we use in the previous paragraphs where General surgery is divided in six classes, the heuristic does not find any better solutions after four swaps.

For the cases with a lower level of detail, the heuristic comes up with twelve (1 class) and fourteen (3 classes) swaps. Table 5.13 shows the decrease of the workload level performance per swap. Because the input distributions are different in every situation, this results in different start solutions and different bed occupancies for every day in the cycle. Table 5.13 shows that, compared to the original situation where General surgery is divided among six classes, the other two situations give an underestimation of the average number expected beds.

Table 5.13: Granularity of the model

	General surgery 1 class		General surgery 3 classes		General surgery 6 classes (original)	
Swap	**Workload level performance**	**Percentage decrease**	**Workload level performance**	**Percentage decrease**	**Workload level performance**	**Percentage decrease**
0	328,64	-	358,07	-	412,29	-
1	266,36	-19,0%	284,36	-20,6%	341,93	-17,1%
2	217,14	-18,5%	225,71	-20,6%	274,00	-19,9%
3	191,43	-11,8%	200,64	-11,1%	244,50	-10,8%
4	182,29	-4,8%	176,93	-11,8%	223,07	-8,8%
5	169,64	-6,9%	159,79	-9,7%		
6	166,57	-1,8%	156,29	-2,2%		
7	155,36	-6,7%	154,86	-0,9%		
8	148,86	-4,2%	143,64	-7,2%		
9	140,86	-5,4%	135,50	-5,7%		
10	137,79	-2,2%	126,93	-6,3%		
11	134,86	-2,1%	124,07	-2,3%		
12	134,64	-0,2%	122,36	-1,4%		
13			121,43	-0,8%		
14			118,50	-2,4%		
Total decrease	**194,00**	**-59,0%**	**239,57**	**-66,9%**	**189,21**	**-45,9%**
Average beds	**53,8**		**54,5**		**61,6**	

The data on the workload level performance in Table 5.13 is graphically shown in Figure 5.8. It shows that the start solutions of the 1 and 3 class situation are lower, but that the decrease of the workload level indicator is comparable for the first three swaps.

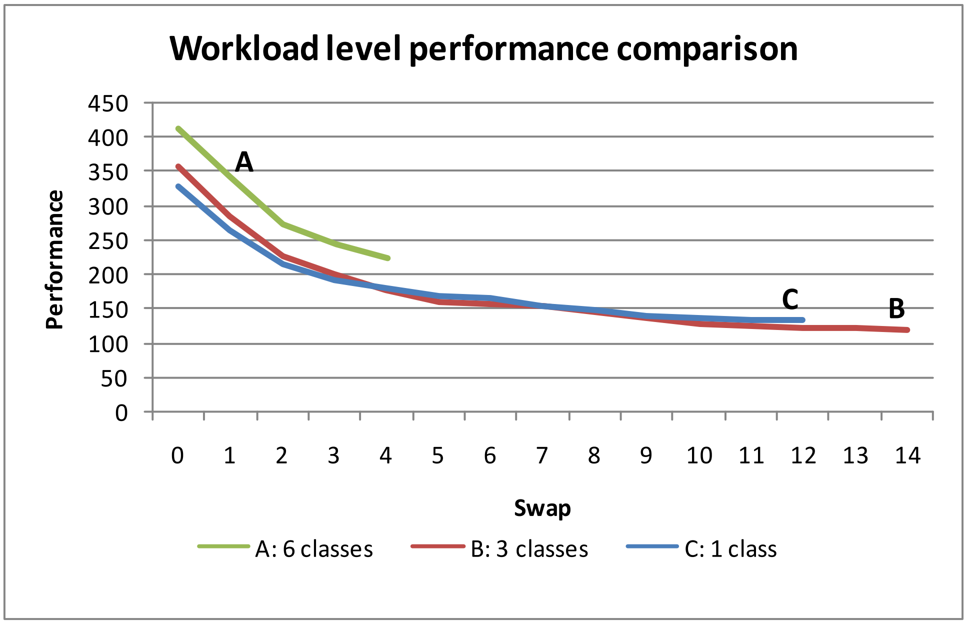

Figure 5.8: Workload level performance comparison

Although the levels for the bed demand and the workload level performance are different, the similar patterns for the first three swaps indicate that the same decisions are taken by the heuristic in all situations. In reality we would expect more variability for the 1 and 3 class versions. Table 5.14 shows the first three swaps for every class.

Table 5.14: Best swaps per experiment

1 class	
Swap 1	swap OR 9 (empty) of day 8 with OR 1 (Orthopedic surgery) of day 10
Swap 2	swap OR 9 (empty) of day 1 with OR 3 (Urology) of day 3
Swap 3	swap OR 3 (General surgery E[X] < 1,75) of day 8 with OR 3 (Urology) of day 4
3 classes	
Swap 1	swap OR 9 (empty) of day 8 with OR 3 (Urology) of day 11
Swap 2	swap OR 9 (empty) of day 1 with OR 1 (Orthopedic surgery) of day 10
Swap 3	swap OR 3 (General surgery) of day 8 with OR 3 (Urology) of day 4
6 classes	
Swap 1	swap OR 9 (empty) of day 8 with OR 2 (Traumatology) of day 9
Swap 2	swap OR 9 (empty) of day 1 with OR 5 (Traumatology) of day 11
Swap 3	swap OR 5 (Vascular surgery) of day 8 with OR 3 (Urology) of day 3

Because General surgery now has different classes, we recalculate the expected values of the number of procedures in an OR block. These tables can be found in Appendix F. Based on Table 5.14 and the appendix; we conclude that the same kind decisions are made. First, the empty ORs on Monday are swapped with OR blocks that have a relatively large expected value on the number of procedures per block. Since the Traumatology blocks are replaced by general blocks, Urology and Orthopedic surgery now have the largest expected value.

To conclude on the granularity of the MSS, we find that the newly defined distributions cause variation in the expected bed demand compared to the original situation. But in all three situations, the same decisions are taken. OR blocks with a high expected value of bed demand, that are planned Tuesday to Thursday, are moved to Monday. A more detailed MSS and input distributions would improve the correctness of the model output, but not change these decisions. This effort is therefore not beneficial.

Summary

Model input

- Since this project considers tactical planning and we therefore need a certain level of patient aggregation, we assume that patients are identically distributed within a specialty type and we are able to define twelve probability distributions based on OR output

Application to the current MSS

- The initial model output gives a overestimation on the expected number of beds compared to the real data
- The initial model output shows a comparable pattern for expected bed demand compared to the real data
- The performance indicator of workload level is introduced and is defined as the sum of the quadratic difference with the mean bed demand for every day in the MSS

Results

- The heuristic reduces the workload level performance indicator with 46,9% percent, taking into account only the Division 1 ORs, by making four swaps
- The maximum bed demand is reduced from 74 (the initial model output) to 71 beds, indicating the possibility of decreasing the number of staffed beds
- An improved workload leveling and reduction of the maximum bed demand is possible when more OR time is available on Monday. The performance indicator of workload leveling then reduces by 65,1% and the maximum bed demand decreases from 74 to 70 beds, but eight swaps are needed to reach this performance
- The decrease in number of beds and an improved leveling of the workload will not compensate the costs of opening an extra OR
- The best two swaps are swapping empty OR blocks of Monday with Traumatology blocks of Tuesday and Thursday in the second week of the MSS
- The best swaps depend heavily on the expected value of OR production (cj-parameter)

Sensitivity analysis

- The 85th and 95th percentile allow more swaps (8 respectively 10)
- Workload reduction shows a comparable pattern for the various percentiles

- The proposed swaps are the same: OR blocks are moved from the second week to the Mondays and the most interesting blocks to swap are those of Traumatology and Urology, having a high expected value on OR production
- Alternative distributions for General surgery with a lower level of detail causes a underestimation on the average expected bed demand
- The essence of the proposed swaps are the same: OR blocks with high workload are moved to Mondays
- Increase of the level of detail of the MSS and the input distributions is not beneficial because the swap decisions stay the same

6 Conclusions & recommendations

In this chapter we discuss the conclusions and recommendations of this study. We also discuss the managerial implications that are involved in this research and propose points for further research in Paragraph 6.4.

6.1 Conclusions

In this paragraph we discuss the conclusions we can draw from the results. In Chapter 2 we indicate that variability in bed occupancy (bed demand) is mainly caused by the elective patient group. The variability causes peak workloads, empty beds, stress for personnel, and makes it harder to plan non-elective patients. We propose alternative MSSs in order to reduce the variability by quantifying the steady-state bed occupancy rates of a MSS. We use the analytical model described by Vanberkel et al., (2009) to perform a case study at LUMC. The model originally serves on the tactical planning level as a tool to quickly evaluate proposed MSS solutions. The output of the model is the steady-state expected bed demand for every day of the MSS. The impact on the wards by small changes in the MSS is directly visible, which is valuable for hospital management in order to make decisions with respect to desired occupancy rates.

The model requires two input parameters and the initial MSS to calculate the demand. Since this project considers tactical planning, we need a certain level of patient aggregation. Therefore we assume that patients are identically distributed within a specialty type, so that we are able to define twelve probability distributions based on OR output. As an addition to the model we introduce the workload level performance indicator which is defined as the sum of the quadratic difference with the mean bed demand for every day in the MSS. Also we propose a heuristic for output generation that is able to come up with alternative solutions which levels the demand for beds over the cycle. The model now serves as a decision support tool. Based on the result, we draw the following conclusions:

- The initial model run quantifies the workload variability by calculating the workload level performance indicator
- The initial model output shows a comparable pattern for expected bed demand compared to the real data
- The heuristic reduces the workload level performance indicator with 46,9% percent, taking into account only the Division 1 ORs, by making four swaps
- The maximum bed demand is reduced from 74 (the initial model output) to 71 beds, indicating the possibility of decreasing the number of staffed beds
- An improved workload leveling and reduction of the maximum bed demand is possible when more OR time is available on Monday. The performance indicator of workload leveling then reduces by 65,1% and the maximum bed demand decreases from 74 to 70 beds, but eight swaps are needed to reach this performance
- The decrease in number of beds and an improved leveling of the workload will not compensate the costs of opening an extra OR.

- The best two swaps are swapping empty OR blocks of Monday with Traumatology blocks of Tuesday and Thursday in the second week of the MSS
- The proposed best swaps are the swapping of OR blocks that have a high expected value of OR production (the input parameter of expected number of patients that follows from one OR block)
- The importance of higher level of detail of the MSS is invalidated for the LUMC case, since the same decisions are proposed by the heuristic when the level of detail is reduced

The swaps make it possible to decrease the number of staffed beds and simultaneously decrease the number of canceled patients. Demand is more constant divided over the Division 1 wards and therefore we expect fewer problems in the admission of non-elective patients and the personnel planning of the wards. A last benefit is that the model is easily adapted to serve other divisions/wards.

6.2 Recommendations

This paragraph provides the recommendations to reach the objective to level the workload of the wards and to decrease peak workloads. The general recommendations that follow from this study are listed below:

- Use the model at the tactical level of planning
- In order to improve the workload leveling of the wards, the OR center should carry out more procedures on Monday by moving OR blocks from Tuesday to Thursday in the second week of the cycle to the Mondays
- Since it is hard to change a MSS, the possibilities of which OR blocks to swap should be investigated (see Paragraph 6.3)

Also we introduce immediate actions for Division 1 management that follow from the study results:

- Inform the physicians about the outcome of this study
- Discuss the possibilities of swapping OR blocks that follow from the proposed best swaps
- Reduce the current workload on Tuesday to Friday by moving at least one OR block to the Mondays of the MSS
- Discuss the possibilities of exchanging OR time with non-division 1 specialties

Other recommendations that follow from this study:

- Increase of the level of detail of the MSS and the input distributions is not encouraged because the swap decisions stay the same when the level of detail is reduced
- The model is easily adapted to serve other divisions and specialties and we encourage to do this

6.3 Managerial implications & further research

Using the model to evaluate a proposed MSS is valuable for LUMC, since the effects of OR-block changes are visible now. In this study we propose alternative MSSs striving for a better synchronization between the OR-center and the wards. Although the proposed changes are relatively small since only limited swaps are necessary, changing the MSS is rather complicated. In the LUMC, the total OR-time is shared by various specialties. For these specialties, various physicians perform the procedures. But physicians have many other tasks next to operating, namely outpatient consultations, conferences, staff meetings, lecturing, and sometimes work at other hospitals too. Next to the physicians, ORs also have limited capacity or are dedicated to specific specialties. It is very likely that the proposed swaps are not possible because of aforementioned reasons. The model can be adapted in such way that specific OR swaps become forbidden, resulting in different solutions. In short, this study provides ideal OR swaps, but does not take into account the limited possibilities of changing an MSS.

In this research we take the three wards of Division 1 as one big ward, because of complexity reasons. At the short stay facility, closed during weekends, patients from all Division 1 specialties can be admitted. The MSS does not determine the ward where the patient will end up after surgery. This makes it impossible to retrieve ward specific results from the model. Further research is needed to see whether it is valuable to make this possible.

References

Adan, I. and Vissers, J. (2002). Patient mix optimisation in hospital admission planning: a case study. International Journal of Operations and Production Management, 22(4):445–461.

Beliën J. and Demeulemeester E. (2007). Building cyclic master surgery schedules with leveled resulting bed occupancy. European Journal of Operational Research, 176(2): 1185–1204.

Blake, J. T., Dexter, F. and Donald, J. (2002). Operating room manager's use of integer programming for assigning block time to surgical groups: A case study. *Anesthesia and Analgesia* 94: 143-148.

de Bruin A. M., Bekker R., van Zanten L. and Koole G.M., Dimensioning Hospital Wards Using the Erlang Loss Model. Submitted to AOR-ORAHS's special volume (2008).

B. Cardoen, E. Demeulemeester, and J. Beliën. Operating room planning and scheduling: A literature review. FED Research Report KBI 0807 Katholieke Universiteit Leuven, 2008.

J. K. Cochran, A. Bharti, A multi-stage stochastic methodology for whole hospital bed planning under peak loading, International Journal of Industrial System Engineering 1 (2006) 8–36.

Harrison, G., Shafer, A., and Mackay, M., Modeling variability in hospital bed occupancy. Health Care Management Science. 8:325–334, 2005.

Houdenhoven, M. v., Wullink, G., Hans, E. W., & Kazemier, G. (2007). A framework for Hospital Planning and Control. In M. v. Houdenhoven, Healthcare Logistics: The Art of Balance (page 23). Schiedam: Uitgeverij Scriptum.

Intranet website LUMC: http://albinusnet.lumc.nl/home/org/div/

Law A. M., Simulation Modeling and Analysis. McGraw-Hill, Inc., fourth edition, 2007 pages 3-6.

van Oostrum, J. M., Van Houdenhoven, M., Hurink, J. L., Hans, E. W., Wullink, G., and Kazemier, G. (2008). A master surgical scheduling approach for cyclic scheduling in operating room departments. OR Spectrum, 30 (2), 355–374.

Strum D. P., Vargas L. G., Length of Stay in a Cardiac Intensive Care Unit Is Well Modelled by a Lognormal Distribution. Anesthesiology & Critical Care, http://www.asaabstracts.com October 20th, 2010.

Vanberkel, P. T., Boucherie R. J., Hans E. W., Hurink J. L., van Lent W. A. M., and van Harten W. H. An exact approach for relating recovering surgical patient workload to the master surgical schedule. November 2009, Internal Report.

Vanberkel P. T., Boucherie R. J., Hans E. W. , Hurink J. L., and Litvak N. (2010) A Survey of Health Care Models that Encompass Multiple Departments. International Journal of Health Management and Information (to appear)

Vissers J. M. H., Bertrand J. W. M. and de Vries G. (2001). A framework for production control in health care organizations. Production Planning & Control, 2001, 12, 6, 591-604

Appendices

Appendix A: Patient discharges

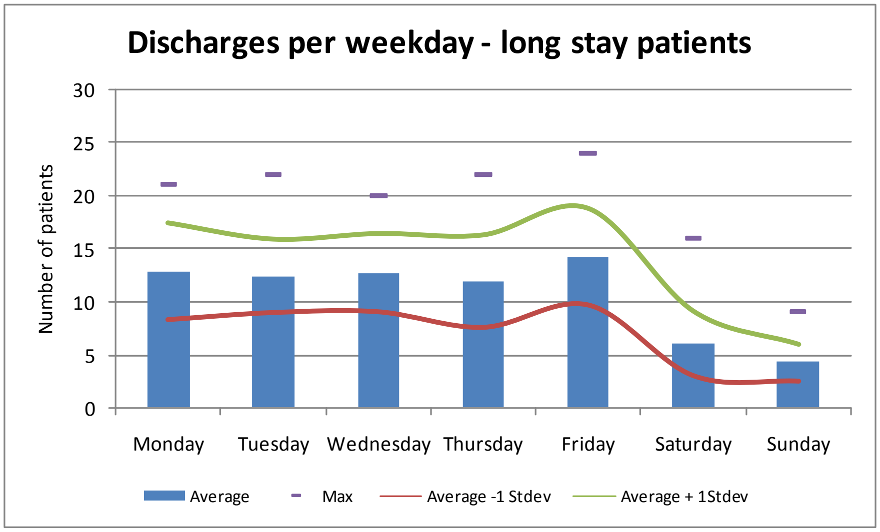

Figure A.1: Discharges per weekday – long stay wards
Source: MIS, 2008, n=3953

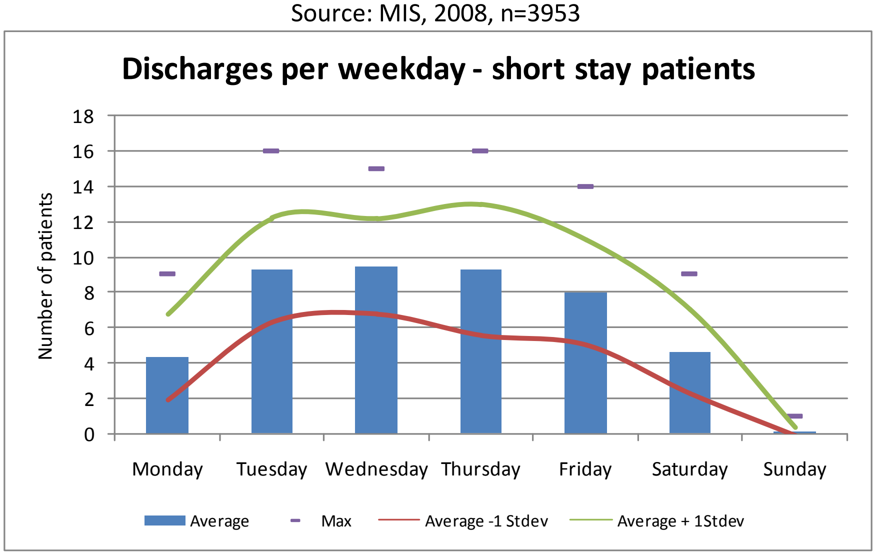

Figure A.2: Discharges per weekday – short stay wards
Source: MIS, 2008, n=2382

Table A.1: Statistical significance of differences among discharges between days of the week

Longstay discharge		Significant difference					
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday		no	no	no	no	yes	yes
Tuesday	no		no	no	no	yes	yes
Wednesday	no	no		no	no	yes	yes
Thursday	no	no	no		no	yes	yes
Friday	no	no	no	no		yes	yes
Saturday	yes	yes	yes	yes	yes		yes
Sunday	yes	yes	yes	yes	yes	yes	

Shortstay discharge		Significant difference					
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday		yes	yes	yes	yes	no	yes
Tuesday	yes		no	no	no	yes	yes
Wednesday	yes	no		no	no	yes	yes
Thursday	yes	no	no		no	yes	yes
Friday	yes	no	no	no		yes	yes
Saturday	no	yes	yes	yes	yes		yes
Sunday	yes	yes	yes	yes	yes	yes	

Appendix B: Length of Stay

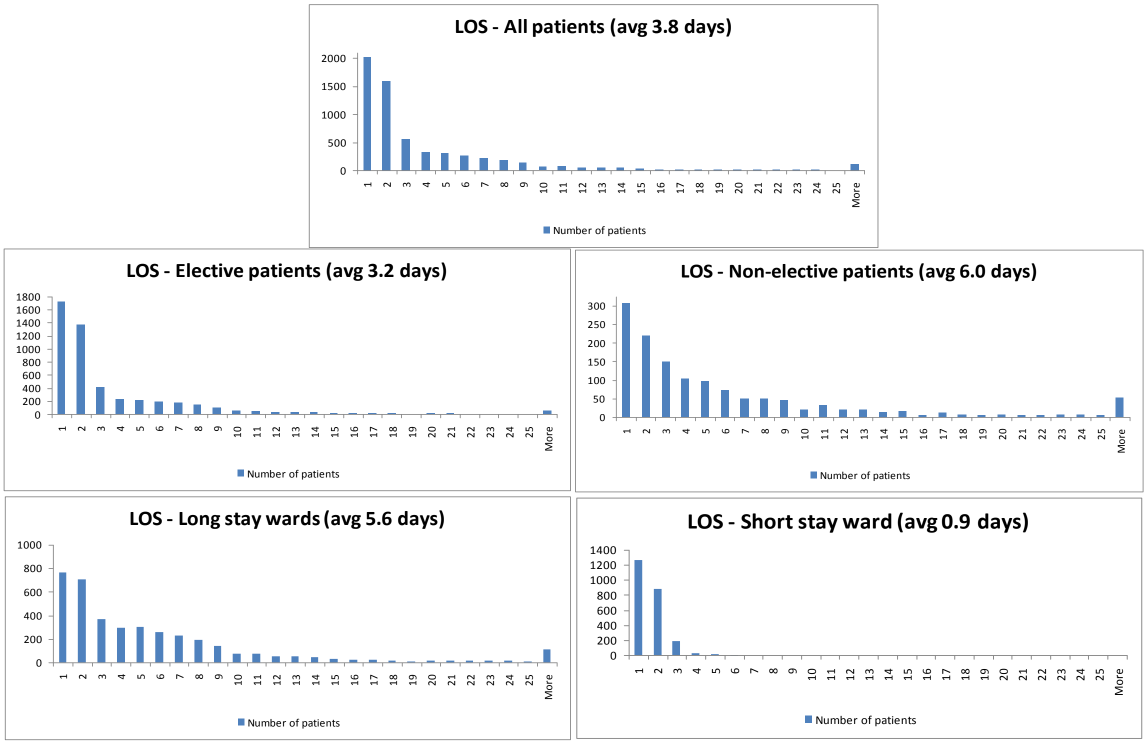

Figure B.1: Length of Stay

Figure B.2 and B.3 show the LOS distribution of respectively all patients and the elective patient group. Table B.1 concludes that the Pareto 80/20 principle is also applicable on the LOS at the wards. In our situation twenty percent of the patient account for seventy percent of the occupied bed time.

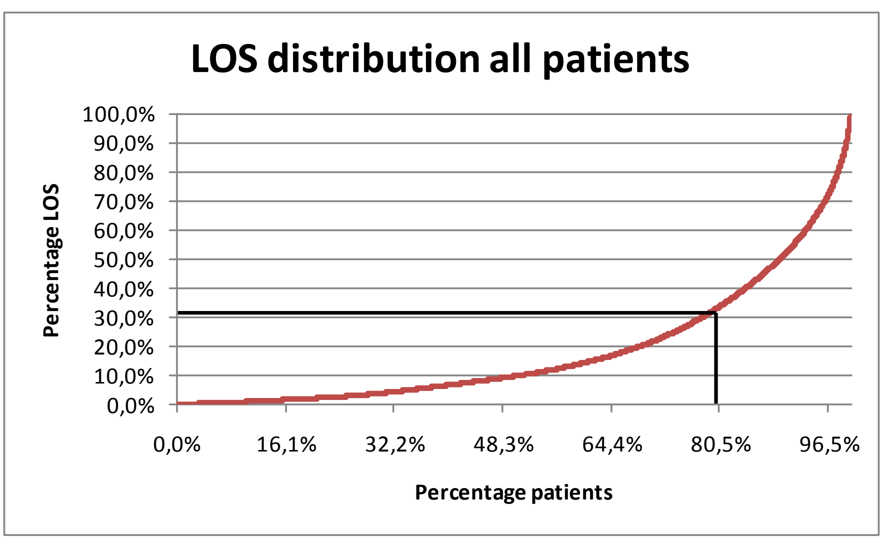

Figure B.2: Pareto's 80/20 principle all patients

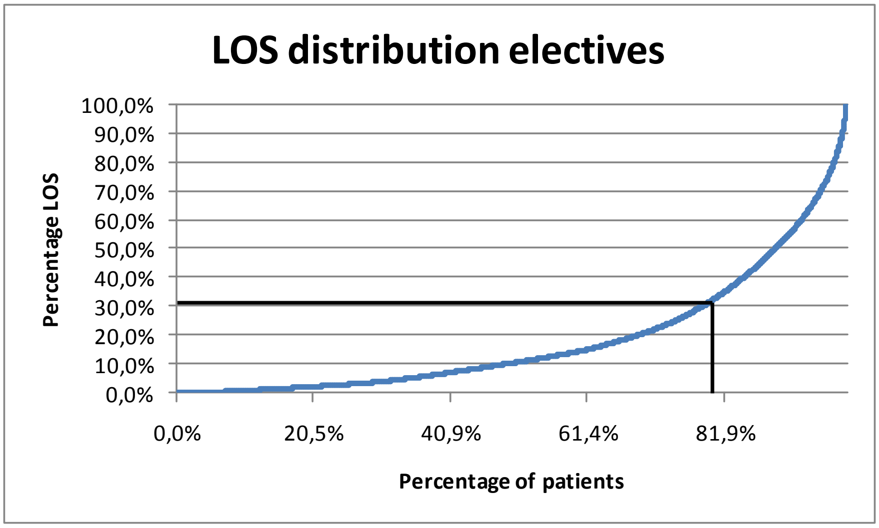

Figure B.3: Pareto's 80/20 principle elective patients

Table B.1: LOS implications

Patient group	20% of patients	80% of LOS
All patients	67.2% LOS	31.1% of patients
Elective patients	67.7% LOS	31.2% of patients

Appendix C: Matlab code

```
% Optimization of the MSS - Jurjen Tjoonk
% September 2010
% Goal of file: propose a new MSS together with an improvement heuristic
% Version 6 with just one performance indicator, workload leveling
% performance

tic % keep track of time
clear all;
clc;
% profile on % to analyse time per calculation step

% Parameters
CycleLength = 14; % MSS cycle length
NumORs = 9; % Number of ORs available
MaxLOS = 50; % Finit LOS of 50 days (for convergence)
MaxCases = 11; % Maximum of 11 patients a day that arrive (for convergence)
MaxSpecs = 12; % Number of specialties defined in Excel 'Input'-sheet
MaxPatients = 200; % Keeps the matrix 'EndEffect'small
BedsCovered = .95; % Percentile of demand for staffed beds

% ----------------------------------------------------
% Read parameters cj, dj and MSS
% ----------------------------------------------------
% read distribution cj
cj_dist = xlsread('input','cj_parameter','D2:O13'); % Matrix spec j times x
patients
% read distribution dj
dj_dist = xlsread('input','dj_parameter','D2:BB13'); % Matrix spec j times n
days
% read MSS
ORblocks = xlsread('input','MSSv2','B2:O10'); % Store MSS in ORblocks matrix

% Parameters optimization algorithm
SwapNumber = 8; % The number of DayMax to evaluate
MaxSwaps = 15; % Maximum number of allowed swaps
% objective = zeros(1,3); % Lexicographic objective
Weekend = [6 7 13 14]; % Weekend days

% --- Solution initial MSS - Run model -------------------------
Step1;
Step3;
Step2;
Outcome;
StartOccupancy = BedsNeeded
StartSolution = TotalPerformance
PerformanceStart = 0;

CurrentObjective = TotalPerformance
% ---------------------------------------------------------------

OriginalMSS = ORblocks;
% disp(['OriginalMSS ', intostr(OriginalMSS)])

% --- Heuristic -------------------------------------------------
StoreSwapDays = zeros(1,2,MaxSwaps);
AllObjectiveValues = zeros(NumORs,NumORs,SwapNumber,MaxSwaps); % zeromatrix to
store solutions
for Swap = 1:MaxSwaps % Maximum allowed swaps
    % Calculate objective with new MSS (MSS after a swap)
    StoreSwapDayTop8 = zeros(SwapNumber,1); % empty matrix
    clear t;
    Step1;
```

```
    Step3;
    Step2;
    Outcome;
    Occupancy = BedsNeeded(:,1)
    OrderedDays = sortrows(BedsNeeded,-1); % Sort BedsNeeded in descending order
(-1)

% --- Select SwapDayMin ------------------------------------------
    SwapDayMin = OrderedDays(14,2); % Choose day with lowest occupancy (not a
weekendday)
    if ((SwapDayMin == Weekend())==0)
    else
    SwapDayMin = OrderedDays(13,2);
        if ((SwapDayMin == Weekend())==0)
        else
        SwapDayMin = OrderedDays(12,2);
            if ((SwapDayMin == Weekend())==0)
            else
            SwapDayMin = OrderedDays(11,2);
                if ((SwapDayMin == Weekend())==0)
                else SwapDayMin = OrderedDays(10,2);
                end
            end
        end
    end % Day with lowest occupancy is chosen (not weekendday)
    disp(['Day ', num2str(SwapDayMin),' with lowest occupancy is evaluated'])
% ----------------------------------------------------------------

% --- Define SwapDayMax ------------------------------------------
% --- Loop over first 8 days of MaxBedsNeeded --------------------
    clear t; % empty the struct (was filled with the initial MSS)
    for SwapDayTop8 = 1:SwapNumber % for all days in top 8 BedsNeeded (days in
column 2)
    SwapDayMax = OrderedDays((1*SwapDayTop8),2);
    disp(['Day ', num2str(SwapDayMax),' with highest occupancy is evaluated'])
        for SelectedORMax = 1:NumORs % for all ORs in that day
            for SelectedORMin = 1:NumORs % for all ORs in that day

                % --- Start Swap ---- Swap two days means 100 possibilities
                tempblock1 = ORblocks(SelectedORMax,SwapDayMax);
                tempblock2 = ORblocks(SelectedORMin,SwapDayMin);
                ORblocks(SelectedORMax,SwapDayMax) = tempblock2;
                ORblocks(SelectedORMin,SwapDayMin) = tempblock1;
                % --- End Swap ----

                % --- Run model ---
                Step2; % only step 2 in needed
                Outcome; % workload level performance
                % -----------------

                AllObjectiveValues(SelectedORMin,SelectedORMax,SwapDayTop8,Swap)
= TotalPerformance; % fill matrix
                clear t; % empty the struct
                ORblocks = OriginalMSS; % take original MSS
            end
            % disp(['OR ', num2str(SelectedORMax),' is done']);
            BestObjectiveOR =
min(min(AllObjectiveValues(:,:,SwapDayTop8,Swap))); % take best performance
        end
        disp(['Day ', num2str(SwapDayMax),' has been calculated'])
        BestObjectiveOfAllSwapDays =
(min(min(AllObjectiveValues(:,:,SwapDayTop8,Swap)))); % take best performance
        StoreSwapDayTop8(SwapDayTop8,1) = BestObjectiveOfAllSwapDays;
```

```
    end
    BestObjectiveOverall = min(StoreSwapDayTop8(:,1)); % Best objective value
found compare to current
    CoordinatesOfBestDay = getcoord(BestObjectiveOverall,StoreSwapDayTop8);
    ActualDay = OrderedDays(CoordinatesOfBestDay(1,1),2); % we now know the
actual day
    BestSwap =
getcoord(BestObjectiveOverall,AllObjectiveValues(:,:,CoordinatesOfBestDay(1,1),S
wap)); % Look up the right OR swap
    SwapsPossible = BestSwap
    ORfromDayMinToSwap = BestSwap(1,1);
    ORfromDayMaxToSwap = BestSwap(1,2);
    MinDayChosen = SwapDayMin;
    disp(['Swap number ', num2str(Swap) ': OR ', num2str(ORfromDayMinToSwap) '
of day ',num2str(MinDayChosen), ', with OR ',num2str(ORfromDayMaxToSwap),' of
day ',num2str(ActualDay)])
    disp(['Best is to swap an OR of day ',num2str(MinDayChosen), ', with an OR
of day ',num2str(ActualDay)])

    % Adapt objective
    if BestObjectiveOverall < CurrentObjective % is the performance better?
    objective = BestObjectiveOverall; % set as new
    CurrentObjective = objective
    tempORblock1 = ORblocks(ORfromDayMaxToSwap,ActualDay); % perform best swap
    tempORblock2 = ORblocks(ORfromDayMinToSwap,MinDayChosen);
    ORblocks(ORfromDayMaxToSwap,ActualDay)= tempORblock2;
    ORblocks(ORfromDayMinToSwap,MinDayChosen)= tempORblock1;
    OriginalMSS = ORblocks; % adapt MSS
    ORblocks;
    else
        disp('There is no better swap possible')
        break % Stop heuristic
        % Display current solution
    end
    % StoreSwaps
    StoreSwapDays(1,1,Swap) = MinDayChosen; % DayMin to swap
    StoreSwapDays(1,2,Swap) = ActualDay; % DayMax to swap
    SizeOfSwapsPossible = size(SwapsPossible);
    StoreBestSwaps(1:SizeOfSwapsPossible(1),1:2,Swap) = SwapsPossible; % Which
ORs to swap
    SwapPerformance(Swap,1) = CurrentObjective;
end
% Show end result
OriginalMSS; % MSS of best result
clear t;
Step2;
Outcome;
OrderedDays = sortrows(BedsNeeded,-1); % Sort BedsNeeded in descending order (-
1)
% StartSolution
EndSolution = TotalPerformance
DifferenceStartEnd = StartSolution-EndSolution;
SizeOfPerformances = size(SwapPerformance);
for Solution = 1:SizeOfPerformances(1)
    SwapPerformance(Solution,2) = ((StartSolution -
SwapPerformance(Solution,1))/DifferenceStartEnd);
end

% profile off
toc
% profile viewer
```

Model Steps

```
% -------------------------------------------------------------------------
% Step 1: Distribution of recovering pat. from spec. j from single OR block
% Goal: define hj_dist(n,x) that is P(n days after surgery of spec. j, x
% pts of this block still in recovery) Matrix NxX for every j.
% -------------------------------------------------------------------------
for j=1:MaxSpecs % for every specialty a matrix is defined
    for n=0:MaxLOS % matrix is filled for every n,x combination
        for x=0:MaxCases
            if n==0
                vector_step1(1,x+1) = cj_dist(j,x+1); % pick value from Excel
                % (x is +1 omdat x=0:MaxCases bij 0 begint)
                % dj_dist = P(discharge on same day, n=0)
            else
                tempsum = 0; % start summation when hj_dist als n<>0
                for k=x:MaxCases
                    tempsum = tempsum + (nchoosek(k,x)*(dj_dist(j,n)^(k-x)*((1-
dj_dist(j,n))^x) * matrix_step1(n,k+1)));
                end
                vector_step1(1,x+1)=tempsum; % fill vector for x:0 till MaxCases
            end
        matrix_step1(n+1,x+1) = vector_step1(1,x+1); % fill matrix with vectors
        end
    end
    s(j).Step1 = matrix_step1(); % for every j, a matrix is stored in structure
s
     % call via s(1).Step1 for j=1 (gives hnj(x))
end

% -------------------------------------------------------------------------
% Step 3: Steady state distribution
% -------------------------------------------------------------------------
% It is easier to perform Step 3 before Step 2
M = MaxLOS+1+CycleLength; % second Friday in cycle is last day spec j can be
performed
NumCycles = ceil(M/CycleLength); % round number of cycles for steady-state
for j=1:MaxSpecs
    cycle = 1; % start with first cycle
    for q=1:CycleLength % convolution for every day in the cycle
        for x=0:MaxCases % calculate chance of x patients through convolution
            for cycle = 1:NumCycles
                if cycle == 1
                    vector_q = s(j).Step1(q,1:end); % enter first cycle
                else
                    Check1 = q+(cycle-1)*CycleLength; % define the day to pick
from h(j,n,x)
                        if Check1>50 % days does not exists
                        % no convolution needed
                        else % convolution per vector
                        vector_Step1 = s(j).Step1(Check1,1:end); % pick correct
row
                        % -------------- CONVOLUTION START ---------------
                        vector_q = conv2(vector_q,vector_Step1); %
                        % -------------- CONVOLUTION END -----------------
                        end
                 end
            end
            vector_step3 = vector_q;
            Length_Matrix = length(vector_step3); % define length
            matrix_q(q,1:Length_Matrix) = vector_step3; % fill matrix with
vectors
        end
    end
```

```
    s(j).Step3 = matrix_q(); % put matrix in structure s
end

% ------------------------------------------------------------------------
% Step 2: Aggregate distribution from single MSS cycle
% Goal: Calculate the total number of pts in recovery for every day in one MSS
% Shift distribution from Step 1 to the day the surgery is performed
% Input: matrix_n(n,x) of every specialty and a given MSS
% ------------------------------------------------------------------------
% Start with zerosmatrix for probability distribution of x patients of the
% MSS still in recovery on day m (hm(i,q,x))

for i=1:NumORs
    for q=1:CycleLength % we need the the distribution for every i,q combination
        matrix_step2 = zeros(CycleLength,MaxPatients); % force matrix to stay
small
        for j=1:MaxSpecs
            if ORblocks(i,q) == j
                % pick distribution from structure s
                for m=1:CycleLength
                    if m>=q % put vector on correct day
                        vector_step2 = s(1,j).Step3(m-q+1,1:end);
                    else
                        vector_step2 =s(1,j).Step3(CycleLength+m-q+1,1:end);
                    end
                    Length_Matrix = length(vector_step2);
                    matrix_step2(m,1:Length_Matrix) = vector_step2; %
                end
                t(i,q).Step2 = matrix_step2(); % put distribution in correct OR
block
            end
        end
    end % start with new ORblock
end
% Combine specialties
% Summation of all b_i,q with convolutions
length_m = length(t); % determine how many ORs are filled in MSS
size_t = size(t);
length_ORs = size_t(1);
matrix_end = zeros(CycleLength,MaxPatients);
for q=1:CycleLength % EndEffect for every day in cycle
    % Sum distribution with convolutions
    vector_hulp = 1; % pick correct row
    for m=1:length_m
        for i=1:length_ORs % include all ORs
            if isempty(t(i,m).Step2) == 0 % OR(isempty(s(i,m).Step2) ==
1,s(i,m).Step2 exists)
                % 1 is leeg, naar volgende blok
                % -------------- CONVOLUTION START ---------------
                vector_end = conv2(vector_hulp,t(i,m).Step2(q,1:end));
                % -------------- CONVOLUTION End -----------------
                vector_hulp = vector_end;
            end % endif, go to next ORblock
        end
    end
    Length_Matrix = length(vector_end);
    matrix_end(q,1:Length_Matrix) = vector_end; % put vector in matrix
end
EndEffect = matrix_end(1:CycleLength,1:MaxPatients);
```

Appendix D: Heuristic results

Table D.1: Results – 9 ORs – 90th percentile of demand

Results - 9 ORs - 90th percentile of demand						
Swap id	0	1	2	3	4	
Max. occupancy	74	74	72	71	71	
Max occupancy weekend	57	56	55	55	55	Impr.
WL Performance	412,29	341,93	274,00	244,50	223,07	189,21
Reduction in workload	n/a	70,36	67,93	29,50	21,43	
Part of total reduction	n/a	0,37	0,36	0,16	0,11	
Cumulative part	0,00	0,37	0,73	0,89	1,00	
Swap day min	n/a	8	1	8	1	
OR min	n/a	9	9	5	5	
Swap day max	n/a	9	11	3	10	
OR max	n/a	2	5	3	3	
Specialty OR block min	n/a	empty OR	empty OR	11	11	
Specialty OR block max	n/a	10	10	5	5	

Table D.2: Results - 10 Ors - 90th percentile of demand

Results - 10 Ors - 90th percentile of demand										
Swap id	0	1	2	3	4	5	6	7	8	
Max. occupancy	74	74	72	72	71	71	71	71	70	
Max occupancy weekend	57	56	55	55	55	54	54	54	54	
WL Performance	412,29	341,93	274,00	229,71	182,50	164,93	154,00	150,50	143,64	Total reduction 268,64
Reduction in workload	n/a	70,36	67,93	44,29	47,21	17,57	10,93	3,50	6,86	
Part of total reduction	n/a	0,26	0,25	0,16	0,18	0,07	0,04	0,01	0,03	
Cumulative part	0,00	0,26	0,51	0,68	0,86	0,92	0,96	0,97	1,00	
Swap day min	n/a	8	1	8	1	1	8	1	1	
OR min	n/a	4	4	9	9	5	5	5	8	
Swap day max	n/a	9	11	10	2	11	2	5	2	
OR max	n/a	2	5	8	3	3	2	10	1	
Specialty OR block min	n/a	empty	empty	empty	empty	11	11	5	7	
Specialty OR block max	n/a	10	10	8	5	5	10	2	4	

Table D.3: Expected number of patients E[X] of input distributions

cj-distribution			**dj-distribution**		
Specialty	**Spec ID**	**E[X] # patients**	**Specialty**	**Spec ID**	**E[X] # patients**
Traumatology	**10**	**2,818**	Transplantation	9	4,872483
Oncology and Gastro	8	2,700	General surgery	7	4,645604
General surgery	7	2,474	Oncology and Gastro	8	4,575676
Urology (full day)	5	2,397	Orthopedic	4	3,942607
Orthopedic	4	2,365	Vascular surgery	11	3,63745
Plastic surgery (full day)	2	2,287	Oral and Maxillofacial surgery	1	2,761934
Transplantation	9	2,211	Mixed general surgery	12	2,761934
Mixed general surgery	12	2,105	**Traumatology**	**10**	**2,681818**
Urology (half day)	6	1,951	Urology (full day)	5	2,523752
Plastic surgery (half day)	3	1,923	Urology (half day)	6	2,523752
Vascular surgery	11	1,737	Plastic surgery (full day)	2	1,720721
Oral and Maxillofacial surgery	1	1,516	Plastic surgery (half day)	3	1,720721

Appendix E: Sensitivity analysis on workload performance with 10 ORs

Table E.1: Sensitivity analysis on workload performance with 10 ORs

Workload performance	10 ORs					
Swap	**85%**	**Cum. Perc. of decrease**	**90%**	**Cum. Perc. of decrease**	**95%**	**Cum. Perc. of decrease**
0	422,29	0,0	412,29	0,0	403,71	0,0
1	336,50	30,0	341,93	26,2	350,36	22,4
2	277,36	50,7	274,00	51,5	270,79	55,9
3	228,21	67,9	229,71	68,0	225,07	75,1
4	191,14	80,8	182,50	85,5	183,93	92,3
5	171,14	87,8	164,93	92,1	174,93	96,1
6	167,36	89,2	154,00	96,1	165,71	100,0
7	164,00	90,3	150,50	97,4		
8	150,64	95,0	143,64	100,0		
9	139,71	98,8				
10	137,79	99,5				
11	136,36	100,0				
Decrease	285,93		268,64		238,00	
% decrease	67,7		65,2		59,0	

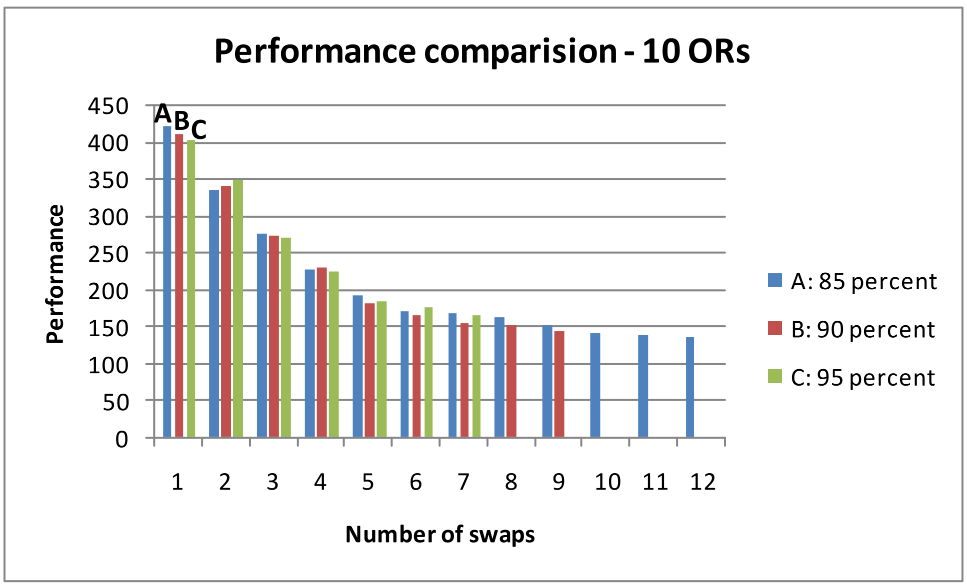

Figure E.1: Sensitivity analysis 10 ORs

Appendix F: Expected values of the input distributions

Table F.1: Expected values of input distributions

General surgery as 3 classes			General surgery as 1 class		
ID	**Specialty**	**E[X] # patients**	**ID**	**Specialty**	**E[X] # patients**
5	Urology 1 OR	2,397351	**5**	Urology 1 OR	2,397351
4	Orthopedic	2,365424	**4**	Orthopedic	2,365424
2	Plastic surgery 1 OR	2,286957	**2**	Plastic surgery 1 OR	2,286957
9	Class 3	2,221277	**6**	Urology shared OR	1,95122
6	Urology shared OR	1,95122	**3**	Plastic surgery shared OR	1,923077
3	Plastic surgery shared OR	1,923077	**7**	1 class	1,844106
8	Class 2	1,808765	**1**	Oral and Maxillofacial surgery	1,516484
7	Class 1	1,552529			
1	Oral and Maxillofacial surgery	1,516484			